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MODELLING AND NUMERICAL OPTIMIZATION METHODS FOR DECISION SUPPORT IN ROBUST EMBODIMENT DESIGN OF PRODUCTS AND PROCESSES

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Modelling and Numerical Optimization Methods for Decision Support in Robust Embodiment Design of Products and Processes

by

Thomas Quirante

In partial fulfilment of the
requirements for the degree of
Doctor of Philosophy

Abstract

In order to converge as soon as possible toward the most preferable design solution, taking robust decisions appears as a topical issue to ensure the best choices in engineering design. In particular, started from a selected concept, embodiment design consists in determining the main dimensioning and monitoring parameters of the system while meeting the design requirements. The continuity of the design process between the preliminary and detailed phases strongly depends on the efficiency of the embodiment design phase in providing embodied solutions with a validated physical behaviour and an optimized functional structure. Embodiment design problems are thus generally turned toward numerical optimization. This requires an accurate modelling of embodiment design problems, and in particular, investigation of large design spaces, representation and evaluation of candidate solutions and a priori formalization of preferences are topical issues.

Research works presented in this thesis deal with the development of methodologies and tools to support decision making during embodiment design of industrial systems and machines. In particular, it aims to provide designers with a convenient way to structure objectives functions for optimization in embodiment design. This approach consists in linking the physical behaviour of the system to be designed, with the design criteria and objectives through the modelling of designer's preferences according to observation, interpretation and aggregation steps. Based on the concept of desirability, this modelling procedure is used to formulate design objectives and to quantify the overall level of satisfaction achieved by candidate solutions. In the scope of robust design, this method is applied first to formulate design objectives related to performances, and then, to formulate design objectives related to the sensitivity of performances. Robust design problems are thus tackled as a trade-off between these two design objectives. Measurement methods for performance dispersion and original trade-off function specific to robust design are proposed.

Finally, an application of the modelling methodology through the embodiment design of a two-staged flash evaporator for must concentration in the wine industry is presented. Objective is to find robust design solutions, i.e. configurations with simultaneously a desirable level of performance, including the quality of the vintage, the transportability of the system and the costs of ownership, and a low sensitivity of some performances, namely the temperature of the outlet product and the final alcoholic strength.

Keywords

Embodiment Design, Robust Design, Desirability, Preferences modelling, Computer-Aided, Decision-making

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Méthode de Modélisation et Optimisation Numérique pour l'Aide à la Décision en Conception Architecturale Robuste des Produits et des Procédés

par

Thomas Quirante

Présentée pour obtenir le titre de
Docteur en Mécanique et Ingénierie

Résumé

Afin de déterminer le plus tôt possible dans le processus de conception, les solutions les plus pertinentes, la prise de décisions robuste apparait comme fondamentale pour garantir les meilleurs choix. A partir de solutions conceptuelles, l'étape de conception architecturale, dite de pré-dimensionnement, vise à déterminer les principales grandeurs dimensionnantes et pilotantes du système à concevoir, tout en satisfaisant l'ensemble des exigences du cahier des charges. La continuité du processus de conception entre les phases préliminaires et détaillées dépend alors de l'efficacité de la phase de conception architecturale à fournir des solutions avec un comportement physique validé et une architecture fonctionnelle optimisée. Les activités de pré-dimensionnement sont donc fortement tournées vers l'optimisation numérique. L'utilisation de ces techniques requiert une modélisation précise du problème de conception architecturale. En particulier, l'exploration de vastes espaces de conception, la représentation et l'évaluation de solutions candidates, ainsi que la formulation a priori des préférences sont des enjeux majeurs.

Les travaux de recherche présentés dans cette thèse concernent le développement de méthodologies et la proposition d'outils pour l'aide à la décision en conception architecturale des produits et des machines. Plus précisément, l'ensemble de ces travaux vise à fournir aux concepteurs une démarche adaptée pour structurer et formuler des fonctions objectifs lorsque l'activité de conception est abordée par l'optimisation. Notre approche consiste à relier par la modélisation de préférences, le comportement physique du système à concevoir avec les critères et les objectifs de conception, selon des étapes d'observation, d'interprétation et d'agrégation. A partir du concept de désirabilité, cette méthode de modélisation est utilisée pour formuler les objectifs de conceptions et pour quantifier le niveau de satisfaction global atteint par les solutions candidates. Cette approche est utilisée pour aborder les problèmes de conception robuste où les objectifs de performance et de sensibilité sont mis en balance. Dans cette perspective, des mesures de dispersion des performances, ainsi qu'une fonction de compromis spécifique au problème de conception robuste en ingénierie, sont proposés.

Enfin, l'application de ces méthodes et outils est illustrée au travers du pré-dimensionnement d'un évaporateur flash bi-étagé, utilisé pour le traitement des moûts dans l'industrie viticole. L'objectif est alors de trouver des solutions de conception robustes, c'est-à-dire, des architectures présentant à la fois un niveau de performance globale satisfaisant, incluant la qualité du produit, la transportabilité de la machine ou les coûts, et une faible sensibilités de la température de sortie du produit, ainsi que de son titre alcoolémique.

Mots clés

Conception architectural, Conception Robuste, Désirabilité, Modélisation des Préférences, Optimisation, Aide à la décision

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"Per los mens païrs, la men sòr, los mens grans païrs qu'ei espiat en lo cèu"
Adishatz

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CHAPTER 1 Introduction

Un problème sans solution est un problème mal posé.

Albert Einstein, Conscience

1.1 Context

1.1.1 Introduction to engineering design

Design is a fundamental human and goal-directed activity. Whatever the field of endeavour, design is directed toward the fulfilment of human needs. All design activities involve creativity (the generation of alternative solutions) and decision (selection among those alternatives). Although it is difficult to give an exhaustive definition, engineering design can be considered as an applied science, using various techniques and scientific principles to determine relevant solutions, and define systems in sufficient detail for their physical realization.

Engineering design differs from other fields of design by the intensive use of techniques and scientific principles, calculation and mathematical analysis. During preliminary design stages, there is generation, analysis, refinement of alternatives, and finally, decision among a set of candidate solutions. Although the generation of concepts and alternatives may remain informal, the intensive use of modelling and calculation formalizes their evaluation. It follows that decision making can be potentially be made formal as well.

Moreover, engineering design also differs from natural sciences as the resulting solution is a compromise satisfying in unequal way the design requirements. Actually, the development of real products or processes rarely involves one objective, but several conflicting objectives which must be traded-off. For example, costs are often traded-off against system effectiveness in system engineering, since highly effective systems are often expensive. Actually, trade studies and negotiations are intrinsic to the design process, involving judgment, perception, and finally, decision.

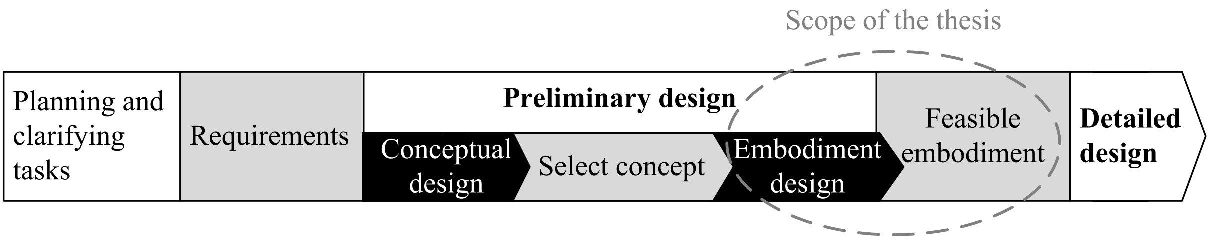

Figure 1. Illustration of the design process

Engineering design as a process can be defined as the transformation of the information from demands, requirements and constraints (functions) into a description of a technical system and a set of instructions for its manufacturing. However, this sequential view of design is not applicable in real life. In fact, designing as a process is iterative. No design problem is simple enough to fit with the mental limitations of short-term human memory. The final design solution which will be manufactured and put on the market is most often an alternative which was not considered at the beginning of the process.

A classical view of design processes consists in an iterative sequence of steps aiming at clarifying the design tasks, conceptualizing, embodying and detailing solutions. This arrangement is represented on figure 1. The clarification of tasks leads to design specification and requirements. Conceptual design produces abstract models of the system to be designed, for the generation of framework and outlines. From conceptual solutions, embodiment design aims to provide preliminary and/or dimensional layouts, components configurations and parameterization of the system. Although there are still disagreements, it can be considered that both conceptual and embodiment stages are involved within the scope of preliminary design activities. The final stage of detailing consists in performing advanced simulations and calculations to provide complete manufacturing information.

The scope of this thesis concerns computer aided design for embodying activities. In particular, we are interested in supporting embodiment design stages of industrial products and machines.

1.1.2 Embodiment design of industrial products

Early stages of design processes are inherently imprecise and are of major economic importance. Preliminary decisions which are often informal and based on imprecise information, can impact up to 70% of the life-cycle costs [Berliner 1987]. Consequently, supporting decision making during preliminary design activities is of main interest to converge as soon as possible toward the most preferred design solutions. In particular, from a selected concept, embodiment design aims at determining the main dimensioning and monitoring parameters of the system in respect with design requirements. While conceptual design aims to discriminate concepts, the purpose of embodiment design consists in the discrimination of physical quantities. Therefore, the continuity of design processes between preliminary and detailed phases mainly depends on the ability of embodiment design phases to provide embodied solutions with validated physical behaviours and optimized functional structures.

From a practical point of view, the existence of embodying steps mainly depends on the type of products to be designed. In general, the design of consumer products or “low-tech” items involves minimal science and knowledge, and low development costs. Consequently, embodiment design is not necessary and conceptual solutions can be directly provided with dimensional layouts. However, the design of industrial products and machines which can perform complex functions, such as gas turbine engines for aircraft propulsion, implies important development costs and risks tend to be critical. Design problems related to these systems are often complex, multidisciplinary and multiobjective. Requirements include extreme demands for improvement of performances, reliability and robustness, ease and flexibility of manufacturing for different production processes. Thus, the phases of generating preliminary design proposals for cost and performance estimating are extensive, and need substantial time and financial expenditures. A careful analysis of requirements by every expert involved in the whole system development is also required to adjust the design specification to the customer's specific needs. Due to progressive increase in the amount of knowledge for the design of systems, changes often occur during designing and manufacturing machinery.

Therefore, the generation of embodied solutions of industrial systems enables to compute first estimates of performances and feasibility. This guides designers toward relevant design alternatives during initial stages of the design process. The integration of complex physical behaviours and objectives in embodiment design improves the efficiency of the whole design process by reducing the number of iterations between preliminary and detailed phases. Embodiment design also limits the intensive use of time consuming computational tools such as CAD or CAE systems. Simulation models involved at this stage of the process are often predictive, parsimonious, but precise enough to carry out the decision-making process.

1.2 Challenges in embodiment design

Embodiment design problems mainly differ from other kinds of design problems by the inherent uncertainty and imprecision related to the prior lack of knowledge about the system to be designed. Consequently, the determination of relevant embodied design solutions cannot rely only on objective knowledge derived from physical or technical laws. Designing is a human activity and embodiment problems necessary require subjective knowledge related to designer's preferences and judgement. At this stage of the design process, most of dimensions and component arrangements remain unknown. In many cases, the main dimensioning and monitoring parameters are determined a priori according to designers' past experience and through "trial and error" approaches. This provides embodiment design problems with many degrees of liberty which tends to complicate the search for optimal embodied solutions.

In particular, embodiment design problems involve high numbers of design variables, each one being related to a range of acceptable values. Therefore, designers have to deal with vast design spaces within which the most preferred solution must be identified. These variables are related to physical units (dimensions, temperature, pressure, etc.), types of materials, alternatives of standard components, but they can also be linked to enumeration or logic values (number of rivets on planes' wings or the presence of air jet impact on warm parts of turbomachinery). Consequently, they can be continuous (interval) and discrete variables (list, table or constructor data). As combinations of design variable values results in different design solutions, the combinatory possibilities are almost limitless, making thus difficult any exhaustive evaluation of the design space.

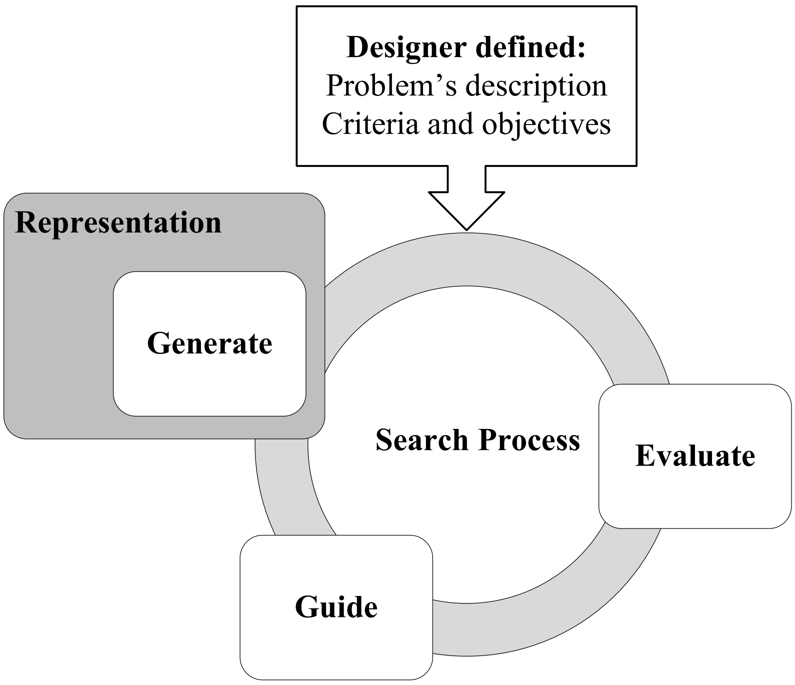

Figure 2. Challenges in engineering design

Evaluation and comparison of design solutions are based on estimates of their ability to satisfy every design requirements. Requirements are based on physical, manufacturing, economical or environmental considerations and are expressed as criteria or objectives.

Design criteria are constraints which are related to performances (satisfaction levels), and thus define feasible domains within the design search space. However, the interpretation of design criteria in the strict mathematical way does not make sense in embodiment design. In such imprecise context, designers can consider as relevant solutions which slightly violate some criteria. Therefore, it is of main interests to be able to rank not only desirable solutions, but also weak satisfactory candidates.

Moreover, embodiment design problems are also characterized by the presence of decision phases involving trade studies between the satisfactions of objectives. Whereas constraints are functional or technical requirements that the system must satisfy, design objectives are specific tasks or goals that the system should meet. Due to antagonist phenomena and coupling effects between variables, these objectives are conflicting and must be traded-off. For example, trades-off between effectiveness and costs are often expected in most industrial problems.

The research works presented in this thesis fall within the scope of methodologies in design engineering aiming at modelling design activities in a formal way to be processed by artificial intelligence systems. In this way, embodiment design problems are turned toward numerical optimization. They consist in investigating a design space to determine the best combination of design variables values, i.e. the solution which simultaneously optimizes every objective and satisfies the set of design criteria. The automation of such a process by optimization techniques requires an accurate modelling of design problems with all their specificities. This is represented on figure 2. The main challenges in modelling such kind of problems deal with:

- How to represent the set of all feasible design solutions?
- How to manage and investigate large design spaces?
- How to generate candidates based on that representation?
- How to evaluate the quality of each candidate?
- How to guide the search for better solutions?

The representation and evaluation of candidate solutions are salient points of this thesis. Due to conflicting objectives, a unique optimal solution is rarely met, but instead, the designer has to cope with a set of equivalent solutions. While the visualization of design solutions has been widely studied in decision-making for problems involving two or three objectives, since 2-D and 3-D graphical means can be used to visualize the solution space, difficulties comes from trading-off hundreds or thousands of design candidates while more than three objectives are considered.

The generation of candidates and guidelines for the search of better solutions concerns numerical techniques used to solve the optimization problem. Research spaces involved by optimization problems in engineering design are discontinuous and present numerous local extrema making difficult the implementation of deterministic methods, such as conjugate gradient, since their efficiency mainly depends on the determination of a started point. Moreover, the accurate determination of the true global optimum has not sense in embodiment design due to the inherent imprecision. This may lead to expensive computational time and waste of resources.

1.3 Contributions and structure of the thesis

The main contribution of this thesis is the development of methodologies and the proposition of tools to support decision making during embodiment design of industrial systems and machines. In particular, it aims to provide designers with a convenient way to structure objectives functions for optimization in embodiment design. The initial multiobjective embodiment design problem is modelled as a mono objective optimization problem using a priori articulation of preferences. The choice of an a priori modelling of preferences enables designers to provide additional information to fully reflect their own preferences and intentions. Moreover, this approach can generate only relevant portions of the whole set of solutions and thus avoids additional efforts.

Although, many design methodologies and methods have been proposed in the literature, the development of a formal approach dedicated to the design of whole systems and machines (involving the management of high number of variables, criteria and complex objectives), is innovative. Designers are neither mathematicians nor programmers, but they know how to design and manufacture machines. One objective of this thesis consists in remaining close to designers' activity and following their reasoning facing design problems. This consists in first observing, then interpreting and finally synthesizing design information to enable the decision making.

Compared to other approaches, in this thesis, embodiment design problem modelling is not only limited to the physical behaviour of the system, but it also includes objectives. This leads to model both physics linked to machine functioning and socio-economic relations related to their environment.

Another contribution of this thesis is the development of an original approach to tackle robust design problems. In this methodology, robustness of system performances and robustness of the choice are both considered. The main idea here consists in formulating two design objectives, one related to the overall performance and another linked to performances sensitivity facing uncertainties, which are then traded-off according to designer's preferences. In this way, a new trade-off function dedicated to robust design problems is proposed. Objective measures of performances dispersion are also proposed.

Facing the lack of a clear framework of desirability in engineering design, a chief contribution of this thesis is the proper definition of desirability and its implications in engineering. In particular, ambiguity between the notions of desirability and utility is intended to be lifted by analyzing their meaning in different research fields.

A further contribution of this thesis concerns the development of metaheuristics, mainly genetic algorithms and particle swarm algorithms [Quirante 2011b], to solve optimization problems in embodiment design. Metaheuristics are iterative optimization algorithms, generally based on stochastic techniques, developed to solve non-trivial optimization problems. Facing specificities of response surfaces in embodiment design problems, the choice of metaheuristics appears as relevant. Although the selection of a particular metaheuristic for a specific class of design problem is not addressed here, recent research works presented by Collignan [Collignan 2012b] deal with such issues.

The structure of this thesis is as follows: Chapter 2 provides a general research context. It depicts a general and suitable framework to situate the research works presented here. Some of the priors work, future challenges and topical issues falling into the scope of this thesis are also described. Fundamental notions and concepts are introduced and defined. Chapter 3 is a review of preference assessments. Two methodologies to express preferences in engineering design, namely the utility theory and the method of imprecision (MoI), are presented and compared. The concept of desirability and desirability functions are then introduced. Benefits of using this approach for embodiment problems are highlighted and discussed. Chapter 4 and chapter 5 concern the modelling methodology proposed in this thesis. Chapter 4 explains how to structure design problems through the formulation of design objectives. In particular, the formulation of objectives related to robust design problems is presented. Chapter 5 deals with the modelling issues related to the trade-off between objectives. Most of concepts used in these chapters have been introduced and defined through chapter 2 and chapter 3. Finally, chapter 6 deals with the embodiment design of a whole machine, namely a two-staged flash evaporator for must concentration in the wine industry. The modelling methodology and some results of this thesis are illustrated through this example. The robustness and the selection of the most preferred design solution is discussed according to different trade-off strategies and scenarios.

CHAPTER 2 State of the Art

The development of methodologies for supporting decision-making in embodiment design is based on several fields of research including design theory, decision theory and optimization. This chapter presents the general framework of our research work. The fundamental notions and concepts covered in this thesis are introduced and defined. Some of the topical issues, priors work and future challenges in engineering design are also presented in this chapter.

2.1 Design Theory and Methodology

2.1.1 Overview of design theories and methodologies

The field of Design Theory and Methodology (DTM) is a rich collection of advances and knowledge resulting from studies and experiments on design processes and activities. Although there is still no consensus on a formal definition of DTM, many design theories and methodologies have been proposed and developed in the past few years. Although all these methodologies and theories have not yet succeeded in covering all the aspects of designing, many observations from individual design cases have led to develop the foundations for rationalizing the design process.

In 1989, Finger and Dixon [Finger 1989a, Finger 1989b] have proposed a classification of DTM into six categories. This classification is represented in table 1. Although the intention of authors was not to be exhaustive, this classification is currently incomplete, since many important theories, such as TRIZ and Quality Function Deployment (QFD) are missing.

DTM categories	Example
1) Descriptive models of design processes	Protocol studies [Ullman 1988], cognitive models [Gero 1985], case studies [Wallace 1987], and so-called German school of design methodologies [Hubka 1989, Pahl 2006]
2) Prescriptive model for design	Canonical design process [Asimow 1962, French 1971], morphological analysis [Pahl 2006] and prescriptive models of the design artefacts, General Design Theory (GDT) [Reich 1995, Tomiyama 1987, Yoshikawa 1981, Yoshikawa 1985] , Suh's Axiomatic Design (AD) and Taguchi Method
3) Computer-based models of design processes	Parametric design, configuration design, AI-based methods for conceptual design [Gero 1985, Sriram 1987, Sriram 1997], distributed agent-based design [Cutkosky 1993]
4) Languages, representation and environment for design	Geometric modelling, shape grammars, behaviour and function modelling [Umeda 1997], feature-based modelling [Dong 1991], product modelling [Krause 1993] integrated design support environment
5) Analysis to support design decisions	Optimization methods [Roy 2008], interfaces for finite element analysis or CAE, decision-making support
6) Design for manufacturing and other life cycle issues such as reliability	Concurrent engineering, DfX, tolerances [Farmer 1986, Tichkiewitch 2007], life cycle engineering [Curran 1996, Hauschild 1998]

Table 1. Classification of DTM adapted from Finger and Dixon [Finger 1989a, Finger 1989b] and completed

Recently, intensive research works have made DTM to evolve toward more abstract and general principles. While the ultimate goal of research in DTM would be to propose a

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universal theory of design (general and abstract), there is still a need in the development of general theories and methodologies for concrete applications. Design methodologies concerns applied design procedures about processes and activities (sometimes denoted as prescriptive theory [Finger 1989a]), and must be distinguished from design methods which deal with the design of a specific class of product such as turbomachines [Gorla 2003] or heat exchangers [Shah 2003]. Design methodologies involve a model of the design process which can be used to develop product specifications. Although there are notable differences between models, in particular in regards to the scope and the use of iterations, they all present similarities in describing a progression through a sequence of logical steps.

In 1997, Tomiyama [Tomiyama 1997] has proposed a classification based on the scope of applicability (concrete/abstract) and level of abstraction (general/individual) of DTM. This classification is given in table 2. Except for abstract design theories, most of these DTM are either a generalisation of design methods, and thus, can be applicable to a wide range of products, or computational methods which are applicable only to a specific class of products. An overview of these DTM is presented by Tomiyama [Tomiyama 2006].

	General	**Individual**
Abstract	*Design theory* Abstract Design Theory (ADT) [Kakuda 2001], General Design Theory (GDT) [Yoshikawa 1981, Yoshikawa 1985], Universal Design Theory (UDT) [Grabowski 1998, Grabowski 2000]	*Math-based methods* Axiomatic Design, Optimization, Taguchi method [Taguchi 2004], Computer programs
Concrete	*Design methodology* Adaptable Design [Gu 2004], Characteristics-Properties Modelling (CPM) [Weber 2005, Weber 2007, Weber 2008], Contact and Channel Model (C&CM) [Albers 2003], Design Structure Matrix (DSM) [Browning 2001], Emergent Synthesis [Ueda 2001, Ueda 2007], Hansen [Hansen 1974], Hubka and Eder [Hubka 1989, Hubka 1996], Integrated Product Development [Andreasen 1987, Andreasen 1994], Pahl and Beitz [Pahl 2006], TRIZ [Altshuller 1984, Altshuller 1999], Ullman [Ullman 2002], Ulrich and Eppinger [Ulrich 1999] *Methodology to achieve concrete goals* Axiomatic Design (AD) [Suh 1990, Suh 2001], Design for X (DfX) [Huang 1996], Design Decision-Making Methods [Lewis 2006], Failure mode and Effects Analysis (FMEA) [Beauregard 1996], Quality Function Deployment (QFD) [Mizuno 1993], Total Design of Pugh [Pugh 1991] *Process methodologies* Concurrent Engineering [Sohlenius 1992], DSM	*Design methods*

Table 2. Classification of DTM adapted from Tomiyama [Tomiyama 1997]

However, as discussed in [Finger 1989a, Finger 1989b, Horváth 2004], design research cannot be limited to DTM. Many other practices and techniques are used in industry, such as the so-called Toyota product development method [Sobek 1999, Morgan 2006]. In multidisciplinary product development, V-models of systems engineering is a widespread development approach used in many industrial areas [VDI 2004]. For example, in mechatronics systems, mechanical engineering, electronics, control engineering and softer engineering are both integrated to achieve superior functions. Therefore, the concurrent execution of the different domains, and the simultaneous resolution of conflicts among them become a topical issue.

Furthermore, computational techniques and Information Communication Technology (ICT) have changed the way in which product development is addressed. Current product development often requires technical information systems, such as Computer-Aided Design (CAD), Computer-Aided Engineering (CAE), and Product Data Management (PDM). During production and further life cycle phases, it is also suitable to use digital engineering systems [Bernard 2005, Bernard 2007] such as Computer Aided Manufacturing (CAM), Enterprise Resource Planning (ERP), Custom Relation Management (CRM), and Product Life Cycle (PLM). Function modelling and knowledge management [Tichkiewitch 2007] are also topical issues in design methodologies.

2.1.2 General Design Theory framework

General Design Theory (GDT) is a theory of design knowledge developed by Yoshikawa [Yoshikawa 1981, Yoshikawa 1985, Tomiyama 1987, Reich 1995] which has inspired lots of researchers, and has resulted for example, in Kakuda's ABT and Grabowski's UDT. GDT is mainly based on Suh's axiomatic set theory [Suh 1990] in which *design* is defined as:

"... the creation of a synthesized solution in the form of product, processes or systems that satisfy perceived needs though mapping between the functional requirements (FRs) in the functional domain and the design parameters (DPs) of the physical domain, though proper selection of the DPs that satisfy the FRs."

GDT's major achievement is to propose a mathematical formulation of design processes. GDT deals with concepts that only exist in our mental recognition and tries to explain how design is conceptually performed with knowledge manipulation based on axiomatic set theory. In this sense GDT is not a design theory but an abstract theory about (design) knowledge and its operation as well. It is based on the statement that our reasoning and knowledge can be mathematically formalized and operated. Three axioms define knowledge as a topology, and reasoning as a set of mathematical operations. Products to be designed perform functions through a set of attributes (properties). The design process is then regarded as a mapping from the function space to the attribute space. Figure 3 illustrates the design process in the GDT's framework.

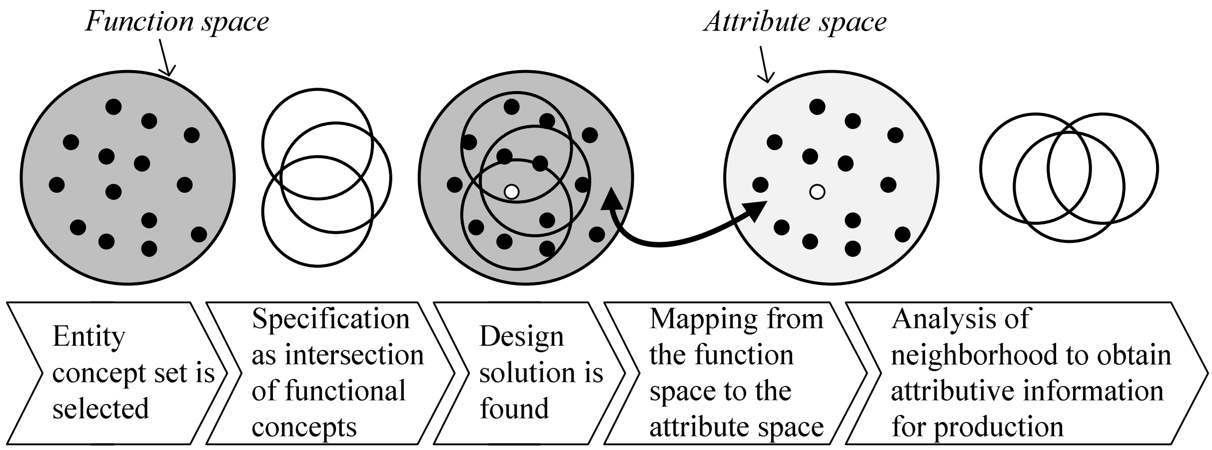


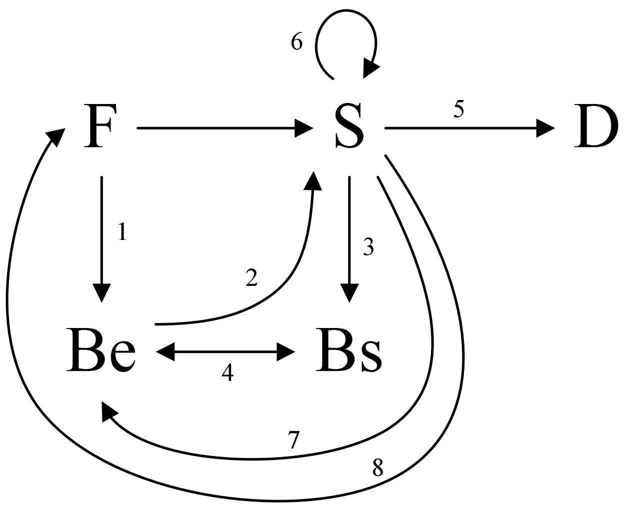
Figure 3. Design process in ideal knowledge [Tomiyama 2009]

According to this representation, Tomiyama [Tomiyama 2006] has proposed a rational classification of DTM into three major categories: DTM to generate a new design solution, DTM to enrich functional and attributive information of design solutions and DTM to manage design and to represent design knowledge [Tomiyama 2009]. Embodiment design falls into the second category. Once one conceptual solution has been selected in respect of functional requirements, analysis of neighbour solutions is required to look for an optimal solution (improvement of the overall satisfaction), not only within the attribute space, but also in the functional space. This leads to the improvement of the performance and the generation of additional information for the physical realization of the product.

2.1.3 John Gero's Function-Behaviour-Structure ontology

From the GDT framework, descriptive models of design processes have been derived in the past few years. In particular, John Gero [Gero 1990a, Gero 1990b] has proposed his Function-Behaviour-Structure (FBS) ontological model of designing. John Gero's FBS ontology extends GDT by covering the notion of interactions between designer (design agent) and its environment through actions such as observation and interpretation. Fundamental relations between physical structure of a product, functions and expected behaviour are established. Consequently, most of design processes can be modelled within the FBS framework, in particular optimization processes.

The basis of Gero's FBS ontology is made of three classes of variables describing different aspects of a design object (also called artefact): Function (F) variables, Behaviour (B) variables and Structure variables (S). According to Gero, designers establish connections between functions, behaviour and structure through experience. In particular, designers link function to behaviour and derive behaviour from structure. However, a direct connection between function and structure is not established.



Be = expected behviour
Bs = beaviour derived from structure
D = Design description
F = Function
S = Structure

→ = transformation
↔ = comparison

Figure 4. John Gero's FBS framework [Gero 2004]

The FBS framework represents the design process as a set of elementary design steps in which function, behaviour and structure are linked together. Figure 4 shows the FBS framework as described in [Gero 2004]. Eight elementary steps common to every designing activity are considered. Five of them are sequential and transform the expressed functions into design description. The first step is called *formulation step* (1) and transforms the design problem expressed as functions (F), into behaviour (Be) which is expected to perform these functions. Secondly, the expected behaviour is transformed by a *synthesis step* (2) into a solution structure (S) intending to achieve the desired behaviour (Be). In a third step, the actual behaviour (Bs) is derived from the *analysis* (3) of the synthesis structure (S). Fourthly, this actual behaviour (Bs) is *evaluated* (4) and compared with the desired behaviour (Be). If the evaluation is satisfactory, a design description *D* is *documented* (5) for manufacturing the product. Otherwise designers have to go back to previous steps in the sequence. This defines three elementary loop-back steps, turning designing into an iterative procedure [Gero 2004]. Reformulation steps (6, 7, 8) address changes in the design state space in terms of structure variables (S'), behaviour variables (Be'), function variables (F') and ranges of values.

Gero's FBS ontology presents a fundamental difference with other approaches of designing within the notion of *Situatedness* [Gero 2004]. According to Gero, designing is an activity in which designers perform actions to interact and change the environment, by carrying out observation and interpretation on the results of their actions. This also covers the notion of constructive memory, since designers' concepts may change according to their own past experience and the phenomena they observe.

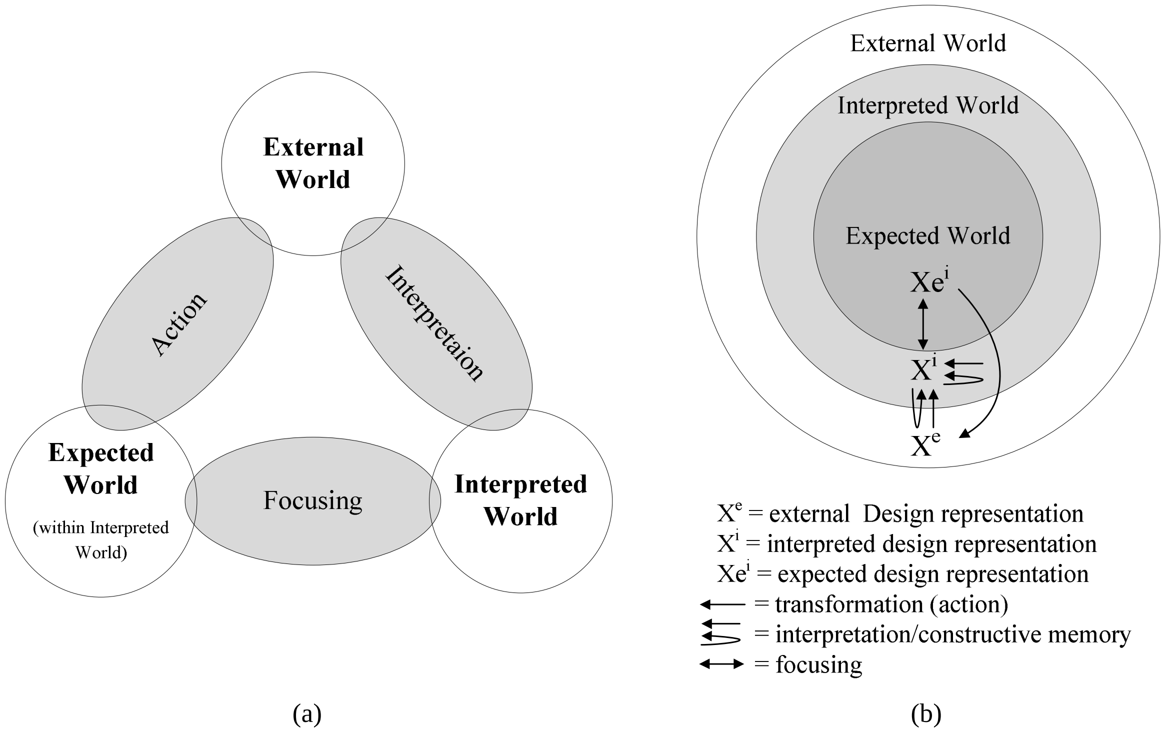


Figure 5. Situatedness as the interaction of three worlds [Gero 2004]: (a) general model, (b) specialized model for design representation

The model of *Situatedness* proposed by Gero and Kannengiesser [Gero 2004], represented in figure 5a, is based on the interaction of three different worlds (including the designer's internal and external world). In this model, designer's internal world is subdivided into an interpreted world and an expected world. These two worlds are linked by a process of concept definition in the interpreted world, and using them as goals (design objectives) located in the expected world. Goals are used to inform actions changing the external world.

The notion of interaction appears as fundamental in the framework proposed by Gero. According to situatedness, changes can impact every entity involved in one particular interaction. Another important aspect linked to situatedness is the notion of interpretation, which is regarded as being more than a simple flow of information; it is a kind of designer's action coming from both external and internal environment, and resulting in changes in the internal world.

From the general model of Situatedness, it is derived a specialized model for design representation purpose (see figure 5b) [Gero 2004]. According to this model, designers are situated within the external world and the different design representations belong to the other layers of the model. The design space (i.e. the space of all possible design solutions that satisfy the set of requirements) corresponds to the set of expected design representation (Xe^i). The explicit integration of an expected world into a model of interaction accounts for situated designing, as changes in the internal and external world provides the basis for further changes of the current design process via reformulations of the design space.

In 2006, from its original FBS framework and situatedness model, Gero has proposed a framework for situated design optimization [Gero 2006]. The three fundamental processes in optimization are identified. They refer to *synthesis*, *analysis* and *evaluation*. This framework involves changes in all relevant aspects of situated optimization such as changes in design space, changes in designer's experience and changes in external design representation.

2.2 Optimization techniques in engineering design

2.2.1 Introduction

Designing is a goal-directed activity. Whatever the field of application, a product is designed to satisfy human needs. To improve customer satisfaction, designers try to determine the solution which satisfies every requirement in the best way. This process refers to optimization. However, the terms *optimization* and *optimum* are often used in very loose senses without necessarily referring to the use of specific optimization techniques. For example, in engineering design, optimization often refers to "trial and error" approaches, i.e. iterative processes where the final solution is improved step-by-step. These approaches are often manual and time consuming. Moreover, optimal solutions are rarely achieved since such approaches do not allow a global exploration of the design research space.

In a highly competitive and technology-driven industry, it is necessary to develop suitable methods to automate engineering design optimization and design systems which satisfy human needs in the most effective manner. This has motivated many research works in design optimization for the purpose of developing efficient techniques for engineering problems [Ray 1995, Sobieszczanski 1997, Dornberger 2000, Murawski 2000, Costa 2008, Schiffmann 2010].

2.2.2 Design evaluation model

Design optimization problems require the formulation of a design (evaluation) model to evaluate candidate solutions. This model depends on the design stage, and thus, differs from preliminary design to detailed design. The complexity and efforts provided to solve design problems depend on the nature of the relations and variables involved in the design evaluation model. As a general rule, a design evaluation model requires the definition of design variables ($\mathbf{x}$) and their domain of values (Ω), performance variables ($\mathbf{y}$), objectives ($\mathbf{f}$), design criteria and design parameters (constants). Then, the simulation model of the physical behaviour of the system links the independent and dependent variables. Thus, a design solution is defined from a set of design variables and is evaluated according to its ability in satisfying every design criterion and objective. Depending on authors, the decomposition into design performances and objectives seems not to be systematic. Sometimes the expression of design performances is implicit to the criteria formulation, such as there is a mapping between the design space (domain of design variables) and the objective space (domain of design objectives).

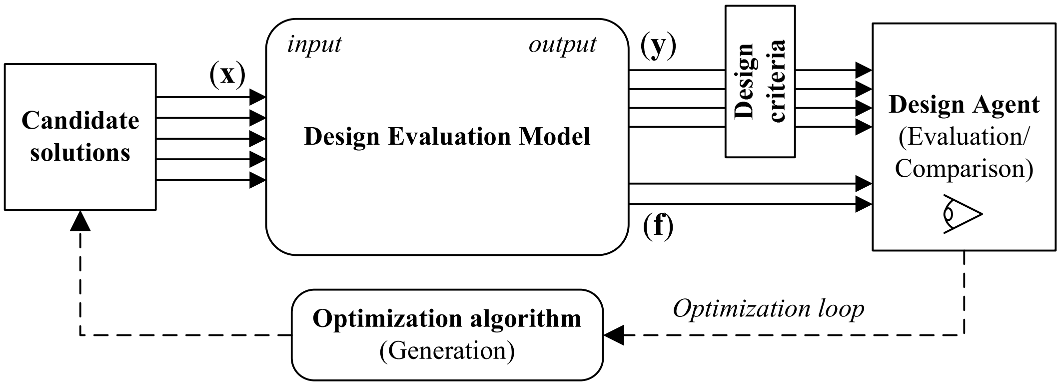


Figure 6. Design evaluation model represented as “black-box” system

Classically in optimization, one or several objective functions are expected to be minimized, or maximized, subjected to a set of constraints. In general, the design evaluation model corresponds to the objective function(s). According to automatics, the design evaluation model can be regarded as a “black-box” system in which physical models are encapsulated in such a way that designers can only control inputs (design variables) and observe outputs (performance measurement or objectives). A “black-box” representation of the design evaluation model is given by figure 6. According to this figure, design criteria can be regarded as filter acting on the performance measurements, discriminating feasible from unfeasible solutions. This process serves as basis for the evaluation process.

2.2.3 Classification of engineering design optimization problems

In 2008, Roy [Roy 2008] has proposed a classification of engineering design optimization problems into five categories and two points of view. While categories refer to design variables, constraints, objective functions, problem domains, and environment of the design, the two points of view concern the design evaluation complexity and the degrees of freedom of the design problem. According to Roy, the number of design variables, their nature (static or dynamic) and admissible values (integer, continuous or mixed) and dependence among design variables deeply impact the overall complexity of the optimization problem. Here, complexity is defined as the amount of effort required to formulate the optimization problem and identify the optimal solution(s).

Moreover, the presence of constraints impacts the optimization techniques used to solve the design problem [Coello 2002a]. Constraints can be linear or non-linear, expressed in equality or inequality forms and are separable or not. Number of constraints and constraints modelling directly affects computational times of optimization processes. Recent advances in constraint programming techniques (programming paradigm in which relations between variables are stated in the form of constraints) results in promising perspectives to deal with multicriteria optimization problems [Rossi 2006].

As previously mentioned, objective functions are used in optimization to evaluate design solutions. Quantitative objective functions are related to simulation-based (FEA, CFD), analytical (linear or non-linear mathematical model) and empirical techniques, whereas qualitative objective functions concerns issues like manufacturability or aesthetics. Number of objective functions, their (non-linear, continuous or discontinuous) nature and dependency also impacts the complexity of the optimization problem. In particular, Corne [Corne 2007] considers that the complexity of multiobjective optimization problems strongly increases from the minimum of ten objectives (large scale multiobjective problems). One of the major challenges in engineering design optimization is to deal with computationally expensive objective functions. Moreover, the existence of numerous local optimums often makes difficult the determination of the global optimum.

Engineering design optimization approaches	**Examples**
Expert-based optimization	Knowledge based, Simulation based
Design of Experiment based optimization	Taguchi's approach, Experiment arrays based methods
Algorithmic optimization	
Dealing with increasing complexity of design problems	Constrained (Lagrange-multiplier, gradient projection, generalized gradient projection, feasible direction, evolutionary algorithm, genetic algorithm, direct search method, leap-frog method and penalty function, linearised search method, simulated annealing, swarm intelligence, ant colony algorithm, co-evolutionary approach); Multiobjective (evolutionary algorithm, genetic algorithm, goal programming, fuzzy set theory, heuristic, immunity based, swarm intelligence, Tabu search); Multi-modal (Evolutionary algorithm, immunity based, random search algorithm, simulated annealing, swarm intelligence); Multi-disciplinary
Dealing with real life design requirements	Reliability-based (discrete optimization technique, evolutionary algorithm, inverse reliability strategy, analysis of variance) Robust (Mathematical programming, Monte-Carlo simulations based, analysis of variance , deterministic approach, evolutionary algorithm) Uncertain environment (evolutionary algorithm, sequential approximate optimization, deterministic algorithm, method of imprecision)
Increasing designer confidence	Interactive (Mathematical programming, evolutionary algorithm, fuzzy set theory) Qualitative (evolutionary algorithm, evidence theory)
Hybrid, Other	

Table 3. Engineering design optimization approaches: current trends and challenges (adapted from [Roy 2008])

The two last categories identified by Roy concern the problem domains and optimization environment. While the problem domain is related to the physics of the problem and multi-disciplinary approaches used to solve it (mechanics, thermofluids, electromagnetic), optimization environment concern uncertainties (robust and reliability-based approaches) [Wood 1989, Beyer 2007, Schueller 2008], existing knowledge about the problem (imprecision, incomplete data) [Wood 1989, Antonsson 1995], levels of confidence (qualitative or interactive evaluation) [Collignan 2012a, Collignan 2012b] and nature of the environment (static or dynamic).

In [Roy 2008], another classification based on current trends and challenges in design optimization techniques (Expert-based optimization, Design of Experiment based optimization, Algorithmic optimization) is proposed. This classification is presented in table 3. According to this table, it appears that the automation of engineering design optimization process has motivated the development of a vast range of algorithms in the past few years.

2.2.4 Challenges in engineering design optimization

Facing real application problems, major design challenges in engineering design optimization arise in the past few years. In [Roy 2008], Roy highlights that these challenges concern:

- Global exploration of design spaces
- Identification of robust solution areas

- Identification of the largest set of satisfying solutions
- Interactions and coupling effects between design variables
- Analysis, modelling and propagation of uncertainties
- Reduction of computational costs of the evaluation models
- Modelling of human knowledge and preference
- CAD systems interfacing feature-based parametric CAD models and optimization models

This thesis tackles some of these issues. In particular, we propose techniques to investigate large design spaces and determine relevant robust design solutions. Difficulties in investigating design spaces of real design engineering problems arise from the presence of multiple mixed design variables, nonlinear constraints, discontinuities and pitfalls. Thus, as these design models are often non-differentiable, classical optimization techniques based on gradient and hessian matrices computation cannot be implemented. Moreover, the global optimum should also be robust, i.e. it is desirable that optimal solution presents a low sensitivity to uncertainties [Beyer 2007, Arvidsson 2008]. A design is thus said robust if it maintains the same level of performance facing with design variable variations. Global optimum, local optimum and robust optimum are represented on figure 7a.

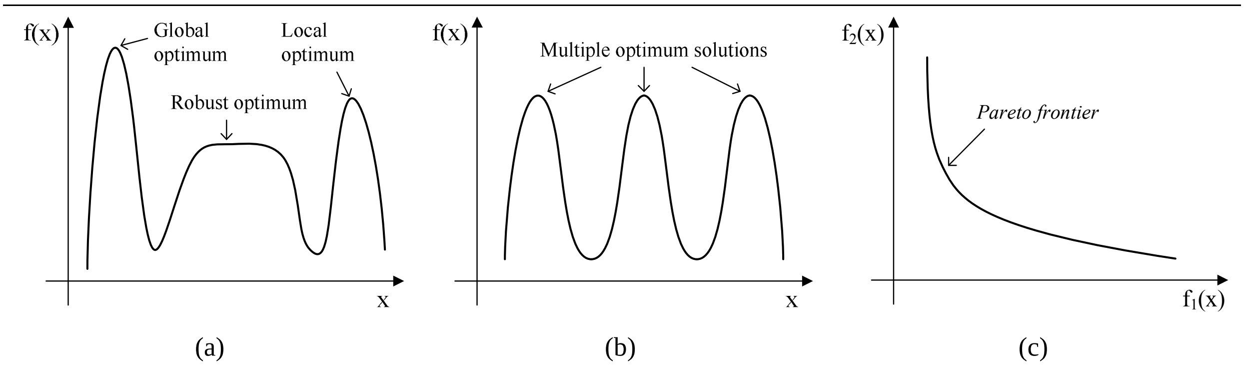


Figure 7. Representation of optimal solutions in design engineering optimization from [Roy 2008]: (a) global, local and robust optimal solutions, (b) multi-modal optimization problem, (c) Pareto frontier in multiobjective optimization problem

The search for robust solutions has led to analyze and model uncertainties due to manufacturing dispersions, environmental parameters variations and error modelling. These uncertainties can be aleatory or epistemic by nature [Oberkampf 2004]. In the past few years, many approaches have been developed to deal with uncertainty such as robust design methodology (RDM) [Messac 2002a], utility function optimization [Chen 1999] and reliability-based design optimization (RBDO) [Samson 2009b]. Major challenges linked to uncertainty in design engineering concern the reduction of computational costs and the establishment of a mathematical criterion to identify deep "valleys" [Shan 2008, Samson 2009a].

Furthermore, many design problems involve more than one admissible solution (multi-modal optimization) as shown on figure 7b. In multiobjective optimization, this refers to the identification of Pareto optimal solutions (for details see section 2.3.2). Pareto frontier has been represented on figure 7c. The definition of Pareto optimal solutions enables to filter the whole set of feasible solutions and thus to reduce the set of candidates. As real engineering design problems often involve multiple conflicting objectives which must be traded-off, the expression of designer's preferences is required to select the final solution. Thus, the formulation of expert knowledge and preferences in a formal way to be used by artificial systems [Oduguwa 2007] create major challenges in engineering design and partly explains why optimization techniques have difficulties to be applied in industry. The next section further details multiobjective optimization problems and presents some insights and issues linked to their implications in design engineering.

2.3 Multiobjective optimization methods for engineering design problems

2.3.1 Introduction

Initially, multiobjective optimization (MO) techniques have been developed within the fields of economic *equilibrium and welfare theories*, game theory [Vincent 1983], and mathematics [Stadler 1988]. These techniques intend to accurately model the decision-makers' preferences, for ranking or filtering alternatives. For this reason, many terms and concepts such as *preference*, *utility* and *trade-off*, are derived from economics and decision-making theory [Lewis 2006]. However, the terminology must be adapted according to the domain of study. For example, in engineering applications, the so-called decision-maker may be identified as the designer or teams of persons belonging to design departments. In the same way, design variables in engineering design are denoted as *decision variables* in decisions theories.

Fundamental basis of MO are presented by Coello [Coello 2002a, Coello 2002b] and Miettinen [Miettinen 1999]. The general MO problem is usually expressed as:

$$\begin{aligned}
&\text{minimize } \mathbf{f}(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x}) \right]^T \\
&\text{subject to:} \\
&\quad g_i(\mathbf{x}) \geq 0 \quad i = 1,2,\ldots,m \\
&\quad h_j(\mathbf{x}) = 0 \quad j = 1,2,\ldots,p
\end{aligned} \tag{2.3.1.1}$$

where **x** is a vector of *n* decision variables. The vectorial function **f**(**x**) is composed by the *k* objective functions (also denoted as *criteria*, *payoff* or *costs* functions) to be jointly minimized. The functions g_i and h_i refer respectively to the *m* inequality and *p* equality constraints to be satisfied. In this thesis, the design search space (**Ω**) is defined as the union of the design variables domain of value as:

$$\Omega = \bigcup_{i=1}^{n} \left[x_i^-, x_i^+ \right], \quad x_i^- \leq x_i \leq x_i^+ \tag{2.3.1.2}$$

Figure 8 illustrates the mapping between the design space and the objective space, for a bi-objective maximization problem, with two design variables and two design criteria. Design constraints shear the design space in two distinct domains. The feasible design/decision space (**X**) is defined as the set of solutions which satisfy the set of constraints (**g**):

$$\mathbf{X} = \{ \mathbf{x} \mid \mathbf{x} \in \Omega, g(\mathbf{x}) \geq 0 \} \tag{2.3.1.3}$$

Inversely, the unfeasible domain represents the set of solutions which do not verify at least one of the constraints. Then, the feasible *criterion space* **Z** (also called *attainable set*) is defined as the set:

$$\mathbf{Z} = \{ f(\mathbf{x}) \mid \mathbf{x} \in \mathbf{X} \} \tag{2.3.1.4}$$

The terms *feasible criterion* and *attainable set* are both used in the literature to describe the objective space. However, feasibility implies that no constraint is violated, whereas attainability means that a point in the criterion space maps to a point in the design space.

While every point in the design space maps to a single point in the criteria space, the opposite can be false, and thus, every point in the criteria space is not necessary attained.

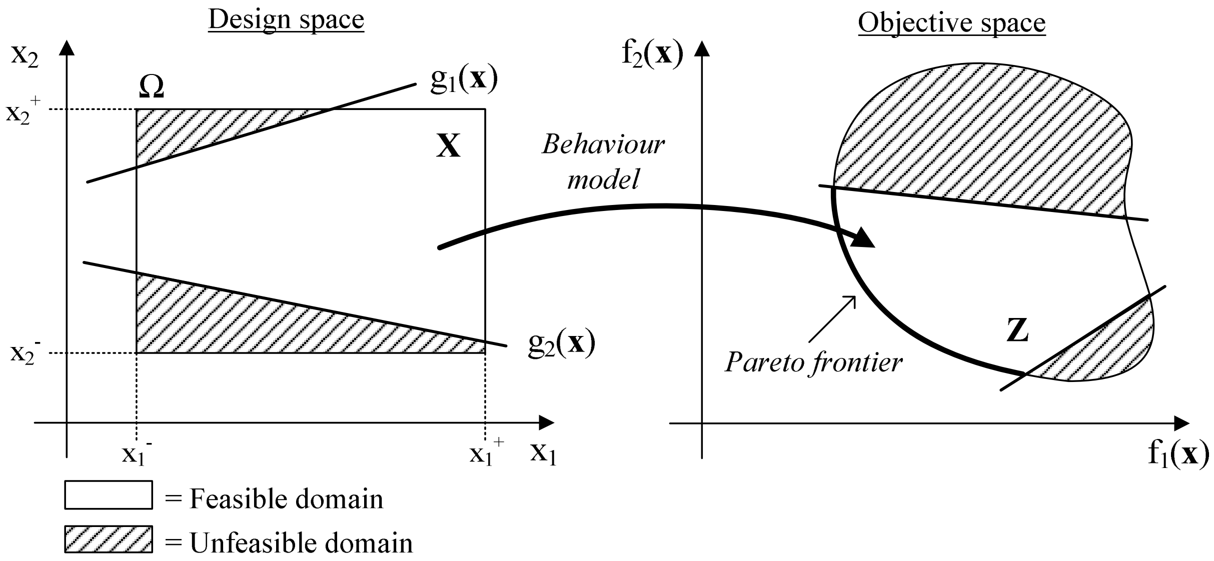


Figure 8. Mapping between design space and objectives space for a bi-objective minimization problem with two design variables (**x**) and two design criteria (**g**)

The mapping relation between the design research space and the objective space is represented on figure 8. Within the feasible design space, there is a particular sub-set of solutions denoted as Pareto frontier or non-dominated set, which is often expected in design optimization. The determination of the Pareto frontier is particularly relevant in engineering since it represents the set of solutions such as there are no others solutions which are better simultaneously on every objective. The notion of Pareto optimality and domination, defined in the next section, are fundamental for solving MO problems.

2.3.2 Pareto optimality and relations of domination

Principles of MO are different from classical mono-objective approaches. While mono-objective optimization consists in determining the global optimum, i.e. the solution which minimizes (or maximizes) a single objective function, MO problems deals with the determination of a set of equivalent solutions which must be traded-off. Consequently, the classical concept of *optimum* is no longer appropriate, and the concept of *Pareto optimality* (or *efficiency*) is used instead.

Definition: 1) For minimization problems, a solution point $\mathbf{x}^* \in \mathbf{X}$ is Pareto optimal if there is no other point $\mathbf{x} \in \mathbf{X}$ such that $\mathbf{f}(\mathbf{x}) \leq \mathbf{f}(\mathbf{x}^*)$, and $f_i(\mathbf{x}) < f_i(\mathbf{x}^*)$ for at least one objective function. The set of all Pareto optimal solutions defines the so-called Pareto frontier.

2) For maximization problems, a solution point $\mathbf{x}^* \in \mathbf{X}$ is Pareto optimal if there is no other point $\mathbf{x} \in \mathbf{X}$ such that $\mathbf{f}(\mathbf{x}) \geq \mathbf{f}(\mathbf{x}^*)$, and $f_i(\mathbf{x}) > f_i(\mathbf{x}^*)$ for at least one objective function. The set of all Pareto optimal solutions defines the so-called Pareto frontier.

All Pareto optimal points lie within the feasible criterion space **Z** [Athan 1996]. Some methods for determining Pareto optimality are described in [Miettinen 1999]. Although Pareto optimal solutions are often relevant in engineering design, Pareto optimality is not systematically expected. In fact, many algorithms provide solutions satisfying other criteria and making them relevant for practical applications. From these considerations, it is derived the concept of weak Pareto optimality.

Definition: 1) For minimization problems, a solution point $\mathbf{x}^* \in \mathbf{X}$ is weakly Pareto optimal if there is no other point $\mathbf{x} \in \mathbf{X}$ such as $\mathbf{f}(\mathbf{x}) < \mathbf{f}(\mathbf{x}^*)$.

2) For maximization problems, a solution point $\mathbf{x}^* \in \mathbf{X}$ is weakly Pareto optimal if there is no other point $\mathbf{x} \in \mathbf{X}$ such as $\mathbf{f}(\mathbf{x}) > \mathbf{f}(\mathbf{x}^*)$.

A solution is weakly Pareto optimal if there is no other solution which improves all objectives of the objective functions simultaneously. In contrast, a solution is Pareto optimal if there is no other point improving at least one objective function. The notion of proper Pareto optimality had also been introduced [Geoffrion 1968, Miettinen 1999] as a trade-off expressed by the ratio between the increment in one objective function and the resulting decrement in another objective function.

Whatever the MO problem, the resulting Pareto optimal set can involve an infinite number of relevant solutions. Therefore, MO techniques and methods must be distinguished according to they provide the whole Pareto set, some parts (filtering), or a single solution point.

In [Steuer 1999], the Pareto optimality criterion is introduced using the notion of domination. While Pareto optimality concerns a vector of design variables in the design space, relations of domination between solutions refers to a functional vector in the criteria space.

Definition: 1) For minimization problems, a vector of objective functions $\mathbf{f}(\mathbf{x}^*) \in \mathbf{Z}$ is non-dominated if there is no other vector $\mathbf{f}(\mathbf{x}) \in \mathbf{Z}$ such as $\mathbf{f}(\mathbf{x}) \leq \mathbf{f}(\mathbf{x}^*)$, with at least one.

2) For maximization problems, a vector of objective functions $\mathbf{f}(\mathbf{x}^*) \in \mathbf{Z}$ is non-dominated if there is no other vector $\mathbf{f}(\mathbf{x}) \in \mathbf{Z}$ such as $\mathbf{f}(\mathbf{x}) \geq \mathbf{f}(\mathbf{x}^*)$, with at least one.

Let us consider the two solutions B and C represented on figure 9. These solutions are such as that $f_2(C) > f_2(B)$ and $f_1(C) > f_1(B)$. Therefore, B dominates C, and C is dominated by B. According to the domination criterion, B is preferred to C, which is noted $B \succ C$. Let us consider now, solutions A and B which are two non-dominated solutions and belongs to the non-dominated set. Consequently, it is impossible to operate a rational choice between these two solutions. They are regarded as equivalent or equally preferred. In this case, we note this equivalence as $A \sim B$. The domination in the whole set of candidate solutions results in the definition of the Pareto frontier and multiple sub-Pareto fronts, which is equivalent to rank solutions. Many MO techniques, such as the non-dominated sorting genetic algorithm NGSAII [Deb 2002], are based on the principle of domination to generate the Pareto frontier in the best way.

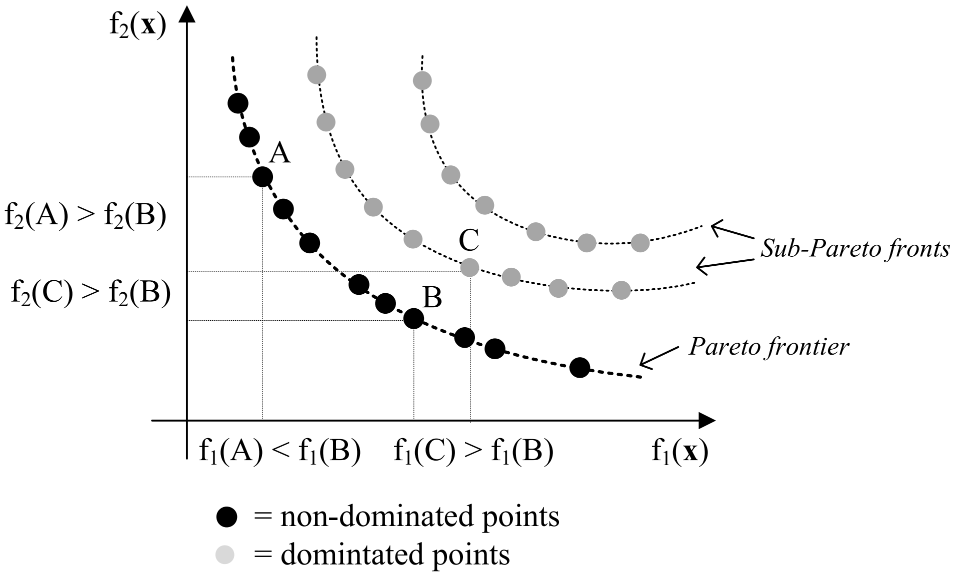


Figure 9. Pareto frontier and relations of domination for a bi-objective minimization problem

A survey of necessary and sufficient conditions for objective functions to generate Pareto optimal solutions can be found in [Miettinen 1999]. On the one side, objective functions based on a necessary condition formulation of Pareto optimality, imply that every Pareto optimal solution is attainable, performing some adjustments on the function parameters (weights, exponents, etc). If a point is attainable using a particular objective function, then this point is said to be *capturable* by the function [Messac 2000a, Messac 2000b]. However, this formulation may provide solutions which are not Pareto optimal. On the other side, objective functions based on a sufficient condition formulation of Pareto optimality, ensure that every captured solution is Pareto optimal, although it is noticeable that certain Pareto optimal points are unattainable.

2.3.3 Convex and non-convex set of points

The convexity property of the Pareto set is of main interest for designer and their practical applications. In general, solutions located in the concave parts of the Pareto frontier are of low interest for designers. In fact, the compromise represented by these solutions, i.e. the increment of one objective compared to the decrement of another one, can be improved by considering solutions located in the convex parts.

Formally, a convex Pareto set (S) implies that for every point A and B taken in S, the segment [AB] completely lies within the boundaries of S.

Definition: A set of points S is said convex iff $\forall A, B \in S, \forall \lambda \in [0,1], \quad \lambda A + (1-\lambda) B \in S$

Figure 10 represents a non-convex Pareto set for a bi-objective minimization problem. Points A and C are located on the convex parts of the Pareto frontier, whereas point B lies on a concave part. The dashed line between solutions A and C represents the convex hull of the Pareto set. We define the gain and the loss on one objective respectively as the decrement and the increment of this objective. To illustrate the relevancy of convex Pareto solutions, suppose that point A represents a solution of reference, and that solutions B and C are alternative choices. The trade-off represented by the selection of B or C is expressed by the ratio “gain/loss” defined as:

$$\mathrm{T}(\mathrm{B}) = \frac{f_2(\mathrm{A}) - f_2(\mathrm{B})}{f_1(\mathrm{A}) - f_1(\mathrm{B})}$$
$$\mathrm{T}(\mathrm{C}) = \frac{f_2(\mathrm{A}) - f_2(\mathrm{C})}{f_1(\mathrm{A}) - f_1(\mathrm{C})} \tag{2.3.3}$$

According to figure 10, it is obvious that T(C)>T(B), since the selection of B implies an important loss on objective f_1 for a small gain on objective f_2, whereas the selection of C implies equivalent levels of gain and loss on the two objectives. Therefore, solution C is regarded as a better alternative to solution A than solution B.

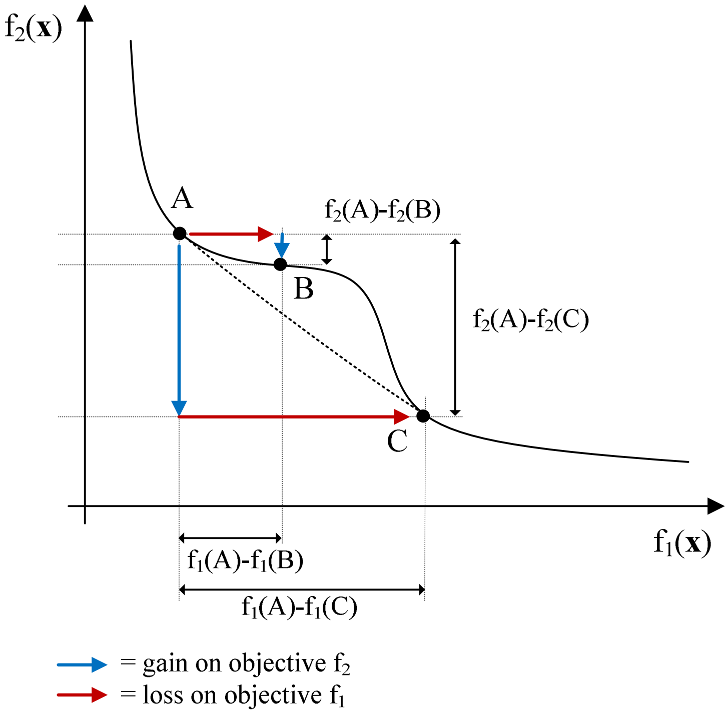


Figure 10. Non-convex Pareto frontier for a bi-objective minimization problem

2.3.4 Ability of objective functions to generate Pareto optimal solutions

In engineering design, the notion of Pareto optimality is used to support the selection of the most preferred design alternatives by filtering the whole set of solutions. As every Pareto point is potentially of interest for the designer, each point should be capturable by the objective function. But, as previously explained, certain portions of the Pareto frontier are of low interest for designers. For example, non-convex parts usually correspond to areas of unattractive trades-off. Therefore, challenges for the selection of suitable objective functions in MO are mainly concerned with modelling designers' intentions. In particular, mathematical behaviour of functions must reflect designer's preferences in the best way.

In this thesis, we are mainly interested in the formulation of preferences within the objective functions, and thus, we focus on aggregated objective functions (AOF). For scalarization methods (or global criterion approach), Sadler has proposed that the minimization of the global objective function (i.e. the AOF) is a sufficient condition for Pareto optimality if the global objective function increases monotonically in respect to each aggregated objective function [Stadler 1988]. This implies that the Hessian of the objective function in respect to aggregated objective functions must be negative definite [Athan 1996].

Moreover, for every Pareto optimal point, there is an AOF satisfying the previous requirements and captures each point of the front [Messac 2000a].

In [Messac 2000b], Messac tackles the issue related to the ability of AOF to generate points lying on non-convex parts of Pareto frontiers. He distinguishes locally capturable points, which correspond to local minima of a given AOF specified with a particular parameterization, from globally capturable points which are global minima. Messac provides a sufficient and necessary condition that must be verify by AOF for local capturability of points lying on non-convex Pareto frontier. In particular, he shows that a solution is locally capturable by weighted sum AOF if this solution lies on convex parts of Pareto frontiers. Although globally capturable points are locally capturable too, the reverse is not true, and locally capturable points are not necessary globally capturable.

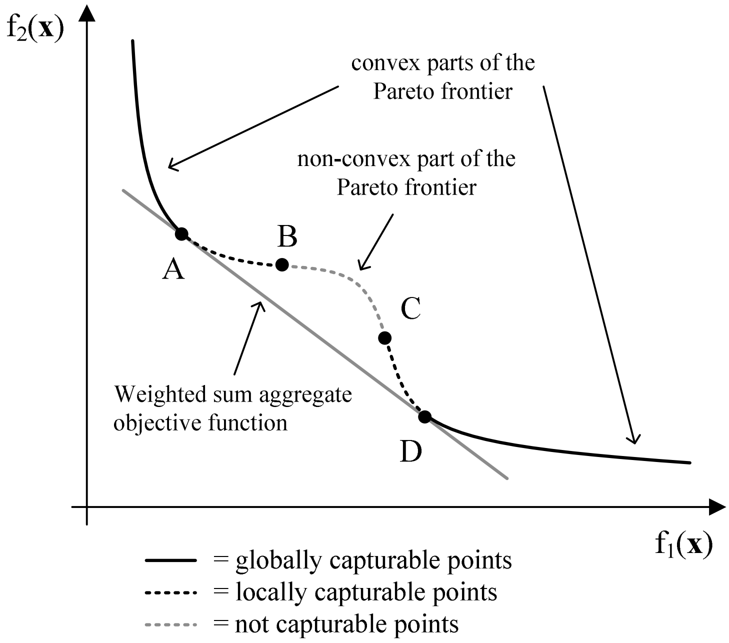


Figure 11. Illustration of globally and locally capturable points by minimization of the weighted sum AOF

Figure 11 shows the non-convex Pareto frontier of a bi-objective minimization problem. Points A and D lie on the convex parts of the Pareto frontier. These points are globally capturable since they correspond respectively to global minima of the objective function. Points B and C lie on convex parts of the Pareto frontier too and correspond to local minima of the objective function. Thus, points B and C are only locally capturable. Points located on the concave part of the Pareto frontier (segment BC) are not capturable. Consequently, in a MO context, using the weighted sum AOF doesn’t enable to detect the solutions located on the segment AD of the front. This illustrates why the weighted sum aggregation approach suffers from serious drawbacks [Das 1997] for preferences assessment. In particular, in engineering design, it excludes vast areas of solutions which may be considered as relevant for designers.

2.3.5 Classification of the MO methodologies according to the articulation of preferences

As previously mentioned, the main issues in MO are related to the accurate modelling of designers’ preferences. In decision theory, preference refers to the decision-maker opinion about solution points within the criteria space (or objective space). Preference functions are defined as abstract functions in the mind of decision-makers which integrate criteria, objectives and preferences. Preference assessment aims to reflect preference functions in the best way in order to select the most preferred solutions among a set of plausible alternatives. As presented in table 4, most of MO methodologies and techniques can be classified according to a priori or a posteriori preferences modelling [Marler 2004].

In this research work, we are mainly interested in techniques based on a priori articulation of preferences. Table 4 presents some of these methods. They are based on models of decision-makers' judgment and perception before computing design solutions. Preferences are express within the objective function(s) and are formulated as goals, trade-offs or relative importance relations between objectives (priorities). These methods are based on the specification of a set of parameters (coefficients or weights, exponents, constraint limits, utopia point) whose values enable to accurately model the designers' preferences within the decision model. Since multiple objectives introduce degree of freedom within the design/decision MO problem, the expression of preferences provides additional constraints to the problem, and consequently, the initial MO problem can be turned into a mono-objective optimization problem. It can be noticed that, depending on methods, continuous modifications of parameters enable the generation of the whole Pareto set or just some parts of this set. Therefore, the selection of a particular MO technique based on a priori articulation of preferences depends on its ability in modelling designers' preferences within a given context. Finally, a priori articulation of preference requires additional efforts in modelling processes to formalize much more knowledge about the design problem.

Articulation of preference	**Methodologies and techniques**
A priori formulation	Weighted Global Criterion method and its extensions (including utopia point method) [Yu 1974, Zeleny 1981, Wierzbicki 1982, Chankong 1983, Miettinen 1999]
	Weighted Sum method [Zadeh 1963, Steuer 1989, Chankong 1983, Athan 1996, Das 1997, Koski 2005]
	Weighted Min-Max method (or Tchebycheff method) [Miettinen 1999, Messac 2000a, Messac 2000b]
	Weighted Product method [Bridgman 1922]
	Exponential Weighted method [Athan 1996]
	Lexicographic method [Stadler 1988]
	Goal Programming method [Charnes 1977, Tamiz 1998]
	Bounded objective method (ε-constraint approach) [Haimes 1971, Hwang 1979]
	Physical Programming [Messac 1996, Messac 2002a]
A posteriori formulation	Physical Programming [Messac 2002b]
	Normal Boundary Intersection (NBI) method [Das 1998]
	Normal Constraint (NC) method [Messac 2003]

Table 4. Classification of MO methodologies and techniques according to a priori or posteriori formulation of preferences

However, preferences are sometime so complex that it is difficult to express them in a formal way. Therefore, it is suitable to allow designers to select the most preferred solution among a set of effective solutions (in general the Pareto set). Therefore, methods based on a posteriori articulation of preferences imply the development of algorithms for generating and representing the set of Pareto optimal solutions in the best way. In general, the final solution is very close to the expected preference function. Some of methods involving a posteriori formulation of preferences are given in table 4. These methods are in general coupled with visualization techniques to support the representation of design solutions, which is obviously relevant while the number of objectives doesn't exceed three.

Finally, some methods with no articulation of preference, called mixed methods or interactive methods, allow designers to adjust the optimal solution according to their preferences after each iteration of the optimization process [Steuer 1983, Xiao 2007, Jeong 2009]. This approach enables to integrate the designer within the optimization loop and provides guidelines to orient the search of relevant solutions.

2.3.6 Genetic algorithms

Recently, a particular class of algorithms, called genetic algorithms (GA), has received increased interests to solve MO problems. As GA do not require gradient computations, they are efficient to deal with non trivial optimization problems, independently of the nature of the objective function(s) (continuous/discontinuous, non differentiable) and constraints (equality/inequality, linear/nonlinear). These algorithms are efficient as global optimization algorithms and hybridation techniques with classical approaches can be used for local optimization. Although computing costs are often expensive while optimizing design problems, parallelization computing and clustering techniques can be used to cover this issue and increase the performance of GA [Deb 1989, Cantú-Paz 2000, Bonham 2004]. Finally, in an industrial context, benefits of using GA come from their ease of implementation as "black-box" systems, making them popular in many areas of application.

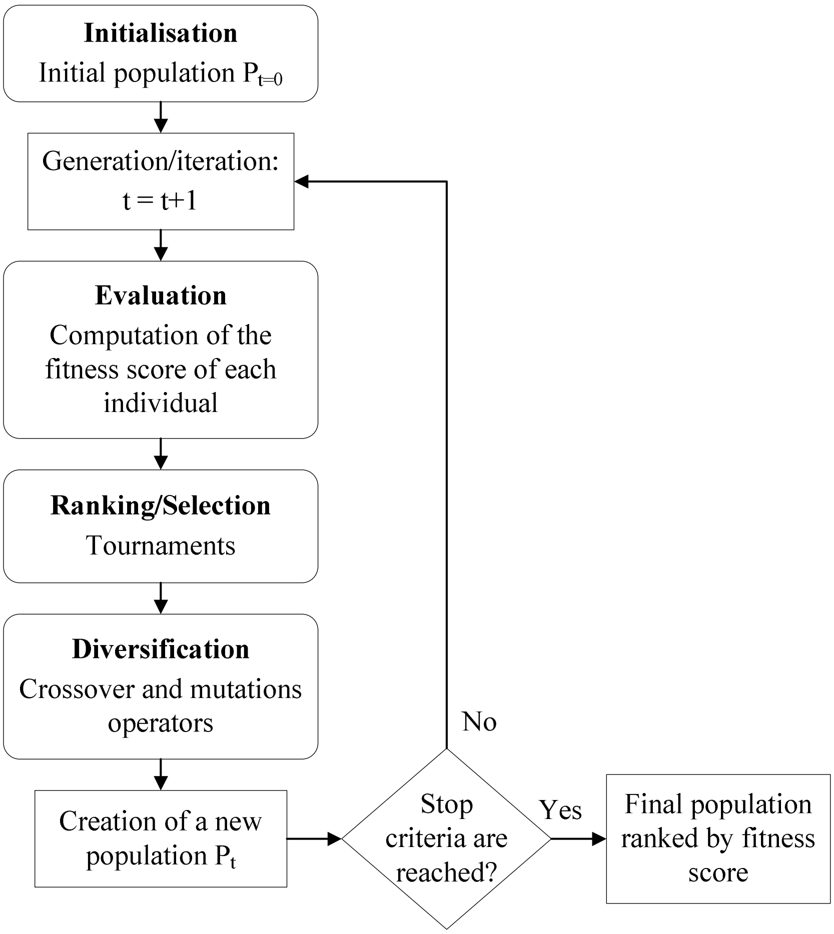


Figure 12. Principles of Genetic Algorithms

GA use stochastic optimization techniques to simulate the natural selection process of individuals in selective environments. The concept of *survival of the fittest* [Goldberg 1996] states that within a population, the most adapted individuals tend to live long enough to breed whereas the weakest individuals tend to disappear. By analogy with this natural evolution rules, GA consists in making a population of individuals evolve toward the optimum of the optimization problem. Each individual corresponds to a candidate solution represented by a set of design variables values. Individuals are evaluated and ranked according to their fitness, i.e. their ability in optimizing the objective function.

Figure 12 represents the principles of GA in graph form. The best individuals of the current population are first selected by comparison of their fitness scores, and then, a new population of solutions is created for the next generation by tournament selection, crossover and mutation operators. This process is performed generation after generation, until termination criteria are reached (the maximum number of iterations for example). Each generation corresponds to one iteration. Further details on GA mechanisms are given in the literature [Srinivas 1994, Goldberg 1996, Oduguwa 2005, Chiong 2009].

According to Deb [Deb 1999], one of the major challenge in the development of such algorithms for MO is to ensure the convergence toward the Pareto frontier taking into account the uniformity of the repartition of the non-dominated solutions. In 1985, Schaffer presents the first GA for MO problems, called VEGA (Vector Evaluated Genetic Algorithm) [Schaffer 1985]. In 2002, Deb proposed his NSGA-II (Non Dominated Sorting Genetic Algorithm) [Deb 2002] which is currently regarded as a reference evolutionary MO. The algorithm NGSA-II is very effective in generating the Pareto set with a high accuracy and a high converge speed. Due to the elitist approach, it preserves the best individuals from one generation to another (acting as a memory). It uses a selection procedure, based on the non-domination principle, and a comparison operator using the computation of crowding distance.

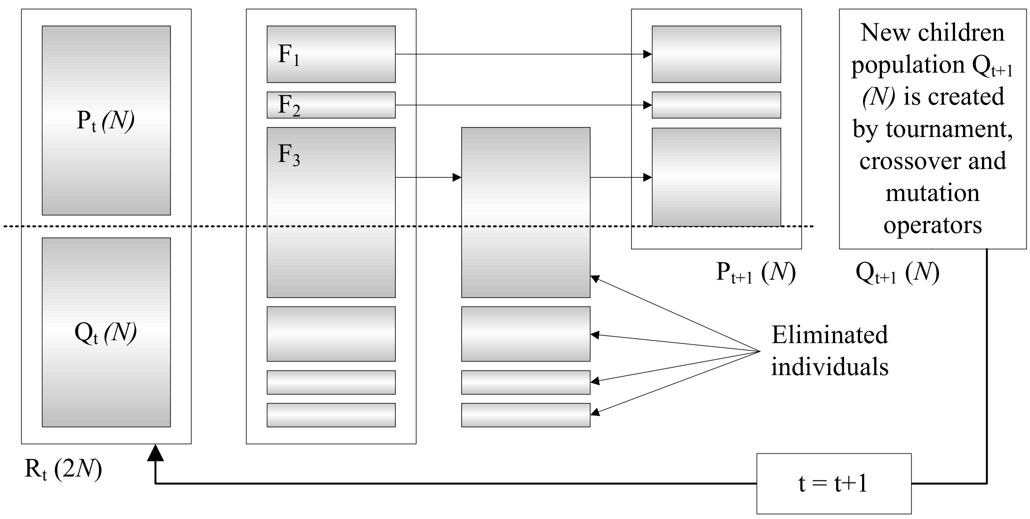


Figure 13. Illustration of the NGSA-II principles [Deb 2002]

Principles of NGSA-II are represented on figure 13. A parent population Pt and a children population Qt composed by N individuals are gathered into a population Rt of 2N individuals. This operation enables to apply the elitist strategy. Individual of the resulting population Rt are sorted according to a non-domination criterion to identify the different frontiers (F_i). A rank is assigned to every individual of the population based on the front on which they lie. The best individuals belong to the first frontier (fitness value of 1). In addition to the fitness value, a crowding distance is calculated for each individual with respect to the others. The crowding is computed from the perimeter formed by every closest individual's neighbour and for each objective. Large average crowding distance results in better diversity within the population. Parents are selected from the population by using binary tournament selection based on the rank and crowding distance. A new children population is then created by genetic operators (crossover and mutation). Simulated Binary Crossover (SBX) and Polynomial Mutation were also proposed for real-coded GA operators [Deb 1995].

2.4 Design optimization methodologies under uncertainties

2.4.1 Introduction

Design optimization methodologies under uncertainties aim to develop systems satisfying a certain level of performance during their lifetime. In most cases, models and optimization techniques are deterministic. Consequently, variations of design variables, tolerances on dimensions, dispersion of materials properties, fluctuation of environmental parameters or modelling errors are either not taken into account, or introduced in the design process by simplifying assumptions (worst-case based design, application of safety factors). These assumptions often penalize the performances of systems by increasing their dimensions, which increases material costs and costs of production.

Moreover, classical optimization techniques tend to push design toward admissible domains boundaries while performances are expected to be improved, leading to optimal design solutions with a low level of reliability and robustness, since a slight variation of design variables, or changes in the environmental parameters, may cause violation of constraints or deep degradation of performances.

Due to recent advances in high-speed computing, optimization techniques considering uncertainty have received increasing interests while designing systems. Figure 14 represents the different types of uncertainty which are classically identified in engineering design. They can be classified into four categories listed as:

- Fluctuations of environmental and operational parameters
- Variations of design variables such as manufacturing tolerances and actuator imprecision
- Modelling errors and imprecision
- Uncertainty related to constraints satisfaction

The first source of uncertainty refers to fluctuations of environmental and operational parameters such as humidity, operating temperature or pressure. They are considered as noise factors or uncontrollable parameters, and refer to *Type I variations* according to Chen [Chen 1996]. It is modelled by introducing an additional parameter ($\boldsymbol{\alpha}$) in the simulation model. The second type of uncertainty is linked to variations of design variables, such as manufacturing tolerances and actuator imprecision. In mechanical design, dimensions can be realized only with a certain degree of accuracy, which introduces dimensional dispersions. This kind of uncertainty is regarded as control factor and refers to *Type II variations* [Chen 1996]. This type of uncertainty is introduced in the evaluation model using a perturbation vector ($\boldsymbol{\delta}$) related to the design variables ($\mathbf{x}$). For example, $\delta=\varepsilon\mathbf{x}$ may model the relative uncertainty of measurements provided for materials Young modulus or mechanical strength estimations. Uncertainty in performances predictions can also results from modelling errors and inherent imprecision. This type of uncertainty is caused by modelling assumptions, measurements errors or experimental correlations, which can be modelled as a random function of the nominal performance ($\mathbf{y}$). The last type of uncertainty to be taken into account is related to the constraints satisfaction and concerns the uncertainty reflecting the designer choices. Methods to deal with this kind of uncertainty are presented in chapter 3.

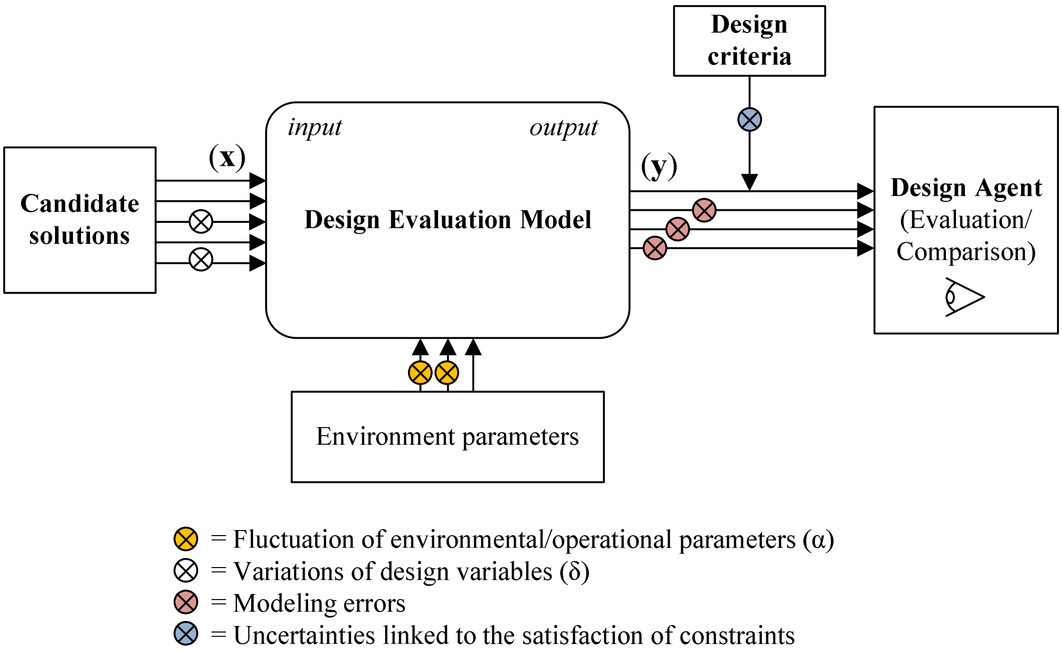


Figure 14. Representation of uncertainty in engineering design

However, uncertainty can be also classified into aleatory and epistemic uncertainty [Oberkampf 2004, Samson 2009b]. While aleatory uncertainties are linked to the intrinsic stochastic nature of physical phenomena (humidity, temperature, pressure or material parameters), and so, cannot be removed or reduced by design parameters, epistemic uncertainties reflect the lack of knowledge about the design problem and .can be reduced by increased efforts. This kind of uncertainty also includes uncertainties about the model used to describe the system behaviour, its boundaries and operating conditions, and the errors linked to the numerical solving methods (such as discretization, convergence, approximation). Discrete/continuous interval and fuzzy sets are suitable to model this type of uncertainty, whereas probability distributions are suitable to model aleatory uncertainty due to their probabilistic nature.

2.4.2 Uncertainty modelling

The simulation of the performance variations, while design variables and parameters are moved from their nominal values, requires the development of methodologies for uncertainty modelling and methods for uncertainty propagation through evaluation models. These challenges have motivated many research works in the past few years [Du 2000a, Padulo 2007, Lee 2009].

In general, the easiest way to deal with uncertainty is to use Monte Carlo simulation method, Taylor series expansion or orthogonal arrays based simulation [Shyam 2002] to introduced stochastic variations within evaluation models as follows:

$$\tilde{\mathbf{y}} = \tilde{\mu}\left[\mu\left(\tilde{\mathbf{x}},\boldsymbol{\alpha}\right)\right], \quad \tilde{\mathbf{x}} = \mathbf{x} + \boldsymbol{\delta} \tag{2.4.2}$$

where $\tilde{\mathbf{x}}$, $\tilde{\mathbf{y}}$, and $\tilde{\mu}$ represent respectively the vector of disturbed design variables, the vector of disturbed performances and a random function simulating inherent errors within simulation models. Parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\delta}$ model uncertainties linked to fluctuations of environmental parameters and manufacturing dispersions. They define interval of variations around the nominal value, which is equivalent to define a neighbourhood of solutions around the nominal value. The dispersion of the performances is then observed in the performance space (or criteria space) as represented on figure 15.

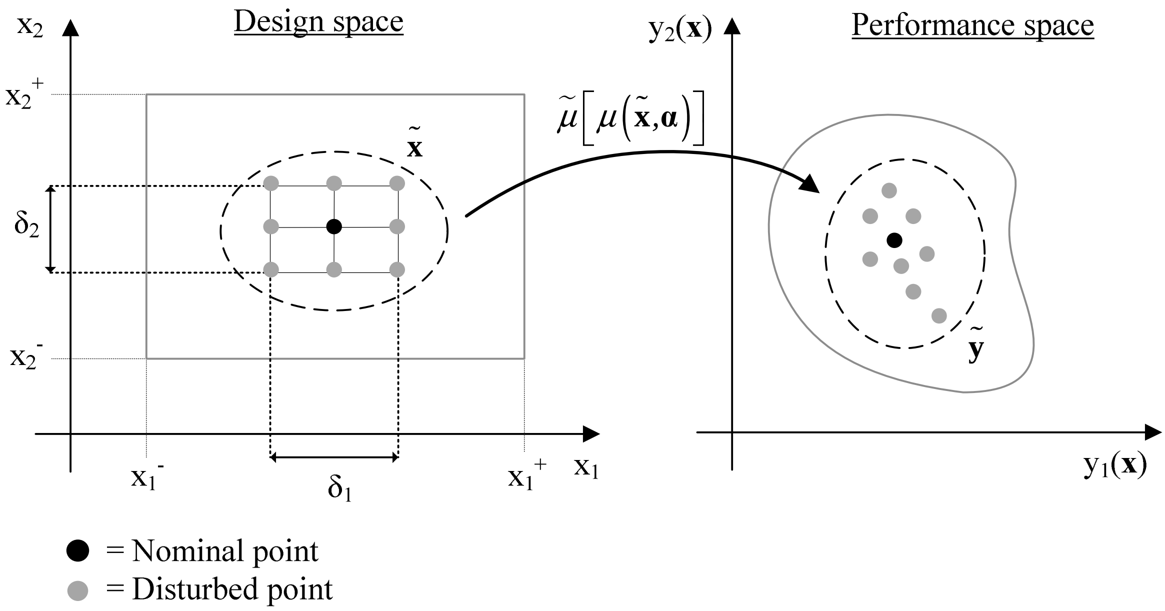


Figure 15. Representation of nominal and disturbed points while uncertainty is stochastically modelled

2.4.3 Reliability-based optimization

The most commonly used methods to deal with uncertainty refer to reliability-based optimization (RBDO). RBDO methods are based on probability distributions to describe variability of design variables and model parameters. Variations are represented by standard deviations (typically assumed to be constant). Mean performance measures are then optimized subjected to a set of probabilistic constraints (failure probabilities and expected values), i.e. with an associated reliability. As the improvement of reliability of systems often leads to penalize its performances (in particular increasing of overall dimensions and costs), RBDO methods intend to achieve systems with an acceptable level of reliability and a satisfying level of performance. Classical RBDO problems are formulated as follows:

$$\begin{aligned}
&\underset{\mathbf{d},\mu_{\mathbf{X}}}{\text{minimize}}\ \ f\left(\mathbf{d},\mu_{\mathbf{X}},\mu_{\mathbf{P}}\right)\\
&\text{subject to:}\\
&\quad P\left[G_i\left(\mathbf{d},\mathbf{X},\mathbf{P}\right)\geq 0\right]\geq R_i \quad i=1,2,\dots,n \qquad (2.4.3)\\
&\quad \mathbf{d}^L \leq \mathbf{d} \leq \mathbf{d}^U\\
&\quad \mu_{\mathbf{X}}^L \leq \mu_{\mathbf{X}} \leq \mu_{\mathbf{X}}^U
\end{aligned}$$

where **d** is the vector of deterministic design variables, **X** is the vector of random design variables and **P** is the vector of random design parameters. The objective function *f* represents the performance to be minimized (costs for example). A solution is said reliable if the probability of satisfying each constraint is greater than a specified reliability (confidence) level R. Reliable and performance optima are both represented on figure 16. The performance optimum (C) appears as non-reliable since the performance constraint is violated while design variables (**x**) are disturbed. The reliable optimum (A) satisfies the constraint whatever the value of **x** within its domain of variation. However, this implies a slight performance decrement.

In mechanical design, RBDO approaches are particularly effective to increase the confidence of designers toward a design solution in regards to safety criteria (mechanical strength of bridges facing to wind vibrations for example) [Enevoldsen 1994, Gasser 1997, Youn 2004, Jensen 2005, Samson 2009b]. Two class of RBDO methods are commonly used to solve the problem (2.4.2). The first class consists in decoupling the RBDO process into a sequence of deterministic design optimizations which are followed by a set of reliability assessments loops [Royset 2001, Du 2004]. The deterministic and reliability loops are iteratively repeated until convergence. The second class of RBDO methods converts the problem into an equivalent single-loop deterministic optimization [Liang 2008], leading to significant computational efficiency improvements. The reliability assessment can be performed according to the reliability index approach (RIA) or the performance measure approaches (PMA). Every time the optimization loops call for a constraint evaluation, estimates on the failure probability are based on first-order or second-order reliability methods (FORM and SORM) [Ditlevsen 1996] in order to determine the so-called most probable point (MPP) of failure.

2.4.4 Robust design optimization

While RBDO methods concern the probability of constraints satisfaction facing aleatory uncertainly, robust design optimization (RDO) aims at minimizing the variations of the performance under epistemic uncertainty (no distributions on the input variables). Although there is still not a clear definition of *robustness* in engineering, most of the authors agree to say that robust design aims at sizing systems which are intrinsically low sensitive to all sources of uncertainty, rather than trying to reduce or control them [Park 2006, Beyer 2007]. Concepts of robustness and RDO have been developed simultaneously in the fields of operational research (OR) [Mulvey 1995] and engineering design.

In engineering, robust design has been initiated by G. Taguchi in quality engineering [Taguchi 1984, Taguchi 2004]. The methodology proposed by Taguchi is divided into three steps. In particular, the phase of parameter design aims at optimizing design parameters in respect with the variations of performances under noise factors. Taguchi introduces a “signal-to-noise” ratio (SNR) to evaluate the robustness of a selected configuration. This ratio is generally expressed as follows:

$$SNR = -10\log\left(\frac{\bar{y}}{\sigma}\right) \tag{2.4.4.1}$$

where $\bar{y}$ represents the mean performance and σ represents the standard deviation. However, the methodology proposed by Taguchi doesn't really use an automated optimization process to maximize the SNR since he suggests the use of design of experiments (DOE) for designing evaluation of design solutions robustness. This approach is therefore limited by the number of alternatives and the number of design variables. Controversial debates about the Taguchi methods are summarized in [Nair 1992].

According to figure 16, point B corresponds to a robust optimal solution. However, the selection of this solution implies the decreasing of the performance. Although in this case, the robust optimum solution is also reliable, in general, robustness doesn't imply reliability, and inversely, reliability doesn't mean robustness. Robust solutions closed to the bounds of the feasible domain may present slight performance variations around their nominal values, and then, fall beyond the admissible limits. On the contrary, reliable optimal solutions may present important performance variations while remaining within the feasible domain.

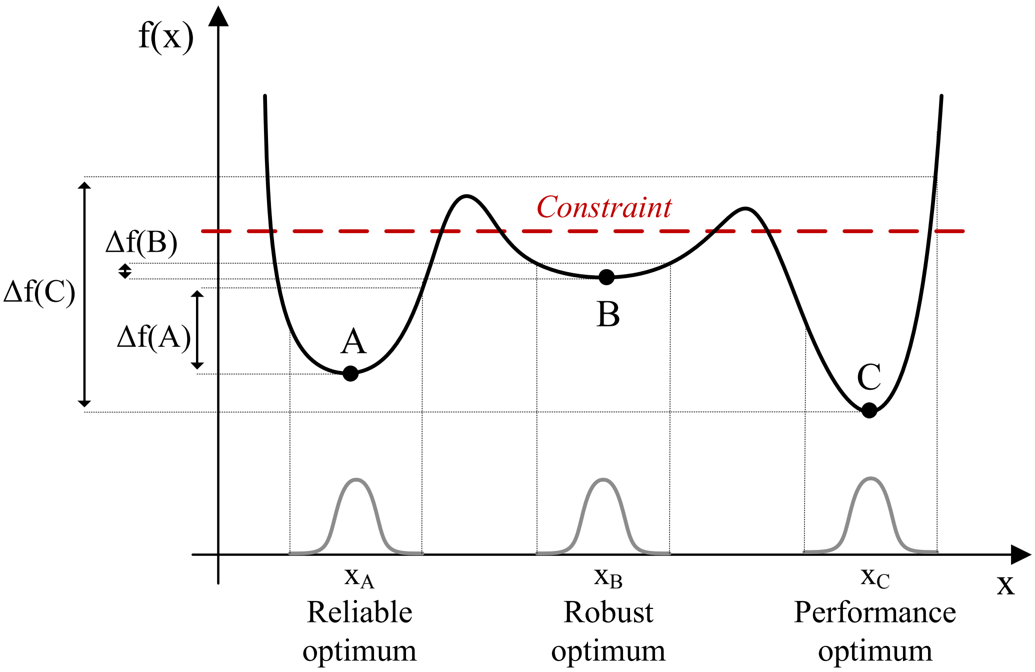


Figure 16. Representation of different optimal solutions achieved by optimization methods under uncertainties: (A) Reliable-based design optimization, (B) Robust design optimization and (C) Deterministic optimization

Reviews of existing RDO methodologies and methods are presented in [Beyer 2007, Arvidsson 2008, Schueller 2008]. While many RDO techniques developed in the past few years are based on the computation of the mean performance and standard deviation [Brotchie 1997, Parkinson 1997, Du 2000b, Ardakani 2009], some of them have proposed to tackle robust design as MO problems [Chen 1996, Chen 1999, Greiner 2011]. In fact, using the MO formulation (2.3.1.1), RDO problems can be formulated as follows:

$$\begin{aligned}
&\underset{\mathbf{d},\mu_{\mathbf{X}}}{\text{minimize}}\ \ V_f\left(\mathbf{d},\mu_{\mathbf{X}},\mu_{\mathbf{P}}\right)\\
&\text{subject to:}\\
&\quad g_i\left(\mathbf{d},\mathbf{X},\mathbf{P}\right)\geq 0\\
&\quad \mathbf{d}^L\leq\mathbf{d}\leq\mathbf{d}^U\\
&\quad \mu_{\mathbf{X}}^L\leq\mu_{\mathbf{X}}\leq\mu_{\mathbf{X}}^U
\end{aligned} \tag{2.4.4.2}$$

where V_f is a variation measure of the performance *f*. It is equivalent to trade performance against variability. Although, trade-off between performance and variability has already been tackled in some recent studies [Chen 1999, Du 2004], this approach seems to be still not extensively applied in industry.

2.5 Summary

Fundamental notions and concepts related to formal design theories and methodologies are introduced in this chapter. The FBS ontology proposed by John Gero offers a suitable framework to link real and expected behaviour in design and thus enables to situate optimization in engineering design. Some of the topical issues, priors work and future challenges related to address engineering problems with optimization techniques are also presented through this chapter. In particular, it highlights that most of these techniques have not meet yet designer's needs in industry. The development of suitable tools dedicated to support decision making in embodiment design is thus required to improve the whole design process of machines.

The research work presented in this thesis uses the Gero’s FBS framework to develop a modelling methodology for embodiment design problems. In particular, we propose a preference model to link physical behaviour, design criteria and objectives, with an observation, interpretation and aggregation decomposition. While design optimization involves generation and evaluation of solutions, we focus here on how candidate solutions can be evaluated and ranked according to the design requirements and designers’ intentions. Finally, as optimal solutions are often disturbed by inherent uncertainty, it is obvious that they must also be robust. Two levels of robustness are considered here. While the first level of robustness concerns the sensitivity of systems performances facing physical uncertainty, the second level of robustness deals with uncertainty of the choice and tackle trade-off between two design objectives, namely (1) the improvement of the overall performance and (2) the minimization of the performances' variability. Therefore, a more relevant definition of robustness in engineering may be that a robust design solution is a solution whose performance is desirable in regards to its sensitivity under uncertainty. The formulation of these two types of robustness within a global robust design approach is one of the salient points developed in this thesis.

CHAPTER 3 Preference modelling in Engineering Design

Preference modelling has a central role in engineering design to support decision-making and guide designers toward the most preferred solutions. As the selection of a particular methodology can impact the outcomes of decision-making, different approaches result in different final solutions for the same set of preferences. Thus, the best fit for a given design problem mainly depends on the ability of methodologies to reflect the intentions of the designer through the set of assumptions on which methodologies are based. Facing with multiple criteria, one possibility for preference assessment is to determine individual preference functions, and then, generate adequate aggregation strategies to form a single global criterion, used as a metric for alternatives evaluation. This chapter aims to introduce the main concepts and issues related to preference modelling in engineering design. Three different approaches, namely utility theory, method of imprecision and desirability index, are presented and discussed according to their ability in modelling preferences in engineering design.

3.1 Concepts and definitions

3.1.1 Alternative and attribute

Any formal methods developed in decision theory aims to model and compare the acceptability of different alternatives. In economics, alternatives are usually regarded as bundles of goods, and are often represented as vectors, in which each position represents a specific good. The scalar value associated to this position denotes the number of units of this goods. In engineering design, the definition of alternatives depends on the stage of the design process. In conceptual design, alternatives are often abstraction of products, represented as whole artefacts, whereas in embodiment and detailed design, alternatives designate combinations of design variables values describing products.

Definition: In embodiment design, a design alternative X is represented as a vector of controllable design variables $\mathbf{x}=[x_1, x_{2,}\ldots,x_n]^T$ whose scalar values quantify the main characteristics of the system to be designed and enable to differentiate two alternatives between them.

Alternatives evaluation is based on their attributes which refer to some properties of the system, performance measures or objective achievement indicators.

3.1.2 Preferences and order of relation

The basic concept in ranking alternatives is the simple comparison. This comparison involves no association of numbers with alternatives, but only the idea that an alternative A is preferred to an alternative B. A ranking method involving a simple comparison between two alternatives A and B is a weak order of relation.

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Definition: A weak order of relation among a set of alternatives **X** is a binary transitive relation $\succeq$ such that $\forall A,B \in \mathbf{X}$, $A \succeq B$ (A is at least as preferable as B), or $A \preceq B$ (B is at least as preferable as A). The indifference relation $A \sim B$ is obtained when $A \succeq B$ and $A \preceq B$. In this case, A and B are equally preferred and it is impossible to perform a direct rational choice. Inversely, the strict preference relation $A \succ B$ (A is strictly preferred to B) is equivalent to $A \succeq B$ and $A \not\preceq B$.

A weak order ranking is an ordinal ranking. Alternatives are ranked alternatives without assigning any numerical scalar quantities. However, any computational method in decision-making requires the definition of an interpretable numerical scale of value to sort alternatives according to a cardinal ranking.

3.1.3 Value functions

Cardinal ranking of alternatives consists in interpreting preferences in term of value. Value is commonly defined as a numerical quantity used to illustrate the goodness of the attributes of alternatives. Utility, desirability and level of acceptability are common value used to measure preference. A value function designates the mapping between the weak ordered set of alternatives and the scale of value.

Definition: A value function *v* is an assignment of scalar values to alternatives such as the weak order of acceptability among these alternative is preserved. It allows the construction of a model of preference such as $A \succeq B \text{ iff } v(A) \geq v(B)$. In general, a value functions maps the levels of alternatives' attributes onto the interval [0,1].

While it is always possible to derive a value function from a weak order relation [Krantz 1971], there is nothing inherent in the definition of value function for the quantification of the level of acceptability or degree of satisfaction achieved by alternatives. In other words, beyond a set of alternative, there is a possible interpretation of the relative value. Therefore, preference modelling requires additional information about the structure of value functions.

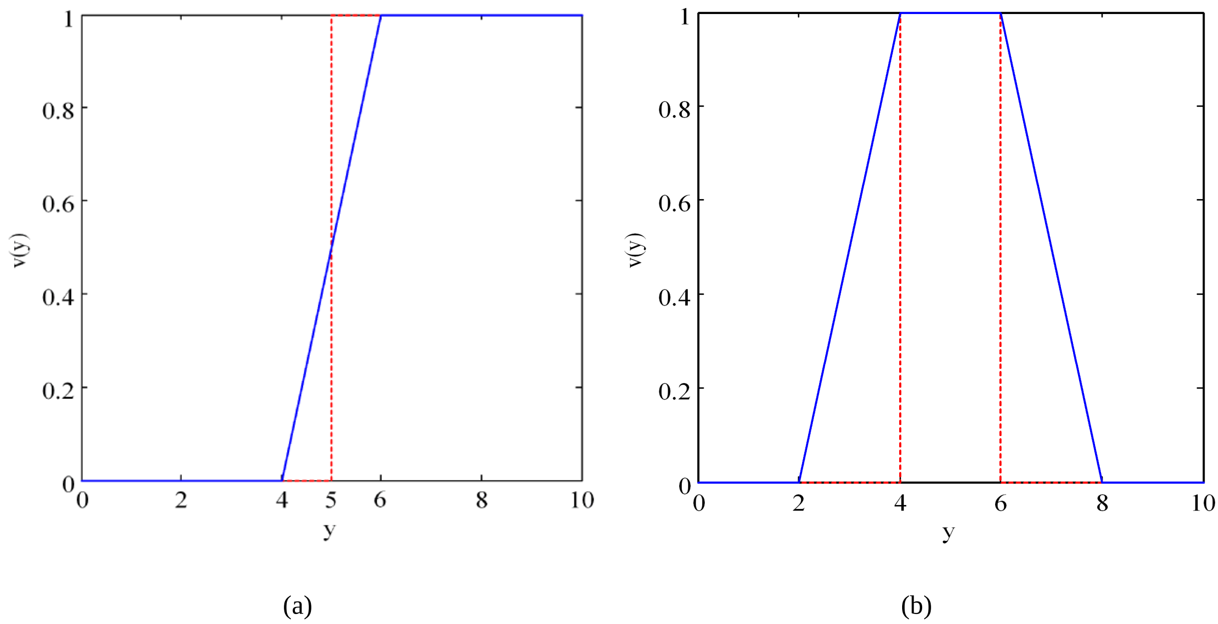


Figure 17. Two basic value functions: (a) “bound low values is better” and (b) “close to a target value is better”

The selection of a particular structure for a value function should reflect the designer's interpretation of preferences. Value functions used in engineering design often models three major intentions which can be expressed as follows: "bounding low values is better", the "bounding high values is better" and "close to a target value is better". A value equal to one means that design attributes completely meet the designer's expectations, whereas a value equal to zero reflects the inadequacy of design attributes with design requirements. Between these extreme values, the behaviour of the value function intends to model variations of designer's preferences according to attributes values.

Figure 17 represents two basic value functions. On figure 17a, the value function in crisp form (plotted in dashed line) implies that a property with a value $y=5+\varepsilon$ ($\varepsilon\rightarrow 0$) is completely satisfying, whereas the same property with a value $y=5-\varepsilon$ ($\varepsilon\rightarrow 0$) is regarded as completely unsatisfying. This is obviously not suitable to model preference since extremely close property values result in two extreme different values. Change of preference value is actually progressive with the gain of value of the property. A more convenient model is represented by the function plotted in solid line on figure 17. This function indicates a progressive transition of the preference from the not satisfying property value $v(y)=0$ to the most satisfying property value $v(y)=1$.

In the following, we present three different value functions for preference modelling in engineering design, namely multiattribute utility functions, preference functions of the method of imprecision and desirability functions.

3.2 Utility theory

3.2.1 Introduction

Utility theory is an analytical method based on a probabilistic model to support multicriteria decision-making under risk and uncertainty. Utility is defined as a numerical quantity lying in the range [0,1] which is used to illustrate the goodness of alternatives' attributes under uncertainty. Originally developed in economics, utility theory has been extensively used in the past few years to design products and systems [Hazelrigg 1996, Lewis 2006].

Utility theory fundamentals consist in a set of axioms restricting the way by which designers can express preferential judgments among a set of alternatives facing risk and uncertainty. Under these assumptions, utility theory is the only way to provide consistent outcomes with designers' preferences. In this approach, preference modelling is based on lottery assessments from which single-preference utility functions $u(y)$ and scaling constant are derived.

3.2.2 Assessment of utility functions

According to the von Neumann-Morgenstern axioms [Von Neumann 1947], a single-attribute function (SAU) can be derived from designer's judgment facing a lottery assessment. SAUs are defined as monotonic function with a utility $u_{best}=1$ for the most preferred attribute value, and with a utility $u_{worst}=0$ for the less preferred attribute value. These functions model designers' compromises between the best and worst cases according to the priority orders derived from the lottery assessment [Keeney 1993].

The definition of SAUs is based on the notion of *certainty equivalent*. A certainty value can be regarded as a guaranteed outcome facing a lottery between the two extreme values, in which there is a probability p_0 for obtaining the best value and a probability $1-p_0$ for obtaining the worst value. A probability $p_0=1$ results in the selection of the lottery, whereas a probability of $p_0=0$ results in the selection of the certainty. The value of the indifference probability p_0 corresponds to the utility of the certainty equivalent which is equal to the mathematical expectation of the lottery outcome. While lottery questions are necessary to describe the implications of attributes between them, analytical function formulations (linear, exponential) are required to describe the preference structure of SAUs.

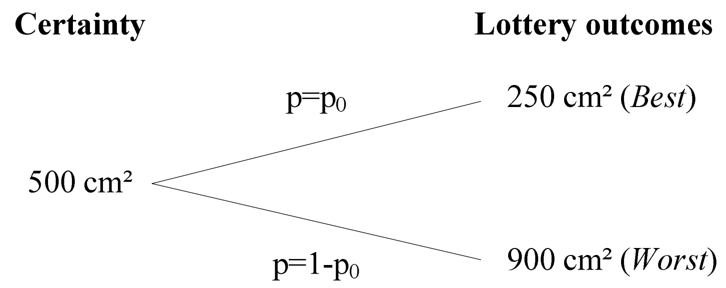


Figure 18. Typical lottery assessment [Krishnamurty 2006]

As an example, figure 18 illustrates a typical lottery assessment for the cross-section of an I-beam [Krishnamurty 2006]. In this case, a cross-section area of 500cm² represents a guaranteed result (certainty) compared to the two lottery outcomes in which there is a probability p_0 of obtaining the best value of 250cm² and a probability ($1-p_0$) of obtaining the worst value of 900cm². Here, the best value (250cm²) may refer to the lowest admissible cross-section area according to safety criteria, whereas the highest value (900cm²) can be determined from costs considerations. Therefore, the utility of the certainty equivalent (500cm²) corresponds to the mathematical expectation of the lottery which is expressed as follows:

$$u\left(500\text{cm}^2\right) = \text{p}_0 \cdot u\left(250\text{cm}^2\right) + \left(1-\text{p}_0\right) \cdot u\left(900\text{cm}^2\right) \tag{3.2.2.1}$$

While decision problems involve multiple attributes, it is necessary to define a multiattribute (MAU) function to evaluate the alternatives overall utility. The overall utility over a set of *n* attributes values $u(y_1, y_2, \ldots, y_n)$ can be either directly estimated over the values of the *n* attributes, or computed from the mathematical combination of *n* SAUs functions $u_i(y_i)$ through some scaling constants. The structure of MAU functions can be provided with additive, multilinear or multiplicative formulations. Due to its relative simplicity, additive formulation is the most popular form. In this case, the MAU to be maximized is expressed as:

$$u\left(y_1, y_2, \ldots, y_n\right) = \sum_{i=1}^{n} k_i \cdot u_i\left(y_i\right) \tag{3.2.2.2}$$

where k_i refer to scaling constants (weights). These constants reflect the designer's preferences about attributes. They can be determined by evaluating the marginal rate of substitution of one objective in term of another or by lottery assessment.

3.2.3 Why does utility theory partly fail to meet designers' needs in engineering design?

According to Scott [Scott 1999], utility theory intends to treat decision-making problems under probabilistic uncertainty or risk, rather than intend to define solutions of multicriteria decision problem. Although the lottery assessment seems to be suitable to derive numerical scale of value for preference assessment facing risk and uncertainty, engineering design may not fall into these assumptions, and consequently, the definition of SAUs are no longer relevant.

Indeed, utility theory had been initially developed to deal with a particular range of problems, in which the estimation of expectation for each alternative is regarded as the most relevant information. For example, in production stages, it can be suitable to use utility theory to deal with the probability distributions linked to manufacturing tolerances. However, early stages of the design process differ from classical decision problems by the existence of epistemic uncertainties, incomplete data and high degree of imprecision due to a lack of knowledge about the design. Thus, design variables and performance measures (attributes) values change without any probability distribution, falling out of the scope of utility theory.

Moreover, while engineering design is a goal-directed activity in which multiple preferences are expressed from different experts involved in the design process, the assumptions of utility theory make difficult any interpersonal comparison of utility (preference) between multiple attributes.

Finally, according to Keeney [Keeney 1993], the additive form used in MAU fails to completely capture designers' intentions in engineering design. Additive formulation implies that any decrement of the overall preference (utility) caused by any changes of one performance variable value, is always compensated by an increment of any other performance variable value. This reflects for example the behaviour of a designer who wishes to compensate an increase of the overall mass of the system by an appropriate decrease in costs. Although the notion of compensatory is inherent in design, the compensatory situation modelled by the additive form of utility does not always map the intentions of designers. Others trade-off strategies can be expected by designers. For example, in engineering design, alternatives are often considered as unacceptable if at least one of the attributes doesn't meet design criteria. Such a situation is modelled in the method of imprecision (MoI) through the axiom of *Annihilation*, and thus, represents a fundamental difference between these two approaches.

3.3 The Method of Imprecision

The Method of Imprecision (MoI) was initiated by Anthonsson and Wood [Wood 1989] to deal with the inherent levels of imprecision in preliminary design. It is based on the assumption that the imprecise information in engineering design can be handled and modelled by formal methods. In the past few years, the MoI has been developed through many research works [Otto 1991, Antonsson 1995, Scott 1998, Scott 1999, Scott 2000] which are synthesized in [Anthonsson 2001].

Preferences of MoI are modelled by mapping the design space (or the performance space) onto the interval [0,1]. They are expressed on an absolute scale of value where a preference p=1 indicates a completely acceptable value, and a preference μ=0 indicates a completely unacceptable value. Preference function of the MoI does not express vagueness like in fuzzy set theory, but the wish of designers to use a particular value within the admissible range. Unlike utility theory, the notions of *acceptability* and *desirability* are here fundamentals.

Preference functions concern the performance, expressing some requirements for potential performance values or the design space, modelling some non-formalized considerations about design variables. While the definition of performance preference functions is partly objective, since it is based on design requirements, the specification of design preference functions depends on the subjectivity of designers. For example, they can be derived from interpolation between data points.

However, the MoI does not provide guidelines, or methods, about how the designer should specify an individual preference function for a specific performance measure or design variable. In particular, the method suffers from a lack of some effective techniques to handle and interpret the degree of constraint satisfaction.

The MoI rather focuses on the combination of the individual preferences into an overall preference. As it is often impossible to maximize simultaneously every individual preference, the MoI is interested in the definition of appropriate aggregation operators to model trade-off strategies in engineering design. Overall preference involves all individual preferences and is expressed as [Scott 1998]:

$$\mathrm{p} = \mathcal{P}\left(\mathrm{p}_1,\dots,\mathrm{p}_n;\mathrm{w}_1,\dots,\mathrm{w}_n\right), \quad \mathrm{n} \in \mathbb{N}^* \tag{3.3.1}$$

where the overall preference p results from the combination of the *n* individual preferences p_i through the aggregation function $\mathcal{P}$ and the weighting parameters w_i. However, all aggregate operators are not suitable to model rational decisions. A fundamental result of the MoI is the definition of relevant aggregation function for preference modelling in engineering design.

3.3.1 Axioms of the MoI

The development of the MoI as a formal theory intends to formalize the intuitive notions of the rational human behaviour within a set of axioms that aggregation functions must satisfy. These axioms form a consistent basis to set restrictions on any preference aggregation function for rational preference modelling in engineering design [Otto 1992]. The axioms of the MoI are illustrated in table 5 and are detailed in [Scott 1998].

For example, the *Continuity* axiom implies that an increase of preference on a particular attribute should never result in a decrease of the overall preference, while the *Symmetry* axiom indicates that the overall preference should only depend on the assigned individual preferences, independently of the order in which they are expressed.

Axioms	Formulation
Monotonicity	$P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) \le P\left(p_1,\mathrm{p}_2';\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) \quad \forall\, p_2(\mathbf{x}) \le p_2'(\mathbf{x})$ $P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) \le P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2'\right)(\mathbf{x}) \quad \forall \mathrm{w}_2(\mathbf{x}) \le \mathrm{w}_2'(\mathbf{x});\ p_1(\mathbf{x}) < p_2(\mathbf{x})$
Symmetry	$P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) = P\left(p_2,p_1;\mathrm{w}_2,\mathrm{w}_1\right)(\mathbf{x})$
Continuity	$P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) = lim_{p_2'(\mathbf{x})\to p_2(\mathbf{x})} P\left(p_1,p_2';\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x})$ $P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) = lim_{\mathrm{w}_2'(\mathbf{x})\to \mathrm{w}_2(\mathbf{x})} P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2'\right)(\mathbf{x})$
Idempotency	$P\left(p,p;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) = p(\mathbf{x}) \quad \forall \mathrm{w}_1+\mathrm{w}_2>0$
Annihilation	$P\left(p,0;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}) = 0 \quad \forall \mathrm{w}_2 \neq 0$
Self-scaling weights	$P\left(p_1,p_2;\mathrm{w}_1\cdot\mathrm{t},\mathrm{w}_2\cdot\mathrm{t}\right)(\mathbf{x}) = P\left(p_1,p_2;\mathrm{w}_1,\mathrm{w}_2\right)(\mathbf{x}), \quad \forall \mathrm{w}_1+\mathrm{w}_2,\mathrm{t}>0$
Zero weights	$P\left(p_1,p_2;\mathrm{w}_1,0\right)(\mathbf{x}) = p_1(\mathbf{x}) \quad \forall \mathrm{w}_1 \neq 0$

Table 5. Axioms of the MoI for design appropriate aggregation functions

Axioms of *Idempotency* and *Annihilation* are specific to engineering design and differentiate MoI from other approaches in multicriteria decision-making. The *Idempotency* axiom refers to the notion of rational behaviour and states that if several identical individual preferences are combined, then the resulted overall preference must be equal to the individual preferences. This axiom has major implications for the specification of consistent preference functions through the simultaneous comparison of attributes. As previously mentioned, the axiom of

Annihilation implies that if one individual preference is equal to zero (unacceptable attribute value), then the resulted overall preference should be equal to zero too (unacceptable alternative). This differentiates engineering design from most of classical decision-making problems where objectives can always be traded-off.

3.3.2 Design-appropriate aggregation functions

According to Scott [Scott 1991], an aggregation function is said to be *design-appropriate* if it satisfies every axioms of the MoI. In particular, Scott suggests the class of weighted means as a family of aggregation functions in engineering design, and shows that any weighted mean satisfying the *Annihilation* axiom is design-appropriate. The general form of the weighted mean aggregation functions can be expressed as follows:

$$P_s\left(p_1, p_2; \mathrm{w}_1, \mathrm{w}_2\right) = \left(\frac{\mathrm{w}_1\, p_1^s + \mathrm{w}_2\, p_2^s}{\mathrm{w}_1 + \mathrm{w}_2}\right)^{\frac{1}{s}}, \quad s \in \mathbb{R} \tag{3.3.2.1}$$

where *s* is the trade-off strategy parameter, also called compensatory level parameter. From this general expression, changes of the parameter *s* values results in the generation of weighted mean aggregation functions. In particular:

- the *min* aggregation function $P_{\min}$ while $s \to -\infty$
- the weighted geometric mean (or weighted product) aggregation function P_0 for s=0
- the weighted arithmetic mean (or weighted sum) aggregation function P_1 for s=1
- the *max* aggregation function $P_{\max}$ while $s \to +\infty$

Further details are provided in Annex 1. According to the *Annihilation* axiom, design-appropriate aggregation functions correspond to the set of weighted means generated while s≤0. In particular, the *min* aggregation ($s \to -\infty$) and the weighted geometric mean aggregation functions (s=0) are both design appropriate. The weighted sum aggregation obtained for s=1 is therefore considered as not design appropriate within the MoI framework.

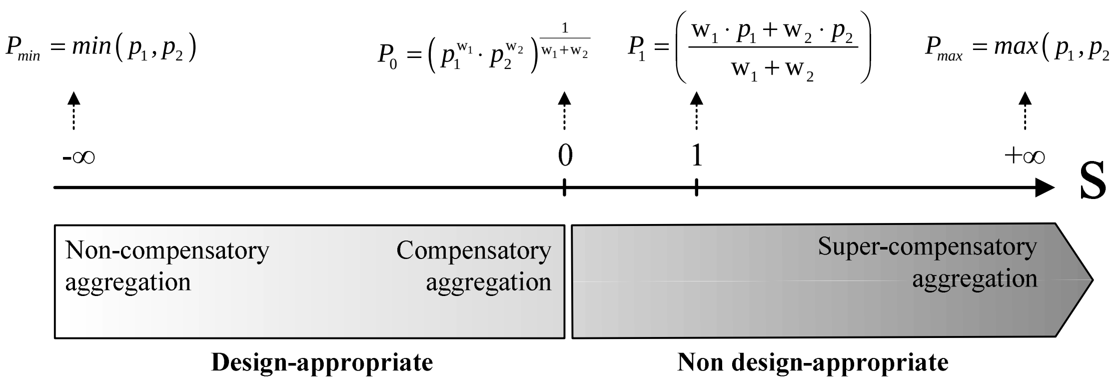


Figure 19. Representation of the weighted mean aggregation functions continuum

Figure 19 illustrates the continuum of weighted mean aggregation functions generated while the value of the parameter s is spanning its domain of values. Actually, it is not a real continuum since there is a discontinuity for s=0. The compensatory level of the aggregation function increases progressively with the value of s. Aggregation functions can be thus classified into non-compensatory, compensatory and super-compensatory aggregation functions. Super-compensatory aggregation functions are generated while s>1 and thus, are not design appropriate.

In particular, the weighted geometric mean aggregation (s=0) is compensatory. It is denoted as *aggressive* strategy by Otto [Otto 1991] since it traduces the intention of improving the overall preference by worsening the lowest individual preference. Indeed, design optimization is often hampered by one criterion which is more difficult to satisfy than the others. On the contrary, the *min* aggregation is non-compensatory. It is denoted as *conservative* strategy by Otto, since in this case, designers expect to improve the lowest individual preference against a decrement of the overall preference.

3.4 Desirability approach in engineering design

3.4.1 Desirability and Utility

Desirability is a preference measurement which reflects the level of satisfaction achieved by design alternatives' properties according to designers' point of view. Since Harrington has introduced the concept of desirability and desirability functions to deal with multicriteria optimization in quality engineering [Harrington 1965], this approach has been massively used to tackle MO problems in a large range of scientific areas including engineering design [Derringer 1980, Derringer 1994, Kim 2000, Réthy 2004, Trautmann 2005, Trautmann 2009, Kruisselbrink 2009, Chen 2011]. However, the basis and implications of the desirability concept in engineering design are still unclear.

In fact, there is some ambiguity between the notions of desirability and utility in engineering design, and the "desirability" of an alternative often refers to its utility value [Keeney 1993]:

"Expected utility theory ... can provide a normative analytical method for obtaining the utility value ("desirability") of a design ..." Krishnamurty, 2006

"A natural measure of the desirability of choice ... is the expected maximum utility", Kenneth, 2006

Facing the lack of clear definition of desirability in engineering design, we intend to cover this issue in the following by proposing definitions of desirability and utility in different fields of science and insights on how they are closely related.

a. Desirability/Utility in economic sciences

In economics, Fischer [Fischer 1906] discusses utility and desirability of goods where "goods" refer to any services, properties or wealth. According to his point of view, utility is linked to the satisfaction of the desire rather to the desire itself. Utility requires experience and duration in time for its existence, whereas desirability is defined rather as the intensity or the strength of individuals' desire for goods under certain conditions. Desirability merely reflects the state of individuals' mind at a particular moment. However, the concepts of utility and desirability are closely linked since the desirability of goods represents the current esteem on which future satisfactions are based.

Moreover, the term "utility" in economics also covers technical meaning and often refers to money. Utility is a financial compensation resulting from a monetary exchange. For example, diamonds are commonly considered as ornamental artefacts, and thus, are useless by definition, whereas in economics, they are regarded as useful.

Finally, it can be useful to distinguish total desirability which is defined as the desirability of an entire group of goods, from the marginal desirability which is the desirability associated to the loss or the gain of one more good within the group.

b. Desirability/Utility in social sciences

According to Beauvois [Beauvois 1995, Cambon 2006], the value associated to a person, or an artefact, results from a particular kind of social interactions and is determined from two different components denoted respectively as social desirability and social utility.

Social desirability refers to people's awareness about what it is considered desirable within a society or a group. Social desirability differs from individual desirability which is rather related to the particular feeling that one person can develop for an artefact or another person. For example, some social behaviour such as altruism or politeness can be considered as socially desirable, whereas one individual cannot stand such behaviours due to his past experience (individual desirability).

Social utility refers to the value assigned to an artefact or an individual, in respect with its ability to meet some fundamental properties of social functioning. Social utility reflects the awareness of the chances of success or failure for a person living in a society. It is mainly related to the economic sense of the “market” value of a person, rather than the fact to render services to someone.

Finally, Beauvois concludes that the social value of individuals is composed by the desire value which is represented by social desirability (cordial, friendly), and the market value which is represented by social utility (efficient, ambitious).

c. Desirability/Utility in design sciences

In design sciences, the notions of utility and desirability are often met in User Experience Design (UXD). UXD covers all aspects of a user experience facing a system including interface, physical interactions and human-computer interactions design [Law 2009].

User experience (UX) intends to reflect the feeling of an individual using a product, a system or a service. UX does not only focus on interactions between human and product, but also includes individual's perceptions of practical aspects such as utility, desirability and usability. Figure 20 illustrates a common view in UXD which admits that the optimal UX exists at the intersection of the three following factors: Desirability, Utility and Usability. Focusing only on one of them may cause confusion, apathy or frustration among users. Consequently, the “ideal” system should results from a balance of these three factors.

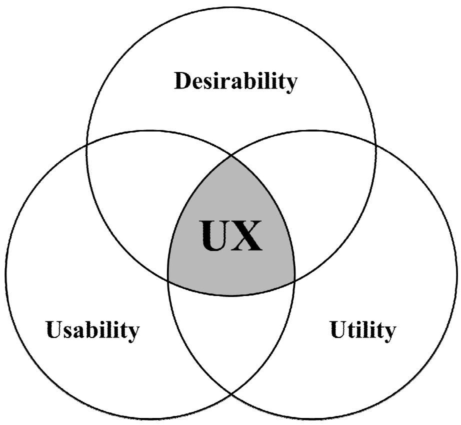


Figure 20. The optimal User Experience

Usability refers to the ease of use and learning ability of a system or a product. ISO standards (ISO/TR 16982:2002, ISO 9241) define usability as “The extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use”. The concept of usability leads in general to systems which are simple to understand, easy to master, responding to basic needs of humans.

In UX, desirability is required to make attractive product in regards of what is commonly admitted as desirable in the society. It is a measure of the desire intensity for a product. However, focusing on the desirability aspect may results in unintuitive or excessive products. On the contrary, utility is of practical implications. It implies that systems do what they are expected to do. In return, systems may require additional efforts for control or use.

d. Summary

According to the different views of desirability and utility met in different fields of science, it appears that desirability and utility are considered as two separate and distinct concepts which are closely linked. Therefore, the same distinction should be made in engineering design.

Desirability doesn't express preference under risk or uncertainty like utility, but rather intend to model experts knowledge and designers' judgment about how should be designed. It reflects the level of satisfaction (or the desire intensity) of designers for particular design property values. Desirability links objective and subjective knowledge about the system to be designed in respect with requirements and designers' past experiences.

Through desirability functions, designers can express their so-called "feel for design" [Hubka 1975] which refers to the ability in estimating appropriate dimensions, forms, temperatures or performances of a design, without any calculations. This subjective knowledge is developed through past experiences and is generally formulated as experts' rules, heuristic advises or guidelines. For example, larger dimensions and smooth transitions favour the mechanical strength in the higher stressed areas of mechanical systems. In the same way, progressive changes of pipe cross-sections with the largest possible channel radius are suitable for fluid flowing. Such expert knowledge is fundamental to tackle any design problem. It provides additional non-formalized information (i.e. more constraints and less degrees of freedom). This enables to distinguish early undesirable design solutions and to converge quickly toward the most desirable ones.

Therefore, desirability enables to model preferences related to the true knowledge of designers about design. It is not concerned neither with risk, nor imprecision, but with the level of satisfaction resulting from the adequation between the real behaviour of alternatives and the expected behaviour expressed by designers.

3.4.2 Desirability functions

Desirability functions are value functions which express the level of satisfaction of designers for attributes values according to the design requirements and his expectations. They are non-dimensional, monotonous, or piecewise monotonous functions, whose values are ranged in the interval [0, 1]. A desirability d=0 represents an unacceptable property value, whereas a desirability d=1 represents a completely acceptable property value such as slight improvements of this property will not further change its level of satisfaction. In particular, desirability functions can be used to model the degree of satisfaction associated to one particular design criteria. Two classes of desirability functions, namely Harrington's desirability functions and Derringer's desirability functions are usually used in multicriteria optimization problems.

a. Harrington's desirability functions

In 1965, Harrington [Harrington 1965] proposed two types of continuous desirability functions to deal with MO problem. While the one-sided formulation is suitable to reflect "bounding low values is better" and "bounding high values is better", the two-sided formulation is used to express that "closer to a particular target value is better". The general

Harrington's one-sided desirability function for bounding low values (minimization) is expressed as:

$$d^H(\mathrm{y}) = exp\left(-exp\left(\alpha + \beta \cdot \mathrm{y}\right)\right)$$
$$\begin{cases} \alpha = \dfrac{ln\left(ln\left(d^H(\mathrm{AC})\right) / ln\left(d^H(\mathrm{SL})\right)\right)}{\mathrm{AC} - \mathrm{SL}} \\ \beta = ln\left(-ln\left(d^H(\mathrm{SL})\right)\right) - \alpha \cdot \mathrm{SL} \end{cases} \quad (3.4.2.1)$$

where the parameters AC and SL refer respectively to an absolute constraint and a soft limit such as SL<AC. This function is represented on figure 21. In the same way, the Harrington's one-sided desirability function for bounding high values (maximization) is expressed as:

$$d^H(\mathrm{y}) = exp\left(-exp\left(\alpha + \beta \cdot \mathrm{y}\right)\right)$$
$$\begin{cases} \alpha = \dfrac{ln\left(ln\left(d^H(\mathrm{SL})\right) / ln\left(d^H(\mathrm{AC})\right)\right)}{\mathrm{SL} - \mathrm{AC}} \\ \beta = ln\left(-ln\left(d^H(\mathrm{SL})\right)\right) - \alpha \cdot \mathrm{SL} \end{cases} \quad (3.4.2.2)$$

where the parameters AC and SL are such as AC<SL. In general, the desirability levels associated to the desirability function parameters are such as d^H(AC)=0.01 and d^H(SL)=0.99. But, other desirability values can be assigned to the AC and SL bounds according to design requirements and designers' intentions. While AC bounds correspond to the strict satisfaction of design criteria, SL bounds are related to the flexibility of design requirements.

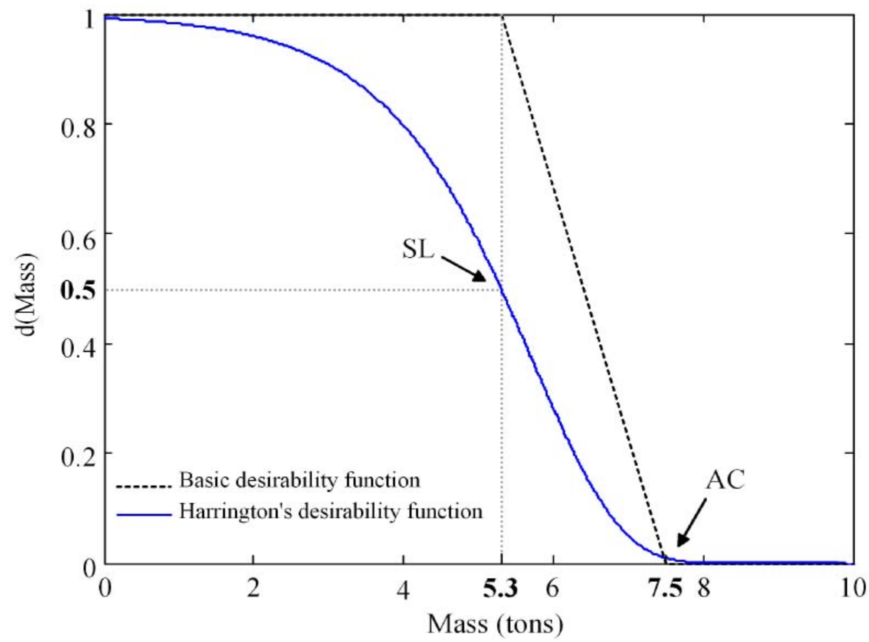


Figure 21. Representation of the one-sided Harrington's desirability function

As an example, figure 21 represents the desirability function associated to the mass requirements of the two-staged flash evaporator described in chapter 6. This system has been designed for must concentration in the wine industry. As the evaporator must be transportable from a production site to another, the mass requirements has been derived from the dimensions and maximal carrying capacities of medium-sized flat bed trucks (PTAC<7.5t).

Moreover, as explained in section 6.4.1, existing evaporators proposed by competing constructors can be used to define reference systems with a mass of intermediate desirability $d^H(\text{Mass}_{ref})=0.5$ with $\text{Mass}_{ref}=5.3$t. From these considerations, the preferences related to the mass of the two-staged flash evaporator are modelled by specifying the Harrington's desirability with AC=7.5t, SL=5.3t, d(AC)=0.01 and d(SL)=0.5. The basic value function associated to these constraints has also been plotted in dashed line. Compared to this basic modelling, Harrington's function presents progressive desirability variations approaching the bounds. As a consequence, the desirability of alternatives with a mass of 7.5t+ε (with ε→0) is very low but not null. This actually models the preference of designers facing alternatives which are closed to the admissible limits of the design problem. Although these alternatives do not satisfy constraints, they can remain relevant for designers, and therefore, their level of desirability should not be null.

The Harrington's two-sided desirability functions are specified with four parameters, namely: a lower absolute constraint (AC_L), a lower soft limit (SL_L), an upper soft limit (SL_U) and an upper absolute constraint (AC_U). The general form of the Harrington's two-sided desirability functions is expressed as follows:

$$
\begin{aligned}
&d^H(y) = exp\left(-\left|y'\right|^n\right) \\
&y' = \frac{2y-(U+L)}{U-L} \\
&\text{where} \\
&\text{case (1):}\quad U = AC_U \qquad L = AC_L \\
&\text{case (2):}\quad U = SL_U \qquad L = SL_L \\
&\text{case (3):}\quad U = (AC_U + SL_U)/2 \quad L = (AC_L + SL_L)/2
\end{aligned}
\tag{3.4.2.3}
$$

However, the initial formulation proposed by Harrington doesn't support non-symmetric boundaries. There are three possibilities to make symmetric boundaries: (1) use absolute constraints boundaries and use a soft limit to determine n, (2) use soft limits boundaries and use a constraint limit to determine n, or (3) use an average value between absolute constraints and soft limits boundaries, and then use a constraint limit to determine n.

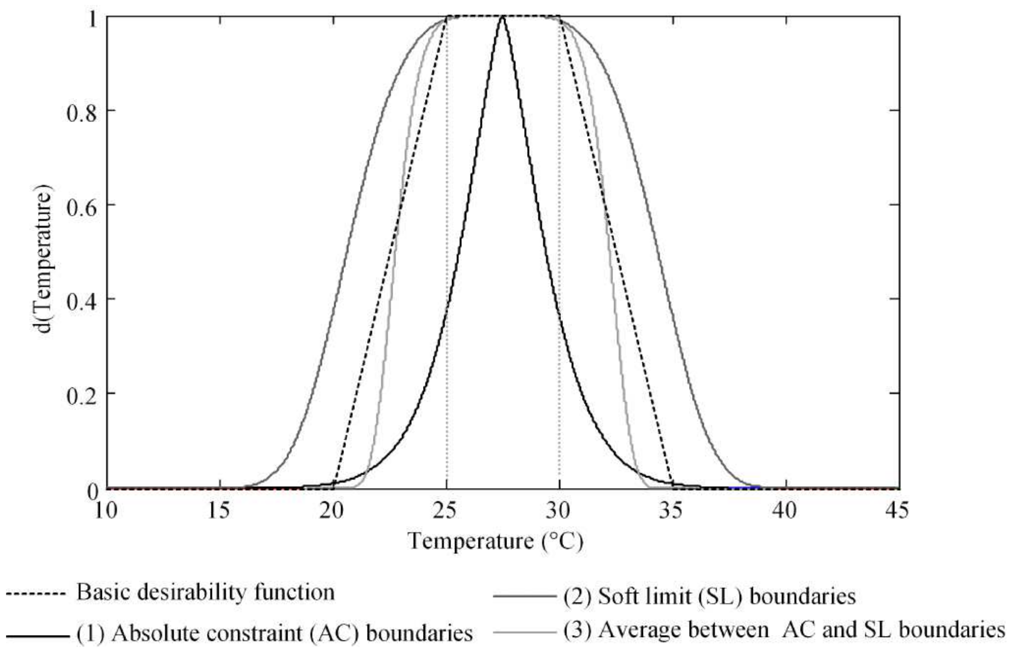


Figure 22. Representation of the two-sided Harrington's desirability function

Figure 22 represents the two-sided Harrington's desirability function associated to the temperature requirements for the vintage at the outlet of the previous two-staged flash evaporator. As it is explained in chapter 6, the continuity and efficiency of the fermentation process is ensured for temperatures comprised 25°C and 30°C. Therefore, the related desirability function has been specified with AC_L=20°C, SL_L=25°C, SL_U=30°C and AC_U=35°C. The basic value function associated to these constraints has been plotted in dashed line. The different curves plotted in solid line correspond to the two-sided Harrington's desirability functions specified with the three types of symmetric boundaries given in the relation (3.4.2.3).

b. Derringer's desirability functions

In 1980, Derringer [Derringer 1980] has proposed another class of desirability functions to balance multiple responses in quality engineering. He used a modified formula of the Harrington’s desirability functions combined with a response surface methodology to form a so-called Desirability Optimization methodology (DOM). Unlike Harrington's desirability functions, Derringer's desirability functions are discontinuous and piecewise-defined functions. The general form of the Derringer's one-sided desirability function for bounding low values (minimization) is expressed as:

$$d^D(\mathrm{y}) = \begin{cases} 1 & \mathrm{y} \le \mathrm{L} \\ \left(\dfrac{\mathrm{U}-\mathrm{y}}{\mathrm{U}-\mathrm{L}}\right)^{\mathrm{l}} & \mathrm{L} < \mathrm{y} \le \mathrm{U} \quad \text{with} \quad \mathrm{l} \in \mathbb{R}_+^* \\ 0 & \mathrm{y} < \mathrm{U} \end{cases} \tag{3.4.2.4}$$

where the parameters U and L refer designate respectively the upper and lower bounds such as L<U (see figure 23). In the same way, the Derringer’s one-sided desirability function for bounding high values (maximization) is expressed as:

$$d^D(\mathrm{y}) = \begin{cases} 1 & \mathrm{y} \ge \mathrm{U} \\ \left(\dfrac{\mathrm{y}-\mathrm{L}}{\mathrm{U}-\mathrm{L}}\right)^{\mathrm{l}} & \mathrm{L} < \mathrm{y} \le \mathrm{U} \quad \text{with} \quad \mathrm{l} \in \mathbb{R}_+^* \\ 0 & \mathrm{y} < \mathrm{L} \end{cases} \tag{3.4.2.5}$$

The parameter l is used to modify the variations of desirability between the bounds. Assigning different values of this parameter modifies the shape of the desirability function and thus, enables to fit the designer’s preferences. Figure 23 represents the Derringer's desirability function related to the mass requirements of the two-staged flash evaporator. In this example, from the relation (3.4.2.4), the Derringer's desirability function with a lower bound of L=4.5t and an upper bound U=7.5t. The value of the parameter l has been determined according to the mass of the reference system with an the intermediate desirability d^D(5.3t)=0.5. From relation (3.4.2.3), it follows that:

$$\mathrm{l} = -log(2)/log\left(\frac{5.3-7.5}{4.5-7.5}\right) = 2.2348 \tag{3.4.2.6}$$

It can be noticed that the basic desirability function is obtained for l=1. However, unlike the formulation proposed by Harrington, the use of Derringer’s desirability functions implies that every solution with a mass lower than 4.5t are equally preferred, since d^D(Mass≤4.5t)=1, and, in the same way, every solution with a mass higher than 7.5t are undesirable since

d^D(Mass≥7.5t)=0. Therefore, the existence of such threshold values does not enable to rank neither completely satisfying solutions between them, nor undesirable solutions between them.

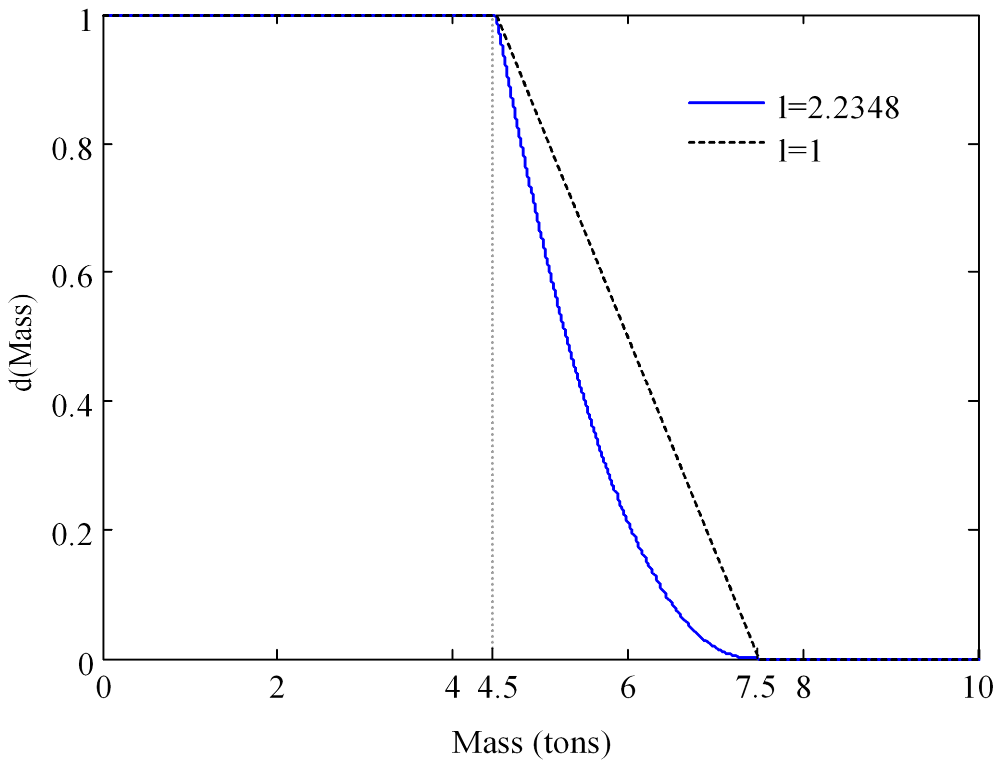


Figure 23. Representation of the one-sided Derringer's desirability function

For target problems, the formulation of the Derringer's two-sided desirability function requires the specification of five parameters. Two parameters are required to set the lower and upper bounds, another specifies the target values, and finally, the two last parameters are used to adjust the slope of the function on both sides of the target value. The general form of the Derringer's two-sided desirability functions is expressed as follows:

$$d^D(y) = \begin{cases} 0 & y < L \\ \left(\dfrac{y-L}{T-L}\right)^l & L < y \le T \\ \left(\dfrac{y-U}{T-U}\right)^u & T < y \le U \\ 0 & y > U \end{cases} \qquad l \in \mathbb{R}_+^*, \quad u \in \mathbb{R}_+^* \tag{3.4.2.7}$$

where T represents the target value. The parameters (l, u) can be set independently to approach the target value in different way from both sides. Figure 24 represents the target temperature requirements linked to the design of the previous flash evaporator. The two-sided Derringer's desirability functions have been specified with L=20°C, T=27.5°C and U=30°C, and have been plotted for different values of (l,u). The three functions model different designer's intentions, in particular in regards to the variations of preferences approaching the bounds and the target value. According to this modelling, only solutions presenting an outlet temperature equal to the target, i.e. 37.5°C, achieve a desirability value equal to one.

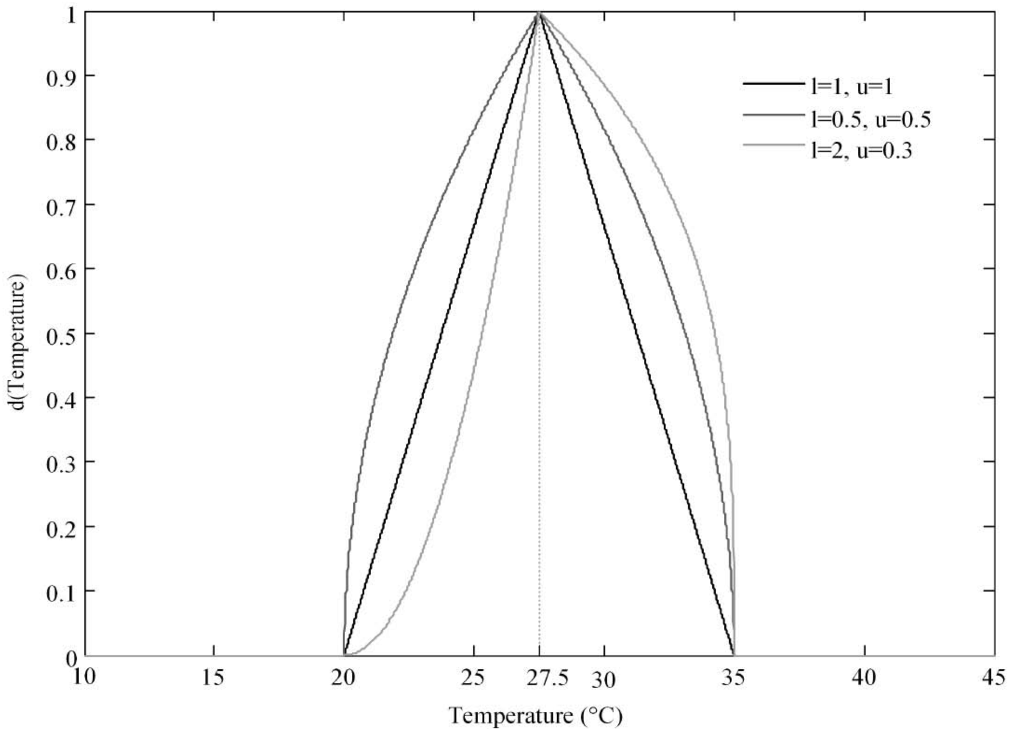


Figure 24. Representation of the two-sided Derringer's desirability function

c. Summary on desirability functions

Although the specification of Derringer's desirability function is easier than Harrington's, they are less suitable to accurately express designers' preferences. Due to the threshold values, Derringer's formula don't differentiate the most satisfying design solutions between them (d=1) and unacceptable design solutions between them (d=0). Therefore, a ranking between "good" (or "bad") cannot be established.

On the contrary, due to their exponential form, Harrington's desirability functions allow progressive desirability variations approaching the bounds, and consequently, assign different desirability scores to every design performance value. Consequently, using Harrington's desirability functions in design problem are used to rank the whole set of solutions, including acceptable and unacceptable solutions.

According to the example illustrated on figure 21, it may happen that there is no solution satisfying the absolute constraint of 7.5 tons. Harrington's desirability functions overcome this difficulty by providing a soft formulation of constraints. Due to the monotonicity of the functions; even if the absolute constraint has been violated, the desirability value of the performance measure remains very low but not null. Consequently, a design solution with a performance value equal to 7.5 t+ε will remain relatively desirable, and the design problem can be solved.

To conclude, Harrington's desirability functions appear to be relevant functions to interpret properties values and model preference based on design requirements and designers' expectation. Once individual desirability functions have been specified on every property, they are then aggregated into single global criterion called Desirability Index (DI). This criterion represents the overall level of desirability achieved by design solutions and is used as a metric for their evaluations.

3.4.3 Desirability Index

Derringer proposed to aggregate individual desirability function into a single Desirability Index (DI) using a weighted geometric mean aggregation [Derringer 1960]. As a function, the DI is expressed as follows:

$$DI(\mathbf{y}) = \prod_{i=1}^{k} d_i(y_i)^{w_i} \quad \text{with} \quad \sum_{i=1}^{k} w_i = 1 \qquad (3.4.3.1)$$

where w_i represents the numerical weight assigned to the i^{th} desirability function. Numerical weights reflect the relative importance of properties between them. DI corresponds to the overall desirability of a design solution over all its properties. As it is still a desirability level, it lies in the interval [0,1]. The formulation of the DI as the average of the individual desirability scores enables synthesizing the set of preferences expressed on the design. This reduces the number of criteria and consequently, allows a direct comparison of alternatives. Derringer has proposed a weighted geometric mean to aggregate the desirability functions into a single desirability value. This proposition results from the statement that during most of product development processes, a single property with an unacceptable value makes the product useless (*Annihilation* axiom of the MoI).

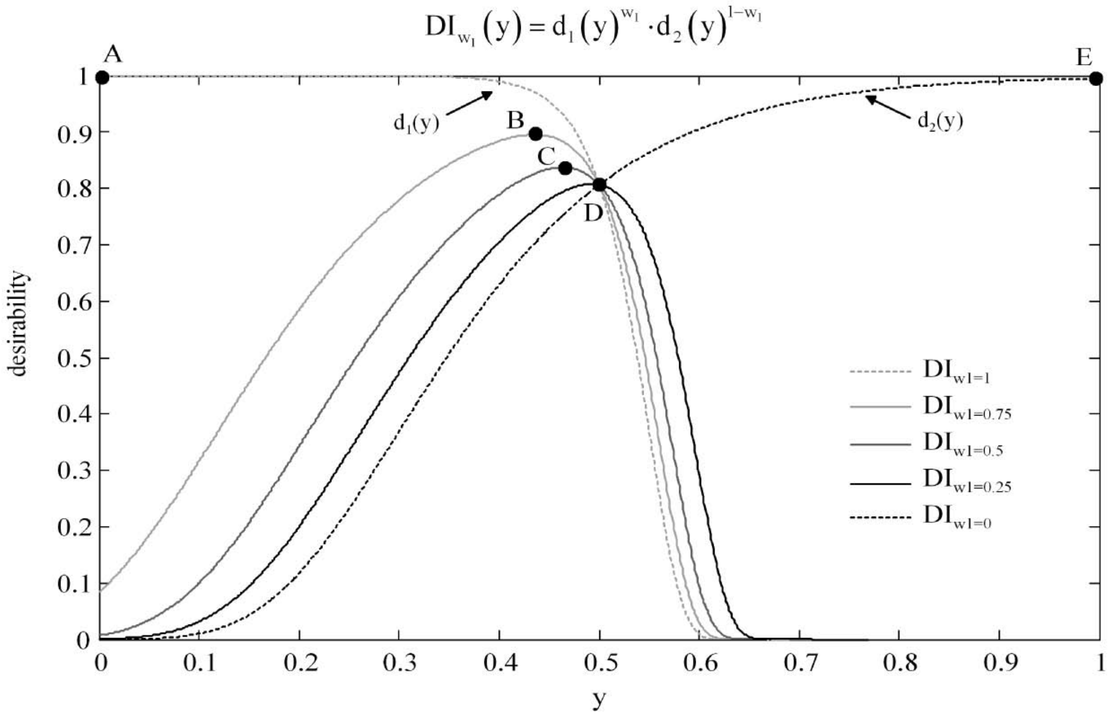


Figure 25. Representation of the Desirability Index for different weight assignments

Figure 25 illustrates the influence of the weights on the DI values for an aggregation of two individual Harrington's desirability functions, namely d_1(y) and d_2(y). According to the relation (3.4.2.1), the desirability function d_1 has been specified with SL=0.4 (d_1(SL)=0.99) and AC=0.6 (d_1(AC)=0.01) using the relation (3.4.2.2). The desirability function d_2 has been specified with AC=0.1 (d_2(AC)=0.01) and SL=0.9 (d_2(SL)=0.99). The weight w_2 is expressed as w_2=1-w_1, and the weight w_1 is decreased from 1 to 0 with a step of 0.25 to generate the different DI functions. When w_1=1, it results that w_2=0 and DI_1(y)=d_1(y). Inversely, when w_1=0, it comes that w_2=1 and DI_0(y)=d_2(y). Decreasing the value of w_1 makes DI(y) to deviate from d_1(y) and it tends toward d_2(y). As DI(y) is expected to be maximized, another interesting point concerns the variations of the optimum with the weights. According to this figure, points A, B, C, D and E correspond respectively to the optimum of the functions $DI_{w1=1}$, $DI_{w1=0.75}$, $DI_{w1=0.5}$, $DI_{w1=0.25}$ and $DI_{w1=0}$. These points correspond to the optimal solutions resulting from the optimization of the DI functions. The DI scores linked to these solutions are such as:

$$DI(\mathrm{D})_{w_1=0.25} < DI(\mathrm{C})_{w_1=0.5} < DI(\mathrm{B})_{w_1=0.75} < DI(\mathrm{A})_{w_1=1} = DI(\mathrm{E})_{w_1=0} \quad (3.4.3.2)$$

However, the relation (3.4.3.2) does not induce a preference relation order between these solutions. In fact, these solutions correspond to different optimization problems, and thus, cannot be directly compared. Therefore, the ranking of solutions resulting from the optimization of DI functions is possible only for a given set of weights. For example, for $w_1=0.5$, the comparison of the solutions B and C requires the computation of $DI(\mathrm{B})_{w1=0.5}$ and $DI(\mathrm{C})_{w1=0.5}$. In chapter 5, it is explained that variations of weight combinations enables to determine optimal solutions along the Pareto frontier.

Later, another approach is proposed by Kim and Lin [Kim 2000] to avoid the use of numerical weights. They suggest an aggregation function based on the minimum of the individual desirability scores. The DI is then expressed as follows:

$$DI(\mathbf{y}) = \min_{i=1\ldots k}\left(d_i(y_i)\right) \quad (3.4.3.3)$$

While the optimization of the aggregation function proposed by Derringer (weighted geometric mean) enables to improve the DI value by worsening the lowest individual desirability score, the aggregation formula suggested by Kim and Lin aims to improve the lowest individual desirability against a decrement of the overall desirability (DI value). According to the axioms of the MoI, these two aggregation functions are *design appropriate*, and thus, are suitable to model preference in engineering design (for details see section 3.3). Consequently, we propose here to combine the concept of desirability with the concept of *design appropriate* aggregation functions. The formulation of the DI is thus extended to the class of weighted means as follows:

$$DI(\mathbf{y}) = \left(\sum_{i=1}^{k} w_i \cdot d_i(y_i)^s\right)^{\frac{1}{s}} \quad \text{with} \quad \sum_{i=1}^{k} w_i = 1 \quad (3.4.3.4)$$

As it is explained in section 3.3, only aggregation functions generated with $s \le 0$ are *design appropriate*. Figure 26 illustrates the impact of the parameter s ($s \le 0$) on the DI values for an aggregation of the two previous desirability functions $d_1(y)$ and $d_2(y)$ according to the relation (3.4.3.4). The weights are set such as $w_1=w_2=0.5$. The formulations proposed by Derringer and Kim correspond respectively to $DI_{s=0}$ and $DI_{s\to-\infty}$. Decreasing the value of s causes a decrement of the compensatory level between the two desirability functions. For high negative values ($s<-10$), the generated aggregation functions tend quickly toward the *min* aggregation function ($DI_{s\to-\infty}$). On the interval [0;0.5], the *min* aggregation function leads to $DI(y)_{s\to-\infty}=d_2(y)$, whereas on the interval [0.5,1], it leads to $DI(y)_{s\to-\infty}=d_1(y)$. Like weight assignment, variations of the trade-off parameter value also modify the optimum of the DI function. Each value of s corresponds to a particular trade-off strategy and leads to a specific type of solution. This is further discussed in chapter 5 where a procedure to determine consistent values of s according to designers' preferences is presented.

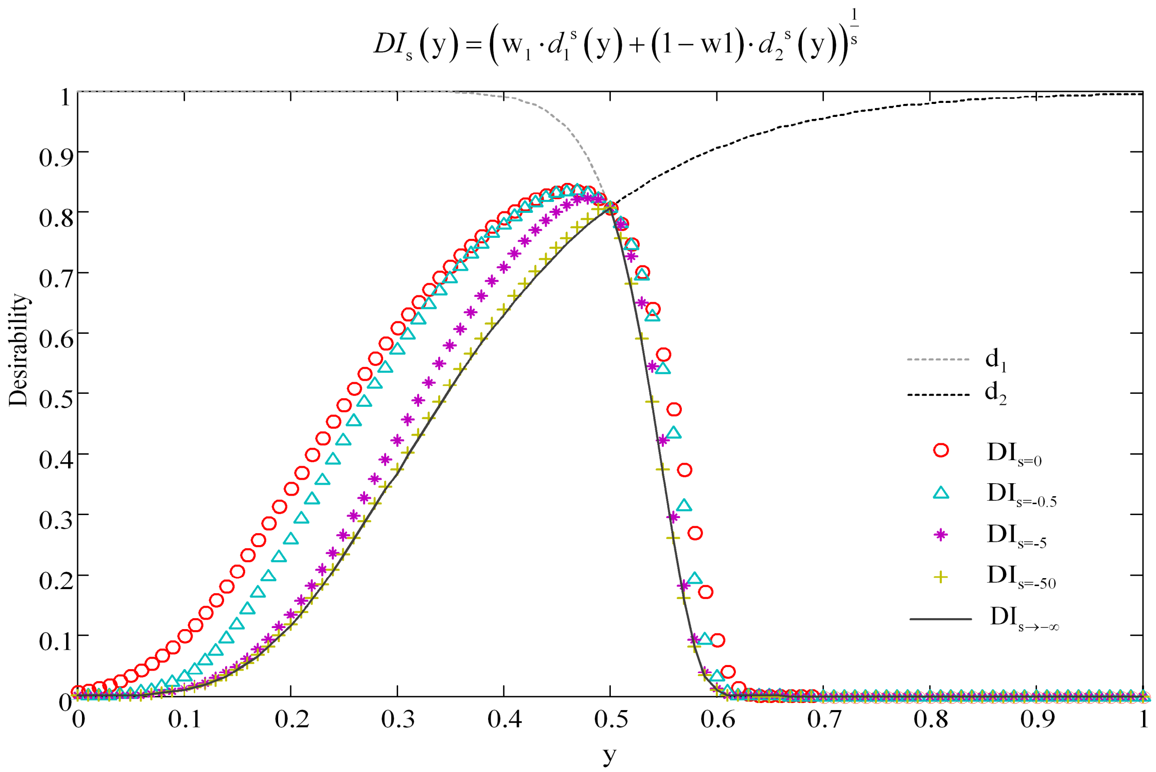


Figure 26. Illustration of the Desirability Index for different values of trade-off strategy parameter (s)

3.5 Summary

As design is a human activity, embodiment design problems differentiate themselves from others kinds of problems by the expression and the formulation of designer's preferences. Facing multiple criteria, preference assessments can be tackled by determining individual preference functions, and generating adequate aggregation strategy to form a single global criterion used as a metric for alternatives evaluation. This chapter 3 introduces the main concepts and issues related to preference modelling in engineering design. Three different approaches, namely utility theory, method of imprecision and desirability index, are presented and discussed according to their ability in modelling preferences in engineering design. The desirability approach appears as the most relevant to reflect designers' intention in embodiment design. Desirability enables to model preferences related to the true knowledge of designers about design. It is not concerned neither whit risk, nor imprecision, but with the level of satisfaction resulting from the adequation between the real behaviour of alternatives and the expected behaviour expressed by designers. In particular, Harrington's desirability functions appear as relevant functions to interpret properties values and model preference based on design requirements and designers' expectation. Due to their exponential form, Harrington's desirability functions allow progressive desirability variations approaching the bounds, and consequently, enable to rank the whole set of solutions, including acceptable and unacceptable solutions. Moreover this class of desirability functions provides the design problem with a soft formulation of constraints which reflects better the designer's behaviour evaluating design candidates. Individual desirability functions are then aggregated into desirability index according to the general weighted mean. The concept of desirability index has been extended here in respect with the definition of design appropriate aggregation functions proposed by the MoI. This enables to express different trade-off and compensatory levels between objectives.

CHAPTER 4 Methodology for design problem modelling based on observation, interpretation and aggregation

From a selected concept, embodiment design purpose consists in determining the main dimensions and monitoring parameters of the system to provide designers with embodied solutions with validated physical behaviours and optimized functional structures. Consequently, embodiment design problems are naturally oriented toward numerical optimization. The automation of this optimization process using artificial systems requires suitable methods to reach the most preferred design solutions. In particular, models in engineering design should involve not only objective knowledge, derived from physical and technical laws, but also subjective knowledge related to designers' preferences. In this chapter, we propose a modelling methodology for design problems, based on observation, interpretation and aggregation models, linking physical behaviours with functional constraints and design objectives. This methodology is then applied for modelling robust design problems.

4.1 Design definitions

4.1.1 Design variables

Design solutions are formally represented by vectors of design variable (**x**). Design variables define the main dimensioning and monitoring elements of the system and their values enable to distinguish design solutions between them. A vector of design variables is expressed as:

$$\mathbf{x} = \left[x_1, x_2, \ldots, x_n\right]^T, \quad n \in \mathbb{N}^*, \quad \mathbf{x} \in \Omega \qquad (4.1.1)$$

In embodiment and detailed design, design variables often concern physical and technical units. They can be continuous (length, flow rate, temperature) or discrete (type of material, standard component). Each design variables is related to a minimum (x_i^-) and a maximum (x_i^+) bound defining its range of admissible values (value domain). The union of the design variables domains of value forms the so-called design space (Ω) (or research space) as defined by the relation 2.3.1.2.

4.1.2 Observation variables

Observation variables (**y**) are quantitative measures of system effectiveness, performance or technical attributes (mass, cost, efficiency, temperature). These variables are also denoted as *performance variables, criteria variables* or *outcome variables* in the literature. They are closely related to the definition of goals and objectives, and thus can be derived from functional analysis steps. Observation variables are expressed as:

$$\mathbf{y} = [y_1, y_2, \ldots, y_m]^T, \quad m \in \mathbb{N}^* \qquad (4.1.2)$$

Observation variables (**y**) are dependent of the design variables (**x**), and possibly some other model parameters. Moreover, these performance measures are also associated to a set of design criteria. Observation of performances through the filter of design criteria forms the basis for the evaluation and comparison of design solutions.

4.1.3 Design criteria

Design criteria are physical or technical requirements that design solutions must satisfy to be considered as acceptable. They are equality or inequality relations between observation variables and a set of threshold values. Criteria are expressed as constraints, defining its physical or functional limits. They are expressed as logic relations or interval ranges. Design criteria can be formulated as functions of design variables as follows:

$$\begin{aligned} g_i(\mathbf{x}) &\geq 0 \quad i = 1,2,\ldots,m \quad m \in \mathbb{N} \\ h_j(\mathbf{x}) &= 0 \quad j = 1,2,\ldots,p \quad p \in \mathbb{N} \end{aligned} \qquad (4.1.3)$$

For example, facing the requirement of transportability linked to the design of sized system constraints the mass (M) to be lower than the maximum permissible weight in charge of a flat bed truck (M_{max}) such as $M(\mathbf{x})<M_{max}$. According to economical stakes, the development costs are often constrained by budgeted amount such as $C(\mathbf{x})<C_{max}$. In manufacturing, a tolerance (ε) on a dimension (L) is often expressed as the following inequality constraint $L_{max}-\varepsilon \leq L(x) \leq L_{max}+\varepsilon$.

However, the constraint satisfaction in the strict mathematical sense fails in reflecting the preferences of designers who may consider solutions as acceptable if some of constraints are slightly violated. As a general rule, constraints in engineering design can be more or less satisfied, and consequently, they need to be expressed with a soft formulation. In our approach, this issue is addressed by using Harrington's desirability functions

4.1.4 Design objectives

Design objectives (or goals) are task specific requirements, or desired performance characteristics, that the system should meet. In general, they are linked to functions of systems and can be identified by performing functional analysis at each stage of the life cycle of the system. Unlike design criteria, design objectives are evaluated by designers in a qualitative way and cannot be directly estimated from the simulation model of the physical behaviour of the system. Design objectives can be more or less satisfied by design candidates. The achievement of particular design objectives is the purpose of "design for X" approaches. The reduction of manufacturing costs, minimization of environmental impacts, improvement of the transportability and robustness of the system are classical design objectives in industrial applications. In classical MO methodologies, the set of objectives to be optimized is expressed as follows:

$$\mathbf{f}(\mathbf{x}) = \left[f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x}) \right]^T, \quad k \in \mathbb{N} \qquad (4.1.4)$$

As design engineering problems involve design objectives which cannot be satisfied in the same way, they must be traded-off. A typical trade study process is described in the NASA engineering handbook [NASA 1995]. Trade studies and decision analysis must be performed jointly by designers and every expert involved in the design or life cycle of the system. Such studies require the application of human experience, judgment and perception, and result in the expression of preferences, priorities and compromises among design solutions. The modelling of design objectives and trade-off is one of the major issues tackled in this thesis.

4.2 Overview of the modelling methodology

The modelling methodology proposed here aims to support the decision making process to guide designer toward the selection of the best design solutions. These solutions correspond to different configurations of the system to be designed and are modelled through a vector of design variables (**x**). From this representation and using an optimization approach, the modelling methodology presented in this thesis provides designers with a sequence of logical steps to build relevant objective functions in regards to design requirements and preferences.

This methodology is inspired from the natural process used by humans to make judgment and operative choices. This process is based first on the observation and interpretation of performances in regards to design criteria and designers' expectations, and then, on the synthesis of the resulting design information. It results in a design model composed by three kinds of model:

1. The observation model (μ),
2. The interpretation model (δ),
3. The aggregation model (ζ).

The first layer of the model structure is the observation model (μ). From a set of design variables (**x**), it consists in observing relevant properties or performance measures (mass, cost, strength, etc) through a set of observation variables (**y**). The second layer of the model concerns the interpretation model (δ). It qualifies the degree of acceptability achieved by every observation variables in regards to the design constraints and designers' expectations. It results in a set of interpretation variables (**z**) which can be regarded as individual preferences set on the design criteria. The last layer of the design structure concerns the aggregation model (ζ) and consists in aggregating together all the interpretation variables participating to the achievement of the same design objective. According to this modelling methodology, the preferences are expressed inside the interpretation and aggregation models to link the physical behavior with the functional constraints and design objectives. From this priori expression of preferences, it results an overall preference (p) expressed as:

$$\mathrm{p} = \varphi(\mathbf{x}) = \xi \circ \delta \circ \mu(\mathbf{x}) \tag{4.2.1}$$

This general expression of the preference is enhanced by using the concept of desirability. It follows that interpretation functions are desirability functions (and interpretation variable values are desirability values) which are aggregated successively into multiple design objective indices (DOI) and one single global desirability index (GDI). The whole preference model is represented in graph form on figure 27.

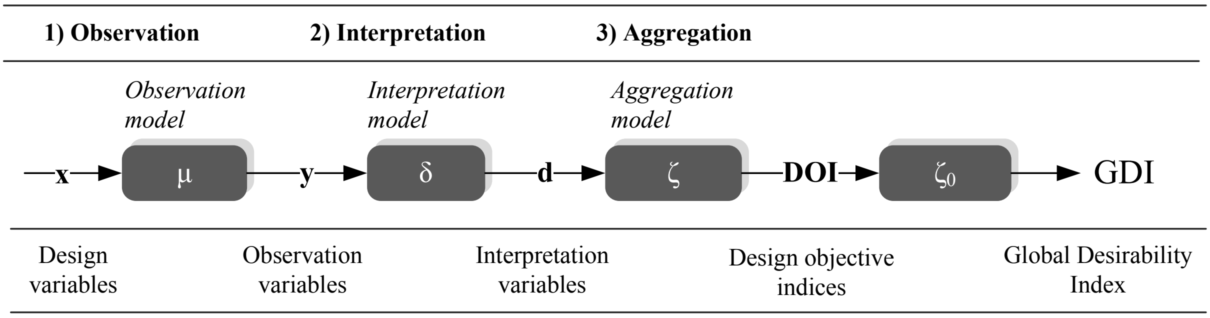


Figure 27. Observation, interpretation and aggregation models using desirability functions

The global formulation of the single criterion GDI corresponds to the objective function (φ) to be maximized, and consequently, the initial MO design problem (see relation 2.3.1.1) related to the performances optimization is synthesised as:

$$\begin{aligned} &\text{maximize GDI} \\ &\text{subject to} \quad \mathbf{x} \in \Omega \end{aligned} \tag{4.2.2}$$

According to this formulation, design objectives and constraints are no longer explicitly expressed in the design problem formulation, but now, are intrinsic to its definition through desirability functions. In the following, the proposed design model is situated within the framework of the Gero's FBS ontology and its structure is detailed. The methodology is applied first to model preferences linked to the performance of the system. It is then extended to robust design problems by modelling the preferences related to the robustness of design solutions.

4.3 Structure of the design model

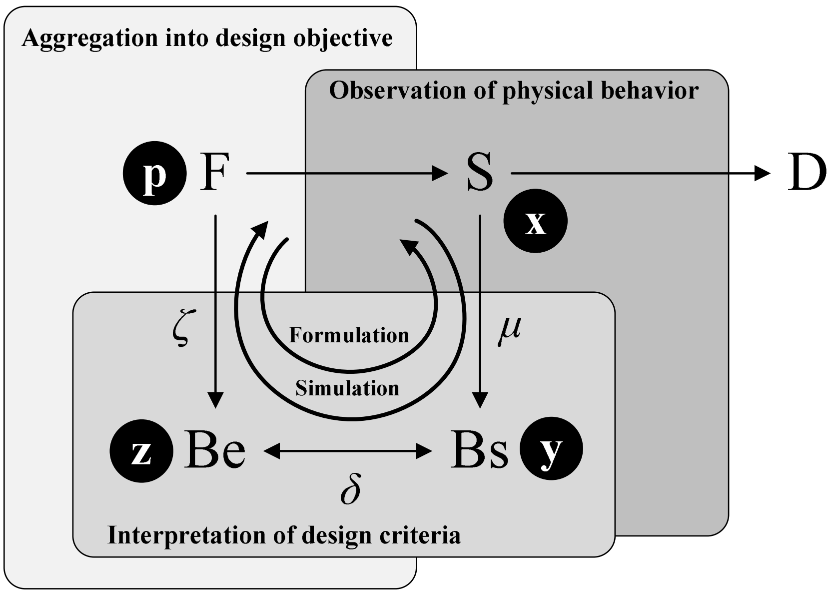
4.3.1 Situatedness of the design model within the FBS framework

The design model presented here may be mapped onto the FBS ontological model proposed by John Gero (see section 2.1.3). In this framework, the system to be designed is three fundamental concepts: function, behaviour and structure. The real behaviour of the system (BS) depends on its structure (S). The function (F) is linked to the expected behaviour of the system (Be) and represents the designer's expectations. Gero emphasizes that the main difficulty in modelling design problems consists in linking observable and expected behaviours of systems. According to the design model proposed in this thesis, the structure of the system (S) is associated to the set of design variables (**x**). The function (F) is represented by the satisfaction of design objectives which are quantified by the overall preference (p). The real behaviour (Bs) of the system is observed through the observation variables (**y**), whereas the expected behaviour (Be) corresponds to the interpretation of the observation variables (**z**) in regards to the functional constraints.

As previously mentioned, the satisfaction of one specific design objective corresponds to the achievement of one particular function. To ensure the consistence of the global design model, the main idea here is to derive its structure from the functional analysis of the system. In preliminary design, function analysis describes the functions of the system and indicates their mutual relations for a given life cycle situation. It is on the assumption that a function structure can be defined from a limited number of elementary functions. Functions are abstractions characterizing what the system is expected to do. Once the main function has been identified (satisfaction of the global need), the auxiliary functions must be determined for each situation of the system life cycle. Functions are usually classified into two categories:

- The "service" functions link two components of the system environment
- The "constraint" functions are requirements imposed by the environment

In our approach, the achievement of a particular function is associated to the satisfaction of a specific design objective, and so, to a specific DOI. It can be noticed that "constraint" functions are expressed through design criteria which are tuned into objectives by interpretation functions. Consequently, from the decomposition of the systems into functions and sub-functions, we derive a preference model structure composed by design objective indices, interpretation variables and observation variables. In this way, the consistency of the design model is guaranteed, in particular in regards to the aggregation model.



Be = expected behviour	x = Design variables	μ = Observation model
Bs = beaviour derived from structure	y = Observation variables	δ = Interpretation model
D = Design description	z = Interpretation variables	ζ = Aggregation model
F = Function	p = Preference	
S = Structure		

Figure 28. Observation, interpretation and aggregation models within the FBS framework

Figure 28 represents the design model developed in this thesis situated within the FBS framework. This model intends to formalize the implicit and explicit relations existing between function and structure through a set of variables and functions. In particular, it links the physical behavior of the system to be designed with the satisfaction of functional constraints and design objectives (expected behavior), using a priori modelling of preferences. According to this figure, two processes are highlighted, namely the "formulation" and the "simulation" process. On the one side, the "formulation" process enables to build the whole design model from the definition of functions (design objectives) to the characterization of the structure (design variables). On the other side, the "simulation" process computes numerical values for the overall preference p from a set of design variable values. This process is used by the optimization algorithm to evaluate candidate solutions (computation of the fitness scores). Although the "formulation" process is the convenient way to build the global design model, in the following, we detail the structure of the model following the "simulation" process, i.e. we begin with the description of the observation model, followed by the description of the interpretation and aggregation models.

4.3.2 Observation of performances

In real world, observation is the first thing that enables designers to apply their own judgment. Performances of systems to be designed are observed through measurements methods previously defined by designers. They are measures of relevant characteristics required to support the decision-making process. Within the modelling methodology developed in this chapter, performances are observed through a set of observation variables (**y**) as follows:

$$\mathbf{y} = \mu(\mathbf{x}) \tag{4.3.2.1}$$

The observation model (μ) is a simulation model of the system behaviour. It can be composed by physical, technical, economical and environmental models. Therefore, the simulation model of the system behaviour can be regarded as a vector of *m* equations, each one resulting in a particular observation variable such as:

$$\mu(\mathbf{x}) = \left[\mu_1(\mathbf{x}), \mu_2(\mathbf{x}), \ldots, \mu_m(\mathbf{x})\right]^T, \quad m \in \mathbb{N}^* \tag{4.3.2.2}$$

Figure 29 represents the structure of the observation model. The level *l* concerns the definition of the design variables. It constitutes the basic actions required to instantiate all the other variables. Each actions of the group A_{l-1} necessarily involves a unique observation variable and a behavioural model linked to a set of design variables.

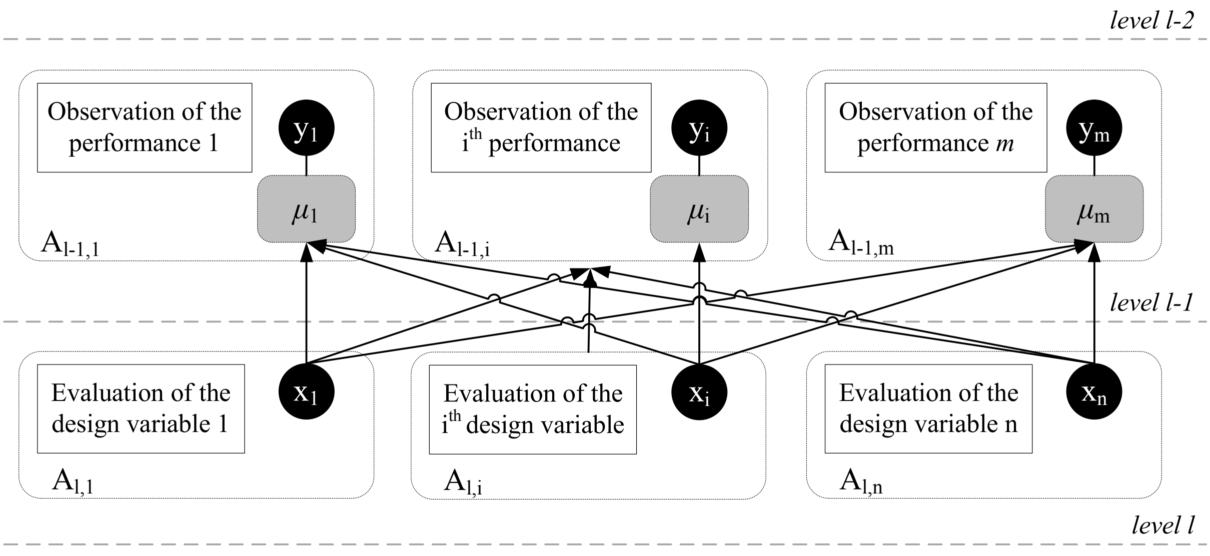


Figure 29. Observation model structure

As, by definition, such predictive models are abstractions of reality, compromises must be made in modelling phases according to designers' requirements. Models used in design applications are qualified by Vernat [Vernat 2010] through four intrinsic characteristics: Precision, Exactness, Parsimony and Specialization (PEPS). Simulation models used in preliminary design, must be mainly predictive, involving the strict minimum of variables, but enough detailed to enable designers to perform a quick evaluation and comparison between design solutions. Consequently, trades-off between precision, exactness, parsimony and specialization must be performed according to designer's requirements.

4.3.3 Interpretation of the satisfaction levels of design criteria

As design is a goal-directed activity responding to some human needs, designers have to interpret the value of each observation variable according to requirements. In other words, they have to estimate if a candidate solution is acceptable or not facing with design constraints, design objectives and also their own expertise (confidence). For a given design problem, the acceptability of a design solution mainly depends on its ability in satisfying every design criterion. These criteria are often expressed in different units making difficult a direct comparison between them. The interpretation of observation variables consists in defining a scale of value (design scale according to Messac [Messac 1996]) to bring every criterion onto a same scale of comparison. Thus, interpretation functions are value functions taking observation variables as parameters:

$$z_i = \delta_i(y_i) \;, \quad \text{with} \;\; z_i \in [0,1] \qquad (4.3.3.1)$$

where z_i is the interpretation variable associated to the i^{th} observation variable. Interpretation variables reflect the ability of design solutions to meet designer's expectations for every criterion in a given context. Therefore, they also correspond to individual preference measurements which have been set on the performances of the system. Figure 30 represents the interpretation model structure. It can be noticed that each interpretation variable corresponds to one particular observation variable.

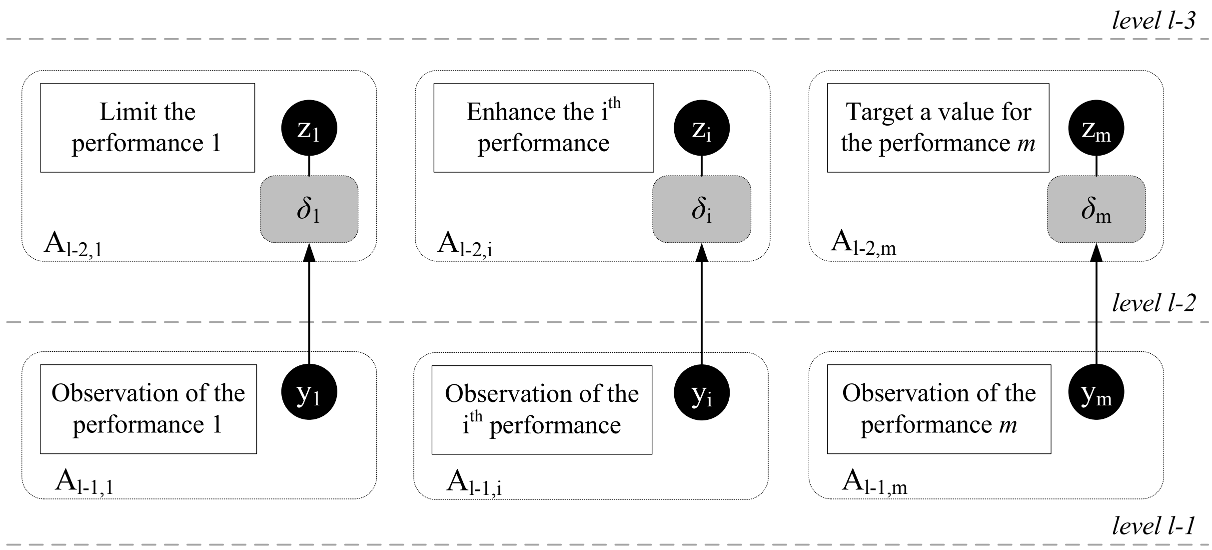


Figure 30. Interpretation model structure

The vectorial interpretation function δ is bijective, monotonous or piecewise monotonous, and computes values lying in the interval [0,1]. In section 3.4.2, we conclude that Harrington's desirability functions are relevant for preference modelling in engineering design. Consequently, observation variables are turned into desirability values and relation (4.3.3.1) becomes:

$$d_i = d_i^H(y_i) \quad \text{with} \;\; d_i \in [0,1] \qquad (4.3.3.2)$$

where d_i is the desirability value resulted from the Harrington desirability function d^H_i. Advantages and benefits of Harrington's desirability functions for preference modelling in engineering have already been discussed in details in section 3.4.2. Finally, it can be noticed that design variables can also be interpreted by desirability functions. In this case, they are regarded as both design and observation variables. This is equivalent to express some preferences inside the design space.

4.3.4 Aggregation into design objectives indices

As previously mentioned, design objective indices (DOI) qualifies the level of achievement of a particular function. As a general rule, every observation variable and hence, every interpretation variable, can be linked to one or more design objectives. We state that the satisfaction of one particular design objective can be derived from the interpretation of the observation variables participating to the achievement of this objective. For example, the objective linked to the reduction of the environmental impact of a mechanical draft cooling tower depends on the energy supply including electricity, pumps and fans and water consumption. From these considerations and the desirability index proposed by Derringer, we introduce the Design Objective Index (DOI) [Sebastian 2010]. It is a desirability values reflecting the level of achievement of design objectives achievement reached by candidate solutions. The values of the DOI are computed from the aggregation of individual desirability functions as follows:

$$\mathrm{DOI}_j = \zeta_j(\mathbf{d}), \quad j = 1\ldots,k \tag{4.3.4.1}$$

where **d** is a vector of the *p* observation variables involved in the jth design objective satisfaction. As explained in section 3.3, aggregation function (ζ) for preference modelling in engineering design problems are required to be design appropriate. Consequently, as suggested in section 3.4.3, the DOI can be expressed according to a general weighted mean aggregation function. In this case, relation (4.2.4.1) becomes:

$$\mathrm{DOI}_j = \zeta(\mathbf{d}, \mathbf{w}_j, s_j) = \left(\sum_{i=1}^{p} w_{i,j} \cdot d_i(y_i)^{s_j} \right)^{\frac{1}{s_j}} \quad \text{with} \quad \sum_{i=1}^{p} w_{i,j} = 1, \quad j = 1\ldots,k \tag{4.3.4.2}$$

where $\mathbf{w_j}$ and s_j represent respectively the weights vector and the trade-off strategy parameter associated to the definition of the jth DOI. The normalized weights vector $\mathbf{w_j}$ is used to adjust the relative importance of satisfaction criteria between them; strong weights result in high priorities. In the following, we note:

$$\zeta_j(\mathbf{d}) = \zeta(\mathbf{d}, \mathbf{w}_j, s_j) \qquad j = 1\ldots,k \tag{4.3.4.3}$$

While observation variables and criteria are identified from the preliminary steps of the design process, the non-physical meaning of weights makes difficult the assignment of numerical values [Saary 2006]. In the fields of operational research and decision theory, methodologies related to analytic hierarchy process (AHP) initiated by Saaty [Saaty 2008], have received increasing interest to deal with such an issue. Principles of this approach are first based on the decomposition of the initial multicriteria problem into a hierarchy of sub-criteria problems, and then, on the statement of normalized priorities derived from pairwise comparisons. In [Semassou 2011], the AHP is coupled with the failure mode, effects, and criticality analysis (FMECA). The FMECA is used to classify design objectives according to their level of criticity, making thus easier the pairwise comparison between objectives. In chapter 6, the AHP method is used for the design of a two staged-flash evaporator. In section 5.3, a procedure to determine consistent values for the trade-off strategy parameter (s) is presented.

Definition: Design Objective Index (DOI) measures the ability of a candidate solution in satisfying one particular design objective (function). It is expressed as a desirability level and thus, its value lies in the range [0,1]. The set of the DOIs to be jointly optimized is noted $DOI=[DOI_1,DOI_2,\ldots,DOI_k]^T$ with $k \in \mathbb{N}$. The definition of a DOI requires the specification of the following variables and parameters:

1. the set of observation variables (**y**) and criteria participating to its achievement
2. the weights (**w**) reflecting priority orders between aggregated desirability functions
3. the trade-off strategy parameter (s) expressing the compensatory level between aggregated desirability functions

The definition and formulation of the DOIs is a fundamental result of this thesis since DOIs enhance the original design model with a preference modelling structure. Figure 31 represents the aggregation model structure derived from the definition of DOIs. According to this figure, the interpretation variables (z_i) are aggregated into DOIs. The aggregation process into DOI must involve at least one interpretation variables. According to figure 31, the computation of DOI_1 is performed from the interpretation variables z_1 and z_i, whereas the computation of DOI_k is performed from the interpretation variable z_m. For example, the design objective linked to the transportability of systems may depend on both their masses and floor areas. In the same way, one particular interpretation variable (and so one particular observation variable) may participate to the achievement of multiple design objectives. For example, the mass may be taken into account for the achievement of the transportability objective and may also participate to an improvement of the environmental impact objective. The total amount of material used to manufacture a mechanical system increases its weight and its environmental impact.

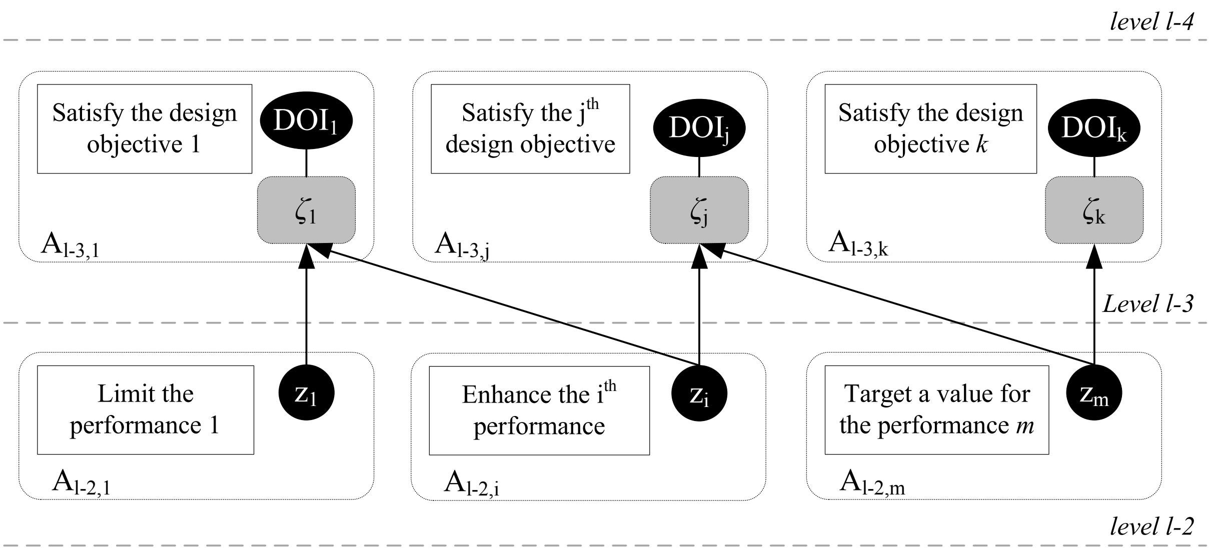


Figure 31. Aggregation model structure

Aggregation models aim at synthesizing design information to reduce the number of variables and criteria, and make easier the direct comparison of candidate solutions. Therefore, a part of the initial information is lost during the aggregation process. Preference aggregation models are thus filters which discriminate the less relevant candidates among the whole set of feasible solutions.

a. Global desirability index

In the same way, design objectives participate to the achievement of a global design objective, reflecting the overall satisfaction of the designer for a candidate design. Therefore, we introduce the Global Desirability Index (GDI) as result of the DOIs aggregation.

Definition: The Global Desirability Index (GDI) is a measure of the overall ability of candidate solutions in meeting designers' expectations. It is expressed as a desirability value and its value lies in the range [0,1]. GDI measures the overall preference for candidate solutions and is used to compare them.

The global desirability index GDI is a particular DOI responding to global designers' need and which can be formulated as follows:

$$\mathrm{GDI} = \zeta_0\left(\mathbf{DOI}\right) = \zeta\left(\mathbf{DOI}, \mathbf{w}_0, s_0\right) \tag{4.3.4.4}$$

The numerical weights $\mathbf{w}_0$ enable to deal with priorities of conflicting design objectives. Assigning a strong weight to a one particular DOI favours its maximization during the optimization process, and thus, enables the designer to carry out "Design for X" approaches (see chapter 6).

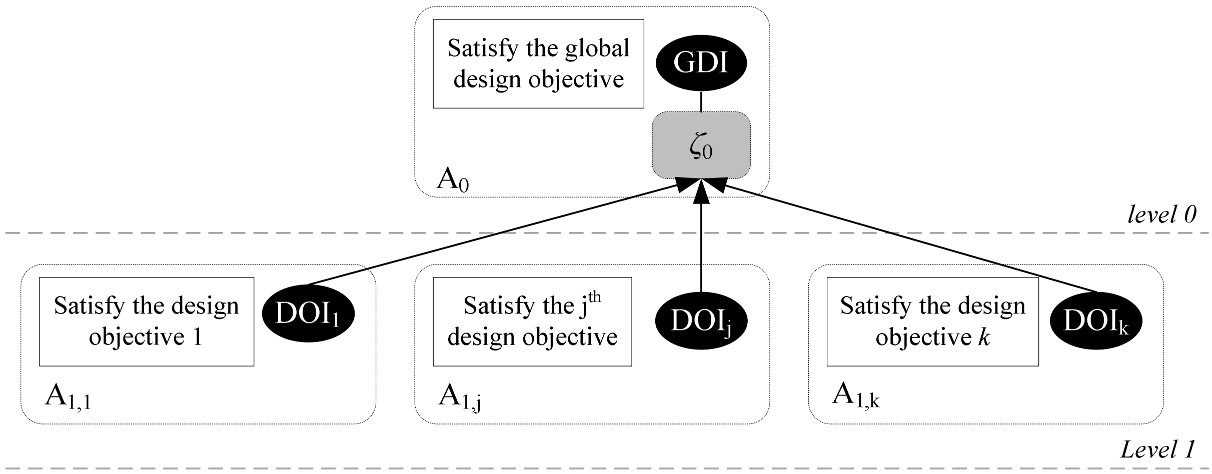


Figure 32. Aggregation of design objective indices into global desirability index

Figure 32 illustrates the aggregation of objective indices into a global desirability index. The satisfaction of the global design objective is the first goal of the designer and adds another layer to the preference model. It synthesizes the whole information about the design from the design variables to the design objectives. However, multiple intermediate aggregation steps can be inserted between the definition of the GDI and DOIs.

b. Multi-level aggregation

Each design objective can be decomposed into multiple sub-objectives. The division of global objectives into sub-objectives results from the functional analysis. It is equivalent to decompose the overall preference into smaller groups of individual preferences which are obviously easier to evaluate. This improves the preference modelling while respecting the design problem structure. The aggregation model can be enhanced with several aggregation steps as follows:

$$\mathrm{DOI}_j = \zeta_j\left(\mathbf{d}\right) = \zeta_{j,1} \circ \zeta_{j,2} \ldots \circ \zeta_{j,q}\left(\mathbf{d}\right), \quad j = 1\ldots,k \tag{4.3.4.5}$$

The decomposition of design objectives into sub-objectives and the whole extended aggregation model are represented on figure 33. Each aggregation level constitutes a synthesis of the information provided by the lower levels, and thus, gradually filters the whole set of feasible solutions. Weights and trade-off parameter values introduce information related to priority relative levels between sub-objectives.

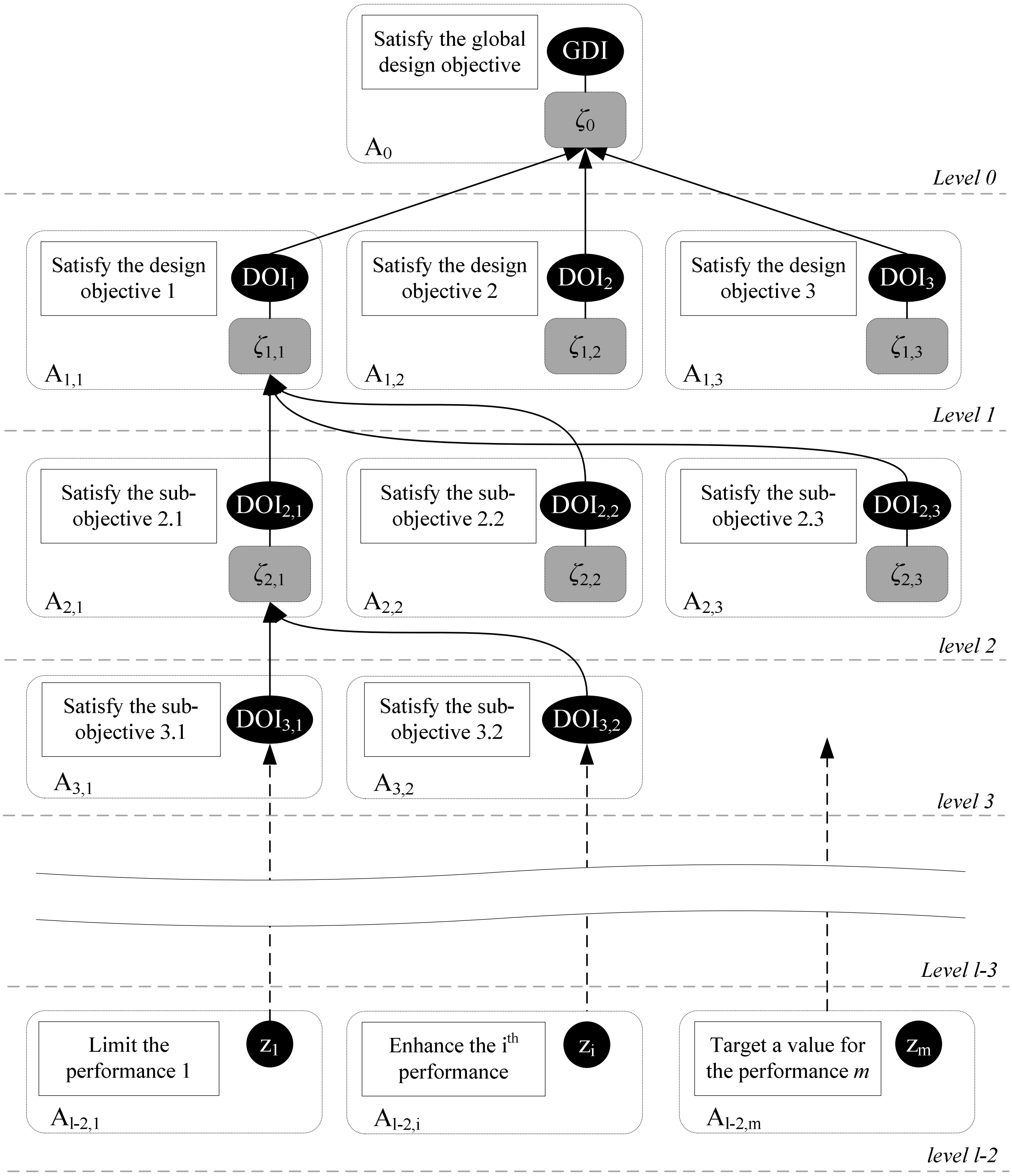


Figure 33. Decomposition of the aggregation model

However, these successive aggregation operations, called hierarchical aggregation by Otto and Scott [Otto 1993, Scott 1999], present some issues which must be highlighted. First, if the aggregative functions ($\zeta_{j,i}$) involved in the aggregation process are *design appropriate* and the same values are used for the trade-off strategies parameters (s), then the resulted aggregation function (ζ_j) is still *design appropriate*. On the contrary, different values for the trade-off strategies parameters (s) will result in a non-design appropriate global aggregation function (although some axioms of the MoI are still satisfied).

For weighted geometric mean aggregation, Trautmann [Trautmann 1994] has shown that optimizing these objective functions leads to Pareto optimal solutions. In the same way, it can be shown that the weighted aggregation mean also computes Pareto optimal solutions for s≤0 (see Annexe 2 for details). However, Trautmann [Trautmann 1994] has also proved that the *min* aggregation function may lead to solutions which are not Pareto optimal (see Annexe 2 for details). To conclude, the Pareto optimality of solutions is guaranteed only if the minimum aggregation function is not used in the different aggregation steps. However, the property of Pareto optimality is not always expected the designers and the relevance of the final solution is justified by the structure of the preference model.

c. Summary on the aggregation model

From interpretation variables (individual desirability function), the aggregation model enables to derive a global indicator (GDI) to quantity the overall desirability of solutions. The GDI reflects the adequation between design solutions and the global need derive from the design problem. It can be regarded as a synthesis of the whole design information. Based on function analysis and the decomposition of the system into functions and sub-functions, objectives can be divided into a hierarchy of many sub-design objectives whose levels of satisfaction are assessed by DOIs. Such decomposition structures the design problem by setting intermediate preference modelling steps and guarantees the consistency of the whole design model.

In the same way, DOIs express the capability of candidates to satisfy design objectives. The definition of the DOIs is a fundamental result of this thesis. They enhance the initial design model with a preference modelling structure, and enable the formulation of an overall preference from both objective and subjective knowledge. According to the DOI formulation (4.2.4.2), aggregation functions must specified with s≤0 (trade-off strategy parameter) to be *design appropriate*. Different trade-off strategies can be used to fit designers' preferences in the best way. In particular, weighted geometric mean and minimum aggregation functions refer respectively to aggressive and conservative strategies. Moreover, suitable weights assignment enables to deal with the priority orders between objectives. Finally, we suggest some existing techniques to help designers in building aggregation models, namely functional analysis, continuum of *design appropriate* aggregation functions, and using AHP to derive numerical weight assignment.

4.3.5 Conclusion on the design model structure

The design model structure developed in the previous sections enables to assess the overall desirability level of candidate solutions by the computation of a GDI. From a set of design variables (x), the general formula of the GDI related to performance is expressed as:

$$\mathrm{GDI}_{\mathrm{perfo}} = \varphi(\mathbf{x}) = \zeta \circ \delta \circ \mu(\mathbf{x}) \tag{4.3.5}$$

where μ is the observation model, δ refers to the interpretation model and ζ designates the aggregation model. The resulted function φ corresponds to the objective function to be optimized. In this case, the GDI value is expected to be maximized. Figure 34 represents the full design model structure. According to this figure, the modelling methodology suggests the decomposition of the design problem into a formal structure starting from the identification of global design objectives to the selection of design variables. Based on the decomposition of the system into functions and sub-functions, the “formulation” process allows an easier identification of design objectives and criteria and ensures the consistency of the whole model structure. The modelling methodology presented here can be summed up into a sequence of logical steps as follows:

1. Decomposition of the design problem into a hierarchy sub-objectives,
2. Determination of the trade-off strategy (**w**,s) for each aggregation stage
3. Specification of the individual interpretation function,
4. Determination of the observation variables,
5. Representation of the design solutions (design variables)

However, the “simulation” process follows the reverse order and starts from a candidate solution (design variables) to compute the GDI as follows:

1. Definition of a candidate solution (design variable values)
2. Computation of the observation variables through the behaviour model
3. Computation of the individual desirability functions
4. Computation of the multiple DOIs
5. Computation of the GDI

In the next section, the modelling methodology is used to tackle robust design problems. According to the observation, interpretation and aggregation models, the purpose is to model an objective linked to the sensitivity of the performances which will be traded-off with another objective related to the overall level of performance. While uncertainly are simulated, the observation model must compute an estimate of the performance dispersion. Two measurement methods are proposed. These measures are then interpreted and finally aggregated into a global desirability index linked to the sensitivity of the performances.

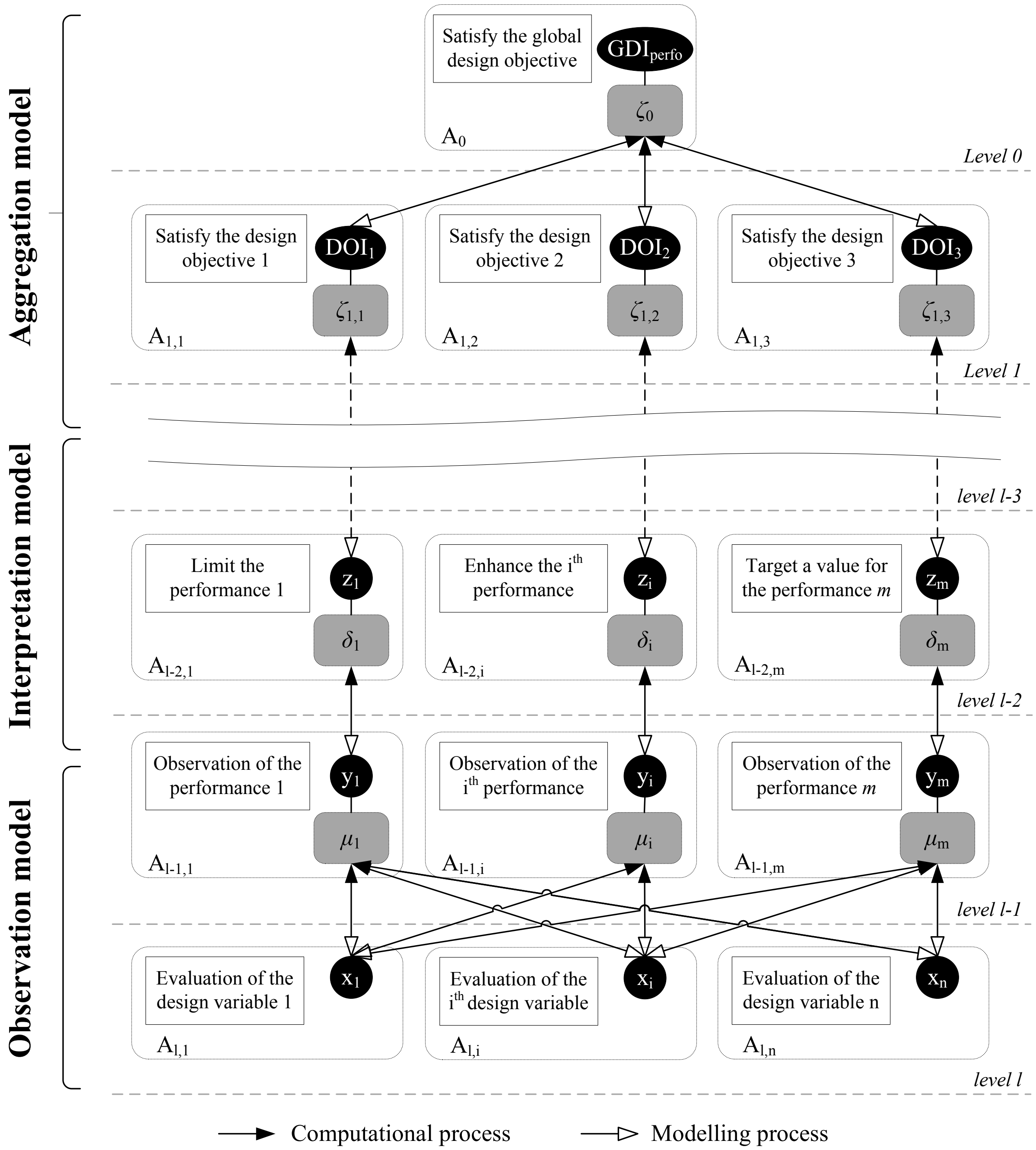


Figure 34. Full structure of the design model

4.4 Robust design problem modelling

4.4.1 Introduction

As highlighted in section 2.4.4, most of robust design methodologies are based on the formulation of a ratio between two objective measurements, namely the mean performance and the standard deviation of the performance. The optimization of such a robustness indicator does not allow designers to express independently the satisfaction levels expected for these two measurements. Obviously, a design solution can be preferred to another due to its high overall performance. Inversely, design solutions with an extreme low sensitivity to uncertainty can be relevant in some contexts. In this case, design solutions often achieve poor levels of performances. The improvement of the overall performance and the reduction of the performance sensitivity facing uncertainty are two design objectives which must be traded-off according to the designer's preferences.

Definition: A candidate solution is said robust if it achieves a desirable level of overall performance compared to the level of sensitivity of its performances under uncertainties.

In other words, robust solutions achieve desirable trade-offs between performance and sensitivity and must be evaluated simultaneously on these two objectives. Performance and sensitivity objectives are formulated according to the modelling methodology developed in this chapter.

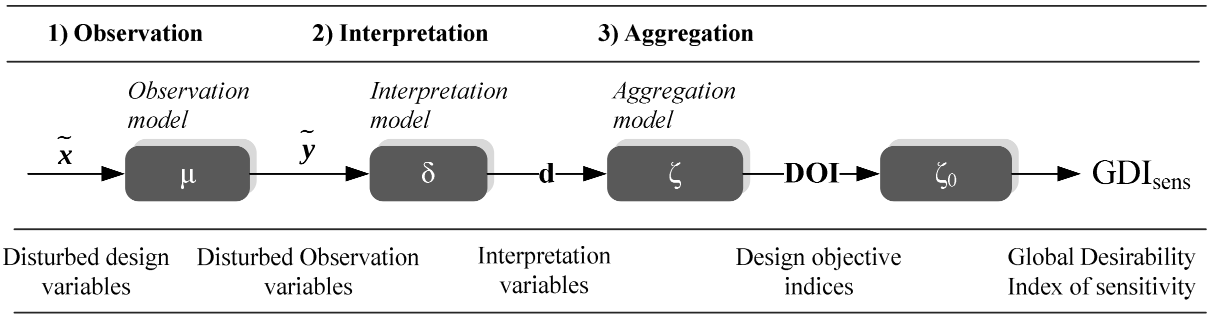


Figure 35. Computation process of GDI related to the performances sensitivity

The performance objective results from the nominal evaluation of design solutions (i.e. without taking into account uncertainties). The ability of candidates to achieve this objective is quantified by a desirability score GDI_{perfo} expressed by the relation (4.2.5). The same modelling structure is used to formulate the sensitivity objective. It is represented on figure 35.

The formulation of the sensitivity objective results in a desirability score GDI_{sens} which quantifies the ability of candidate solutions to keep low performance variations while the design variables are disturbed. The observation of the performance dispersion around the nominal value requires the evaluation of the neighbourhood of the solution. This is addressed by introducing variability according to the relation (2.4.2). We propose two measures for the performances dispersion, namely: the bandwidth of variation and the tolerance to nominal.

Facing epistemic uncertainties and non-Gaussian distributions of aleatory uncertainty, no assessment on the noise factors distributions is made. This contributes to the generalization of the methodology to a vast range of robust design problems.

4.4.2 Observation of the performances dispersion

From a normal distribution, it is known that 68% of the values are within one standard deviation σ away from the mean; about 95% of the values lie within two standard deviations; and about 99.7% are within three standard deviations. However, this is no longer true for non-Gaussian distributions, and the interpretation of the average and standard deviation values becomes more difficult. To overcome this difficulty, we propose two other measures for the performance dispersion. They are respectively the bandwidth of variation (α) and the tolerance to nominal (β). Each measure is applied to the observation variables neighbourhood while design variables and model parameters are numerically disturbed according to equation (2.4.2).

a. Bandwidth of variation

The bandwidth of variation (α) is the distance between the extreme values achieved for the observation variable disturbing design variables. It traduces the maximum range of variation to be expected for the performance. This measure is expected to be minimized and is defined as:

$$\alpha_i = \left| \max\left(\widetilde{\boldsymbol{y}_i}\right) - \min\left(\widetilde{\boldsymbol{y}_i}\right) \right| \tag{4.3.2.1}$$

This measure is equivalent to define an interval of confidence around the target value to be satisfied. However, this does not provide any information about the dispersion of the performance around its nominal value. Consequently, a second measure denoted “tolerance to nominal” is proposed.

b. Tolerance to nominal

The tolerance to nominal (β) measures the relative eccentricity of the nominal from the set of tested points (neighbourhood). This measure aims to achieve solutions with dispersions of performance which are uniformly distributed around the centre of gravity of the neighbourhood (see figure 36). This measure is also submitted to minimization and is expressed as:

$$\beta_i = \left| \overline{y_i} - y_i \right|, \quad \overline{y_i} = mean\left(\widetilde{y_i}\right) \tag{4.3.2.2}$$

Figure 36 represents the sensitivity measures α and β for three observation variables. The convex hull formed by the set of tested points is also represented. The sensitivity measures are evaluated through a set of constraints which is equivalent to the definition of a volume of control around the nominal performance. Thus, the objective is to keep the performance dispersion within this volume of control. These two measurement methods are used in section 6 for the robust design of flash evaporators.

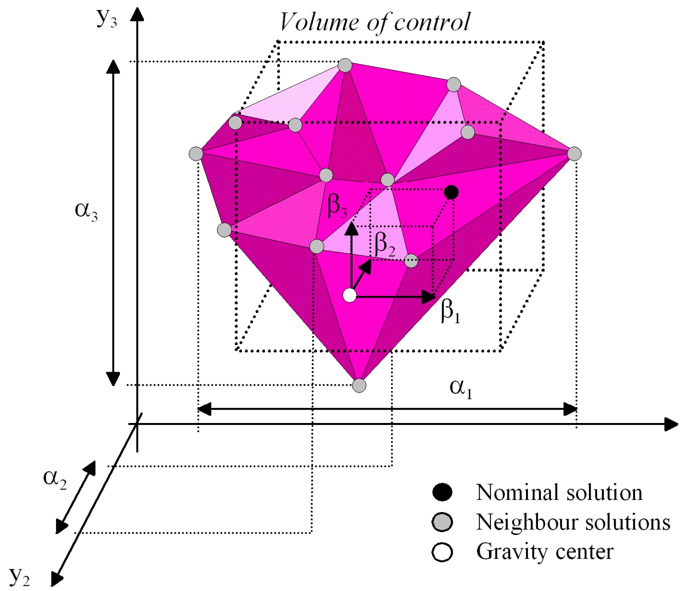


Figure 36. Representation of the performance sensitivity measures

4.4.3 Interpretation and aggregation of the sensitivity measures

The performance sensitivity parameters are then interpreted through Harrington's desirability functions. The one-sided Harrington's desirability function is suitable to interpret both measures of bandwidth of variation and tolerance to nominal. The resulted interpretation variables are then aggregated into DOIs according to the procedure presented in the previous section. These DOIs linked reflect the ability of candidate solution to minimize the variations of performances while uncertainties are taken into account. Sub-design objectives can also been identified according to the needs of the designer.

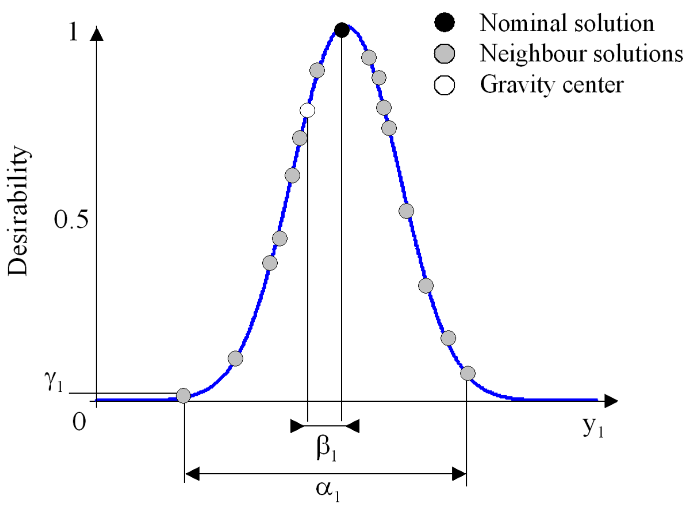


Figure 37. Reliability-based approach by taking the minimum of the desirability scores

For example, reliability-based approach consists in keeping performance variations within the range of admissible values. As represented on figure 37, the sub-design objective (γ) called "minimum performance value" may be directly formulated by taking the minimum of the desirability scores among the neighbourhood of the nominal performance:

$$\gamma_i = min\left(d\left(\widetilde{y}_i\right)\right) \tag{5.2.2}$$

Obviously, the nominal performance of a solution can be close to the bounds of the admissible domain and thus small variations may result in the non-satisfaction of the constraints. Therefore, this design objective favours design solutions whose maximal variation remains close to the admissible domain. This objective is used in section 6 for the robust design of flash evaporators.

4.5 Summary

The design modelling structure proposed in this chapter intends to enhance classical design models with a preference model involving the concept of desirability. Preference modelling is used to link the physical behaviour of the system to be designed with constraints and design objectives. While physical behaviour is intrinsic to candidate solutions, depending on physical laws and objective knowledge, their ability to satisfy design constraint and objectives depends on designers' expectations, and so on a subjective considerations. Consequently, the observation model is concerned with objective knowledge whereas interpretation and aggregation models deal with the subjectivity of the design activity. According to the FBS framework, this natural and intuitive decomposition enables to model designers' reasoning and express preferences. This makes a significant difference from other methodologies such as the utility theory or MoI.

In particular, the definition of DOIs allows a synthesis of the whole design information at different levels of the problem decomposition and acts as filters on the initial set of admissible candidate solutions. The aggregation of the different desirability scores using design appropriate functions, such as the general weight mean while $s \leq 0$, and weights assignments, allow different trade-off strategies between objectives, and thus, are suitable to reflect the designer's preferences. The formulation of DOIs can be applied to robust design problems.

In this thesis, we consider two levels of robustness. While the first level of robustness concerns the physical sensitivity of the system performance, the second level of robustness deals with uncertainty in the expression of preference, and thus, aims to take robust decisions. This second aspect of robustness consists in decreasing the sensitivity of the selected solution facing with the uncertainty of choices. This can be regarded as a trade-off between two design objectives, namely the improvement of the performance and the reduction of the performance variability.

Due to its proximity with the designers' reasoning and its simplicity of its implementation, the developed model is applied and extended to a large scope of engineering problems. The methodology has been initially applied and validated with the preliminary design of a two-staged flash evaporator [Ho Kon Tiat 2010, Sebastian 2010] (see chapter 6). Later, the approach has been applied to the design of aeronautic structures and a design objective of confidence has been introduced using an arc-elasticity measure [Sebastian 2012, Collignan 2012a, Collignan 2012b]. In the field of turbo-machinery, the model has been integrated to the design methodology of a high pressure distributor [Girardeau 2012]. Moreover, recent works in energetic system design [Semassou 2011] and building engineering [Valderrama Ulloa 2012] have also shown promising results in this research area.

CHAPTER 5 Aggregation and trade-off strategy modelling for robust decision making

As mentioned in the previous chapters, engineering design problems involve multiple conflicting objectives which must be traded-off. In this context, trade studies attempt to determine design solutions which meet every design objectives in the best ways in regards to admissible compromises. The design modelling methodology proposed in this thesis suggests three distinct inputs by which designers can express their preferences, namely specification of individual desirability functions, weighs assignment and selection of aggregation strategies. Trade-off is mainly concerned with the selection of weights and suitable trade-off parameter values. Different trade-off specifications can lead to final solutions with equivalent overall preference levels. Therefore, trade-off modelling by aggregation functions is a critical part of the preference assessment process. In particular, designers must be aware of the zones of design points which can be captured using a particular aggregation strategy.

5.1 Introduction

In engineering design, trading-off is a process in which designers have to degrade one performance for improving another factor. This supposes decision-making with a full comprehension of the positive and negative aspects of one particular choice. In economics the term “opportunity cost” is used, referring to the most preferred alternative given up. Trades-off also involves the notion of sacrifice that must be made to obtain a certain product, rather than other products that can be made using the same required resources.

In political economy, Karl Marx introduces the notion of exchange value to represent, not the price of a product, but the amount of others goods that will be exchanged for it, if it is traded. For example, consider a trade-off between two products A and B. Then, the notion of exchange value states that X amount of the product A is equivalent to Y amount of product B. In design engineering, exchange value can be expressed as “an increment of X on the performance A is equivalent to a decrement of Y on the performance B”. In other words, designers accept a decrement of Y on the performance B for gaining an increment of X on the performance A. In general, this notion refers indirectly to the price paid for the improvement (or the worsening) of the property.

This compromise is not always linear, but can vary according to the level of the property. In fact, the trade-off can be expressed as “an increment of X on the performance A is equivalent to a decrement of Y on the performance B for a particular level of A, but an increment of X on the performance A is equivalent to a decrement of Y' on the performance B for another level of A”. This kind of complex trade-off must also be handled and modelled.

Trade studies are mainly related to decision-making problems. In the FAA Systems Handbook [FAA 2004], the decision analysis matrix (Pugh's method) is proposed to support trade studies, but this method fails to deal with uncertainty, the management of both quantitative and qualitative information or the management of teams. To manage uncertainty

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or teams decisions, the NASA Systems Engineering Handbook [NASA 1995] suggests using the multi-attribute utility theory (MAUT) and the Analytic Hierarchy Process (AHP).

5.2 An introductive example

To illustrate trade-off issues, we present an example tackled by Scott in his own thesis [Scott 1999]. This example deals with a company producing two types of products which differ from their returns in profit and balance of trade. For example, the product #1 yields $2 profit but requires $1 in imports, whereas the product #2 can be exported for $2 revenue but makes only $1 profit. The problem consists in determining the best production schedule to achieve high profit and a favourable balance of trade. The decision variables are the number of product #1 to be manufactured (x_1) and the number of product #2 to be manufactured (x_2). The balance of trade (z_1) and the profit (z_2) are the two objectives to be maximized and are expressed as follows:

$$\begin{aligned} z_1 &= -x_1 + 2x_2 \\ z_2 &= 2x_1 + x_2 \end{aligned} \tag{5.2.1}$$

The production schedule is subjected to capacity constraints modelled as follows:

$$\begin{aligned} &C1: \quad -x_1 + 3x_2 \leq 21 \\ &C2: \quad x_1 + 3x_2 \leq 27 \\ &C3: \quad 4x_1 + 3x_2 \leq 45 \\ &C4: \quad 3x_1 + x_2 \leq 30 \\ &C5: \quad x_1 \geq 0 \\ &C6: \quad x_2 \geq 0 \end{aligned} \tag{5.2.2}$$

As decision variables represent amounts of products, they can be considered here as discrete. The set of non dominated solutions is given in table 6. The decision and objective spaces are represented in figure 38. Constraints from C1 to C4 have been plotted in dashed lines on figure 38a. The Pareto frontier and the non-dominated points have been reported on figure 38b. to illustrate the notion of domination a white circle is used to represent the dominated point $\mathbf{x}$=(1,7). This point gets z_1=13 and z_2=9. In particular, according to table 6, it is dominated by the point $\mathbf{x}$=(3,8) since z_1($\mathbf{x}$=(3,8))=13, and z_2($\mathbf{x}$=(3,8))=14. The decision space and the objective space are represented on figure 38.

$\mathbf{x}=(x_1,x_2)$	z_1	z_2
(0,7)	14	7
(3,8)	13	14
(4,7)	10	15
(5,7)	9	17
(6,7)	8	19
(8,4)	0	20
(9,3)	-3	21

Table 6. Set of non-dominated solutions

According to the approach developed in the previous chapters, the first step of the preference assessment concerns the interpretation of the variables z_1 and z_2, i.e. the determination of preference levels for each one of the two objectives. For sake of simplicity, we assume here that the preference related to the balance of trade objective increases linearly from $p_1(x)=0$ for $z_1(x)=-3$, to $p_1(x)=1$ for $z_1(x)=14$. In the same way, the preference related to the profit objective varies linearly from $p_2(x)=0$ for $z_2(x)=7$, to $p_2(x)=1$ for $z_2(x)=21$. The interpreted space is represented on figure 40. One can notice that the points **x**=(0,7) and **x**=(9,3), i.e. the extremes of the Pareto frontiers, are now considered as dominated points since their overall preference equals zero (axiom of annihilation).

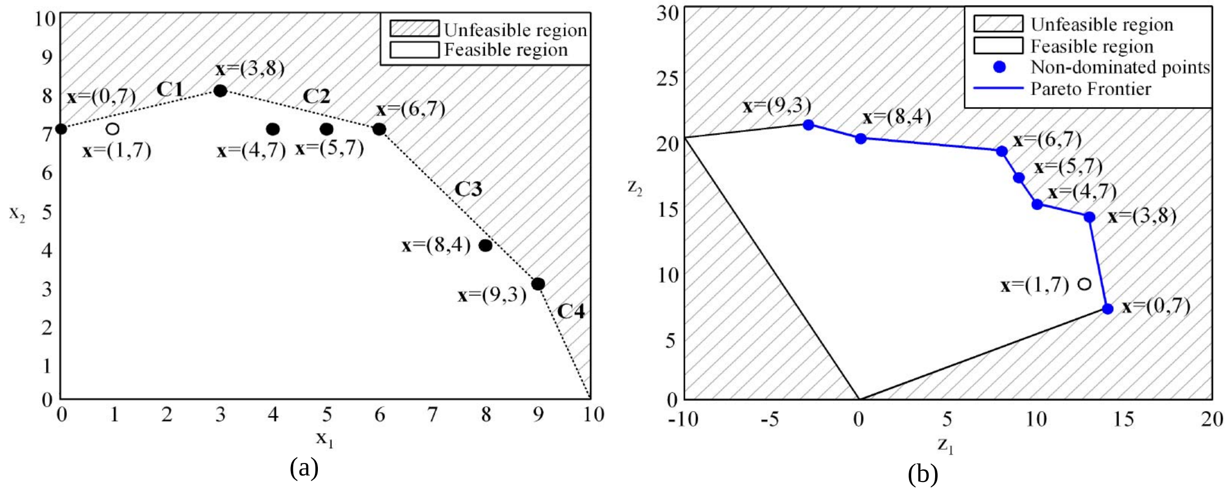

Figure 38. Representation of the decision space (a) and the objective space (b)

The overall level of preference $\mathcal{P}_s$ is then computed by aggregating the individual preferences p_1 and p_2 as follows:

$$P_s(p_1,p_2) = \left(w_1 \cdot p_1^S + w_2 \cdot p_2^S\right)^{1/s} \quad \text{with} \quad w_1 + w_2 = 1 \tag{5.2.3}$$

In this example, weights are supposed to be equal and $(w_1,w_2)=(0.5,0.5)$. Different values of the trade-off parameter (s) corresponds to different trade-off strategies, and so, lead to different final solutions. This is illustrated through figure 39 and figure 40. Figure 39 shows the overall preference P_s of some decision points when the value of the parameter s varies in the range [–10,10] with a step of one. According to this figure, it appears that the point **x**=(5,7) maximizes the overall preference for s∈[–10,–6] since in this interval:

$$P_s(\mathbf{x}=(5,7)) > P_s(\mathbf{x}=(6,7)) > P_s(\mathbf{x}=(3,8)) > P_s(\mathbf{x}=(1,7)) \tag{5.2.4}$$

In this case, the point **x**=(5,7) represents the most preferred solution. In the same way, when s∈]–6,2], the point **x**=(6,7) becomes the optimal solution since P_s(**x**=(6,7))> P_s(**x**=(5,7)). Finally, for s∈]2,10], the point **x**=(3,8) gets the highest overall preference. However, it can be notice that the point **x**=(1,7), which was previously considered as dominated by the point **x**=(3,8), approaches it asymptotically in preference while the compensation level increases. This is a consequence of using supercompensatory functions (s>1). Therefore, for high values of s, the optimization of the overall preference P_s can return dominated solutions.

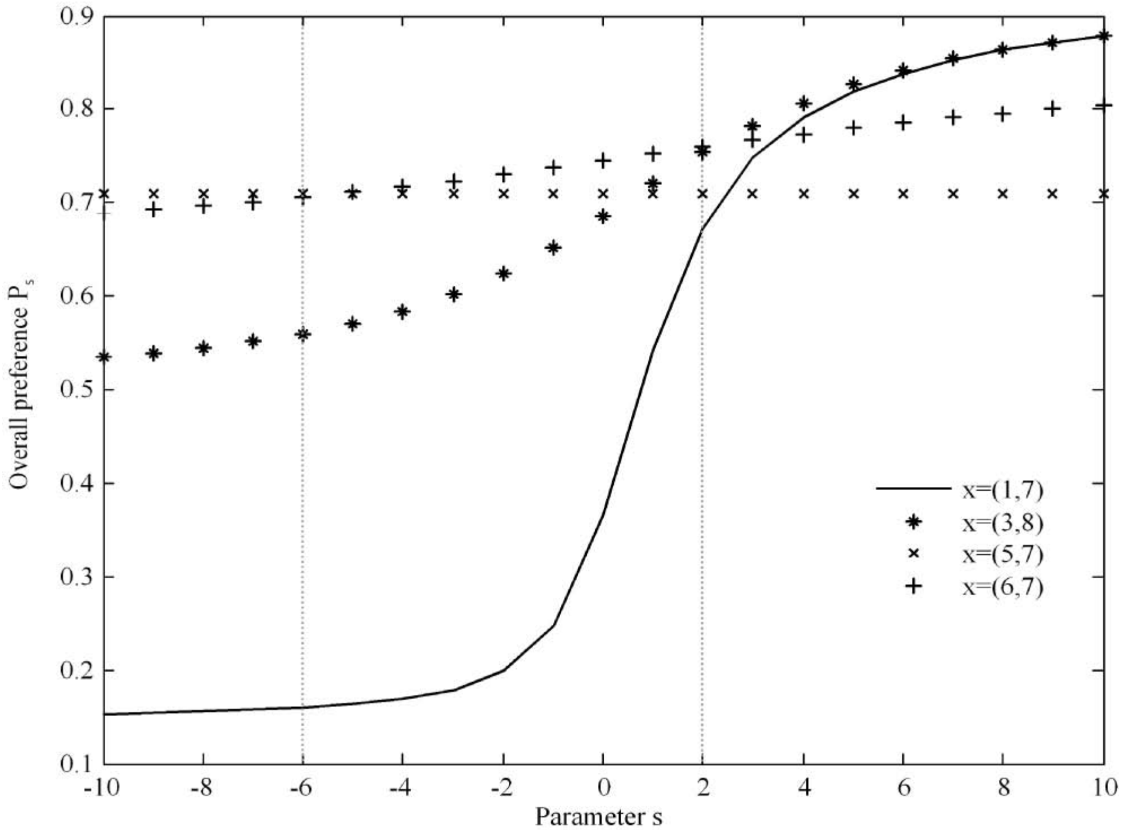

Figure 39. Evolution of the overall preference $\mathcal{P}_s$ of some decision points according to the values of the trade-off parameter

These observations can also be visualized on figure 40. This figure shows the interpreted space and the iso-preference curves when s varies in the range [-10,10]. For a given value of P_s, the iso-preference curve represents the set of points with the same overall preference P_s. From relation (5.2.4), the equation of the iso-preference curve can be expressed as a function of p_1 and P_s such as:

$$p_2\left(p_1,P_s\right)=\left(\frac{P_s^S-\mathrm{w}_1\cdot p_1^S}{\mathrm{w}_2}\right)^{1/s} \tag{5.2.5}$$

where P_s, s, w_1 and w_2 are constant. Thus, the optimal solution is determined by the point at the intersection between the iso-preference curve and the Pareto frontier. This points is then said to be captured by the objective function since there is a combination of values (**w**,s) making it optimal. For example, as previously explained, for s=–9, the point **x**=(5,7) is the optimal solution and the corresponding point (0.70,0.71) within the interpreted space is captured. The resulted overall preference is P_s(**x**=(5,7))=0.71. According to figure 40, the iso-preference curve defined by $p_2(p_1, P_s=0.71)$ passes through the point (0.70,0.71). While the value of s increases from –10 to 10, the points **x**=(5,7), **x**=(6,7) and **x**=(3,8) are successively captured by the objective function.

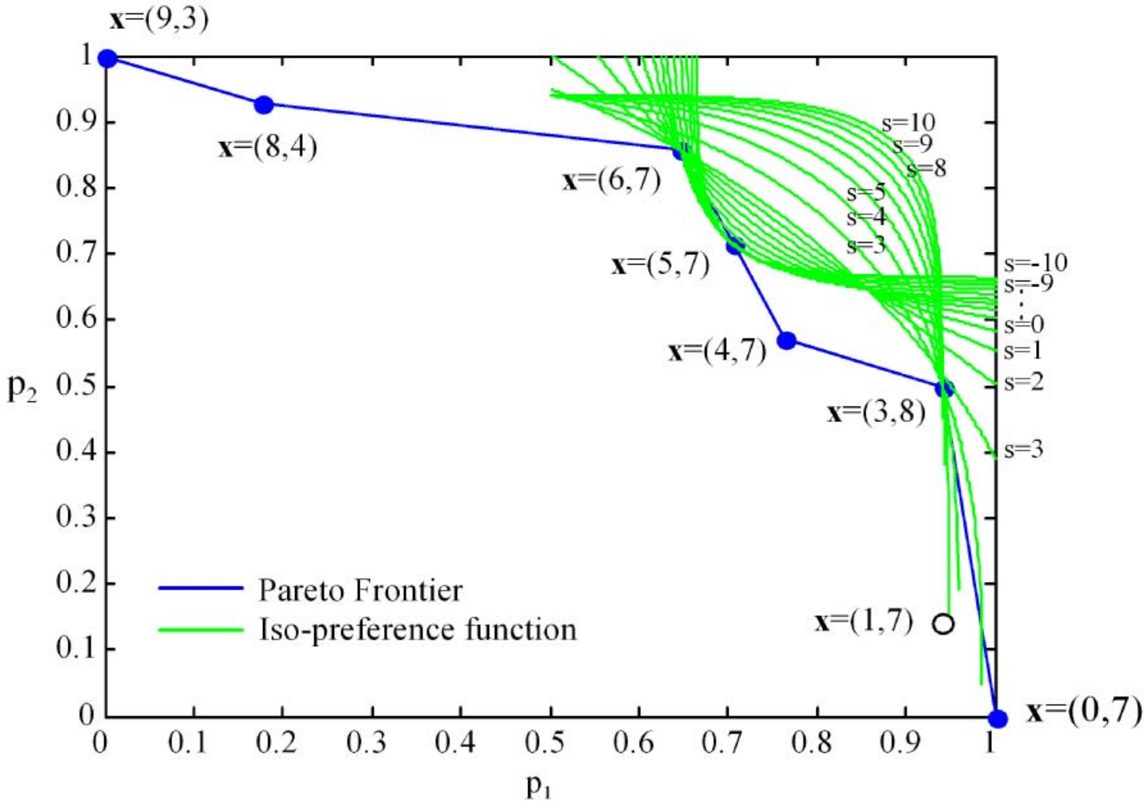

Figure 40. Capturability of the most preferred solutions according to different trade-off parameter values

The specification of a particular combination (**w**,s) enables to express a particular trade-off between objectives and thus, leads to a unique solution. Difficulties arise from the interpretation of the trade-off associated to the specific couple (**w**,s). In particular, designers should be able to interpret these trade-offs in term of gain in one preference against a loss in another one. Inversely, once exchange values are determined, designers should derive consistent values for (**w**,s). According figure 40, it appears that the point associated to **x**=(4,7) is not captured. Consequently, it is of main interest to find if there is a tuple (**w**,s) making it capturable (or optimal), and in this case, to determine the associated trade-off.

Trades-offs modelled by weighted arithmetic mean aggregation (s=1) enables to easily overcome this difficulty since the compromise is linear. For example, consider that the decision-maker decides that he is willing to lose 1$ in the balance of trade objective to gain 2$ in the profit objective. Therefore, the points **x**=(5,7) and **x**=(6,7) are equivalent, and thus, they must reach the same level of overall preference. These solutions reach respectively **z**=(9,17) and **z**=(8,19) (see table 6). This implies that:

$$\mathcal{P}_1\left(\mathbf{x}=(5,7)\right)=P_1\left(\left(\mathbf{x}=(6,7)\right)\right)\Leftrightarrow w_1\cdot p_1(9)+w_2\cdot p_2(17)=w_1\cdot p_1(8)+w_2\cdot p_2(19) \qquad (5.2.6)$$

And we get:

$$\frac{w_1}{w_2}=\frac{p_2(19)-p_2(17)}{p_1(9)-p_1(8)}=\frac{0.8564-0.7326}{0.715-0.648}=\frac{0.1238}{0.067}=1.8478 \qquad (5.2.7)$$

Finally, it follows that w_1=0.3511 and w_2=6489. The overall preference P_s can be then express as follows:

$$P = 0.3511\cdot p_1 + 0.6489\cdot p_2 \qquad (5.2.8)$$

However, the weighted arithmetic mean aggregation is non *design appropriate*. It is not well adapted to treat preliminary design problems. The same kind of approach can be used for design appropriate aggregation function ($s<1$), but requires the specification of three points of equivalence. In fact, the trade-off is non linear and the level of compromise changes with the objectives values. For the weighted geometric mean aggregation ($s=0$), the compromise varies according to a logarithm law with the objectives. In the following, a procedure based on the specification of indifference points is presented to assign consistent values for ($\mathbf{w}$,s) with the preferences of the designer.

5.3 Trade-offs using equivalent points

5.3.1 Description of the methodology

The main advantage of the preference aggregation method proposed hereafter is that it enables designers to directly specify the correct trade-off strategy and weights assignment according to their objectives. In the framework of the MoI, Scott [Scott 1999, Scott 2000] has proposed a method based on the definition of indifference points, to determine simultaneously a unique value for the trade-off strategy and for the weight ratio. In the following, we describe this method for the bi-objective case. The same procedure can be applied to deal with multiobjective cases. We note $b=w_1/w_2$ the weight ratio. Then, from equation (5.2.3), the overall preference p is expressed as:

$$\forall b\in \mathbb{R}^{+}, \forall s\in \mathbb{R}, \quad P_s\left(p_1,p_2;b,s\right)=\left(\frac{p_1^s+b\cdot p_2^s}{1+b}\right)^{1/s} \qquad \text{with} \quad b=\frac{w_2}{w_1} \tag{5.3.1.1}$$

According to designers, two candidate solutions are considered indifferent if they get the same overall preference p_{ref}. This overall preference is also achieved by a third equivalent point associated to the individual preferences (p_{ref},p_{ref}). In fact, from idempotency, we have:

$$\forall b\in \mathbb{R}^{+}, \forall s\in \mathbb{R}, \quad p_{ref}=P_s\left(p_{ref},p_{ref};b,s\right) \tag{5.3.1.2}$$

Figure 41 illustrates the principle of using three equivalent points. According to this figure, points A, B and C are considered as equivalent since they get the same overall preference p_{ref}. The point C gets the same value for the two preferences (p_{ref},p_{ref}). As a consequence, the three points belong to the same iso-preference curve and verify $P_s(p_1,p_2;b,s)=p_{ref}$. From this solution of reference, the value of s and b can be determined using the following relation:

$$P_s\left(a_1,1;b,s\right)=P_s\left(1,a_2;b,s\right)=P_s\left(p_{ref},p_{ref};b,s\right)=p_{ref} \tag{5.3.1.3}$$

where $a_1=p_1(\mathbf{x}_1)$ and $a_2=p_2(\mathbf{x}_2)$ are two values provided by the designer for the individual preferences p_1 and p_2. From a design solution of reference, with an overall preference p_{ref} satisfying the relation (5.3.1.2), the value a_1 is determined by considering that an increment of the second preference from p_{ref} to 1, makes the first preference to decrease from p_{ref} to a_1. In the same way, from the same reference, the value a_2 is determined by considering that an increment of the first preference from p_{ref} to 1, makes the second preference to decrease from p_{ref} to a_2. Consequently, the solution of reference and the solutions represented by $\mathbf{x}_1$ and $\mathbf{x}_2$, are considered as equivalent. Sometimes it is suitable to think in term of design variables and then to compute first the observation variables, and then, the associated preferences.

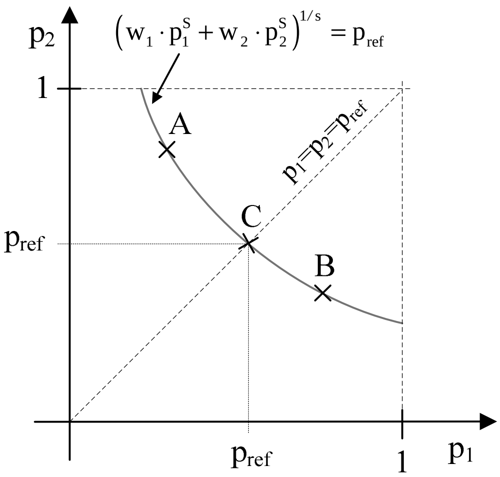

Figure 41. Illustration of three equivalent points evaluated on two preferences

In practice, it is suitable to take p_{ref}=0.5. This represents the overall preference of a system of average. From equation (5.3.1.3), it follows:

$$\forall(a_1,a_2)\in[0,0.5]^2,\exists(b,s)\in\mathbb{R}^+\times\mathbb{R},\quad\left(\frac{a_1^s+b}{1+b}\right)^{1/s}=\left(\frac{1+b\,a_2^s}{1+b}\right)^{1/s}=0.5 \qquad (5.3.1.4)$$

Depending on the values of (a_1,a_2), equation (5.3.1.4) can be solved in different ways. First, if $a_1=a_2$, then b=1, and:

a) If $a_1=0.5$, then $s\to-\infty$
b) If $a_1=0.25$, then s=0
c) If $a_1>0.25$, then $s\in]-\infty,0[$, and if $a_1<0.25$, then $s\in]0,+\infty[$. From equation (5.3.1.4), the value of s is then computed by solving $a_1^s+1=2(0.5)^2$.

If $a_1\neq a_2$, then $b\neq1$. If s=0, we can show that:

$$a_1^m=0.5=a_2^{1-m}\Rightarrow a_2^{1-log_{a_1}(0.5)}=0.5 \qquad (5.3.1.5)$$

And then, it follows that:

d) If $a_2^{1-log_{a_1}(0.5)}=0.5$ then s=0, and $b=\left(1-log_{a_1}(0.5)\right)/\,log_{a_1}(0.5)$
e) If $a_2^{1-log_{a_1}(0.5)}>0.5$ then s<0, and if $a_2^{1-log_{a_1}(0.5)}<0.5$ then s>0. From equation (5.3.1.4), the value of s is then computed by solving the following equation:

$$\left(a_1^s-0.5^s\right)\left(a_2^s-0.5^s\right)=\left(1-0.5^s\right)^2 \qquad (5.3.1.6)$$

<u>Proof:</u>

a) If $a_1=0.5$ then $P_s(0.5,1)=P_s(1,0.5)=0.5$, then the only aggregation function which can verify the relation is the min aggregation function ($s\to-\infty$).
b) If $a_1=0.25$, then it comes from equation (5.3.4) that:

$$\left(\frac{1}{4}\right)^s+1=2\left(\frac{1}{2}\right)^s\Leftrightarrow\left(\frac{1}{2^s}\right)^2-2\left(\frac{1}{2^s}\right)+1=0$$

Setting $X = \frac{1}{2^s}$ *, it comes that X=1=2^s^, and finally, s=0.*

If s=0 the aggregation function is the weighted geometric mean and thus, the equivalent point $(a_1,1)$ *must verify* $a_1^m=0.5$*. In the same way, the equivalent point* $(1,a_2)$ *must satisfy* $a_2^{1-m} = 0.5$ *. Thus, taking the logarithm form leads to:*

$$m\log(a_1) = \log(0.5) \Leftrightarrow m = \frac{\log(0.5)}{\log(a_1)} = \log_{a_1}(0.5)$$

And finally, we get $a_2^{1-\log_{a_1}(0.5)} = 0.5$.

Once equation (5.3.6) is numerically solved, then b can be determined with the following relation derived from equation (5.3.1.4):

$$b = \frac{1-a_1^s}{1-a_2^s} \tag{5.3.1.7}$$

5.3.2 Discussion about the equivalent points methods

The preceding procedure is suitable to generate *design appropriate* functions since it never returns results such as $s>1$. However, the procedure can compute values of s in the range [0,1]. Some precautions are required while equation (5.3.1.6) is solved from numerical computation and the results are numerical approximations. In fact, whatever the value of (a_1,a_2), the solution $s=0$ is always solution to equation (5.3.1.6). Moreover, parameters (s,b) become very sensitive to the variations of a_1 and a_2 while either a_1 or a_2 are close to zero. This also makes difficult the process of the numerical solving of equation (5.3.1.6). It has been observed that this procedure returns consistent results while $s\in[-10,0]$. For $s<-10$, it can be assume that $s\to-\infty$, and thus, the related aggregation function is the *min* operator. It is also noticeable that this procedure can be used with another starting point than (0.5,0.5).

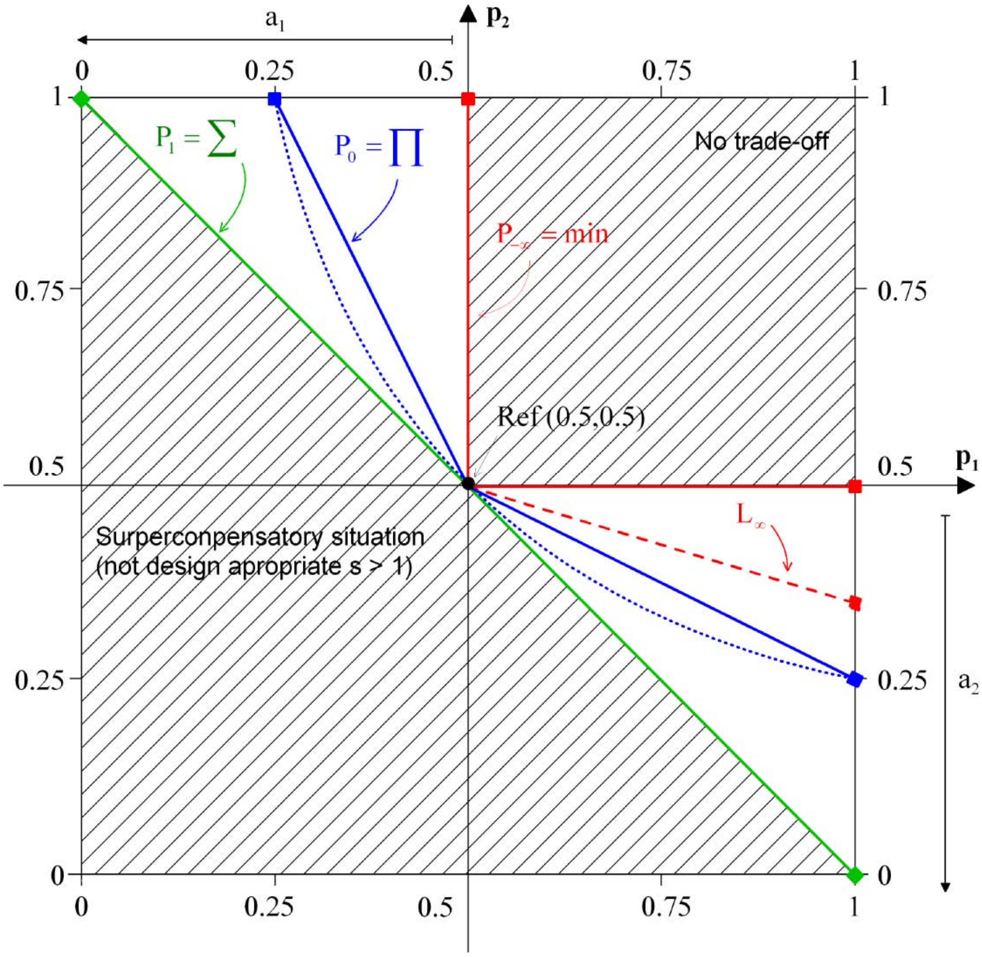

Figure 42. Representation of the indifference points method

Figure 42 represents the indifference point method in graph form taking the preference point (0.5,0.5) as reference. The shaded lower triangular area represents the space of the supercompensatory functions. Since $(a_1,a_2) \in [0,0.5]$, it appears that any values of a_1 or a_2 can lead to supercompensatory situations. The weighted arithmetic aggregation (s=1) represents the frontier between the two domains. It is reached while either $a_1=0$ or $a_2=0$. The shaded upper right square area represents situations where there are no trade-off. In this case, the two preferences should increase simultaneously and correspond to a “win-win” configuration. This is impossible in practice since, due to antagonist physical phenomena, the optimization of one objective is always hampered by some others.

For $a_1=a_2=0.25$, the generated aggregation function is the geometric weighted mean. It is plotted by the dashed curved line in blue through the three points (0.25,1), (0.5,0.5) and (1,0.25). While $a_1=a_2=0.5$, the generated aggregation function corresponds to the *min* aggregation function. It is plotted by the line passing through the three points (0.5,1), (0.5,0.5) and (1,0.5). Compared to the geometric weighted mean, this aggregation function no longer corresponds to smooth curve but to a crisp line.

An interesting case appears while the equivalent preference points are (0.5,1) and $(1,a_2)$ with $a_2<0.5$. According to equation (5.3.1.4), the aggregation function must satisfy the following relation:

$$p(0.5,1) = p(1,a_2) = 0.5 \tag{5.3.2.1}$$

This configuration is represented in dashed line. In this case, the procedure proposed by Scott doesn't enable to compute a consistent value for s. Looking at figure 42, it appears that in this configuration, there is no functions (derived from the general weighted mean) which can be plotted through the three points (0.5, 1), (0.5, 0.5) and (1,a_2). The only way to achieve the equality (5.3.2.1) is to use the Tchebycheff aggregation method. This method is a weighted minimum aggregation of the individual preference values. Thus, it follows:

$$min(0.5,b) = min(1,b \cdot a_2) = 0.5 \Rightarrow b = \frac{1}{2a_2} > 0.5 \qquad (5.3.2.2)$$

As b>0.5 (since $a_2 \in [0,0.5]$), we have also *min*(0.5,b)=0.5, and so, the equality (5.3.2.1) is satisfied. However, the Tchebycheff aggregation is not derived from the general weighted mean. It is a particular case of the procedure proposed by Scott. Although Tchebycheff aggregation method enables to capture the whole Pareto frontier, including solutions located in the non-convex parts (for every Pareto optimal point, there is a unique combination of weights such as this point is captured [Miettinen 1999, Messac 2000a, Messac 2000b]), its interpretation in term of preference remains difficult.

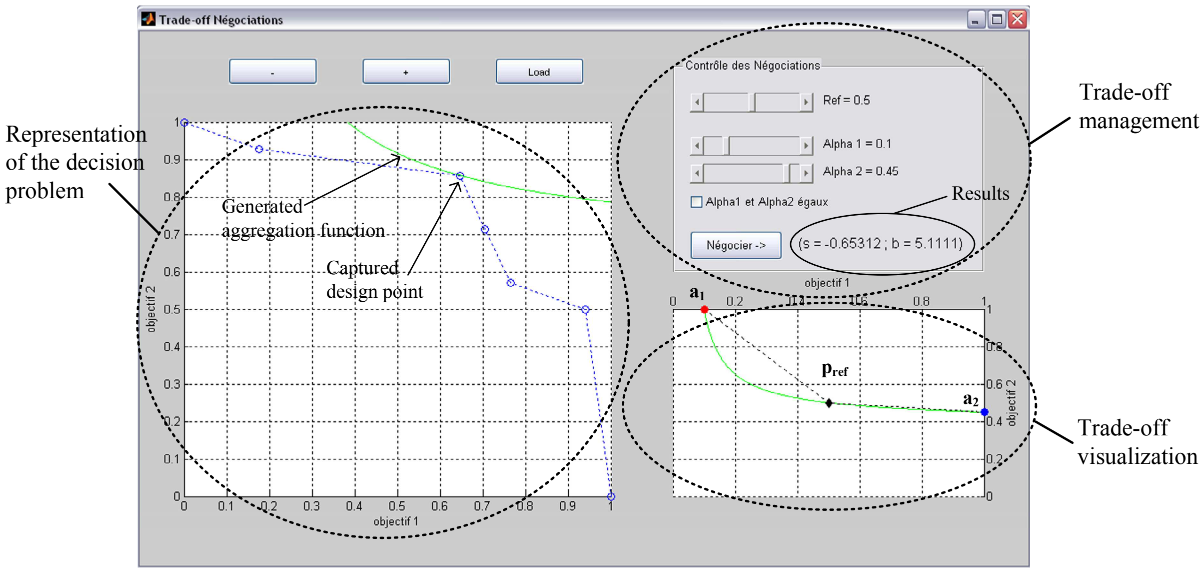

Figure 43. Screenshot of the GUI implementing the equivalent point method in a Matlab© environment

For a better understanding of practical implications and limits of the procedure proposed by Scott, a demonstrator had been implemented in the Matlab© environment. Figure 43 is a screenshot of the GUI allowing the computation of the trade-off strategy and weights ratio according to the equivalent points method. The left side of the GUI is related to the representation of the decision problem whereas the right side of the GUI concerns the management of the trade-off. On the right side, the objective space and the set of Pareto solutions to be traded are presented. In this example, the Pareto frontier being investigated is non-convex. The left side is dedicated to the interactions with designers. Cursors on the top are used to assign the reference value of the overall preference of (p_{ref}=0.5) and the preference values of equivalent points (a_1=0.1 and a_2=0.45). The positions of the reference and equivalent points are updated simultaneously on the graph located at the right bottom of the screen. The checkbox enables to set a_1=a_2. Once these three parameters have been specified, trade-off strategy parameter and weights ratio can be computed. In this example, the equivalent points are specified with p_{ref}=0.5, a_1=0.1 and a_2=0.45. This leads to s=-0.65312 and b=5.11111. The related aggregation function is plotted both on the graph at the right bottom of the screen, and on the objective space at the left of the screen. The final solution is the one which maximizes the objective function, i.e. the one which is located on the aggregation function curve.

The equivalent points method proposed by Scott seems relevant to manage trade-offs and support decision making in engineering design. This approach can be completely integrated within the design modelling methodology that we proposed in this thesis.

5.4 Trade-off function for robust decision making in engineering design

5.4.1 Preliminary considerations

It is considered here that robust design approaches in engineering design involves two kinds of robustness. The first level of robustness concerns the physical sensitivity of the system performance whereas the second level of robustness deals with uncertainty of the choice. The later consists in determining solutions such as slight variations of their performances will not further alter the decision of designers. In chapter 4, we have proposed to tackle robust design problems as a trade-off process between two design objectives, namely the improvement of the overall performance and the minimization of the performance sensitivity due to uncertainty. These two objectives have been formulated through the design modelling methodology proposed in chapter 4.

In this chapter, we propose an original function to operate trade-off among candidate solutions using indifference levels. The development of a trade-off function for robust design problems stems from the observation that designers often expect to achieve first the performance of a system and then, its robustness. The objective linked to the improvement of the performance is often of higher priority than the objective of sensitivity reduction. From a solution with a high level of performance, the developed approach consists in investigating the neighbourhood of the nominal solution to find solutions with a quite similar level of performance but less sensitive to uncertainty. In this section, we denote respectively by u and v the preferences related to the satisfaction of the performance objective and sensitivity objective.

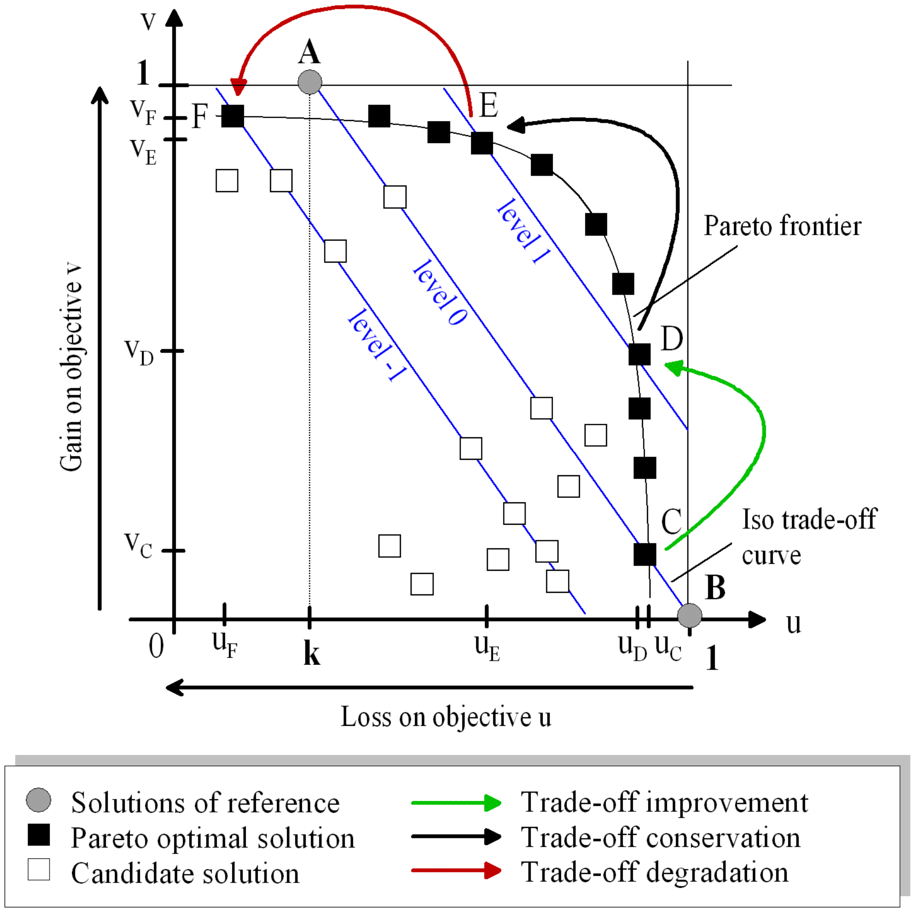

Figure 44. Ranking of candidate solutions according to their belonging to iso trade-off curves

A set of candidate solutions is reported on figure 44. The Pareto dominant solutions are represented by black squares. Let us consider the alternative B with a very high level of performance (u_B=1) and an extreme variability (v_B=0). Although, such a solution is not robust, but remains relevant for the designer since the objective of performance is maximized with this solution. To improve its robustness, and select another alternative, designers should evaluate the admissible compromise between performance loss and robustness gain. This compromise is represented by the solution of reference A with u_A=k and v_A=1. The two solutions A and B are thus equivalent and designers can choose indifferently one of them. Actually, every alternatives belonging to the level curve defined by A and B is equally preferred. This curve (line) is called iso trade-off curve.

5.4.2 Order of relations and iso trade-off curves

The trade-off function developed in this section is mainly based on iso-trade-off curves. An iso-trade-off curve corresponds to the alternatives considered as equally preferred by decision-makers. Let us consider a set of candidates evaluated on the two preferences u and v, such that the tuple (u,v) belongs to the interval $[0,1]^2$. Typically, the ideal decision concerns the solution which achieves the best preferences for both u and v. Such cases are rare in real design problems. Designers often face compensatory situations in which the weak value of one preference is compensated by the high value of another.

Our approach enables them to operate selections by quantifying a trade-off when one of the two preferences is favoured. If the preference u is constrained to keep a minimal value, then the compromise between u and v can be expressed as the maximal degradation allowed by designers to improve the preference v. Let's consider a solution for which the preference u equals one and the preference v equals zero. Then the iso-trade-off curve indicates the minimal admissible value for u to increase v from zero to one.

According to figure 44, the indifference relation states that two alternatives $A(u_A,v_A)$ and $B(u_B,v_B)$ are equivalent provided that it is impossible to operate a rational choice between them. The two solutions are thus equally preferred, and we note A~B. The specification of the two hypothetic solutions defines an initial level of iso-trade-off, and also a value for the sensitivity of choice defined as follows:

$$\chi_{AB} = \left(\frac{v_A - v_B}{u_A - u_B} \right) \tag{5.4.2.1}$$

The set of alternatives N(u,v) equivalent to A and B, belongs to the iso trade-off curve (AB), and each candidate solutions must verify:

$$\left(\frac{v - v_B}{u - u_B} \right) = \left(\frac{v_A - v_B}{u_A - u_B} \right) \tag{5.4.2.2}$$

However, in order to allow designers to express more complex initial compromises, we introduce the parameter n in relation (5.4.2.2):

$$\left(\frac{v^n - v_B^n}{u^n - u_B^n} \right) = \left(\frac{v_A^n - v_B^n}{u_A^n - u_B^n} \right) \qquad n \in \mathbb{R}_+^* \tag{5.4.2.3}$$

Finally, substituting the components of A and B by their own values, the equation of the initial iso-trade off curve is:

$$1 - u^n - v^n\left(1 - k^n\right) = 0$$
$$\text{with} \quad \begin{cases} u > k, \quad k \in [0,1] \\ n \in \mathbb{R}_+^* \end{cases} \tag{5.4.2.4}$$

where k and n are the two specification parameters used to adjust the shape of the function to designers' specifications. Parameter k gives the minimal admissible value reached by preference u to increase the value of preference v from zero to one. The parameter n is used to refine the expression of the compromise expected between the two preferences. Increasing the value of n makes the compromise more restrictive on the minimal admissible value on u. This parameter value is determined by considering a third point of indifference to specify the compromise, and is then numerically computed by solving the equation (5.4.2.4).

Different compromises can be expressed through the specification of these two parameters. Figure 45 presents three iso-trade-off functions specified with different values of parameters. The iso trade-off function represented in solid line (1) is the least restrictive. It states that preference u can be decreased from 1 to 0.5 to improve preference v from zero to one. Both candidate solutions A and B verify equation (5.4.2.4) and thus are considered as equally preferred. In other words, it is equivalent to choose either alternative B or alternative A, if preference v is expected to be improved. The iso-trade-off function plotted in dotted line (2) considers that alternatives C, D and F are considered as equally preferred. By increasing the value of n, designers agree to decrease preference u only if the gain in preference v is important. Solutions F or C can be selected. The compromise is therefore more restrictive than the previous one, since solutions A and C achieve the same preference u. The same remarks can be done with the iso-trade-off function in dashed line (3), which allows very small loss on the preference u, since k=0.8 and n=3.

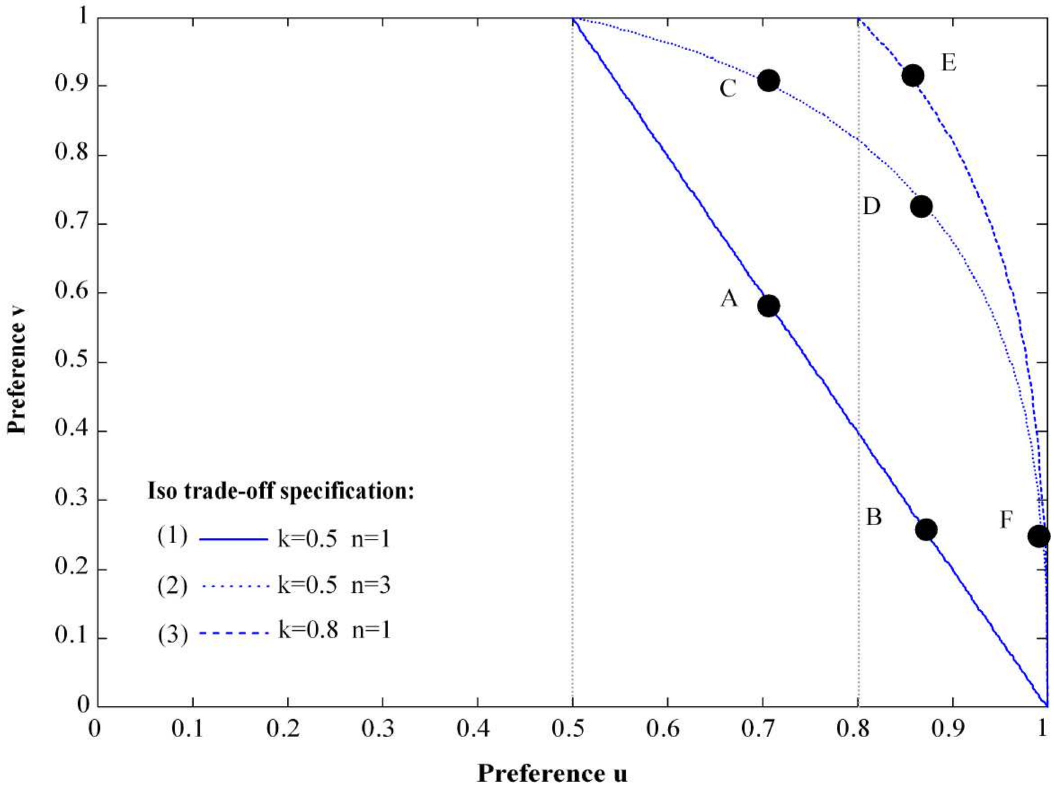

Figure 45. Representation of iso trade-off curves for different parameter values

Similar analyses can be made with solutions represented on figure 44. In this case, it appears that an equivalent choice to both A and B is the alternative C. However, solution D is very close to solution C in regards to the performance but presents a much better level of insensitivity. Thus, we get $u_C \approx u_D$ and $v_C << v_D$. This leads to $C \prec D$. Consequently, the alternative D achieves a better compromise than the one initially specified (level 0), and thus, constitute a better choice than C. According to equation (5.4.2.4), the compromise achieved by D satisfies:

$$1 - u_D^n - v_D^n\left(1 - k^n\right) \le 0, \quad \text{with} \quad k < u_D, \quad n = 1 \tag{5.4.2.5}$$

The alternative D belongs to another iso trade-off curve (level 1) and, as the value of v for D and E remains the same, it follows that D~E. Consequently, the solutions can be gathered and ranked according to their membership to the different iso trade-off levels (curves). The quantification of the iso trade-off levels is the purpose of the trade-off function developed in the next section.

5.4.3 Trade-off function and robustness indicator

The trade-off function assigns numerical values to the iso trade-off levels. From equation (5.4.2.4), the trade-off function *T*(u,v) is formulated as a piecewise function defined as:

$$T: \begin{cases} [0,1] \to [-1,1] \\ (u,v) \mapsto \alpha \cdot \Phi(u,v) + \beta \end{cases} \qquad \text{with} \quad \Phi(u,v) = 1 - u^n - \left(1 - k^n\right) v^n \tag{5.4.3.1}$$

where k and n are the specification parameters of the iso trade-off curves. The coefficients α and β are determined as follows:

$$\begin{cases} (1) \quad \alpha = -\dfrac{1}{\left(1-k^{n}\right)}, \beta = 0 \quad \text{if} \quad u \geq k \ \text{ and } \ \Phi(u,v) \leq 0 \\ (2) \quad \alpha = -1, \beta = 0 \quad \text{if} \quad u \geq k \ \text{ and } \ \Phi(u,v) > 0 \\ (3) \quad \alpha = -\dfrac{u}{k}, \beta = \dfrac{u-k}{k} \quad \text{if} \quad u < k \ \text{ and } \ \Phi(u,v) \leq 0 \end{cases} \tag{5.4.3.2}$$

From equations (5.4.3.1) and (5.4.3.2), we introduce the robustness indicator RI expressed as RI=T(u,v). This indicator to be maximised, quantifies the trade-off achieve by candidate solutions between the performance and the robustness.

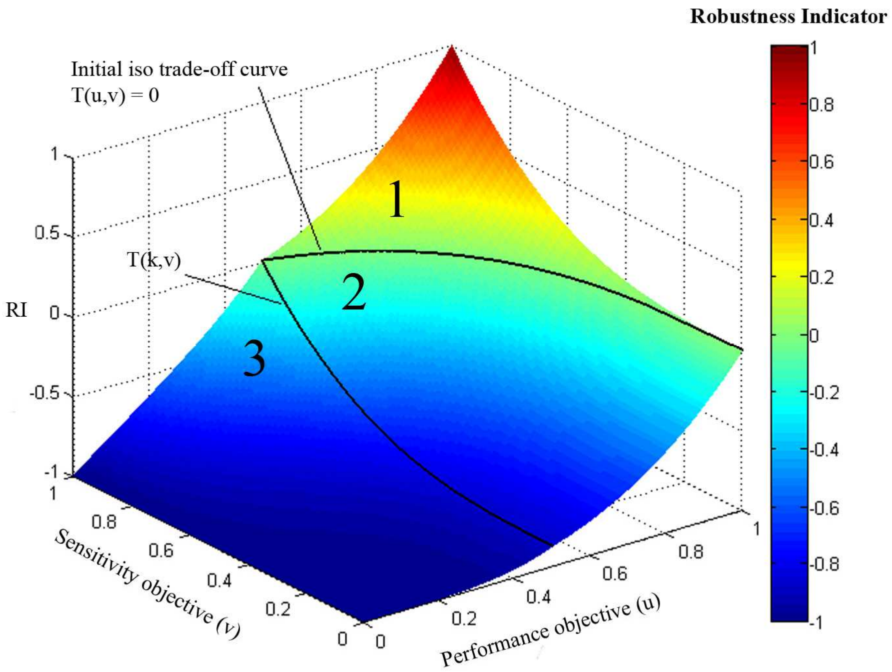

Figure 46. Trade-off function specified with k=0.5 and n=3

Figure 46 represents a trade-off function specified with k=0.5 and n=3. The initial iso-trade-off curve have been plotted and corresponds to T(u,v)=0. Every points of this curve get the same robustness indicator value. The three parts of the trade-off function have also been identified according to relation (5.4.3.2). Considering that for a set of alternatives, the initial iso-trade-off curve corresponds to RI=0, positive values of RI traduce the improvement of the trade-off, whereas negative values of RI imply the degradation of the trade-off. This is illustrated on figure 47. According to this figure, alternatives A and B correspond to compensatory configurations for which any rational decision could be taken. The first example (1) deals with trade-off improvement. Alternative C is equivalent to alternative A in regards to the preference v (robustness), but is also better in regards to the preference u (performance). Compared to alternative B, alternative C is equivalent in regards to the preference u, but is better in regards to the preference v. Therefore alternative C constitutes a better choice than both A and B. The second example (2) deals with the conservation of the trade-off. According to the preference values, it is not possible for the decision-makers to operate a rational choice between alternatives A, B and D, considered as equivalent. The last example (3) refers to the degradation of the trade-off indicator. As solution E is less preferred than both alternatives A and B for u and v, it represents the worst compromise compared to examples (1) and (2). Therefore, the trade-off function enables to rank design solutions according to their ability to improve or worsen the initial compromise specified by designers.

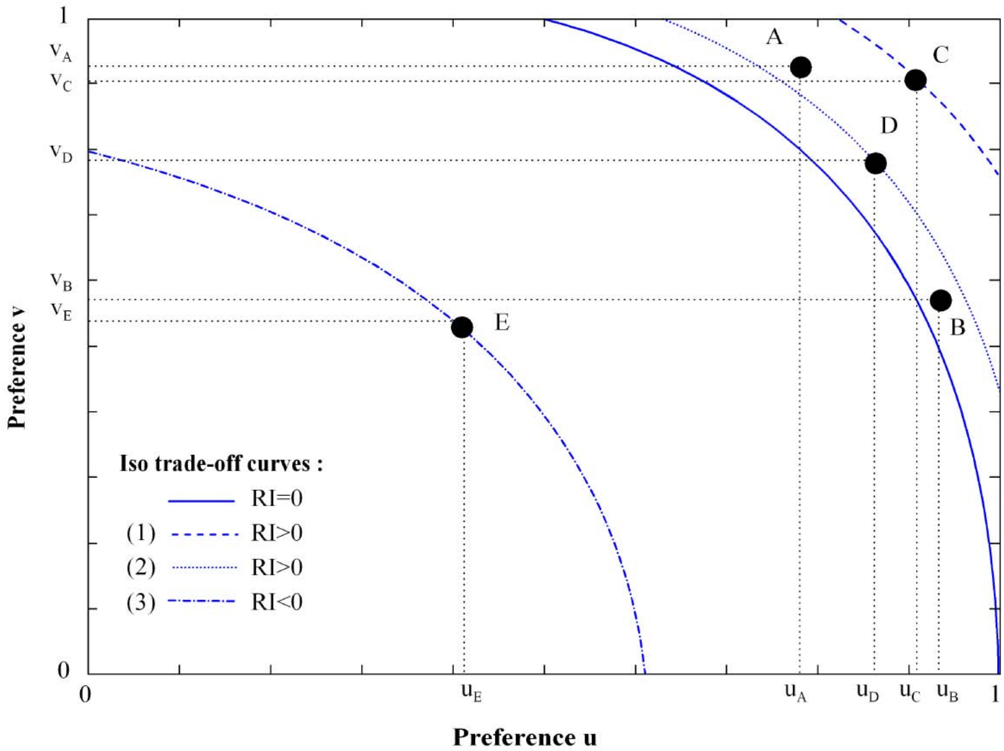

Figure 47. Iso trade-off functions and robustness indicator behaviour

On figure 46, the trade-off values *T*(k,v) have been reported. This corresponds to the set of solutions such as u=k. It appears that for a given value of u (performance objective), the trade-off function ranks the solutions by increasing value of v (sensitivity objective). Conversely, for a given value of v, the solutions are ranked by increasing level of u. From relations (5.4.3.1) and (5.4.3.2), it can be shown that:

$$\forall(u,v)\in[0,1]^2,\quad \left(\frac{\partial T}{\partial u}\right)_v \geq 0 \text{ and } \left(\frac{\partial T}{\partial v}\right)_u \geq 0 \tag{5.4.3.3}$$

In other words, the trade-off function computes consistent ranks even if all the alternatives achieve the same level for preference u or v, or for both of them. Consider the robustness indicators RI_A and RI_B related respectively to the alternatives $A(u_A,v_A)$ and $B(u_B,v_B)$. From relations (5.4.3.1) and (5.4.3.2), the difference between these indicators can be expressed as:

$$\begin{aligned} RI_A - RI_B &= \left[\alpha\left(1-u_A{}^n-\left(1-k^n\right)v_A{}^n\right)+\beta\right]-\left[\alpha\left(1-u_B{}^n-\left(1-k^n\right)v_B{}^n\right)+\beta\right] \\ &= \alpha\left(u_A{}^n-u_B{}^n\right)+\alpha\left(1-k^n\right)\left(v_B{}^n-v_A{}^n\right) \end{aligned} \tag{5.4.3.4}$$

Alternative A is preferred to alternative B if $RI_A>RI_B$, and:

$$RI_A - RI_B \geq 0 \Leftrightarrow \alpha\left(u_A{}^n-u_B{}^n\right)+\alpha\left(1-k^n\right)\left(v_B{}^n-v_A{}^n\right)\geq 0 \tag{5.4.3.5}$$

As α<0, if both alternatives A and B achieve the same preference $u=u_A=u_B$, it follows from relation (5.4.3.5) that:

$$\left(RI_A\right)_{u=cst} - \left(RI_B\right)_{u=cst} \geq 0 \Leftrightarrow \left(v_A{}^n - v_B{}^n\right) \geq 0 \qquad (5.4.3.6)$$

Thus, alternatives A and B are ranked according to preference v. In the same way, if the two alternatives reach the same preference v, then they are ranked according to the preference u. it can be shown that:

$$\left(RI_A\right)_{v=cst} - \left(RI_B\right)_{v=cst} \geq 0 \Leftrightarrow \left(u_A{}^n - u_B{}^n\right) \geq 0 \qquad (5.4.3.8)$$

Finally, if all the alternatives get the same values for both preferences u and v, then the alternatives cannot be ordered, since all candidates achieve equivalent trade-off indicators. Consequently, they all verify the equation of the same iso-trade-off function, and are considered as equally preferred.

5.5 Summary

Major difficulties in engineering design problems come from the balancing act between many design criteria and objectives. Modelling such a trade-off is of main interest in design optimization to compute optimal solutions. Trade-off can be expressed as a compromise allowing increments of one performance against decrements of some others. However, trade-off in engineering design is often complex and requires the definition of compromises for different levels of performances.

In this chapter, we present two approaches to manage trade-off in engineering design. The first methodology proposed by Scott uses equivalent point to determine consistent trade-off parameters values and weights assignment for preference aggregation. This enables to model compromises evolving with several levels of preference. However the weights and trade-off parameter are highly sensitive while preferences values are close to extreme bounds (p=0 and p=1). Consequently, it is suggested to take $s\in[-10,0]$ for the generation of consistent *design appropriate* aggregation functions. Such an approach can be easily implemented within systems to support decision-making in engineering design. Some applications of the equivalent points method are presented in [Scott 1999, Mourelatos 2006].

As the trade-off between performances against their variability is specific to robust design problems, we propose a suitable trade-off function to model designers' preferences facing with these two objectives. The trade-off function has been designed to evaluate the relative sensitivity of choice among a set of alternatives. This is done by quantifying the improvement or the degradation of the compromise between two preferences when one of them is favoured. In the framework of robust design, the improvement of the overall performance is traded-off against the reduction of the performance sensitivity. It results in an objective function to be maximized. Recently, the trade-off function has been applied to improve the robustness of car structure for crashworthiness of vehicle side impact [Quirante 2011b]. In another research work [Quirante 2012], the trade-off function is used to tackle the robust design of a truss structure.

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CHAPTER 6 Design of two-staged flash evaporators for must concentration applications in the wine industry

In the past few years, flash evaporation processes have received an increased attention in the wine industry for must concentration applications. Specific constraints related to the wine industry area had led to many improvements of flash evaporators. Preliminary design of evaporators must deal with many design objectives specific to this area of application. In particular, the robustness of these vinification processes is of main interest since the variations of temperatures and flow rates of liquids at the inlet of the process can deeply impact the quality of the product at the system outlet. The methodology developed in this thesis is applied to achieve robust design of flash evaporators. Each step of the design modelling methodology is described and illustrated with concrete examples. Design objectives are formulated with a preference aggregation method. The selection of the optimal design solution is discussed according to different trade-off strategies. The generation of the Pareto set is addressed by the non dominated sorting genetic algorithm NGSAII. The study developed in this chapter is mainly based on recent publications [Ho Kon Tiat 2010, Sebastian 2010, Quirante 2010, Quirante 2011a].

NOMENCLATURE

Physical variables and parameters		*Decision variables and parameters*	
C	energy consumption	d	desirability score
$\overline{C}$	costs	$\tilde{d}$	desirability score related to the sensitivity objective
Cx	rate of concentration	DOI	design objective index
D	alcoholic strength	$\widetilde{DOI}$	design objective index of the sensitivity objective
EI	environmental impact	GDI	global desirability index
k	heat transfer coefficient	x	vector of design variables
M	mass	$\tilde{\mathbf{x}}$	disturbed design variables vector
N	number of plates within the condensers	y	vector of observation variables
P	pressure	$\tilde{\mathbf{y}}_i$	disturbed vector for the i^{th} observation variable
q	mass flow rate	$\overline{y}_i$	average of the i^{th} observation variable values
S	floor area	w	vector of numerical weights
T	temperature		
t	time		
Greek symbols		*Subscripts*	
Ω	design space	cl	coolant liquid
α	measure of the bandwidth of variation	elec	electric
β	measure of the tolerance to nominal	invest	investment
γ	measure of the minimum admissible value	LP/VLP	low pressure/very low pressure
Δx	variation of control factors	op	operating
ε	variation of noise factors	perfo	performance
σ	standard deviation	pi/po	inlet product/outlet product
φ	flash evaporator simulation model	sens	sensitivity
		sys	system

6.1 Introduction

Due to a drop of the table wine consumption and changes of consumer tastes, there is a growing interest in using flash evaporation processes in the wine industry. Indeed, according to recent studies in the pre-treatment of grapes by flash-release (or flash détente), benefits come from considerable improvements of the wine quality and enhancement of its gustative properties [Ageron 1995, Escudier 1995, Escudier 1998]. In particular, the final content of polyphenol in the wine (chemical agent in the berries skin tissues responsible for the colour and flavour of red wines) is at least 50% higher compared to wines obtained from traditional production techniques [Vinsonneau 2002]. Figure 48 shows the must concentration process by flash evaporation through the wine production process. This operation aims to increase the alcoholic strength of the must until the final desired value is reached. As a general rule, an enrichment of 1% by volume is obtained by evaporating of 10% of the vintage volume. Grapes are usually first heated at temperatures ranging between 70°C to 90°C [Celotti 1998]. The vintage is then suddenly cooled by flash evaporation to temperatures ranging between 25°C to 30°C which may cause the fermentation of the vintage. The word “flash” comes from the phenomena of quasi-instantaneous and partial vaporization of the vintage when it is subjected to a sudden drop of pressure below its saturation pressure [Miyatake 1973]. As a consequence, the liquid temperature drops to the saturation temperature corresponding to the lowered pressure. Additionally, due to this abrupt change of pressure, sudden mechanical constraints appear inside the berry skin tissues, enhancing the release of many different substances such as tannins, and thus, improve the colour and some gustative properties of wines.

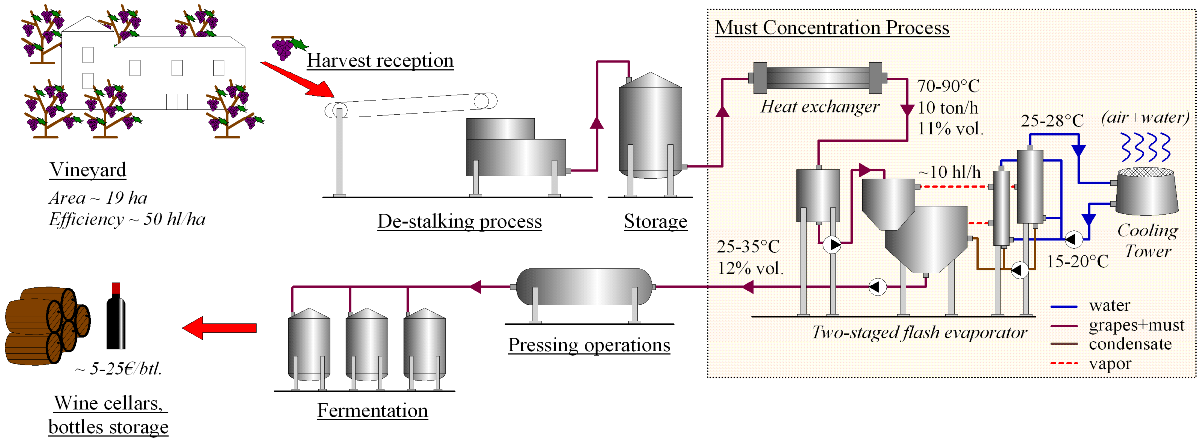
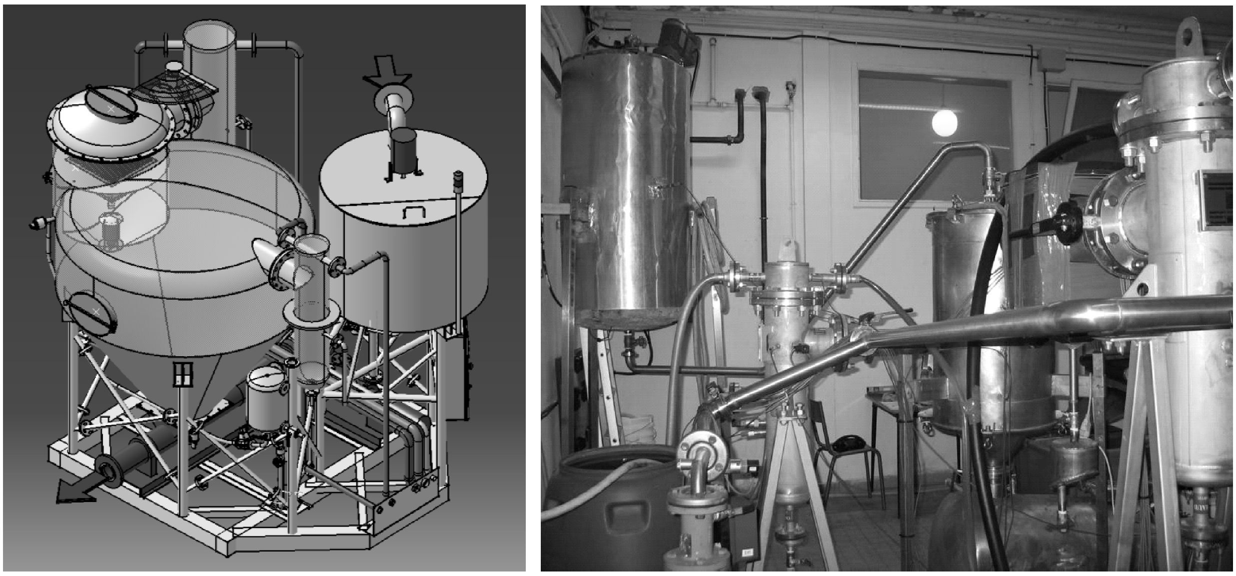


Figure 48. Must concentration by flash evaporation through the wine production process

In practical terms, specific constraints related to the wine industry area had lead to many improvements of flash evaporators initially designed for seawater desalination [Miyatake 2001] and flavours extraction [Sebastian 2002] applications. Typical flash evaporators must be designed to treat at least 10 tons of grapes per hour which corresponds to the treatment of the whole harvest of an average vineyard of 19 ha, with a production efficiency of 50 hl/ha in the region of Bordeaux [Agreste 2010], during a working day (~10 hours). This requirement often leads to oversized systems whereas flash evaporators are required to be transportable from a wine production site to another during the harvest period. But the main weakness of flash evaporators is their high energetic consumption, impacting the environment and increasing the operating costs, and consequently, the price of the wine (given in €/litre of wine). Indeed, thermal and electrical energy (defined in kWh/hl of wine) are required respectively to heat the vintage at the inlet of the evaporator, and to supply pumps for liquids circulation and fan for the air ventilation in the cooling tower (see. figure 50). The water consumption of the system (given in litre of water by litre of wine) is due to the evaporation of the water required to condensate the vapours within the condensers while it goes through the cooling tower.



(a) (b)

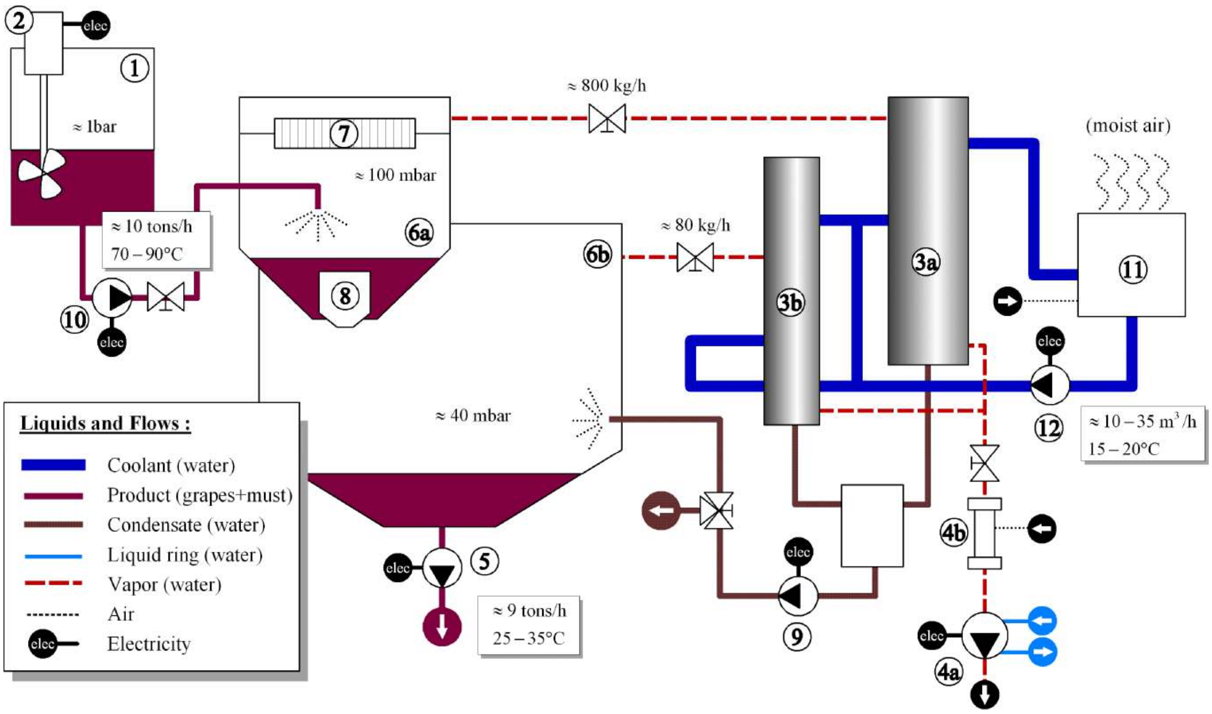
Figure 49. Two-stage flash evaporator: CAD model of the industrial system (a) and its corresponding experimental prototype (b)

Based on these requirements, the system designed by Sebastian et al. [Cadiot 2002, Sebastian 2002] is based on the development of a two-staged evaporator combined with the use of compact condensers and mist eliminators. A CAD view and the corresponding experimental prototype are represented on figure 49. The main components of this process and the industrial system have already been presented in [Bouchama 2003a, Ho Kon Tiat 2008a].

In recent research works [Ho Kon Tiat 2010, Sebastian 2010)], the preliminary design of this flash evaporator has been tackled by trading-off multiple conflicting design objectives of performance such as transportability, environmental impact, operative cost, product quality and cooling power. A multi-objective optimization method based on preferences modelling with desirability functions has been proposed to investigate the design space and determine optimal solutions. However, this approach still cannot be considered as completely satisfactory since we processed a nominal optimization without taking into account the inherent variability of operating conditions and environmental parameters (uncertainties) that may disturb the nominal performances of the system. Obviously, variations of temperatures and flow rates of liquids (must and water) at the inlet of the process can dramatically impact the quality of the product at the system outlet. In particular, deviations from the target values of temperature and alcoholic strength can lead to a severe degradation of the vintage. These two properties are decisive for the final wine quality and thus, their variations must be controlled. Facing this issue, we proposed in a recent study [Quirante 2011] to formulate the sensitivity of the design as a particular design objective to be traded-off. However, this approach doesn't allow designers to express a compromise between the performance and the sensitivity while, these objectives must be obviously balanced according to the designers' expectations.

6.2 Two-staged flash evaporation processes

The two-staged flash evaporator represented in diagram form on figure 50 has been designed to treat about 10 tons/h of grapes. The vintage is initially heated at temperatures ranging between 70°C to 90°C under atmospheric conditions, and stored in the buffer tank (1) where it is stirred by a mixer (2) to maintain a uniform temperature. The system is put under vacuum conditions due to the action of a vacuum pump (4a) coupled with an air ejector (4b). A pump makes the fluid to be sucked up at the low-pressure stage of the evaporation chamber. As soon as the product enters in the low pressure (LP) expansion chamber (6a), a part of the liquid phase is suddenly vaporized, and the level of the remaining fluid rises and activates the float (8) to maintain the pressure difference between the stages. Entering in the very-low pressure (VLP) stage (6b) of the evaporation chamber, the fluid is then once again partially vaporized. The remaining part of the fluid is extracted by the extraction pump (5) which is an eccentric rotor pump of the Archimedes screw type. This type of pump is well adapted for moving fluids containing solid particles such as grapes. The vapour created by the fluid evaporation is condensed through two condensers, one for each stage (3a,3b), to maintain the system under low pressure conditions. Condensates are stored in a tank from where they are extracted by a condensate pump (9). As the vaporization at the low-pressure stage is very violent, droplets are formed and carried out with the vapour. Therefore, a mist eliminator (7) is added to ensure the droplet recovery. The cooling of vapours inside the condensers is performed by the joint action of a mechanical draft cooling tower (11) coupled with a centrifugal pump (12).



1 - Buffer tank	4b - Air ejector	8 - Floater
2 - Mixer	5 - Extraction pump and recovery pump	9 - Condensate pump
3a - Low pressure condenser	6a - Low pressure evaporation chamber	10 - Tank pump
3b - Very low pressure condenser	6b - Very low pressure evaporation chamber	11 - Mechanical draft cooling tower
4a - Liquid ring vacuum pump	7 - Mist eliminator	12 - Centrifugal pump

Figure 50. Illustration of the two-staged flash evaporator principles

6.3 Preliminary design of flash evaporators

6.3.1 Design requirements

From the life-cycle analysis of flash evaporators, we have identified four major design objectives of performance to be satisfied. They concern:

- the improvement of the product quality (DOI_1),
- the improvement of the transportability (DOI_2),
- the minimization of the environmental impact (DOI_3),
- the minimization of the overall costs of ownership (DOI_4)

Initially, the design objective performance related to the cooling power of the evaporator was taken into account [Sebastian 2010, Quirante 2011]. However, it appeared that this design objective is actually not relevant for must concentration applications in the wine industry. Flash evaporator design is often constrained by the evaporative capacity of the system to reach an objective of alcoholic strength and improve the quality of the vintage product.

a. Product quality

Due to the necessity of preserving the gustative properties of wine while meeting international and regional legislations of wine-making practices, the improvement of the product quality (i.e. grapes and must) at the outlet of the flash evaporator is a crucial design objective to be considered by wine producers. The quality of the product depends both on the temperature, the level of final alcoholic strength and the rate of polyphenol of grapes at the outlet of the system. The temperature of the product at the outlet of the flash evaporator (T_{po}) is equal to the saturation temperature of the vapour inside the VLP stage of the evaporation chamber. Depending on the type of wine expected, the desired target temperature can slightly vary from a producer to another. But, in general, the continuity and efficiency of the fermentation process is ensured for temperatures comprised between 10°C (below the temperature is too low to trigger the alcoholic fermentation) and 35°C (stuck of the alcoholic fermentation). The rate of concentration (Cx) of the product is the ratio between the volume of water eliminated during the process and the initial volume of product:

$$Cx = \frac{q_{vapor}}{q_{pi}} = \frac{\left(q_{pi} - q_{po}\right)}{q_{pi}} \qquad (6.3.1.1)$$

where q_{pi} and q_{po} are respectively the input and output product flow rate, q_{vapour} is the volume of water eliminated during the process. The rate of concentration determines the evaporative capacity of the system. The volume of water to be eliminated, and so, the rate of concentration, are constrained by the desired final alcoholic strength of the must. In general, it is estimated using the following formula [Jacquet 2002]:

$$q_{vapor} = q_{pi} - q_{po} \quad \text{with} \quad q_{po} = q_{pi} \cdot \frac{D_{pi}}{D_{po}} \qquad (6.3.1.2)$$

where D_{pi} and D_{po} are respectively the initial and final alcoholic strength of the must. In this study, we are mainly interested in increasing the alcoholic strength from 11% to 12% of 100hL/h of must (≈10tons/h). This implies a vaporization of 12hl/h of water. More to the point, as the release of tannins and polyphenol mainly depends on the drop of pressure in the expansion chambers, and according to the results presented in [Vinsonneau 2002], we considered here that the pressure inside the very low pressure chamber must be at least of 94 mbar.

b. Transportability

As mentioned in the introduction, the transportability of the system is a significant design objective since it must be moved from a wine production site to another during the harvest period. The transportability depends both on the floor area (S_{sys}) and the overall mass (M_{sys}) of the system which must not exceed a limit defined by the standard maximal capacities of flat bed trucks. It is estimated by calculating the mass and size of tanks (expansion chambers, buffer and condensates tanks), condensers and pumps which are the biggest and heaviest components of the system. The total mass of the system also involves the weight of the metallic structure used to support the flash evaporator.

$$\begin{aligned} M_{sys} &= M_{tanks} + M_{condensers} + M_{pumps} + M_{structure} \\ S_{sys} &= S_{tanks} + S_{condensers} \end{aligned} \tag{6.3.1.3}$$

c. Environmental impact

Facing with the emergence of environmental constraints in the agricultural field, the environmental impact of the flash evaporation process must be also considered as a design objective. One of the main inconvenient of flash evaporation processes is their high consumption of energy, materials and fluids. In this study, the material consumption of the system is mainly based on the total amount of steel used for manufacturing the tanks. Based on the EcoIndicator99 methodology [Goedkoop 2000], the relative impact corresponding to one ton of steel is quantified and the related damages coefficients (environment, human health, resources) are derived from this impact:

$$\begin{aligned} & EI_{material} = \left(a_1 + a_2 + a_3\right) \cdot M_{sys} \\ & a_1 = 1.9 \text{ (environment)}, \; a_2 = 13\,233 \text{ (human health)}, \; a_3 = 2.3 \text{ (ressources)} \end{aligned} \tag{6.3.1.4}$$

Similarly, we evaluate the damages coefficients associated to the consumptions of 10kWh and 1m3 of water. Finally, a global score EI is derived from the impacts of material, energy and water consumptions.

$$\begin{aligned} & EI_{99} = EI_{material} + EI_{elec} + EI_{water} \\ & \text{with,} \\ & EI_{elec} = \left(b_1 + b_2 + b_3\right) \cdot C_{elec}, \; b_1 = 0.145, \, b_2 = 0.0139, \, b_3 = 0.0271 \\ & EI_{water} = \left(c_1 + c_2 + c_3\right) \cdot C_{water}, \; c_1 = 0.0187, \, c_2 = 0.00204 \, , \, c_3 = 0.00607 \end{aligned} \tag{6.3.1.5}$$

The energy consumption calculation is based on the power required to supply the different pumps, mixer and fan. The water consumption corresponds to the volume of water used by the cooling tower. Mechanical draft cooling towers consume water in three major ways [Leeper 1981]. Evaporation rate (C_E) is approximately of 1% of the water flow rate per each 10°F (≈5.5°C) of the cooling range. Drift (C_D) is approximately 0.2% of the water flow rate, and refers to the water which leaves the cooling tower carried out with the exiting air. In order to prevent concentration of solid and chemical particles in the cooling water resulting from the evaporation, the blowdown (C_B) is the volume of water removed from the system and replaced by fresh water. It is generally assumed that C_B equals 20% of the evaporation rate.

$$C_{elec} = \left(Power_{mixer} + Power_{fan} + \sum Power_{pumps}\right) \cdot t_{op}$$
$$C_{water} = \left(C_E + C_D + C_B\right) \cdot t_{op} \qquad (6.3.1.6)$$

The electrical consumption and water consumption are respectively expressed in kWh and m^3/h. They are estimated over a period (t_{op}) of 20 years with an average operating time of 10 hours per day during 2 months (duration of the harvest period).

d. Overall costs of ownership

The development of “flash détente” processes in the wine area is also hampered by the initial cost of investment. The economical analysis of the flash evaporator aims at modelling manufacturing costs (material purchase and forming) of tanks, and purchasing costs of other parts of the flash evaporation system (condensers, pumps, etc.). The global purchasing cost of the system is calculated by adding these manufacturing and purchasing costs for each part of the system.

The total investment ($\overline{C}_{invest}$) cost of the process results from this global purchasing cost multiplied by the Lang factor to take into account installation costs, transportation costs and various costs such as insurance costs [Rehfeldt 1997]. From this investment cost, we derive the maintenance cost which is assessed as 2.5% of the investment cost, and the total discounting cost of the system which is estimated from the coefficient of discounting evaluated over a period of twenty years. The overall operating cost ($\overline{C}_{op}$) over this period is derived from the electricity and water consumption costs calculated from the peak charges applied by EDF (0.1275€/kWh) and the average price of water distributed in France (3.39€/m3) in 2011. Finally, the overall cost of ownership ($\overline{C}_{total}$) is calculated by adding the overall costs of discounting and the operating cost of the system.

6.3.2 Measures of performance, observation variables and design criteria

From these requirements, we derive eight observation variables to evaluate the performances of the two-staged flash evaporator. These variables refer to:

- Outlet product temperature,
- Alcoholic strength,
- Pressure within the VLP stage,
- Mass of the system,
- Floor area of the system,
- Eco-indicator,
- Total costs of investment,
- Operating costs

Each observation variable is related to one design criterion, expressed as equality/inequality constraints which must be satisfied. Moreover, every criterion (and so, observation variable) can be associated to the achievement of one of the four design objectives of performance identified in section 6.4.1. The definition of the observation variables and design criteria are summarized in table 7.

Observation variables			Design criteria
$\mathbf{y} = [y_1, y_2, \dots, y_8]^T$	name	unit	
y_1 - Outlet product temperature	T_{po}	(°C)	$25°C \le T_{po} \le 30°C$
y_2 - Alcoholic strength	D_{po}	(%)	$D_{po} \approx 12\%$
y_3 - Pressure within the VLP stage	P_{LP}	(mbar)	$P_{VLP} < 94$mbar
y_4 - Mass of the system	M_{sys}	(tons)	$M_{sys} < 7.5$tons
y_5 - Floor area of the system	S_{sys}	(m2)	$S_{sys} < 16m^2$
y_6 - Eco-indicator	EI_{99}	(-)	$EI_{99} < 50\ 000$
y_7 – Total cost of investment	$\overline{C}_{invest}$	(k€)	$\overline{C}_{invest} < 465$k€
y_8 - Operating costs	$\overline{C}_{op}$	(k€)	$\overline{C}_{op} < 153$k€

Table 7. Definition of the observation variables and design criteria

6.3.3 Design variables

The observation variables are computed from a set of design variables. They are the main dimensioning and monitoring parameters required to completely define the system (regarded as a candidate solution) and its functioning environment (vintage and coolant liquid). The preliminary design of two-staged flash evaporators involves six design variables (**x**):

- inlet temperature of the product (must and grapes),
- inlet temperature and flow rate of the coolant liquid (water),
- flow rate of the coolant added to the LP condenser,
- number of plates in the low-pressure and very low-pressure condensers

Condensers can be composed of 250 plates which represents a maximal heat surface exchange of 40m² per condenser. As the flash evaporator is supposed to be designed for treating 10 tons/h of grapes, the inlet product flow rate is considered here as a constant parameter of the design model. The ranges of admissible design variables values are provided in table 8. As a set of design variable values characterizes one particular candidate solution, different combinations of design variables values lead to flash evaporator configurations with different levels of performance.

Design variables			Domain (Ω)	
$\mathbf{x} = [x_1, x_2, \dots, x_6]^T$	name	unit	range	nature
x_1-Inlet product temperature	T_{pi}	(°C)	[70.0; 90.0]	continuous
x_2-Inlet coolant temperature	T_{cl}	(°C)	[15.0; 25.0]	continuous
x_3-Inlet coolant flow rate	q_{cl}	(m^3/h)	[10.0; 20.0]	continuous
x_4-Flow rate of the coolant added to the LP condenser	q_{cl+}	(m^3/h)	[1.00; 25.0]	continuous
x_5-Number of plates in the low-pressure condenser	N_{LP}	(-)	{6,...,250}	discrete
x_6-Number of plates in the very low-pressure condenser	N_{VLP}	(-)	{6,...,250}	discrete

Table 8. Definition of the design variables and design space

6.3.4 Uncertainty and performance variations

In functioning phases, variations in liquids (must and water) temperatures and flow rates at the inlet of the process can dramatically impact the quality of the product at the system outlet. In particular, deviations of the temperature and alcoholic strength from their target values may lead to severe degradations of the vintage quality. Therefore, the robust design of the two-staged flash evaporator concerns the minimization of the variation of the following performance variables:

- the outlet product temperature (y_1),
- the final alcoholic strength (y_2),
- the pressure within the VLP stage (y_3)

The variations of these variables are observed through the two measures described in section 4.3.2, namely the bandwidth of variation (α) and the tolerance to nominal (β). Moreover, the minimum admissible value criterion (γ) is used to contain the performance dispersion within a desirable domain.

Uncertainties type	**Uncertain variables/parameters**			**Variations range**
		name	unit	
Control factors (**δ**)	Inlet product temperature (x_1)	T_{pi}	(°C)	±1°C
	Inlet coolant temperature (x_2)	T_{cl}	(°C)	±1°C
Noise factors (**α**)	Input product mass flow rate	Q_{pi}	(tons)	±1 ton/h
	heat transfer coefficient for the LP condenser	k_{LP}	(W/m².K)	±1%
	heat transfer coefficient for the VLP condenser	k_{VLP}	(W/m².K)	±1%

Table 9. Definition of uncertainties parameters

We consider the uncertainty associated to the variability of operating conditions and the uncertainty linked to modelling errors. They are considered as random uncertainties without any assessment on their distributions. Variations of uncertain variables and parameters used in this study are given in table 9.

Exp.	**Factors**				
#	T_{pi} (°C)	T_{cl} (°C)	q_{pi} (ton/h)	k_{LP} (%)	k_{VLP} (%)
1-4	±1	±1	0	0	0
5-8	0	0	±1	±1	0
9-12	0	±1	0	0	±1
13-16	±1	0	±1	0	0
17-20	0	0	0	±1	±1
21-24	0	±1	±1	0	0
25-28	±1	0	0	±1	0
29-32	0	0	±1	0	±1
33-36	0	±1	0	±1	0
37-40	0	±1	0	±1	0
41	0	0	0	0	0

Table 10. Box-Behnken design (5 factors, 3 levels)

Fluctuations during operating phases of flash evaporators are due to variations of inlet temperatures and mass flow rates of liquids (product and coolant) which can dramatically impact the quality of vintage by modifying its nominal output temperature and final alcoholic strength from the target value. The temperature variations of the must and coolant are supposed to be up to ±1°C around their nominal values. As the flash evaporator was initially designed to concentrate 10tons/h of must, the inlet product flow rate can vary of ±1ton/h from the initial value depending on the size of the vineyard.

Moreover, heat transfer coefficients values are derived from experimental correlations which are highly sensitive to physical phenomena and with values which are difficult to estimate. Due to their predominant role in the heat transfer within the condensers, modelling errors affecting heat transfer coefficients may cause significant inaccuracies in the predictions of the nominal performances. We add two other variables (k_{LP} and k_{VLP}) to assign a variability of ±1% on these parameters.

Uncertainties are introduced through stochastic variables ($\boldsymbol{\alpha},\boldsymbol{\delta}$) during the evaluation of candidate solutions (see section 2.4.2 for further details) which is equivalent to define and evaluate a neighbourhood around the nominal design configuration:

$$\tilde{\mathbf{y}} = \mu\left(\tilde{\mathbf{x}},\boldsymbol{\alpha}\right), \quad \tilde{\mathbf{x}} = \mathbf{x} + \boldsymbol{\delta} \tag{6.3.4}$$

where $\tilde{\mathbf{y}}$ is the vector of disturbed observation variables computed from the vector of design variables $\mathbf{x}$ submitted to the variations of noise factors $\boldsymbol{\alpha}$ and control factors $\boldsymbol{\delta}$. In nominal evaluation, each combination of design variables results in a unique set of performances. The variability is propagated through the behaviour model of the flash evaporator towards observation variables, and results in a set of different functioning states which are characteristic of one particular candidate solution.

As suggested in section 2.4.2, we use a *Box-Behnken* design of experiment method (5factors, 3 levels) to sample the domain of noise and control factors as shown in table 10. Box-Behnken design is an economical fractionalized design which is useful when numerical experimentations are high time consuming. Here, only 41 experiments are required to evaluate the dispersion of the performance. The choice of a fractional design enables to achieve a homogenous repartition of the experiments around the nominal, and thus, a suitable representation of the observation variables excentration. Although, design of experiments is usually used to derive a numerical model of the behaviour of the system, it is not the purpose of our approach. Here, we use design of experiments to define a set of points to be evaluated.

6.4 Preference modelling

6.4.1 Formulation of the objective of performance

Observation variables are first interpreted through Harrington's desirability functions in respect with design criteria and designers' preferences. The desirability functions are specified with desirability levels related to an absolute constraint (AC) and a soft limit (SL) (see section 3.4.2 for further details). The two-sided Harrington's desirability functions have been parameterized using average values between the absolute constraints and soft limits boundaries. Criteria and desirability function parameters are given in table 11.

Design criteria	Desirability functions		Parameters			
			AC	*d*(AC)	SL	*d*(SL)
$25°C \leq T_{po} \leq 30°C$	d_1	two-sided	20 35	0.05 0.05	25 30	0.9 0.9
$D_{po} \approx 12\%$	d_2	two-sided	11 13	0.05 0.05	11.8 12.2	0.9 0.9
$P_{VLP} < 94mbar$	d_3	one-sided	97	0.01	94	0.9
$M_{sys} < 7.5tons$	d_4	one-sided	7.5	0.01	5.3	0.5
$S_{sys} < 16m^2$	d_5	one-sided	16	0.01	10	0.5
$EI_{99} < 50\,000$	d_6	one-sided	50000	0.01	1000	0.99
$\overline{C}_{invest} < 465k€$	d_7	one-sided	465	0.01	141	0.5
$\overline{C}_{op} < 153k€$	d_8	one-sided	153	0.01	84	0.5

Table 11. Desirability function related to the performances

As the specification of the parameters must be consistent with the physical behaviour of the system, it is suitable to define a system of reference of intermediate performance. This system is characterized by a global desirability value equal to 0.5 (GDI=0.5). Since aggregation functions are design appropriate, all desirability values should be equal to 0.5 (d_i=0.5). In this study, the system of reference is a mono-stage evaporator from the society “Entropie SAS” (see figure 51). It concentrates 10tons/h of product from 11% to 12% by volume which corresponds to an evaporative capacity of 1000l/h of water. From the constructor data, we evaluate the weight and floor occupation of this system respectively equal to 5.3tons and 10m², for an estimated cost of investment close to 141k€. As an example, the SL parameter value related to the mass of the system is determined such as $d(Mass_{ref})=0.5$ with $Mass_{ref}=5.3t$. As the evaporator must be transportable from a production site to another, the AC parameter is derived from the dimensions and maximal carrying capacities of medium-sized flat bed trucks (PTAC<7.5t). The desirability functions associated to the mass is represented on figure 21 in section 3.4.2. From the reference system and the requirements enounced in section 6.3.1, the parameter values of the eight desirability functions are determined.

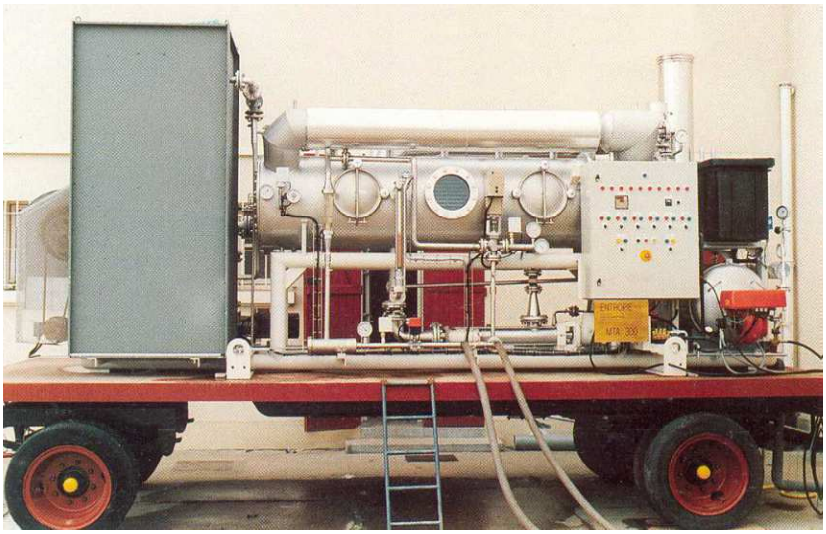


Figure 51. Must concentrator ENTROPY MTA 300 (evaporative capacity: 300l/h)

From the life cycle analysis and functional analysis of the system, four design objectives have been identified. They concern the improvement of the product quality (DOI_1), the improvement of the transportability of the system (DOI_2), the minimization of the environmental impact (DOI_3) and the reduction of total costs of ownership (DOI_4). Each objective is intrinsically linked to the satisfaction of at least one functional goal. It is then possible to identify the observation variables and constraints linked to the achievement of each goal. The output temperature, final alcoholic strength and pressure in the VLP stage impact the product quality. The mass and the overall floor area of the system are related to the improvement of the system transportability. The minimization of the system environmental impact is achieved by the satisfaction of the Eco-Indicator 99 criteria whereas the minimization of the overall costs of ownership takes into account costs of investment and operating costs. The desirability functions are then aggregated into four design objectives indices (DOIs) using a weighted geometric mean aggregation (s=0). At this stage of the aggregation process, the number of aggregated components does not exceed three and it is thus possible to assign directly numerical weights. Furthermore, it is assumed here that the priorities between sub-objectives are equal. Thus, the DOIs are expressed as follows:

$$\mathrm{DOI}_1 = d_1^{1/3} \cdot d_2^{1/3} \cdot d_3^{1/3} \qquad \mathrm{DOI}_2 = d_4^{1/2} \cdot d_5^{1/2}$$
$$\mathrm{DOI}_3 = d_6^{1} \qquad \mathrm{DOI}_4 = d_7^{1/2} \cdot d_8^{1/2} \tag{6.4.1}$$

The DOIs are then aggregated into a global desirability index of performance GDI_{perfo} using a weighted geometric mean (s=0). The GDI related to the performance is thus expressed as follows:

$$\mathrm{GDI}_{\mathrm{perfo}} = \prod_{i=1}^{4} \mathrm{DOI}_i^{w_i} \quad \text{with} \quad \mathbf{w} = \left[0.5660, 0.2647, 0.0399, 0.1267\right]^T \tag{6.4.2}$$

As it is suggested in chapter 4 and 5, the assignment of the numerical weights **w** is performed using the AHP method [Saaty 2008]. From a relative scale of importance ranging from 1 to 9 which corresponds respectively to equal importance and extreme importance, a judgment matrix is defined from pairwise comparisons between objectives. The judgment matrix is positive and symmetrical. The validity of the judgment is qualified through a consistency ratio CR. According to Saaty, consistency ratio values between 1% and 10% validate the consistency of the results computed by the AHP method. In [Semassou 2011], AHP is coupled with to the failure mode, effects, and criticality analysis (FMECA), and the values of the relative scale of importance correspond to the degrees of criticity of the objectives.

"Design for improving the product quality"	Imp. of the product quality	Imp. of the transportability of the system	Reduction of the env. impact	Min. of the total cost of ownership	**w**
Imp. of the product quality	1	3	9	5	**0.5660**
Imp. of the transportability of the system	1/3	1	7	3	**0.2674**
Reduction of the env. impact	1/9	1/7	1/	1/5	**0.0399**
Min. of the total cost of ownership	1/5	1/3	1/5	1	**0.1267**
CR=0.0513					

Table 12. Judgment matrix for the scenario "Design for improving the product quality"

The AHP method enables to define different scenario in respect to the relative importance of objectives between them (Design for X approach). As the main service function of the two staged-flash evaporator concern the must concentration, the satisfaction of the product quality objective is crucial. The transportability of the system is another important objective to be satisfied. Finally, the objectives related to the environmental impact and total costs of ownership are considered as secondary. However, it is considered that the minimization of costs is preferred to the reduction of the environmental impact. Table 12 shows the 4x4 judgment matrix related to a two-stage flash evaporator designed for improving the quality of wine. In this case for instance, the relative importance of the product quality objective is regarded as extreme (value of 9) compared to the environmental objective, whereas the cost is considered as a minor objective (value of 5). The computation of the eigenvector of the matrix provides the normalized values of weights of the aggregation functions. These weights are reported in the right column of the table 12. For this judgment matrix, the CR is equal to 5.13%. The numerical values of the weights computed by the AHP method are thus consistent with the relative order of importance between the objectives satisfaction.

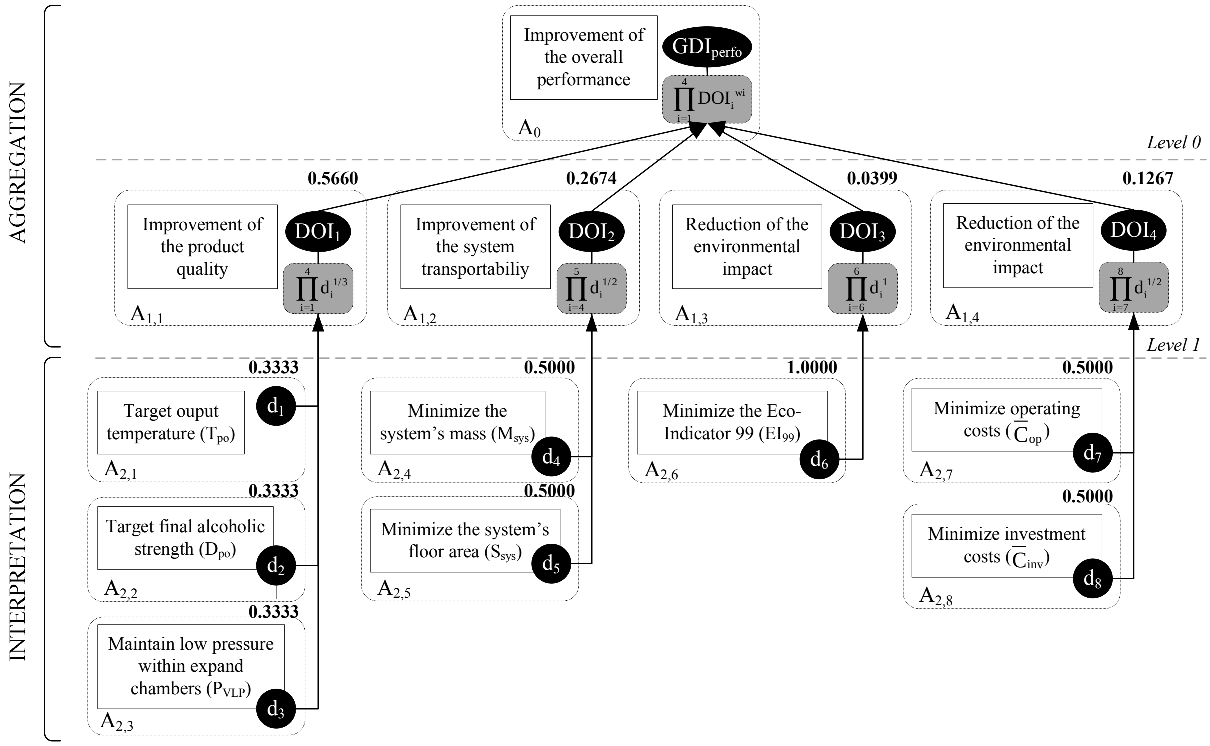


Figure 52. Structure of the preferences aggregation model for the performance

To sum up, the whole structure of the preference aggregation model for the performance is represented in graph form on figure 52. The weights related to each objective have been reported in bold. The design criteria are first interpreted and turned into objectives using Harrington's desirability functions. The desirability function parameters are derived from the requirements and from the definition of a reference system of intermediate desirability. The eight individual desirability functions are then aggregated into four design objective indexes using the weighted geometric mean. At the stage of the process aggregated sub-objective are supposed to be of same priority. Finally, the DOIs are aggregated into a global desirability index of performance using the weighted geometric mean. As the number of objectives now being used is higher, the weigh assignment is performed using the AHP method.

6.4.2 Formulation of the objective of performances sensitivity

The objective of design sensitivity is based on the observation of the dispersion of the output temperature (y_1) of the must, the final alcoholic strength (y_2) and the pressure in the low pressure chamber (y_3). During the functioning phase, flash evaporator users expect uniform juice temperatures at the system outlet to ensure the quality of the product. More to the point, variations of alcoholic strength and pressure in the low pressure chamber can also impact the vintage. As proposed in section 4.3.2, the bandwidth of variation, the limitation of the distance between the nominal value and the centre of gravity of the neighbourhood, and the satisfaction of the minimum admissible value are used to observe the dispersion y_1, y_2 and y_3 when the system is disturbed according to equation (6.3.4). The criteria and desirability function parameters are defined in table 13.

Observation variables			**Desirability functions**		**Parameters**			
	name	unit			AC	*d*(AC)	SL	*d*(SL)
Bandwidth of variation for:								
Output temperature $\left(\widetilde{y_1}\right)$	α1	(°C)	$\widetilde{d_1}$	one-sided	1	0.01	6	0.9
Alcoholic strength $\left(\widetilde{y_2}\right)$	α2	(%)	$\widetilde{d_2}$	one-sided	1	0.01	4	0.9
Pressure $\left(\widetilde{y_2}\right)$	α3	(mbar)	$\widetilde{d_3}$	one-sided	10	0.01	40	0.9
Tolerance to nominal for:								
Output temperature	β1	(°C)	$\widetilde{d_4}$	one-sided	0.25	0.01	2.5	0.9
Alcoholic strength	β2	(%)	$\widetilde{d_5}$	one-sided	0.05	0.01	1.25	0.9
Pressure	β3	(mbar)	$\widetilde{d_6}$	one-sided	5	0.01	20	0.5
Minimum admissible for:								
Output temperature	γ1	(°C)	$\widetilde{d_7}$	two-sided	20 35	0.05 0.05	25 30	0.9 0.9
Alcoholic strength	γ2	(%)	$\widetilde{d_8}$	two-sided	11 13	0.05 0.05	11.8 12.2	0.9 0.9
Pressure	γ3	(mbar)	$\widetilde{d_9}$	one-sided	97	0.01	94	0.9

Table 13. Desirability functions parameters for the objective linked to the performance sensitivity

The first step of the aggregation model consists in aggregating individual desirability functions using the *min* aggregation function (non-compensatory aggregation strategy). The DOIs are expressed as follows:

$$\widetilde{\mathrm{DOI}_1} = \min_{\substack{i=1\ldots3 \\ j=1\ldots3}} \tilde{d}_i\left(\alpha_j\right)$$

$$\widetilde{\mathrm{DOI}_2} = \min_{\substack{i=4\ldots6 \\ j=1\ldots3}} \tilde{d}_i\left(\beta_j\right) \qquad (6.4.2.1)$$

$$\widetilde{\mathrm{DOI}_3} = \min_{\substack{i=7\ldots9 \\ j=1\ldots3}} \gamma_j$$

As mentioned in section 4.3.2, the measure of the minimum admissible value (γ) already corresponds to a desirability value. The *min* aggregation function enables the improvement of the lowest desirability value against the expense of the global desirability level of the design solution. No weights are used in this formulation. The DOIs are then aggregated into a global desirability index of sensitivity GDI_{sens}. This index is expected to be maximized to reduce to sensitivity of the performance under uncertainty. The selected aggregation function is the geometric mean and GDI_{sens} is computed as:

$$GDI_{sens} = \prod_{i=1}^{3} \widetilde{DOI_i}^{v_i} \quad \text{with} \quad v = \left[\frac{4}{10}, \frac{4}{10}, \frac{2}{10}\right]^T \tag{6.4.2.2}$$

Using the weighted geometric mean aggregation tends to improve the global level of desirability by worsening the lowest desirability value. Weights have been determined by considering that the minimization of the objectives linked to the bandwidth of variation and to the tolerance to nominal are of equal importance. The global formulation of the sensitivity objective is summarized in graph form on figure 53.

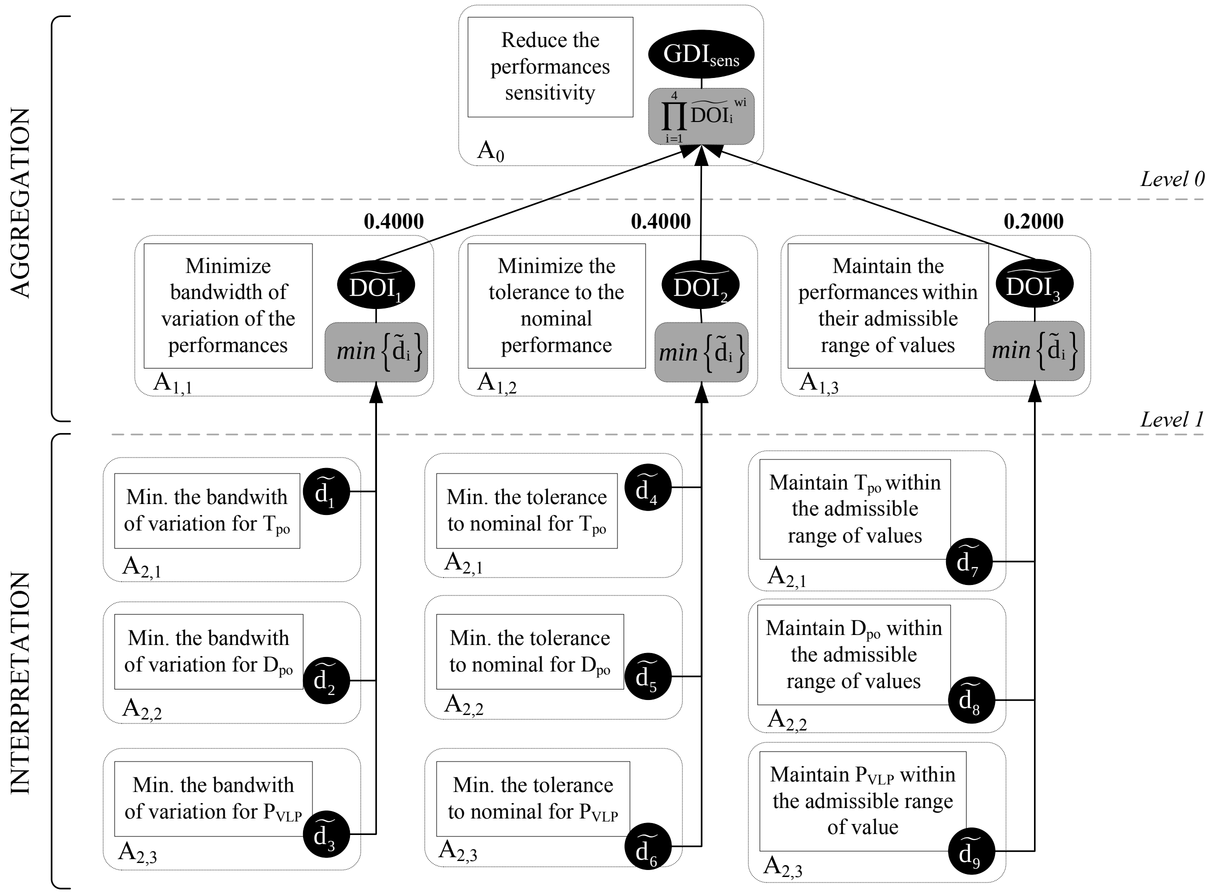


Figure 53. Structure of the preferences aggregation model for the performances sensitivity

6.5 Robust design optimization

6.5.1 Formulation of the optimization problem

A design solution is robust as soon as it achieves a good level of performance while maintaining a low level of variability under uncertainty. This is expressed mathematically by equation (2.3.1.1) in which objectives functions are GDI_{perfo} and GDI_{sens}:

$$\begin{aligned}&\text{maximize } \left[GDI_{\text{perfo}}(\mathbf{x}), GDI_{\text{sens}}(\mathbf{x})\right]^{\mathrm{T}} \\ &\text{subject to: } \quad \mathbf{x} \in \Omega\end{aligned} \tag{6.5.1}$$

Due to the discontinuity of the response surface and numerous local extrema created by weighted aggregations, classical gradient-based optimization approaches are inefficient for solving this numerical problem. Consequently, this MO problem is numerically solved using a genetic algorithm which enables a global investigation of the design space.

6.5.2 Numerical solving

The robust design problem (6.5.1) has been addressed by NGSAII with a population of 250 individuals and a limit criterion of 200 generations. The reader could refer to section 2.3.6 for further details. We use the real-coded GA operator with a distribution index of 20. The fitness computation procedure is presented in flow chart in figure 54. The results are presented and discussed in the following section.

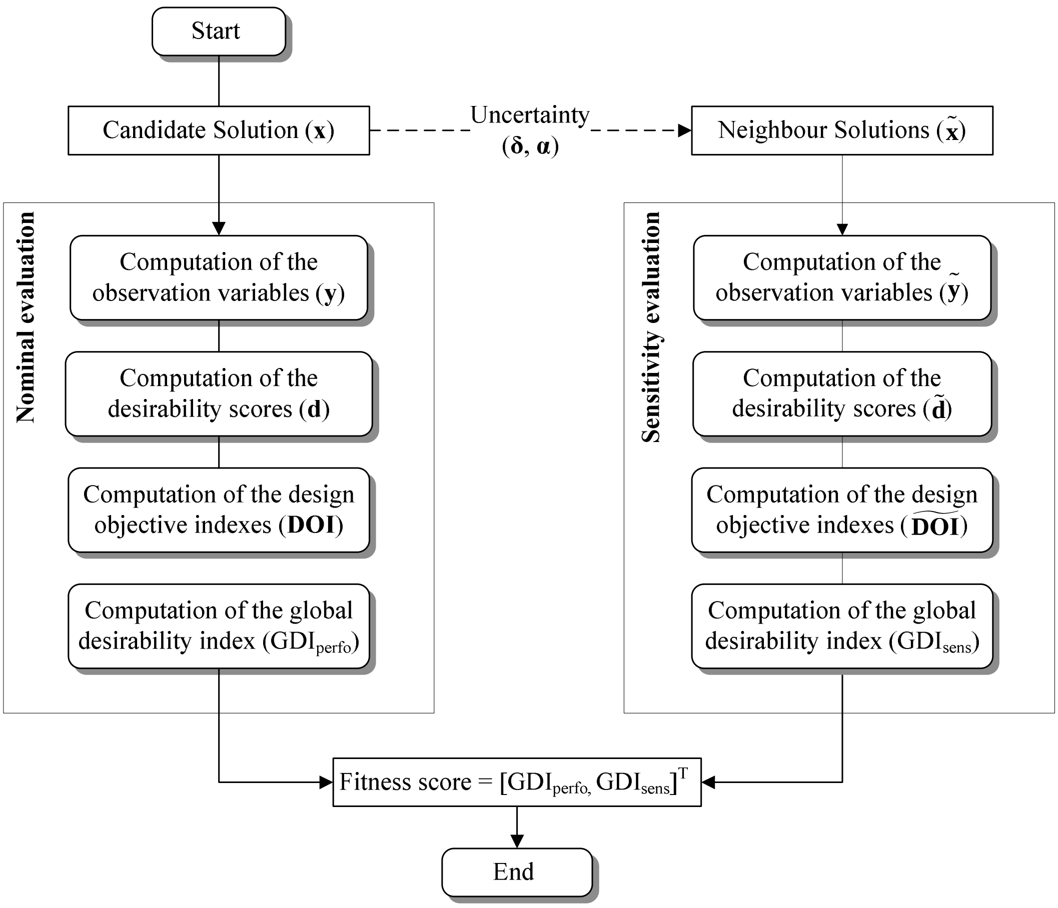


Figure 54. Fitness computation procedure

6.6 Results and discussion

6.6.1 Results

Results are summarized from figure 55 to figure 59. The Pareto set (GDI_{perfo},GDI_{sens}) is represented on figure 55. It is composed of 250 robust design solutions and appears to be non-convex. The two extremities of the frontier correspond respectively to the design solutions with the lowest sensitivity (solution #250) and with the highest level of performance (solution #1). Therefore, the main challenge consist here in determining which one of the Pareto optimal solution is the most relevant for the final design of the two- staged flash evaporator. In the following, the design variables, observation variables and desirability levels have been plotted according to the GDI_{perfo} achieved by the candidate solutions. This is equivalent to represent the evolution of the design properties along the Pareto frontier.

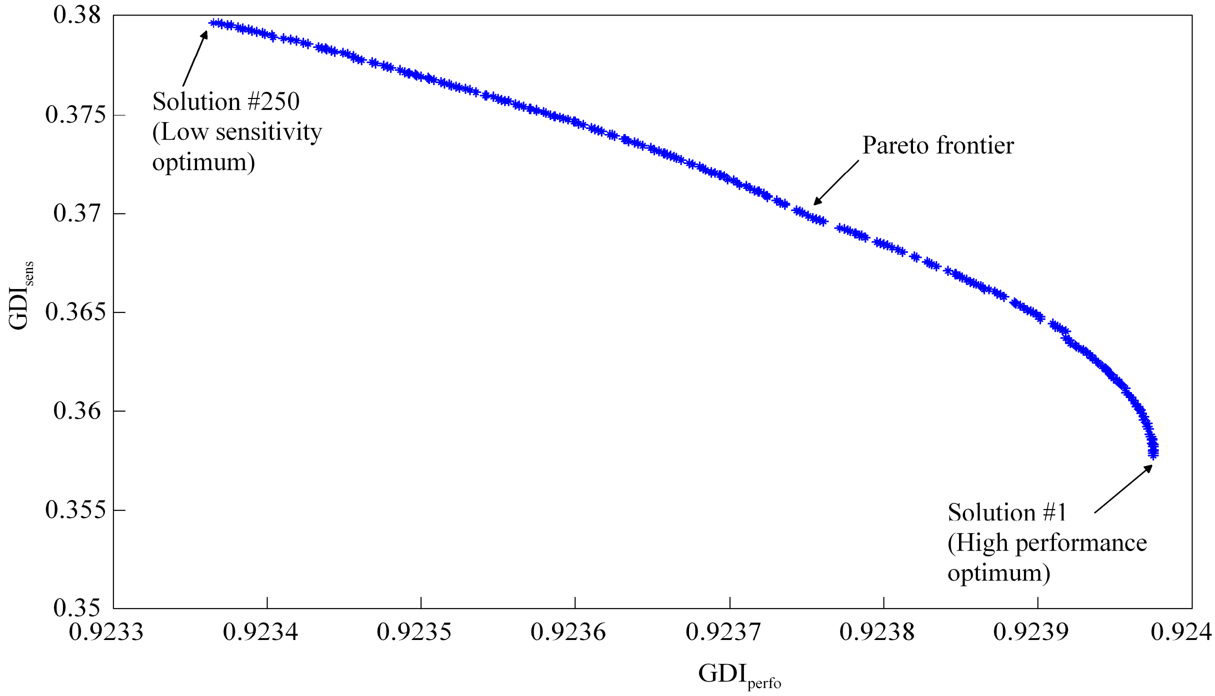


Figure 55. Pareto set for the robust design problem of flash evaporator

The design variables having an impact on the robustness of design solutions are the input product temperature (T_{pi}), the coolant liquid temperature (T_{cl}) and the number of plates in the LP condenser (N_{LP}). The evolution of these three design variables in function of GDI_{perfo} values are reported on figure 56a, figure 56b and figure 56c. The coolant liquid flow rate has a minor influence on the robustness and keep a constant value of 12.5 l/h of water (q_c=5.55l/h, q_{cl+}=6.94l/h). The same remark can be done for the number of plates of the VLP condenser which keeps a constant value of 23 plates (N_{VLP}). The evaporative capacity (expressed in litre of evaporated water per hour) has been also reported on figure 56d. Discontinuities on figure 56 are due to the variation of the number of plates in the LP condensers (N_{LP}) which is a discrete variable. Two kinds of flash evaporator design can be defined. The first one presents a global heat transfer area of 41.87m² which corresponds to a LP condenser composed by 248 plates. The second one gets a global heat transfer area of 41.71m² and involves a LP condenser composed by 247 plates. Consequently, a decrement of the heat transfer area of the LP condenser increases the evaporative capacity of the system (improvement of the cooling power of the system). As the global desirability index of performance mainly depends on the objective linked to the product quality, this leads to the improvement of the overall performance. To the contrary, the evaporative capacity should be slightly decreased to reduce the variability of the product quality. This means that such a system will be able to cool vintage at a lower inlet temperature (decreasing of the cooling power of the system).

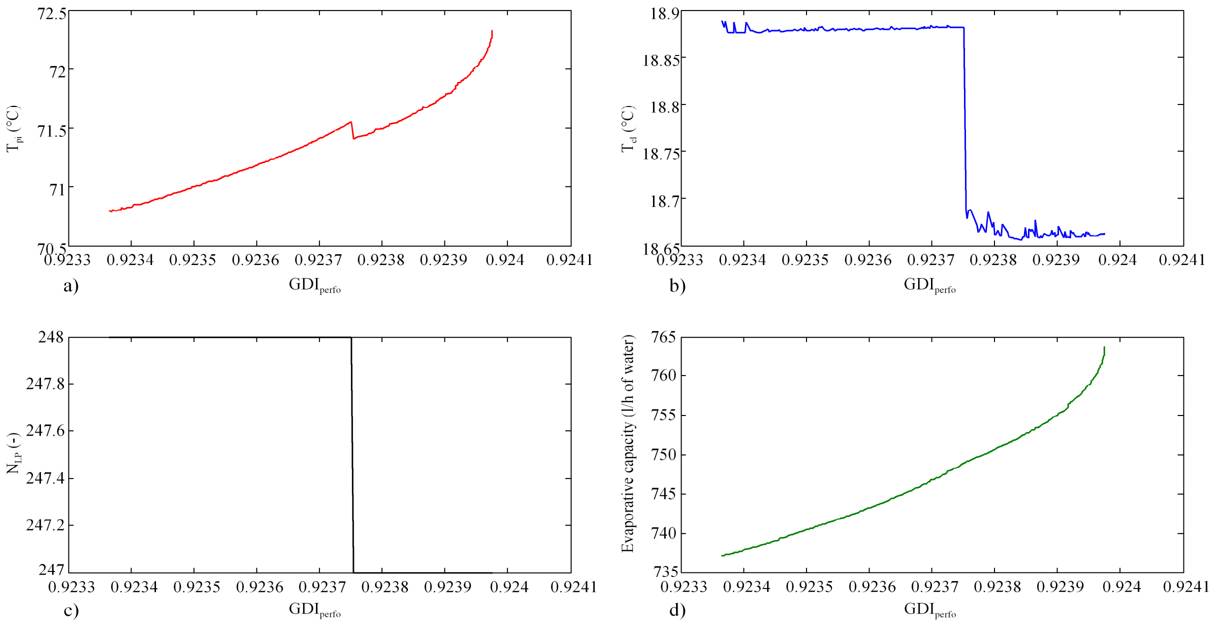


Figure 56. Evolution of design variables along the Pareto frontier

Observation variables and their interpretation into desirability scores are presented on figure 57. The desirability scale is on the right axis. As the achievement of the product quality objective is highly prioritized (numerical weight of 0.5) in the geometric mean aggregation, the performance optimization is mainly driven by the output product temperature (T_{po}), the final alcoholic strength (D_{po}) and the pressure inside the VLP stage (P_{VLP}). Consequently, these three performance measures get very high desirability levels (higher than 0.95). The satisfaction of the final alcoholic strength criterion is linked to the evaporative capacity of the system from the relation (6.3.1.2). The reduction of the variability of the product quality implies a decrement of the system overall performance. Its evaporative capacity is lower, and consequently the design solution moves away from the target objective being realized. The high prioritization of the quality objective also requires an increment of the cooling power of the system, and therefore, an increase of the dimensions. Thus, the reduction of the performance variability leads to design solutions which are more transportable. As a consequence, the energetical consumptions and overall costs are reduced. These results strongly depend on the weight assignment values used in the aggregation formula. The evolution of the design objectives indexes with the GDI_{perfo} are represented on figure 59.

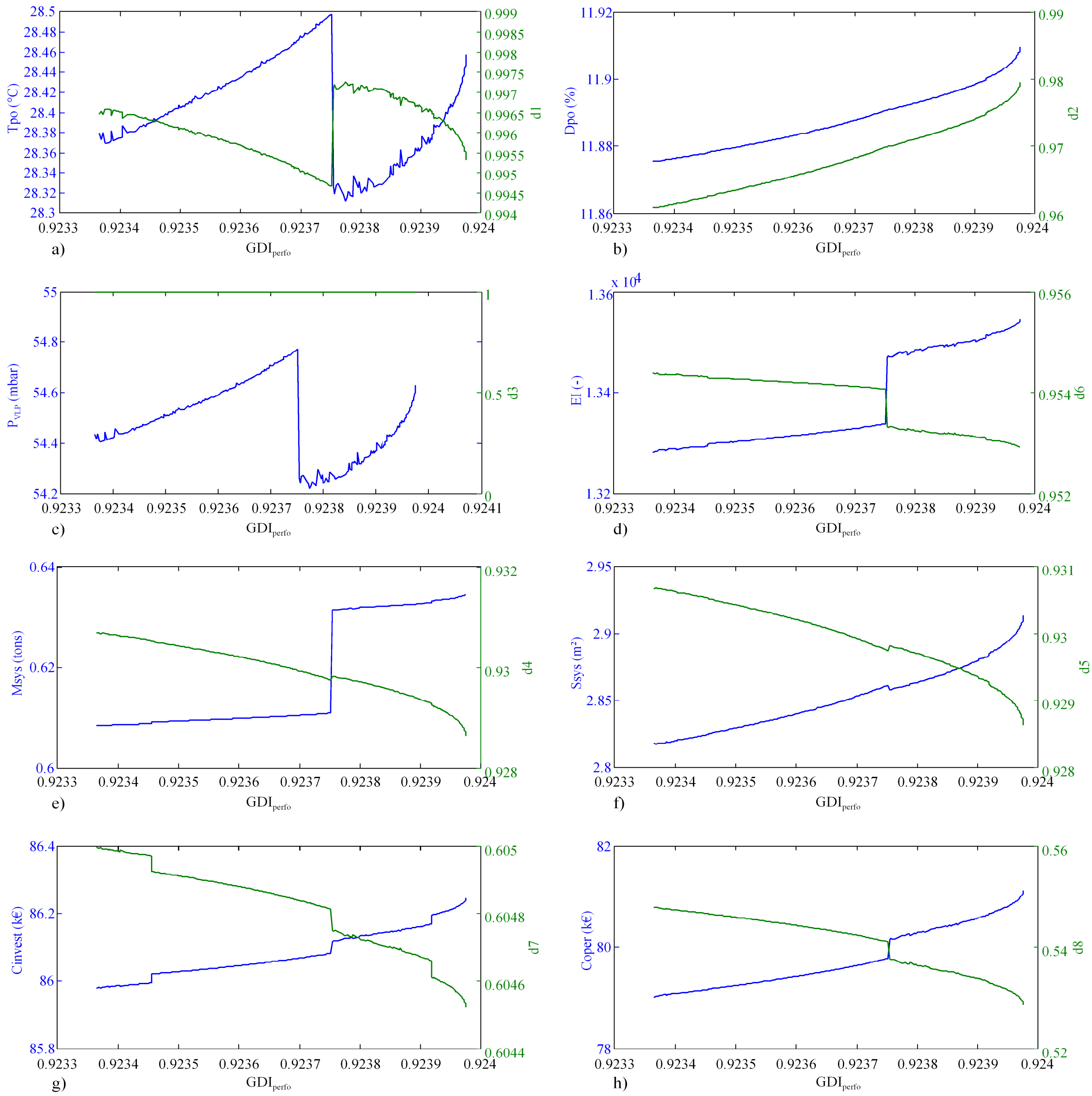


Figure 57. Evolution of the observation variables and desirability levels along the Pareto frontier

Measurements related to the design sensitivity (α_i, β_i, γ_i) are presented on figure 58. The desirability scores associated to α_i and β_i have also been represented (γ_i is already expressed as a desirability value). According to figure 58c, figure 58f and figure 58i, the variation of the pressure inside the VLP chamber is not significant and remains acceptable. However, the dispersions of the output temperature and final alcoholic strength are significant. From the variability of the inlet flow rates and temperatures, it results a bandwidth of variation of 3.4°C for the outlet product temperature (α_1) and 2.48% for the final alcoholic strength (α_2). According to the measure β, it appears that the dispersion of these two variables remains close to the nominal value. Finally, the minimum admissible value (γ) shows that the variability of the final alcoholic strength can lead to undesirable results, i.e. solutions with a desirability level lower than 10^{-2}. The variability of T_{po} and D_{po} tends to be reduced by design solutions with a lower level of performances. The design objective indexes related to the design sensitivity are represented on figure 59.

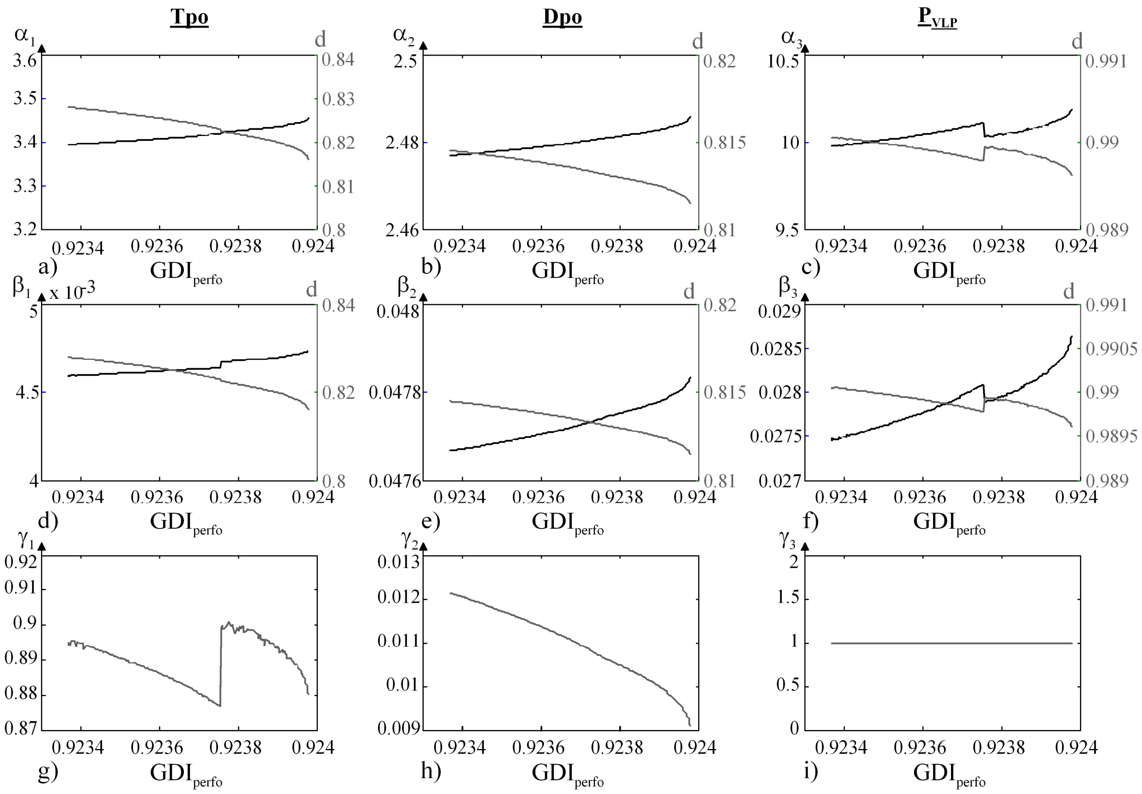


Figure 58. Evolution of the design sensitivity measures along the Pareto frontier

According to the robust design problem definition, the sensitivity of the product quality facing with external uncertainty can be slightly reduced by performing some compromises on the performance. In particular, the cooling power and the evaporative capacity of the system are lower. However, the design objectives linked to the transportability, environmental impact and costs are improved. The purpose of the following section deals with the selection of the optimal solution in the Pareto set by performing different trade-off strategies.

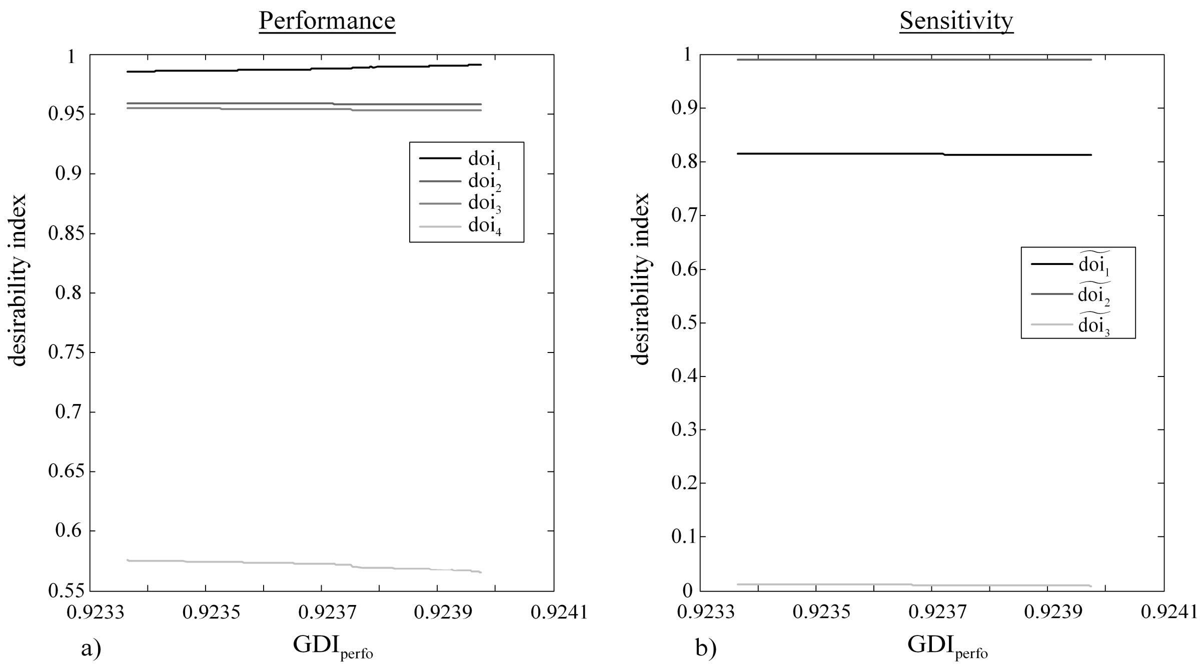


Figure 59. Evolution of the design objective indexes along the Pareto frontier

6.6.2 Decision and trade-off strategy

In the following, we discuss the selection of the optimal solutions for the design of the two-staged flash evaporator the weighted sum aggregation, weighted geometric aggregation and *min* aggregation functions are used. The selected solutions are reported in table 14. Figure 60 represents the iso-preference functions (see section 5.2) and the selection of the optimal solution for the different trade-off strategies

Aggregation function	**Weights**		**Selected solution**	**GDI values**		**Design variables**					
	w_{perfo}	w_{sens}		GDI_{perfo}	GDI_{sens}	T_{pi} (°C)	T_{cl} (°C)	q_{cl} (m^3/h)	q_{cl+} (m^3/h)	N_{LP}	N_{VLP}
Weighted sum (s=1)	0.95	0.05	#237	0.9234	0.3790	70.83	18.88	5.55	6.94	248	23
	0.98	0.02	#56	0.9239	0.3643	71.81	18.66	5.55	6.94	247	23
	0.99	0.01	#27	0.9240	0.3612	72.06	18.66	5.55	6.94	247	23
Weighted product (s=0)	0.95	0.05	#249	0.9234	0.3796	70.79	18.88	5.55	6.94	248	23
	0.98	0.02	#226	0.9234	0.3783	70.89	18.88	5.55	6.94	248	23
	0.99	0.01	#70	0.9239	0.3659	71.69	18.66	5.55	6.94	247	23
Min ($s \to -\infty$)			#250	0.9234	0.3797	70.79	18.89	5.55	6.94	248	23

Table 14. Optimal design solutions selected with different trade-off strategies

It is well known that the weighted sum (WS) aggregation suffers from serious drawbacks due to its inability to detect solutions in the non-convex parts of the Pareto frontier. Here, the Pareto frontier is non-convex. Consequently, many relevant solutions cannot be selected. According to figure 60a, it appears that the WS aggregation function results in 50 selected solutions among 250 (20% of recovery) with a step of discretization of $5e^{-6}$ for the weights. For each detectable point, there is a couple of weights such as this point can be captured [Scott 1995]. Thus, designers can filter Pareto frontiers by adjusting weight values according to their preferences, but many solutions cannot be selected. Assigning the values 0.95, 0.98 and 0.99 to the weight w_{perfo}, leads successively to select the solutions #237, #56 and #27. When the value of the weight w_{perfo} increases, the performance objective is favoured and the solutions tend to be less robust. It can be notice that for $w_{perfo}<0.95$, the low sensitivity optimum (solution #250) is selected.

The weighted geometric mean (WG) aggregation is more effective than the WS aggregation for the detection of solutions lying in the non-convex parts of the Pareto frontier. However, the selection of optimal solutions is often hampered by the high sensitivity of the weights approaching the extremities of the frontier. On figure 60b, it appears that 52 solutions are selected among 250 (20.8%) with the same discretization step. However, increasing the discretization step of the weights leads to capture a high number of solutions. Assigning the values 0.95, 0.98 and 0.99 to the weight w_{perfo}, leads successively to select the solutions #249, #226 and #70. These solutions are different from the ones captured with the WS aggregation function.

Finally, figure 60c has been obtained using the non-compensatory strategy. As the selection is based on the minimum of the GDI values, the low sensitivity optimum (solution #250) belongs to the selected solution. For $w_{perfo}<0.95$, the WS or WG aggregation functions lead to the same result.

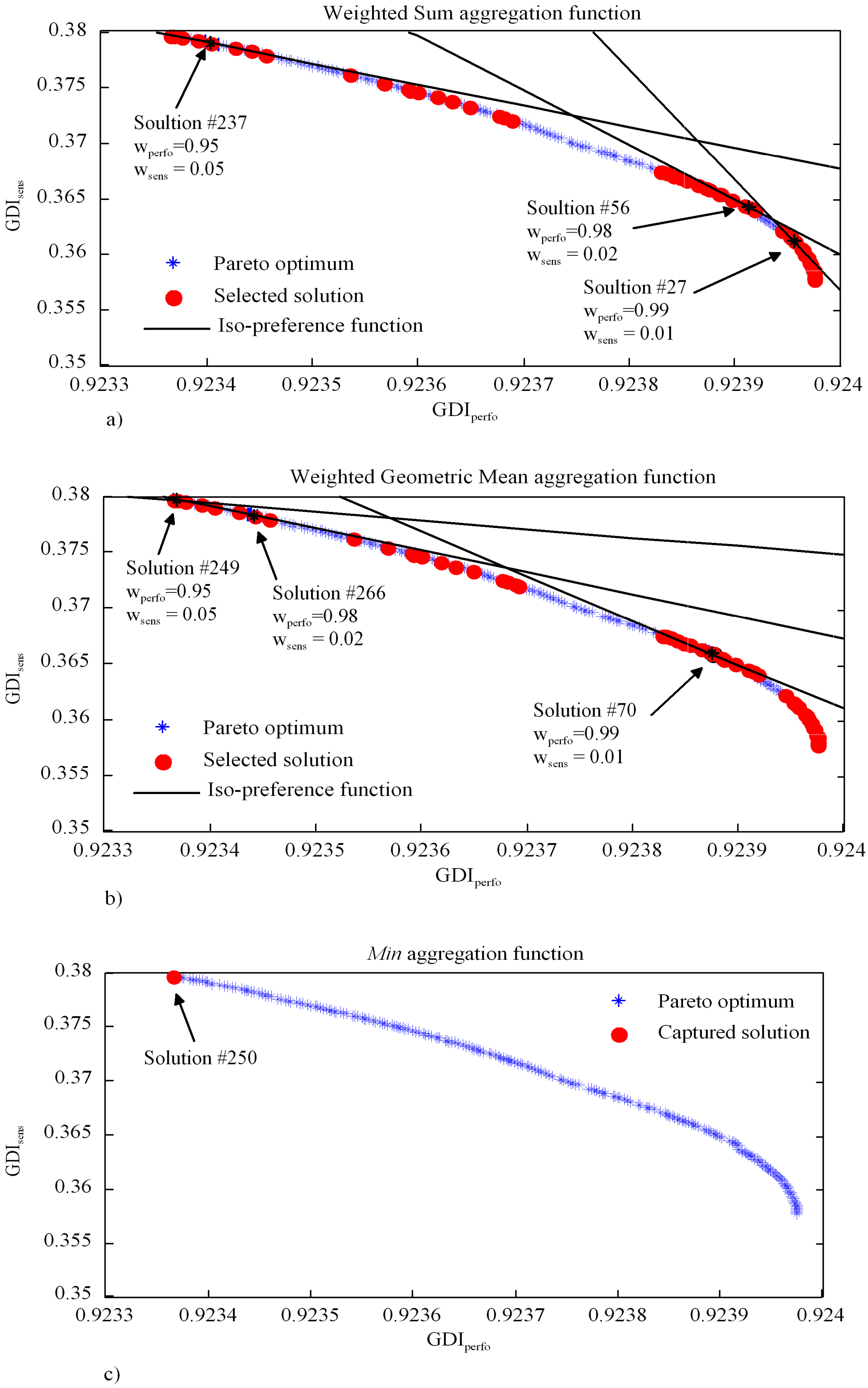


Figure 60. Selection of the optimal design solution for different trade-off strategies

6.6.3 Recommendations

From the previous analysis, we derive some recommendations about the robust design of flash evaporators. First, it appears that the gain in sensitivity compared to the loss of performance is low. For w_{perfo}<0.95, only the low sensitivity optimum is selected with the WS or the WG aggregation function. This traduces an important difference between the two GDI scores and that the low values of GDI_{sens} is compensated by the high value of GDI_{perfo}. Therefore, the selection of the high performance optimum requires very high values for w_{perfo} (close to one). As the development of flash evaporators for must concentration applications is mainly concerned with the quality of the product at the system outlet, the evaporative capacity criterion must be fulfilled and thus highly prioritized. The weak values of the design sensitivity objectives are mainly due to the high sensitivity of the final alcoholic strength. Consequently, in the context of this study, we prove that a system having a high evaporative capacity is able to increase of the alcoholic strength of 1% avoiding the degradation of the product quality when the evaporator is moved from an exploitation site to another.

6.7 Conclusion

In this chapter, a methodology for computing robust optimal solutions of flash evaporators for the wine industry has been presented. The approach tackles the robust design problem as a trade-off between two main objectives: (1) improve the overall level of performance including the quality of the vintage, the transportability of the system and the costs of ownership; (2) reduce the sensitivity of some performances, namely the temperature of the outlet product and the final alcoholic strength, under epistemic uncertainty. One of the originality of the method is to consider uncertainties without probabilistic distributions. Three measures to observe the dispersion of the performances are also suggested. They concern the bandwidth of variation, the tolerance to nominal and the minimum admissible value. A preference aggregation method is used to formulate the two design objectives. The design objective of performance is based on weighted geometric mean aggregations whereas the sensitivity objective involves *min* aggregations function. These two aggregation strategies are considered as design appropriate, and thus, are relevant to reflect the intentions of designers. The Pareto set of the optimal design solutions is generated by the non-dominated sorting genetic algorithm NGSAII. Finally, the selection of the best solution according to different trade-off strategies has been discussed.

From the robust design formulation and criteria definitions, the methodology proves that the variability of the product quality, in particular the vintage output temperature and final alcoholic strength, can be reduced by performing some compromises on the other performance indicators. These two observations variables are crucial for the wine quality and their variations must be controlled. In this way, the quality product objective has been highly prioritized. Such a strategy coupled with a geometric mean aggregation leads to small improvements of the other objectives. Finally, in the last section, the selection of the most preferred design solutions is modelled by a class of function which is more or less compensatory. Designer must express trade-offs between the gain in performance and the reduction of the performance sensitivity. This salient point can be overcome by using equivalent point method or the trade-off function presented in chapter 5.

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CHAPTER 7 Conclusions

This thesis is mainly concerned with the development of suitable methodologies and tools to support designers in machines embodiment design. In this context, investigation of large design spaces, representation and evaluation of candidate solutions, and a priori formalization of preferences are topical issues. In order to converge as soon as possible toward the most preferable design solution, taking robust decisions appears as a topical issue to ensure the best choices in engineering design. In particular, starting from a selected concept, embodiment design consists in determining the main dimensioning and monitoring parameters of the system while meeting the design requirements. The continuity of the design process between the preliminary and detailed phases strongly depends on the efficiency of the embodiment design phase in providing embodied solutions with a validated physical behaviour and an optimized functional structure. Embodiment design problems in engineering are thus generally oriented toward numerical optimization. Indeed, they consist in investigating a research space, also defined as design space, to find the best combination of design variable values, i.e. the solution which optimizes at least one objective function while satisfying a set of constraints derived from the design requirements.

Fundamental notions and concepts related to formal design theories and methodologies are introduced by chapter 2. In particular, the FBS ontology proposed by John Gero offers a suitable framework to link real and expected behaviour in design and thus enables to situate optimization in engineering design. Some of the topical issues, priors work and future challenges related to address engineering problems with optimization techniques are also presented through this chapter. In particular, it highlights that most of these techniques have not meet yet designer's needs in industry. The development of suitable tools dedicated to support decision making in embodiment design is thus required to improve the whole design process of machines.

As design is a human activity, embodiment design problems differentiate themselves from other kinds of problems by the expression and the formulation of designer's preferences. Facing multiple criteria, preference assessments can be tackled by determining individual preference functions, and generating adequate aggregation strategies to form a single global criterion used as a metric for alternatives evaluation. Chapter 3 introduces the main concepts and issues related to preference modelling in engineering design. Three different approaches, namely utility theory, method of imprecision and desirability index, are presented and discussed according to their ability in modelling preferences in engineering design. The desirability approach appears as the most relevant to reflect designers' intentions in embodiment design. Desirability enables to model preferences related to the true knowledge of designers about design. It is not concerned neither with risk, nor imprecision, but with the level of satisfaction resulting from the adequation between the real behaviour of alternatives and the expected behaviour expressed by designers. In particular, Harrington's desirability functions appear as relevant functions to interpret properties values and model preference based on design requirements and designers' expectation. Due to their exponential form, Harrington's desirability functions allow progressive desirability variations approaching the bounds, and consequently, enable to rank the whole set of solutions, including acceptable and unacceptable solutions. Moreover this class of desirability functions provides the design problem with a soft formulation of constraints which reflects better designer's behaviour evaluating design candidates. Individual desirability functions are then aggregated into desirability index according to the general weighted mean. The concept of desirability index has been extended here in respect with the definition of *design appropriate* aggregation

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functions proposed by the MoI. This enables designers to model different trade-off and compensatory levels between objectives.

From the FBS ontology and the concept of desirability, chapter 4 presents a modelling methodology for embodiment design problems, based on observation, interpretation and aggregation models, linking physical behaviour with functional constraints and design objectives. Such natural and intuitive decomposition enables to model designers' reasoning and express its experience and "feeling" about the design. This makes a significant difference from other methodologies such as the utility theory or MoI. In particular, the definition of DOIs allows a synthesis of the whole design information at different level of the problem decomposition and acts as filters on the initial set of admissible candidate. The aggregation of the different desirability scores using design appropriate functions and weights assignments, allow to apply different trade-off strategies between objectives, and thus, to reflect in the best ways the designer's preferences. This approach can be applied to robust design problems through the formulation of two design objectives, namely the improvement of the performance and the reduction of the performances variability, which must be traded-off.

This methodology aims to provide designers with convenient ways to structure objectives functions for optimization in embodiment design. The initial multiobjective embodiment design problem is modelled as a mono objective optimization problem using a priori articulation of preferences. The choice of an a priori articulation of preferences enables designers to provide additional information to fully reflect their own preferences and intentions. Moreover, such an approach generates only relevant portions of the whole set of solutions and thus avoids additional efforts.

As engineering design problems involve multiple conflicting objectives which must be traded-off, the determination of design solutions which meet every design objectives in the best ways in regards to admissible compromises is a topical issue. The design modelling methodology proposed in this thesis suggests three distinct inputs by which designers can express their preferences, namely specification of individual desirability functions, weights assignment and selection of aggregation strategies. Trade-off is mainly concerned with the selection of weights and suitable trade-off parameter values. Different trade-off specifications can lead to final solutions with equivalent overall preference levels. Therefore, trade-off modelling by aggregation functions is a critical part of the preference assessment process. In particular, designers must be aware of the areas of design points which can be captured using a particular aggregation strategy. Chapter 5 presents two approaches to manage trade-off in engineering design. The first methodology proposed by Scott uses equivalent point to determine consistent trade-off parameter values and weights assignment for preference aggregation in engineering design. This models compromises evolving with levels of preference.

Since the trade-off between performances against their variability is specific to robust design problems, we propose a suitable trade-off function to model designers' preferences facing these two objectives. This trade-off function has been designed to provide a suitable measurement for the relative sensitivity of a choice from a set of alternatives, by quantifying the improvement or degradation in the compromise between two preferences when one of them is favoured. It enables to guide the selection between nominal optimality and robustness according to acceptable compromises. It results in an objective function to be maximized, involving not only the optimality and sensitivity of the solution, but also the trade-off expected by the designer.

Finally, chapter 6 shows application of the modelling methodology through the embodiment design of a whole machine: a two-staged flash evaporator for must concentration in the wine industry. In particular, it is expected to achieve robust design configurations. The robust design problem is tackled as a trade-off between the improvement of the overall level of performance including the quality of the vintage, the transportability of the system, the costs of ownership and the reduction of the sensitivity of some performances, namely the temperature of the outlet product and the final alcoholic strength, under epistemic uncertainty. An originality of this approach is to consider uncertainties without any probabilistic distributions. The design objective of performance is based on weighted geometric mean aggregations whereas the sensitivity objective involves min aggregation steps. These two aggregation strategies are considered as design appropriate, and thus, reflects accurately the intentions of the designer. The Pareto set of the optimal design solutions is generated by the non-dominated sorting genetic algorithm NGSAII. Finally, the selection of the most preferred solution according to different trade-off strategies has been discussed.

From the robust design formulation and criteria definitions, this modelling methodology enables to show that the variability of the product quality, in particular the vintage output temperature and final alcoholic strength, can be reduced by performing some compromises on the performances. These two observations variables are decisive for the wine quality and their variations must be controlled. In this way, the quality product objective has been highly prioritized. Such a strategy coupled with a geometric mean aggregation leads to small improvements of the other objectives. But, another assignment of weight values may lead to different system configurations which can be more robust.

During these three past years, I presented most of the research work described in this thesis through several international journal [Quirante 2012, Quirante 2011a, Sebastian 2010] and international conferences publications [Quirante 2011b, Quirante 2010]. This enabled to identify salient points of the developed methodology which required more effort to meet designers' needs. As our work tackles various transverse topics including design theory, knowledge modelling and cognition, or decision-making theory, numerous remarks from all these fields have been discussed and integrated in the modelling methodology to improve it.

The research work presented here presents fundaments of the methodology that we propose to model embodiment design problems. It defines and formalizes concept and basis used in our approach, and therefore, represents solid basis for further developments. Results of this work are of practical implications and can be used to develop and implement numerical tools to help designers in embodiment design of machines. The application of the modelling methodology to the robust design of flash evaporators suggests the achievement of better design. This work does not pretend to provide miracle solution to solve every engineering design problems, but instead, it proposes some guidelines and tools to structure embodiment design problems and support decisions making processes. Due to the desire to remain close to designers' activities, the methodology have been successfully applied to some concrete industrial cases [Collignan 2011b, Girardeau 2012] and extended to meet building engineering purpose [Valderrama Ulloa 2012].

Short-term prospects concern further studies about the coupling effects between weights, trade-off strategy parameters and performance variables. In particular, it may be interesting to derive these parameters from physical or technical relations, and to reach a better understanding about their implications in the improvement of the design solution. Moreover, the analysis of the trade-off strategy parameter for the n-dimensional case is also of main interests. In this thesis, performance and robustness of design solutions are traded-off. However others global objectives may be relevant for the designer. In [Collignan 2011b], the level of confidence of a design solution is proposed as a third objective to be balance against performance and robustness. Broader prospects mainly consist in applying the methodology developed here to link life cycle analysis with embodiment design. Life cycle analysis derives impact factors by using aggregation functions which are not design appropriates. Main challenges aim to developed a global methodology to model the whole design process with design appropriate aggregation functions, and thus, remain consistent with the preferences of designers.

References

Ageron, D., Escudier, J.L., Abbal, Ph., & Moutounet M. (1995). Prétraitement des raisins par Flash Détente sous vide poussé. *Revue Française d'Œnologie*, 35(153):50-54.

Agreste (2010), Ministère de l'agriculture, de l'alimentation, de la pêche, de la ruralité et de l'aménagement du territoire, Statistique Agricole Annuelle, Aquitaine: http://www.agreste.agriculture.gouv.fr.

Akao, Y. (1994). *QFD, the Customer-Driven Approach to Quality Planning and Deployment*. Asian Productivity Organization, Tokyo.

Albers, A., Matthiesen, S. & Ohmer, M. (2003). An innovative new basic model in design methodology for analysis and synthesis of technical systems. *Proceedings of the 14th International Conference on Engineering Design 2003*, Stockholm

Altshuller, G.S. (1984). Creativity as an Exact Science: The Theory of the Solution of Inventive Problems. Taylor & Francis.

Altshuller, G.S. (1999). *Innovation Algorithm: TRIZ, systematic innovation and technical creativity*. 1st ed. Technical Innovation Centre, Worcester, MA.

Andreasen, M.M. (1987). *Integrated Product Development*. Springer-Verlag,

Andreasen, M.M. (1994). Modelling - The Language of the Design. *Journal of Engineering Design*, 5(2):103-115.

Antonsson, E.K., & Otto, K.N. (1995). Imprecision in Engineering Design. *Special combined issue of the transactions of the ASME commemorating the 50th anniversary of the design engineering division of the ASME*, vol.117, pp.25-32.

Antonsson, E.K. (2001). Imprecision in Engineering Design. Engineering Design Research Laboratory, Division of Engineering and Applied Science, California Institute of Technology, Pasadena, California 91125-4400, USA.

Ardakani, M. et al. (2009). Robust Parameter Design Using the Weighted Metric Method-The Case of 'the Smaller the Better'. *International Journal of Applied Mathematics and Computer Science*, 19(1):59-68.

Arvidsson, M., & Gremyr, I. 2008. Principles of robust design methodology. Quality and Reliability Engineering International, 24(1):23-35.

Asimow, M. (1962). *Introduction to design*. Prentice-Hall, New York.

Athan, T.W., & Papalambros, P.Y. (1996), A Note on Weighted Criteria Methods for Compromise Solutions in Multi-Objective Optimization. *Engineering Optimization*, 27(2):155-176.

Basseur, M., & Zitzler, E. (2006). Handling Uncertainty in Indicator-Based Multiobjective Optimization. International Journal of Computational Intelligence Research, 2(3), 255-272.

Beauregard, M.R., McDermott, R., & Beauregard, M. (1996). *The Basics of FMEA*. 1st ed. Productivity Press.

Beauvois, J.L. (1995). La connaissance des utilités sociales. *Psychologie française*, 40:375-388.

Berliner, C., & Brimson, J.A. (1987*), Cost Management for Today's Advanced Manufacturing,*

The CAM.I Conceptual Design, Harvard Business School Press, Boston.

Bernard, A. (2005). Virtual engineering: Methods and tools. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering* Manufacture, 219(5):413-421.

Bernard, A., Ammar-Khodja, S., Perry, N., & Laroche, F. (2007). Virtual engineering based on knowledge integration. *Virtual and Physical Prototyping*, 2(3):137-154.

Beyer, H.G., & Sendhoff, B. (2007). Robust optimization - A comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, 196(33-34): 3190-3218.

Bonham, C.R., & Parmee, I.C. (2004). Developments of the Cluster Oriented Genetic Algorithm (COGA). *Journal of Engineering Optimization*, 36(2):249-279

Bouchama, A., Sebastian, S., & Nadeau, J.P. (2003a). Flash evaporation, modeling and constraints formulation. *Transactions on IChemE*, 81(Part A):1250-1258.

Bouchama, A. (2003b). Refroidissement en cascade par flash détente, modélisation par contraintes et aide à la décision, PhD Thesis, Arts et Métiers Paris Tech.

Bridgman, P. W. (1922). *Dimensional Analysis*. Yale University Press, New Haven.

Brotchie, J.F. (1997). Optimization and robustness of structural engineering systems. *Engineering Structures*, 19(4):289-292.

Browning, T.R. (2001). Applying the design structure matrix to system decomposition and integration problems: a review and new directions. IEEE Transactions on Engineering Management, 48(3):292-306.

Cadiot, D., Sébastian, P., Callede, D., & Nadeau, J.P. (2002). System for cooling a heated juice by partial low-pressure evaporation, Patent WO02096530.

Cambon, L. (2006). Désirabilité sociale et utilité sociale, deux dimensions communiquées par les adjectifs de personnalité. *Revue internationale de psychologie sociale*, 3(19):125-151.

Cantú-Paz, E. (2000). *Efficient and Accurate Parallel Genetic Algorithms*. 1st ed. Springer.

Celotti, E., and Rebecca, S. (1998). Expériences récentes de thermo-macération des raisins rouges. Revue des Œnologues, 25(89), 23-28.

Chankong, V., & Haimes, Y.Y. (1983). *Multiobjective Decision Making: Theory and Methodology*. Elsevier Science Ltd, New York.

Charnes, A., & Cooper, W.W. (1977). Goal programming and multiple objective optimizations: Part 1. *European Journal of Operational Research*, 1(1):39-54.

Chen, W., & Allen, J.K. (1996). A Procedure for Robust Design: Minimizing Variations caused by Noise Factors and Control Factors. *Journal of Mechanical Design*, 118(4):478-485.

Chen, W., Wiecek, M.M., & Zhang, J. (1999). Quality Utility - A Compromise Programming Approach to Robust Design. *Journal of Mechanical Design*, 121(2):179-188.

Chen H.W. (2011). The Augmented Desirability Function: Methods and Applications, PhD thesis, University of California, Los Angeles, California.

Chiong, R.. (2009). *Nature-Inspired Algorithms for Optimization*. Springer.

Coello, C. (2002a). Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. Computer Methods in Applied Mechanics and Engineering, 191(11-12):1245-1287.

Coello, C., et al. (2002b). *Evolutionary Algorithms for Solving Multi-Objective Problems*. 1st ed. Springer.

Collignan, A., Pailhes, J., & Sebastian, P. (2011). Design optimization: management of large solution spaces and optimization algorithm selection. *Proceedings of IMProVe 2011, International conference on Innovative Methods in Product Design* (pp.618-628), Venice, Italy.

Collignan, A., Sebastian, P., Pailhes, J., & Ledoux, Y. (2012a). Arc-elasticity and hierarchical exploration of the neighbourhood of solutions in mechanical design. *Advanced Engineering Informatics*, DOI: 10.1016/j.aei.2012.04.001, In press.

Collignan, A. (2012b), *Méthode d'optimisation et d'aide à la décision en conception mécanique : application à une structure aéronautique*, PhD Thesis, Université de Bordeaux, I2M, UMR CNRS 5295, France.

Corne, D.W., & Knowles, J.D. (2007). Techniques for highly multiobjective optimization: some nondominated points are better than others. *Proceedings of the 9th annual conference on Genetic and evolutionary computation* (pp.773–780). GECCO 2007, New York, USA.

Costa, A.L.H., & Queiroz, E.M. (2008). Design optimization of shell-and-tube heat exchangers. *Applied Thermal Engineering*, 28(14-15):1798-1805.

Curran, M. A. (1996). *Environmental Life-Cycle Assessment*. McGraw-Hill, New York.

Cutkosky, M., Engelmore, R.S., & Fikes, R.E. (1993). PACT: An Experiment in Integrating Concurrent Engineering Systems, *IEEE Computer*, 26(1):28-37.

Das, I., & Dennis, J.E. (1997). A closer look at drawbacks of minimizing weighted sums of objectives for Pareto set generation in multicriteria optimization problems. *Structural Optimization*, 14(1):63-69.

Das, I., & Dennis, J.E. (1998). Normal-Boundary Intersection: A New Method for Generating the Pareto Surface in Nonlinear Multicriteria Optimization Problems. *SIAM Journal on Optimization*, 8(3):631-657.

Deb, K., & Goldberg, D. E. (1989). An investigation of niche and species formation in genetic function optimization. In Schaffer, J.D. (Eds.), *Proceedings of the Third International Conference on Genetic Algorithms* (pp. 42-50). San Mateo, CA: Morgan Kaufmann.

Deb, K., & Agarwal, R.B. (1995). Simulated Binary Crossover for Continuous Search Space. *Complex Systems*, 9(2):115-148.

Deb, K., (1999). Evolutionary Algorithms for Multi-Criterion Optimization in Engineering Design. *Evolutionary Algorithms in Engineering and Computer Science*, 2, 135-161.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2), 182-197.

Del Castillo, E., Montgomery, D.C., & McCarville, D. (1996). Modified Desirability Functions for Multiple Response Optimization. *Journal of Quality Technology*, 28(3):337-345.

Derringer, G., & Suich, R. (1980). Simultaneous Optimization of Several Response Variables. *Journal of Quality Technology*, 12(4):214-219.

Derringer, G. (1994). A Balancing Act: Optimizing a Product’s Properties. *Quality Progress*; 27(4):51-58.

Ditlevsen, O., & Madsen. H.O. (1996). *Structural Reliability Methods*. 1st ed. John Wiley & Sons.

Dong, X., DeVries W.R., & Wozny, M.J. (1991). Feature-Based Reasoning in Fixture Design. *CIRP Annals - Manufacturing Technology*, 40(1):111-114.

Dornberger, R. et al. (2000). Multidisciplinary Optimization in Turbomachinery Design. *European Congress on Computational Methods in Applied Sciences and Engineering 2000*, 102, Barcelona.

Du, X., & Chen, W. (2000a). A Methodology for Managing the Effect of Uncertainty in Simulation-Based Design. A*merican Institute of Aeronautics and Astronautics Journal*, 38(8):1471-1478.

Du, X., & Chen, W. (2000b). Towards a Better Understanding of Modeling Feasibility Robustness in Engineering Design. *Journal of Mechanical Design*, 122(4):385-394

Du, X., & Chen, W. (2004). Sequential optimization and reliability assessment method for efficient probabilistic design. Journal of mechanical design, 126(2):225-233.

Enevoldsen, I., & Sørensen, J.D (1994). Reliability-based optimization in structural engineering. *Structural Safety*, 15(3):169-196.

Escudier, J.L., et al. (1995). Intérêt du traitement des raisins par un vide poussé pour l’œnologie. ONIVINS. Contrat Etat-Région, filière viti-vinicole.

Escudier, J.L., Mikolajczak, M., & Moutounet, M. (1998). Pré-traitement des raisins par flash détente sous vide et caractéristiques des vins. Journal International des Sciences de la Vigne et du Vin, hors série - Traitements Physiques des Moûts et des Vin, 105-110.

Farmer, L.E., & Gladman, C.A. (1986). Tolerance Technology - Computer-Based Analysis. *CIRP Annals - Manufacturing Technology*, 35(1):7-10.

Finger, S, & Dixon, J.R. (1989a). A review of research in mechanical engineering design. Part I: Descriptive, prescriptive, and computer-based models of design processes. Research in Engineering Design, 1(1):51-67.

Finger, S, & Dixon, J.R. (1989b). A review of research in mechanical engineering design. Part II: Representations, Analysis, and Design for the Life Cycle. *Research in Engineering Design*, 1(2):121-137.

Fisher, I. (1906). *The Nature of Capital and Income*. The Macmillan Company.

French, M. J. (1971). *Engineering design: The conceptual stage*. Heinemann Educational, London.

Gasser, M., & Schuëller, G.I. (1997). Reliability-Based Optimization of structural systems. *Mathematical Methods of Operations Research*, 46(3):287-307.

Geoffrion, A.M. (1968). Proper Efficiency And The Theory Of Vector Maximization. Journal of Mathematical Analysis and Applications, vol.22, pp.618-630.

Gero, J.S., (Ed.) (1985), *Knowledge Engineering in Computer-Aided Design*. North-Holland, Amsterdam.

Gero, J.S. (1990a). Design prototypes: a knowledge representation schema for design. *AI Magazine*, 11(4):26-36.

Gero, J.S., &. Rosenman, M. A. (1990b). A conceptual framework for knowledge-based design research at Sydney University's design computing unit. *Artificial Intelligence in Engineering*, 5(2):65-77.

Gero, J.S., & Fujii, H. (2000). A Computational Framework for Concept Formation for a Situated Design Agent. *Knowledge-based Systems*, 13(6):361-368

Gero, J.S. & Kannengiesser, U. (2004). The situated Function-Behaviour-Structure framework. *Design Studies*, 25(4):373-391

Gero, J.S., & Kannengiesser, U. (2006). A Framework for Situated Design Optimization. In Leeuwen, J.P., Timmermans, H.J.P. (Eds.), *Innovations in Design & Decision Support Systems in Architecture and Urban Planning* (pp.309-324), Springer, Netherlands.

Girardeau, J. (2012). Comportement thermo-mécanique et évolution du distributeur d'une turbine haute pression, PhD Thesis, Arts et Métiers Paris Tech, I2M, UMR CNRS 5295, France

Goedkoop, M., Effting, S., & Collignon, M. (2000). *The Eco-indicator 99: A damage oriented method for Life Cycle Impact Assessment, Manual for Designers*, 2nd edition. Pré Consultants B.V., Amersfoort, Netherlands.

Gold, S. & Krishnamurty, S. (1997). Tradeoffs in Robust Engineering Design. *ASME Design Engineering Technical Conferences*, DETC97/DAC-3757, Sacramento, California.

Goldberg, D. E. (1996). *Algorithmes génétiques: Exploration, optimisation et apprentissage automatique*. Addison-Wesley, France.

Gorla, R. S. R., & Khan, A.A (2003). Turbomachinery: Design and Theory. 1st Ed. CRC Press.

Grabowski, H., Rude, S., & Grein, G. (1998). Universal design theory: Elements and Applicability to Computers. In Grabowski, H., Rude, S., Grein, G. (Eds.), Universal Design Theory (pp.209-220). Shaker Verlag, Aachen.

Grabowski, H., Lossack, R. (2000). The Axiomatic Approach in the Universal Design Theory. *Proceedings of the First International Conference in Axiomatic Design*, Cambridge, MA, June 21-23.

Greiner, D., & Hajela, P. (2011). Truss topology optimization for mass and reliability consideration-coevolutionary multiobjective formulations. *Structural and Multidisciplinary Optimization*, 45(4):589-613.

Gu, P., Hashemian, M., &. Nee, A.Y.C. (2004). Adaptable Design. *CIRP Annals - Manufacturing Technology*, 53(2):539-557.

Hansen, F. (1974). Konstruktionswissenschaft-Grundlagen und Methoden (Design Science-Basis and Methods), München: Carl Hanser.

Haimes, Y.Y., Lasdon, L.S., & Wismer D.A. (1971). On a Bicriterion Formulation of the Problems of Integrated System Identification and System Optimization. *Systems, Man and Cybernetics, IEEE Transactions*, 1(3):296-297.

Harrington, E.C. (1965). The Desirability Function. *Industrial Quality Control*, 21(10):494-498.

Hauschild, M.; Wenzel, H. (1998). *Environmental Assessment of products. Vol. 1: Methodology, tools and case studies in product development- Vol. 2: Scientific background*. Chapman & Hall, London 1998.

Hazelrigg, G.A, (1996). Systems Engineering: An Approach to Information-Based Design. 1st ed. Prentice Hall, Upper Saddle River, NJ.

Ho Kon Tiat, V., Sebastian, P., & Nadeau, J.P. (2008a). Multicriteria-oriented preliminary design of a flash evaporation process for cooling in the wine industry. *Journal of Food Engineering*, 85(4):491-508.

Ho Kon Tiat, V. (2008b). Aide à la décision pour la conception préliminaire de procédés d'évaporation flash, PhD Thesis, Université de Bordeaux, I2M, UMR CNRS 5295, France.

Ho Kon Tiat, V., Sebastian, P., & Quirante, T. (2010). Multiobjective optimization of the design of two-stage flash evaporators: Part 1: Process modeling. *International Journal of Thermal Sciences*, 49(12):2453-2458.

Horváth, I. (2004). A treatise on order in engineering design research. *Research in Engineering Design*, 15(3):155-181.

Huang, G.Q. (1996). *Design for X: Concurrent Engineering Imperatives*. Springer, Berlin.

Hubka, V. (1975). Intuition und Konstruktionsgefühl (Intuition and Feel for Design), *Schweizer Maschinenmarkt*, 75(50):42-44.

Hubka, V., & Eder, W.E. (1989). *Principles of Engineering Design*. 1st ed. Springer, London.

Hubka, V., & Eder, W.E. (1996). *Design science: introduction to needs, scope and organization of engineering design knowledge*. Springer.

Kakuda, Y., & Kikuchi, M. (2001), Abstract Design Theory, *Annals of the Japan Association of Philosophical Science*, 10(3):19-35.

Keeney, R.L., & Raïffa, H. (1993). *Decisions with Multiple Objectives: Preferences and Value Tradeoffs*. Cambridge University Press.

Kenneth, A.S. (2006). Fundamentals of Economic Demand Modeling: Lessons from Travel Demand Analysis. In K. Lewis, W. Chen and L. Schmidt (Eds), Decision Making in Engineering Design, ASME Press, Chapter 9, pp.75-88.

Kim, K.J., & Lin, D.KJ. (2000). Simultaneous Optimization of Mechanical Properties of Steel by Maximizing Exponential Desirability Functions. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 49(3):311-325.

Kirkwood, C.W. (1996). Strategic Decision Making: Multiobjective Decision Analysis with Spreadsheets. 1st ed. Duxbury Press.

Koski, J. (2005). Defectiveness of Weighting Method in Multicriteria Optimization of Structures. *Communications in Applied Numerical Methods*. 1(6):333-337.

Krantz, D.H. et al. (1971). *Foundations of Measurement Volume I: Additive and Polynomial Representations*. Academic Press: New York.

Krause, F.L., Kimura, F., Kjellberg, T.; & Lu, S.C.Y. (1993). Product Modeling. *CIRP Annals*, 42(2):695-706.

Krishnamurty, S. (2006). Normative Decision Analysis in Engineering Design. In K. Lewis, W. Chen and L. Schmidt (Eds), *Decision Making in Engineering Design*, ASME Press, Chapter 4, pp.21-35.

Kruisselbrink, J. et al. (2009). Combining Aggregation with Pareto Optimization: A Case Study in Evolutionary Molecular Design. *Evolutionary Multi-Criterion Optimization*, vol.5467, pp.453-467.

Hwang, C.L., & Masud, A.S.M. (1981). Multiple Objective Decision Making: Methods and Applications; A State-Of-The-Art Survey. In Fogarty, T.C. (Eds.), *Lecture Notes in Economic and Mathematical Systems*, vol.164, Springer-Verlag, Berlin.

Jacquet, P., & Capdevielle C. (2002). *Installations vinicoles. Tome 2, Transport de la vendange et vinification*. Féret.

Jensen, H.A. (2005). Design and sensitivity analysis of dynamical systems subjected to stochastic loading. *Computers & Structures*, 83(14):1062-1075.

Jeong, I.J., & Kim, K.J. (2009). An interactive desirability function method to multiresponse optimization. *European Journal of Operational Research*, 195(2):412-426.

Law, E.L.C., et al. (2009). Understanding, scoping and defining user experience: a survey approach. *Proceedings of the 27th international conference on Human factors in computing systems CHI 09*, Boston, MA, USA, ACM, pp.719-728.

Lee, S., & Chen, W. (2009). A comparative study of uncertainty propagation methods for black-box-type problems. *Structural and Multidisciplinary Optimization*, 37(3):239-253.

Leeper, S.A. (1981). *Wet Cooling Tower: “Rule-of-Thumb” Design and Simulation*. U.S. Department of Energy Assistant Secretary for Resource Application, Office of Geothermal, under DOE Contract No. DE-AC07-76ID01570.

Lewis, K., Chen, W ., & Schmidt, L. (2006). *Decision Making in Engineering Design*. ASME Press, New York.

Liang, J., Mourelatos Z.P., & Tu, J. (2008). A single-loop method for reliability-based design optimization. *International Journal of Product Development*, 5(1/2):76-92.

Mansfield, E., & Yohe, G. (2003). Microeconomics: Theory and Applications, Eleventh Edition. W.W. Norton & Company.

Marler, R.T., & Arora, J.S. (2004). Survey of multi-objective optimization methods for engineering. *Structural and Multidisciplinary Optimization*, vol.26, pp.369-395.

Messac, A. (1996). Physical programming - Effective optimization for computational design. *American Institute of Aeronautics and Astronautics Journal*, 34(1):149-158.

Messac, Achille, Puemi-Sukam, C., & Melachrinoudis, E. (2000a). Aggregate Objective Functions and Pareto Frontiers: Required Relationships and Practical Implications. *Optimization and Engineering*, vol.1, pp.171-188.

Messac, A., et al. (2000b). Ability of Objective Functions to Generate Points on Nonconvex Pareto Frontiers. *American Institute of Aeronautics and Astronautics Journal*, 38(6):1084-1091.

Messac, A., & Ismail-Yahaya, A. (2002a). Multiobjective robust design using physical programming. *Structural and Multidisciplinary Optimization*, 23(5):357-371.

Messac, A., & Mattson, C.A. (2002b). Generating Well-Distributed Sets of Pareto Points for Engineering Design Using Physical Programming. Optimization and Engineering, 3(4):431-450.

Messac, A., Ismail-Yahaya, A., & Mattson, C.A. (2003). The normalized normal constraint method for generating the Pareto frontier. *Structural and Multidisciplinary Optimization*, 25(2):86-98.

Miettinen, K. (1999). *Nonlinear multiobjective optimization*. Springer.

Miyatake, O., Murakami, K., Kawata, Y., & Fujii, T. (1973). Fundamental experiments with flash evaporation. *Heat Transfer Japanese Research*, 10(2):89-100.

Miyatake, 0., Kito, Y., Tagawa, K., & Murata, Y. (2001). Transient characteristics and performance of a novel desalination system based on heat storage and spray flashing, Desalination, 137(1-3):157-166.

Morgan, J.M., & Liker, J.K. (2006). *The Toyota Product Development System: Integrating People, Process and Technology*. Productivity Press.

Mourelatos, Z.P., &Liang, J. (2006). A Methodology for Trading-Off Performance and Robustness Under Uncertainty. *Journal of Mechanical Design*, 128:856-863.

Mulvey, J.M., Vanderbei, R.J., & Zenios S.A. (1995). Robust Optimization of Large-Scale Systems ». *Operations Research*, 43(2):264-281.

Murawski, K., Arciszewski, T., & De Jong, K. (2000). Evolutionary Computation in Structural Design, *Engineering with Computers*, 16(3):275-286.

NASA (1995). *NASA Systems Engineering Handbook* (pp.67-77). NASA, SP-610S.

Oberkampf, W.L, et al. (2004). Challenge problems: uncertainty in system response given uncertain parameters. *Reliability Engineering & System Safety*, 85(1-3):11-19.

Nair, V.N et al. (1992), Taguchi's Parameter Design: A Panel Discussion. *Technometrics*, 34(2):127-161.

Oduguwa, V., A. Tiwari, & Roy, R. (2005). Evolutionary computing in manufacturing industry: An overview of recent applications. *Applied Soft Computing Journal*, 5(3):281-299.

Oduguwa, V., Roy, R., & Farrugia, D. (2007). Development of a soft computing-based framework for engineering design optimization with quantitative and qualitative search spaces. *Applied Soft Computing*, 7(1):166-188.

Otto, K.N., & Antonsson, E.K. (1991). Trade-off strategies in engineering design. *Research in Engineering Design*, 3(2):87-103.

Otto, K.N. (1992). *A Formal Representational Theory for Engineering Design*, PhD thesis, California Institute of Technology, Pasadena, California.

Otto, K.N., & Antonsson, E.K. (1993). The Method of Imprecision Compared To Utility Theory For Design Selection Problems. Proceedings of the 5th international Conference on Design Theory and Methodology DTM'93, ASME, 53:167-173, Albuquerque, NM.

Padulo, M., Campobasso, M.S, & Guenov, M.D. (2007). Comparative analysis of uncertainty propagation methods for robust engineering design. *International Conference on Engineering Design, Design for Society*, Paris, France.

Pahl, G., Beitz, W., Feldhusen, J., & Grote, K.H. (2006). *Engineering Design: A Systematic Approach*. 3rd ed. Springer, London.

Park, G.J. et al. (2006). Robust design: An overview. *American Institute of Aeronautics and Astronautics Journal*, 44(1):181-191.

Parkinson, D.B. (1997). Robust design by variability optimization. *Quality and Reliability Engineering International*, 13(2):97-102.

Pugh, S. (1991). *Total Design: Integrated Methods for Successful Product Engineering*. Prentice Hall, New York.

Quirante, T., Sebastian, P., & Ledoux, Y. (2012). A trade-off function to tackle robust design problems in engineering. *Journal of Engineering Design*, DOI:10.1080/09544828.2012.691160

Quirante, T., Ledoux, Y., and Sebastian, P. (2011a). Multiobjective optimization including design robustness objectives for the embodiment design of a two-stage flash evaporator. *International Journal on Interactive Design and Manufacturing*, 6(1):29-39.

Quirante, T., Sebastian, P., & Ledoux, Y. (2011b). Development of a trade-off function for robust optimization problems in design engineering. *Proceedings of IMProVe 2011, International conference on Innovative Methods in Product Design* (pp.603-611), 15-17 June 2011, Venice, Italy.

Quirante, T., Ledoux, Y., & Sebastian, P. (2010). Design optimization of two-stage flash evaporators: a trade-off between design objectives. *Proceedings of IDMME-Virtual Concept 2010*, 20-22 October 2010, Bordeaux, France.

Rangavajhala, S., & Messac, A. (2006). Towards a Better Understanding of Equality Constraints in Robust Design Optimization, *11th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference*, pp.307-324

Ray, T., Gokarn, R.P., & Sha, O.P. (1995). A global optimization model for ship design. Computers in Industry, 26(2):175-192.

Rehfeldt, K., Schwenk, B., and Molly, J.P. (1997). Sensitivity study of different parameters concerning the energy generating costs of wind turbines. *Proceedings of European Wind Energy Conference*, (pp.90-93), Dublin, Ireland.

Reich, Y. (1995). A critical review of General Design Theory. *Research in Engineering Design*, 7(1):1-18.

Réthy, Zs., Koczor, Z.; & Erdélyi, J. (2004):Handling Contradicting Requirements Using Desirability Functions, *Acta Polytechnica Hungarica IV*, pp.5-12.

Rossi, F., Van Beek, P. & Walsh, T. (2006). *Handbook of constraint programming*. Elsevier.

Roy, R. (1997). *Adaptive Search and the Preliminary Design of Gas Turbine Blade Cooling System*, PhD. Thesis, EDC, University of Plymouth

Roy, R., Hinduja, S., & Teti, R. (2008). Recent advances in engineering design optimization: Challenges and future trends. *CIRP Annals - Manufacturing Technology*, 57(2): 697-715.

Royset, J.O., Der Kiureghian, A., & Polak, E. (2001). Reliability-based optimal structural design by the decoupling approach. *Reliability Engineering & System Safety*, 73(3):213-221.

Saaty, T.L. (2008). Relative Measurement and its Generalization in Decision Making: Why Pairwise Comparisons are Central in Mathematics for the Measurement of Intangible Factors - The Analytic Hierarchy/Network Process. *RACSAM Review of the Royal Spanish Academy of Sciences, Mathematics*, 102(2):251-318.

Saari, D.G. (2006). Fundamentals and implications of Decision-Making. In K. Lewis, W. Chen and L. Schmidt (Eds), *Decision Making in Engineering Design*, ASME Press, Chapter 5, pp.35-42.

Samson, S., Reneke, J.A., & Wiecek, M.M. (2009a). A review of different perspectives on uncertainty and risk and an alternative modeling paradigm. *Reliability Engineering & System Safety*, 94(2):558-567.

Samson, S., Thoomu, S., Fadel, G.,& Reneke, J. (2009b). Reliable Design Optimization under Aleatory and Epistemic Uncertainties. *Proceedings of ASME 2009 International Design Engineering Technical Conferences & 35th Design Automation Conference* (vol. 49026, pp. 1093-1104), San Diego, USA.

Schaffer, J.D. (1985). Multiple objective optimization with vector evaluated genetic algorithm. In Grefenstette, J. (Eds.), Proceedings of the International Conference on Genetic Algorithm and their Applications, Morgan-Rauiinan, pp.93-100.

Schiffmann, J., & Favrat, D. (2010). Design, experimental investigation and multi-objective optimization of a small-scale radial compressor for heat pump applications. *Energy*, 35(1):436-450.

Schueller, G.I., & Jensen, H.A. (2008). Computational methods in optimization considering uncertainties - An overview. *Computer Methods in Applied Mechanics and Engineering*, 198(1):2-13.

Scott, M.J., & Antonsson, E.K. (1998). Aggregation Functions for Engineering Design Trade-offs, *Fuzzy Sets and Systems*, 99(3):253-269.

Scott, M.J. (1999), Formalizing negotiation in engineering design. PhD Thesis, California Institute of Technology, Pasadena, California.

Scott, M.J., & Antonsson, E.K. (2000). Using Indifference Points in Engineering Decisions. Proceedings of the 11th International Conference on Design Theory and Methodology, Baltimore, MD, ASME.

Sebastian, P., & Nadeau, J.P. (2002). Experiments and modeling of falling jet flash evaporators for vintage treatment. *International Journal of Thermal Sciences*, 41(3):269-280.

Sebastian, P., Quirante, T., & Ho Kon Tiat, V. (2010). Multiobjective optimization of the design of two-stage flash evaporators: Part 2: Multiobjective optimization. *International Journal of Thermal Sciences*, 49(12):2459-2466.

Sebastian, P., Ledoux, Y., Collignan, A., & Pailhes, J. (2012). Linking objective and subjective modeling in engineering design through arc-elastic dominance. *Expert Systems with Applications*, 39(9): 7743-7756.

Semassou, C. (2011), *Aide a la décision pour le choix de sites et systèmes énergétiques adaptés aux besoins du Benin*, PhD Thesis, Université de Bordeaux, I2M, UMR CNRS 5295, France.

Shah, R.K., & Sekulić, D.P. (2003). Fundamentals of Heat Exchanger Design. John Wiley & Sons.

Shan, S., & Wang, G.G. (2008). Reliable design space and complete single-loop reliability-based design optimization. *Reliability Engineering & System Safety*, 93(8):1218-1230.

Shyam, M.N. (2002). *Robust design*. Department of Aerospace Engineering, Indian Institute of Technology, Seminar Report, Bombay, India.

Smith, S. (2008). *Mechanical and Materials Engineering. Reliability of Deterministic Optimization and Limits of RBDO in Application to a Practical Design Problem*, PhD Thesis, Queen's University, Kingston, Ontario, Canada.

Sobek, K., Durward, W.A., & Liker, J.K. (1999). Toyota's Principles of Set-Based Concurrent Engineering. Sloan management review, 40(2):67-83.

Sobieszczanski-Sobieski, J., &. Haftka, R. T. (1997). Multidisciplinary aerospace design optimization: *survey of recent developments. Structural and Multidisciplinary Optimization*, 14(1):1-23.

Sohlenius, G. (1992). Concurrent Engineering. *CIRP Annals - Manufacturing Technology*, 41(2):645-655.

Srinivas, M., & Patnaik, L.M. (1994). Genetic algorithms: a survey. *Computer*, 27(6):17 -26.

Sriram, D., & Adey R.A. (1987). Knowledge based expert systems in engineering: planning and design. *Computational Mechanics*.

Sriram, R.D. (1997). *Intelligent Systems for Engineering: A Knowledge-based Approach*. Springer.

Stadler, W. (1988). Fundamentals of multicriteria optimization. In Stadler, W. (Eds), *Multicriteria Optimization in Engineering and in the Sciences* (pp.1-25), Plenum Press, New York.

Steuer, R.E., & Choo, E.U. (1983). An interactive weighted Tchebycheff procedure for multiple objective programming. *Mathematical Programming*, 26(1): 326-344.

Steuer, R.E. (1989). Multiple Criteria Optimization: Theory, Computation, and Application. Robert E. Krieger Publishing, Malabar.

Steuer, D (1999). Multi-Criteria-Optimisation and Desirability Indices, Technical report 20/99, University of Dortmund, Statistic department

Suh, N.P. (1990). *The Principles of Design*. Oxford University Press, Oxford.

Suh, N.P. (2001). *Axiomatic Design: Advances and Applications*. Oxford University Press, Oxford.

Sweatman, A., & Simon, M. (1996). Design for environment tools and product innovation. *Proceedings of 3rd CIRP International Seminar on Life Cycle Engineering*, Zurich, pp.185-196.

Taguchi, G. (1984), Quality Engineering Through Design Optimization, Kraus International Publications, New York.

Taguchi, G., Chowdhury, S., & Wu, Y. (2004). Taguchi's Quality Engineering Handbook. 1st ed. Wiley, New York.

Tamiz, M., Jones D., & Romero, C. (1998). Goal programming for decision making: An overview of the current state-of-the-art. European Journal of Operational Research 111(3):569-581.

Tichkiewitch, S., Tollenaere, M., & Ray, P. (2007). *Advances in Integrated Design and Manufacturing in Mechanical Engineering II*. Springer, New York.

Tomiyama, T., & Yoshikawa H. (1987). Extended General Design Theory. In Yoshikawa, H., Warman, E.A. (Eds.), Design Theory for CAD (pp.29-34). North-Holland, Amsterdam.

Tomiyama, T. (1997). A note on research directions of design studies. In Riitahuhta, A. (Eds.), WDK25, *Proceedings of the 11th International Conference on Engineering Design* (Vol.3, pp.29-34). Laboratory of Machine Design, Tampere University of Technology, Tampere, Finland.

Tomiyama, T. (2006). A Classification of Design Theories and Methodologies. *Proceedings of the 2006 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. ASME.

Trautmann, H; Weihs, Claus (2004) : Pareto-Optimality and Desirability Indices, Technical Report/Universität Dortmund, SFB 475 Komplexitätsreduktion in Multivariaten Datenstrukturen, No. 2004,63, http://hdl.handle.net/10419/22576

Trautmann, H., & Mehnen, J. (2005). A method for including a-priori preferences in multicriteria optimization. *Technical Reports 2005*, 49, Technische Universität Dortmund, Sonderforschungsbereich 475: Komplexitätsreduktion in multivariaten Datenstrukturen.

Trautmann, H, & Mehnen, J. (2009). Statistical Methods for Improving Multi-objective Evolutionary Optimization. *International Journal of Computational Intelligence Research*, 5(2):72-78.

Ueda, K. (2001). Emergent Synthesis. *Artificial Intelligence in Engineering*, 15(4): 319-320.

Ueda, K., Fujii, N., & Inoue, R. (2007). An emergent synthesis approach to simultaneous process planning and scheduling. *CIRP annals*, 56(1):463-466.

Ullman, D.G., Dietterich, T.G., & Stauffer, L.A. (1988). A Model of the Mechanical Design Process based on Empirical Data. *AI EDAM*, 2(1): 33-52.

Ullman, D.G. (2009). The Mechanical Design Process. 4th ed. McGraw-Hill.

Ulrich, K., & Eppinger, S. (1999). *Product Design and Development*. 2nd ed. McGraw-Hill.

Umeda, Y., & Tomiyama, T. (1997). Functional reasoning in design. *IEEE Expert*, 12(2):42-48.

Valderrama Ulloa, C., Lagiere, P., & Puiggali, J.R. (2012) A methodology to asses a sustainable evolution of the existing buildings to different user requirements, *Proceedings of PLEA2012, 28th Conference, Opportunities, Limits & Needs Towards an environmentally responsible architecture*, pp.7-9, Lima, Perú.

VDI. (2004). *VDI 2206: Design methodology for Mechatronic Systems*. Beuth Verlag. Berlin, Germany.

Vermaas, P., & Dorst, K. (2007). On the conceptual framework of John Gero's FBS-model and the prescriptive aims of design methodology. *Design Studies*, 28(2):133-157.

Vernat, Y., Nadeau, J.P., & Sebastian, P. (2010). Formalization and qualification of models adapted to preliminary design. *International Journal on Interactive Design and Manufacturing*, 4(1), pp.11-24.

Vincent, T.L. (1983). Game theory as a design tool. *Journal of Mechanisms, Transmissions, and Automation in Design*, vol.105, pp.165-170

Vinsonneau, E., & Escaffre, P. (2002). Evaluation du procédé de vinification par la flash-détente en bordelais - Synthèse de trois années d'essais 1999-2001. CRAT ITV. France.

Von Neumann, J., & Morgenstern, O. (1947). Theory of Games and Economic Behaviour. 1st ed. Princeton University Press.

Wallace, K.M., & Hales, C. (1987). *Detailed analysis of an engineering design project. Proceedings of the International Conference on Engineering Design 1987 in Boston*, ASME, Vol.1, pp.94-101.

Weber, C. (2005), CPM / PDD - An extended theoretical approach to modelling products and product development processes. Proceedings of the 2nd GermanIsraeli Symposium on Advances in Methods and Systems for Development of Products and Processes (Vol.7, pp.1-19). Fraunhofer-IRB-Verlag, Berlin.

Weber, C. (2007). Looking at "DfX" and "Product Maturity" from the Perspective of a New Approach to Modelling Product and Product Development Process. In Krause, K. (Eds) *The Future of Product Development, Proceedings of the 17th CIRP Design Conference*, (pp.85-104), Berlin.

Weber, C. (2008). How to Derive Application-Specific Design Methodologies? *Proceedings of the Design 2008, 10th International Design Conference* (pp.69-80), Dubrovnik, Croatia.

Wierzbicki, A. P. (1982). A mathematical basis for satisfying decision making. *Mathematical Modelling*, 3(5):391-405.

Wood, K.L., & Antonsson, E.K. (1989) Computations with imprecise parameters in engineering design: background and theory. *Journal of mechanisms, transmissions, and automation in design*, 111(4):616-625.

Xiao, N., Bennett D.A., & Armstrong, M.P. (2007). Interactive evolutionary approaches to multiobjective spatial decision making: A synthetic review. *Computers, Environment and Urban Systems*, 31(3):232-252.

Yoshikawa, H. (1981). General design theory and a CAD system. In Sata, T., Warman, E.A. (Eds.), *Man-Machine Communication in CAD/CAM* (pp.35-57). North-Holland, Amsterdam.

Yoshikawa, H., & Uehara, K. (1985). Design theory for CAD/CAM Integration. *CIRP Annals - Manufacturing Technology*, 34(1):173-178.

Youn, B.D., et al. (2004). Reliability-based design optimization for crashworthiness of vehicle side impact. Structural and Multidisciplinary Optimization, 26(3):272-283.

Yu, P. L. (1974). Cone convexity, cone extreme points, and nondominated solutions in decision problems with multiobjective. *Journal of Optimization Theory and Applications*, 14(3):319-377.

Zadeh, L. (1963). Optimality and non-scalar-valued performance criteria. *Automatic Control, IEEE Transactions*, 8(1):59 - 60.

Zeleny, M. (1981). *Multiple Criteria Decision Making*. McGraw-Hill, New York.

Personal Publications

International Journal Publications

Quirante, T., Sebastian, P., & Ledoux, Y. (2012). An approach for the robust design of flash evaporators for must concentration applications in the wine industry. *Applied Thermal Engineering*, accepted with revision.

Quirante, T., Sebastian, P., & Ledoux, Y. (2012). A trade-off function to tackle robust design problems in engineering. *Journal of Engineering Design*, DOI:10.1080/09544828.2012.691160

Quirante, T., Ledoux, Y., and Sebastian, P. (2011). Multiobjective optimization including design robustness objectives for the embodiment design of a two-stage flash evaporator. International Journal on Interactive Design and Manufacturing, 6(1):29-39.

Sebastian, P., Quirante, T., & Ho Kon Tiat, V. (2010). Multiobjective optimization of the design of two-stage flash evaporators: Part 2: Multiobjective optimization. *International Journal of Thermal Sciences*, 49(12):2459-2466.

Ho Kon Tiat, V., Sebastian, P., & Quirante, T. (2010). Multiobjective optimization of the design of two-stage flash evaporators: Part 1: Process modeling. *International Journal of Thermal Sciences*, 49(12):2453-2458.

International Refereed Conference Publications

Quirante, T., Sebastian, P., & Ledoux, Y. (2011). Development of a trade-off function for robust optimization problems in design engineering. *Proceedings of IMProVe 2011, International conference on Innovative Methods in Product Design* (pp.603-611), 15-17 June 2011, Venice, Italy.

Quirante, T., Ledoux, Y., & Sebastian, P. (2010). Design optimization of two-stage flash evaporators: a trade-off between design objectives. *Proceedings of IDMME-Virtual Concept 2010*, 20-22 October 2010, Bordeaux, France.

International Refereed Conference Poster Presentation

Quirante, T., Sebastian, P., & Ledoux, Y. (2012). Development of a trade-off function for robust design problems: a desirability based approach. *Proceedings of DCC'12, Fifth International Conference on Design Computing and Cognition*, 7-9 June 2012, Texas A&M University, College Station, Texas USA.

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ANNEXE I Generation of design appropriate aggregation functions

The family of design appropriate aggregation functions proposed in the scope of the MoI is derived from the formulation of the general weighted mean. Changes of the trade-off parameters *s* enables to generate aggregation functions which are more or less compensatory. However, design-appropriate aggregation functions correspond to the set of weighted means generated while $s \leq 0$. This annex presents the generation of some particular aggregation functions, namely: the weighted sum, the weighted product and the min-max aggregation.

I.1 Generation of the weighted sum aggregation function

For the bi-objective case, the general weighted mean formulation is expressed as:

$$\mathcal{P}_s(\mu_1,\mu_2;w_1,w_2)=\left(\frac{w_1\,\mu_1^s+w_2\,\mu_2^s}{w_1+w_2}\right)^{\frac{1}{s}},\quad s\in\mathbb{R} \tag{I.1.1}$$

where *s* is the trade-off parameter and eh weights (w_1,w_2) are such as $w_1+w_2=1$. For s=1, it is obvious that the resulted aggregation function is the weighted sum (or weighted arithmetic mean) and:

$$\mathcal{P}_1(\mu_1,\mu_2;w_1,w_2)=\frac{w_1\cdot\mu_1+w_2\cdot\mu_2}{w_1+w_2} \tag{I.1.2}$$

I.2 Generation of the weighted product aggregation function

For the bi-objective case, the weighted product aggregation function corresponds to s=0. For s=0, the relation (I.1.1) leads to:

$$\mathcal{P}_0(\mu_1,\mu_2;w_1,w_2)=\lim_{s\to 0}\left(\frac{w_1\,\mu_1^s+w_2\,\mu_2^s}{w_1+w_2}\right)^{\frac{1}{s}} \tag{I.2.1}$$

The logarithm form of expression (7.2.1=) leads to:

$$\mathcal{P}_0(\mu_1,\mu_2;w_1,w_2)=\lim_{s\to 0}\; exp\left[\frac{1}{s}\,log\left(\frac{w_1\,\mu_1^s+w_2\,\mu_2^s}{w_1+w_2}\right)\right] \tag{I.2.2}$$

If we define f(s) such as:

$$f(s)=log\left(\frac{w_1\,\mu_1^s+w_2\,\mu_2^s}{w_1+w_2}\right) \tag{I.2.3}$$

It follows that:

$$\lim_{s\to 0} \frac{1}{s} \log\left(\frac{w_1\, \mu_1^s + w_2\, \mu_2^s}{w_1 + w_2}\right) = \lim_{s\to 0} \frac{f(s) - f(0)}{s - 0} = \frac{d}{ds} f(s)_{s=0}$$
$$= \frac{w_1\, ln(\mu_1) + w_2\, ln(\mu_2)}{w_1 + w_2} \tag{I.2.4}$$

Finally, the weighted geometric mean aggregation function is expressed as:

$$\mathcal{P}_0(\mu_1, \mu_2; w_1, w_2) = e^{\frac{w_1\, ln(\mu_1) + w_2\, ln(\mu_2)}{w_1 + w_2}} = e^{\frac{w_1\, ln(\mu_1)}{w_1 + w_2}} \cdot e^{\frac{w_2\, ln(\mu_2)}{w_1 + w_2}} = \left(\mu_1^{w_1} \cdot \mu_2^{w_2}\right)^{\frac{1}{w_1 + w_2}} \tag{I.2.5}$$

I.3 Generation of the min-max aggregation function

For the bi-objective case, the *min* aggregation function corresponds to s→–∞. For s→–∞, the relation (I.1.1) leads to:

$$\mathcal{P}_{-\infty}(\mu_1, \mu_2; w_1, w_2) = \lim_{s\to -\infty} \left(\frac{w_1\, \mu_1^s + w_2\, \mu_2^s}{w_1 + w_2}\right)^{\frac{1}{s}}$$
$$= \lim_{s\to -\infty} \left(\frac{w_1}{w_1 + w_2}\right)^{\frac{1}{s}} \left(\mu_1^s + \frac{w_2}{w_1}\mu_2^s\right)^{\frac{1}{s}} \tag{I.3.1}$$

Taking t=–s leads to:

$$\mathcal{P}_{-\infty}(\mu_1, \mu_2; w_1, w_2) = \lim_{t\to +\infty} \left(\frac{1}{\mu_1^t} + \frac{w_2}{w_1} \cdot \frac{1}{\mu_2^t}\right)^{-\frac{1}{t}}$$
$$= \lim_{t\to +\infty} \left(\frac{w_1\, \mu_2^t + w_2\, \mu_1^t}{w_1\, \mu_1^t \cdot \mu_2^t}\right)^{-\frac{1}{t}}$$
$$= \lim_{t\to +\infty} \left(\frac{w_1\, \mu_1^t \cdot \mu_2^t}{w_1\, \mu_2^t + w_2}\right)^{\frac{1}{t}} \tag{I.3.2}$$
$$= \lim_{t\to +\infty} \frac{\mu_2}{\left(\left(\frac{\mu_2}{\mu_1}\right)^t + \frac{w_2}{w_1}\right)^{\frac{1}{t}}}$$

If $\mu_2 \le \mu_1$, then:

$$\lim_{t\to +\infty} \left(\left(\frac{\mu_2}{\mu_1}\right)^t + \frac{w_2}{w_1}\right)^{\frac{1}{t}} = 1 \;\Rightarrow\; \mathcal{P}_{-\infty}(\mu_1, \mu_2; w_1, w_2) = \mu_2 \tag{I.3.3}$$

Conversely, if $\mu_1 < \mu_2$, then:

$$\lim_{t\to+\infty}\left(\left(\frac{\mu_2}{\mu_1}\right)^{t}+\frac{w_2}{w_1}\right)^{\frac{1}{t}}=\frac{\mu_2}{\mu_1}\quad\Rightarrow\quad\mathcal{P}_{-\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=\mu_1 \tag{I.3.4}$$

Therefore, it follows that:

$$\mathcal{P}_{-\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=min\left(\mu_1\ ,\mu_2\right) \tag{I.3.5}$$

In the same way, while s→+∞, the relation (I.3.1) leads to:

$$\mathcal{P}_{-\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=\lim_{s\to+\infty}\quad\mu_1\left(1+\frac{w_2}{w_1}\left(\frac{\mu_2}{\mu_1}\right)^{s}\right)^{\frac{1}{s}} \tag{I.3.6}$$

If $\mu_2 \leq \mu_1$, then:

$$\lim_{s\to+\infty}\left(1+\frac{w_2}{w_1}\left(\frac{\mu_2}{\mu_1}\right)^{s}\right)^{\frac{1}{s}}=1\quad\Rightarrow\quad\mathcal{P}_{+\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=\mu_1 \tag{I.3.7}$$

Conversely, if $\mu_1 < \mu_2$, then:

$$\lim_{s\to+\infty}\left(1+\frac{w_2}{w_1}\left(\frac{\mu_2}{\mu_1}\right)^{s}\right)^{\frac{1}{s}}=\frac{\mu_2}{\mu_1}\quad\Rightarrow\quad\mathcal{P}_{+\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=\mu_2 \tag{I.3.8}$$

Therefore, it follows that:

$$\mathcal{P}_{+\infty}\left(\mu_1,\mu_2;w_1,w_2\right)=max\left(\mu_1\ ,\mu_2\right) \tag{I.3.9}$$

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ANNEXE II Pareto optimality and desirability index

In [Steuer 1999], the property of Pareto optimality is introduced using the concept of domination. For maximization problem, a vector of observation variables $\mathbf{y}=[y_1,...,y_k]^T$ is defined as Pareto optimal if there is no other vector $\mathbf{y}^*$ which dominates $\mathbf{y}$. The vector $\mathbf{y}^*$ dominates the vector $\mathbf{y}$ if $y_j^* \geq y_j$ with $j=1,...,k$ and $y_i^* > y_i$ for $i \in \{1,...,k\}$. Therefore, a Pareto optimal solution cannot be improved without a degradation of one the criterion. As observation variables are computed from a set of design variables such as $\mathbf{y}(\mathbf{x})$, if $\mathbf{y}$ is Pareto optimal in the observation space, then $\mathbf{x}=[x_1,...,x_k]^T$ is Pareto optimal is the design space. In this annexe, the Pareto optimality criterion resulting from the maximization of the desirability index is analysed and discussed.

II.1 Pareto optimality criterion for desirability index resulting from the weighted geometric mean aggregation

Consider a design problem characterised by k observation variables $\mathbf{y}=[y_1,...,y_k]^T$ resulting from n design variables $\mathbf{x}=[x_1,...,x_n]^T$ and interpreted through k desirability functions d_i (i=1,...,k). Suppose that the optimal solution $\mathbf{x}^{opt}=[x_1^{opt},...,x_n^{opt}]^T$ has been determined by maximizing the desirability index DI defined by:

$$\mathrm{DI} = \prod_{i=1}^{k} \left(d_i\right)^{w_i} \quad \text{with } d_i = d_i\left(y_i \mid x_i\right) \in [0,1],\ w_i \in [0,1] \tag{II.1.1}$$

Consider now that the solution $\mathbf{x}^{opt}$ is not Pareto optimal. This means that there exists a solution $\mathbf{x}^*$ which dominates $\mathbf{x}^{opt}$. It follows that:

$$\begin{cases} d_t\left(y_t \mid \mathbf{x}^*\right) > d_t\left(y_t \mid \mathbf{x}^{opt}\right) & \text{for} \quad t \in \{1,\dots,k\} \\ d_j\left(y_j \mid \mathbf{x}^*\right) \geq d_j\left(y_j \mid \mathbf{x}^{opt}\right) & \text{for} \quad j = 1,\dots,k;\ j \neq t \end{cases}$$

$$\Rightarrow \begin{cases} d_1\left(y_1 \mid \mathbf{x}^*\right)^{w_1} \geq d_1\left(y_1 \mid \mathbf{x}^{opt}\right)^{w_1} \\ \vdots \\ d_t\left(y_t \mid \mathbf{x}^*\right)^{w_t} > d_t\left(y_t \mid \mathbf{x}^{opt}\right)^{w_t} \\ \vdots \\ d_k\left(y_k \mid \mathbf{x}^*\right)^{w_k} \geq d_k\left(y_k \mid \mathbf{x}^{opt}\right)^{w_k} \end{cases} \tag{II.1.2}$$

$$\Rightarrow \prod_{i=1}^{k} d_i\left(y_i \mid \mathbf{x}^*\right)^{w_i} > \prod_{i=1}^{k} d_i\left(y_i \mid \mathbf{x}^{opt}\right)^{w_i}$$

$$\Rightarrow \mathrm{DI}^* > \mathrm{DI}^{opt}$$

This result is in contradiction with the assumption that $\mathbf{x}^{opt}$ maximizes the DI. Therefore $\mathbf{x}^{opt}$ must be Pareto optimal. To conclude, the maximization of the DI computed by the weighted geometric mean aggregation leads to Pareto optimal solutions.

II.2 Pareto optimality criterion for desirability index resulting from the *min* aggregation

Consider a design problem characterised by k observation variables $\mathbf{y}=[y_1,...,y_k]^T$ resulting from n design variables $\mathbf{x}=[x_1,...,x_n]^T$ and interpreted through k desirability functions d_i (i=1,...,k). Suppose that the optimal solution $\mathbf{x}^{opt}=[\ x_1^{opt},...,x_n^{opt}]^T$ has been determined by maximizing the desirability index DI expressed as:

$$\mathrm{DI} = \min_{i=1,\dots,k}\left\{\mathrm{d_i}\right\} \quad \text{with } \mathrm{d_i} = d_i\left(\mathrm{y_i} \mid \mathrm{x_i}\right) \tag{II.2.1}$$

The desirability value DI^{opt} related to the optimal solution is $\mathbf{x}^{opt}$ is such as:

$$\mathrm{DI}^{opt} = d_p\left(\mathrm{y_p} \mid \mathbf{x}^{opt}\right) = \min_{i=1,\dots,k}\left\{d_i\left(\mathrm{y_i} \mid \mathbf{x}^{opt}\right)\right\}, \quad \mathrm{p} \in \{1,\dots,\mathrm{k}\} \tag{II.2.2}$$

Consider now that the solution $\mathbf{x}^{opt}$ is not Pareto optimal. This means that there exists a solution $\mathbf{x}^*$ which dominates $\mathbf{x}^{opt}$. It follows that:

$$\begin{cases} d_t\left(\mathrm{y_t} \mid \mathbf{x}^*\right) > d_t\left(\mathrm{y_t} \mid \mathbf{x}^{opt}\right) & \text{for} \quad \mathrm{t} \in \{1,\dots,\mathrm{k}\} \\ d_j\left(\mathrm{y_j} \mid \mathbf{x}^*\right) \geq d_j\left(\mathrm{y_j} \mid \mathbf{x}^{opt}\right) & \text{for} \quad \mathrm{j} = 1,\dots,\mathrm{k};\ \mathrm{j} \neq \mathrm{t} \end{cases} \tag{II.2.3}$$

According to the values of d_p and d_s, three cases can be identified: $d_p=d_t$, $d_p \neq d_t$ and $(y_p|\mathbf{x}^{opt}) \neq (y_p|\mathbf{x}^*)$, $d_p \neq d_t$ and $(y_p|\mathbf{x}^{opt})=(y_p|\mathbf{x}^*)$.

<u>Case 1:$d_p=d_t$</u>

From relations (7.2.2) and (7.2.3), it follows that:

$$\begin{aligned} &\begin{cases} d_p\left(\mathrm{y_p} \mid \mathbf{x}^*\right) > d_p\left(\mathrm{y_p} \mid \mathbf{x}^{opt}\right) & \text{for} \quad \mathrm{p} \in \{1,\dots,\mathrm{k}\} \\ d_j\left(\mathrm{y_j} \mid \mathbf{x}^*\right) \geq d_j\left(\mathrm{y_j} \mid \mathbf{x}^{opt}\right) & \text{for} \quad \mathrm{j} = 1,\dots,\mathrm{k};\ \mathrm{j} \neq \mathrm{p} \end{cases} \\ &\Rightarrow \min_{i=1,\dots,k}\left\{d_i\left(\mathrm{y_i} \mid \mathbf{x}^*\right)\right\} > \min_{i=1,\dots,k}\left\{d_i\left(\mathrm{y_i} \mid \mathbf{x}^{opt}\right)\right\} \\ &\Rightarrow \mathrm{DI}^* > \mathrm{DI}^{opt} \end{aligned} \tag{II.2.4}$$

This result is in contradiction with the assumption that $\mathbf{x}^{opt}$ maximizes the DI. Therefore, for $d_p=d_t$, $\mathbf{x}^{opt}$ must be Pareto optimal.

<u>Case 2:</u> $d_p \neq d_t$ and $(y_p|\mathbf{x}^{opt}) \neq (y_p|\mathbf{x}^*)$

In this case, the Pareto optimality criterion depends on the monotonicity of the desirability function d_p. If the function d_p is strictly monotonic, it follows from relation (II.2.3) that:

$$\begin{aligned} \left(\mathrm{y_p} \mid \mathbf{x}^*\right) \neq \left(\mathrm{y_p} \mid \mathbf{x}^{opt}\right) &\Rightarrow d_p\left(\mathrm{y_p} \mid \mathbf{x}^*\right) > d_p\left(\mathrm{y_p} \mid \mathbf{x}^{opt}\right) \\ &\Rightarrow \mathrm{DI}^* > \mathrm{DI}^{opt} \end{aligned} \tag{II.2.5}$$

This result is in contradiction with the assumption that $\mathbf{x}^{opt}$ maximizes the DI and thus $\mathbf{x}^{opt}$ must be Pareto optimal. For non-strictly monotonic functions, such as Derringer's desirability functions (see section 3.4.2), the situations $d_p=1$ and $d_p=0$ may append. In particular, for $d_p=1$, the situation $d_t(y_t|\mathbf{x}^{opt})=d_p(y_p|\mathbf{x}^{opt})$ may arise and lead to non Pareto optimal solutions. Non-monotonic desirability functions are thus non suitable for preference modelling in engineering design. This partly explains why Harrington's desirability functions are preferred to Derringer's desirability functions.

Case 3: $d_p \neq d_t$ and $(y_p|\mathbf{x}^{opt})=(y_p|\mathbf{x}^*)$

Using the relation (II.2.3), it comes:

$$\begin{aligned}\left(y_p \mid \mathbf{x}^*\right)=\left(y_p \mid \mathbf{x}^{opt}\right) &\Rightarrow d_p\left(y_p \mid \mathbf{x}^*\right)=d_p\left(y_p \mid \mathbf{x}^{opt}\right)\\ &\Rightarrow DI^* = DI^{opt}\end{aligned} \tag{II.2.6}$$

Therefore, the assumption that $\mathbf{x}^{opt}$ maximizes the DI is true, and thus, the solution $\mathbf{x}^{opt}$ is Pareto optimal.

To conclude, the computation of the DI by the *min* aggregation function may lead to non Pareto optimal solutions. Designers have to be aware of this non-Pareto optimality when they select the min aggregation strategy. This can be seen as a disadvantage for problems in which the Pareto optimality criterion is required.

II.3 Pareto optimality criterion for desirability index resulting from the general weighted mean aggregation

Consider a design problem characterised by k observation variables $\mathbf{y}=[y_1,...,y_k]^T$ resulting from n design variables $\mathbf{x}=[x_1,...,x_n]^T$ and interpreted through k desirability functions d_i (i=1,...,k). Suppose that the optimal solution $\mathbf{x}^{opt}=[x_1^{opt},...,x_n^{opt}]^T$ has been determined by maximizing the desirability index DI defined by:

$$DI=\left(\sum_{i=1}^{k} w_i \cdot d_i^s\right)^{1/s} \quad \text{with } d_i = d_i\left(y_i \mid x_i\right)\in[0,1],\ w_i \in [0,1] \text{ and } \sum_{i=1}^{k} w_i = 1 \tag{II.3.1}$$

Consider now that the solution $\mathbf{x}^{opt}$ is not Pareto optimal. This means that there exists a solution $\mathbf{x}^*$ which dominates $\mathbf{x}^{opt}$. It follows that:

$$\begin{cases} d_t\left(y_t \mid \mathbf{x}^*\right) > d_t\left(y_t \mid \mathbf{x}^{opt}\right) & \text{for} \quad t \in \{1,\dots,k\} \\ d_j\left(y_j \mid \mathbf{x}^*\right) \geq d_j\left(y_j \mid \mathbf{x}^{opt}\right) & \text{for} \quad j=1,\dots,k;\ j \neq t \end{cases} \tag{II.3.2}$$

The Pareto optimality criterion must be analysis according to the values of the trade-off strategy parameter s. For s=0, the aggregation function is the weighted geometric mean and in this case, the Pareto optimality criterion has been disused in section II.1. For s>0, the relation (II.3.2) leads to:

$$\begin{cases} \mathrm{w}_1 \cdot d_1\left(\mathrm{y}_1 \mid \mathbf{x}^*\right)^{\mathrm{s}} \geq \mathrm{w}_1 \cdot d_1\left(\mathrm{y}_1 \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \\ \vdots \\ \mathrm{w}_{\mathrm{t}} \cdot d_{\mathrm{t}}\left(\mathrm{y}_{\mathrm{t}} \mid \mathbf{x}^*\right)^{\mathrm{s}} > \mathrm{w}_{\mathrm{t}} \cdot d_{\mathrm{t}}\left(\mathrm{y}_{\mathrm{t}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \\ \vdots \\ \mathrm{w}_{\mathrm{k}} \cdot d_{\mathrm{k}}\left(\mathrm{y}_{\mathrm{k}} \mid \mathbf{x}^*\right)^{\mathrm{s}} \geq \mathrm{w}_{\mathrm{k}} \cdot d_{\mathrm{k}}\left(\mathrm{y}_{\mathrm{k}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \end{cases}$$

$$\Rightarrow \left(\prod_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w}_{\mathrm{i}} \cdot d_{\mathrm{i}}\left(\mathrm{y}_{\mathrm{i}} \mid \mathbf{x}^*\right)^{\mathrm{s}}\right)^{1/\mathrm{s}} > \left(\prod_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w}_{\mathrm{i}} \cdot d_{\mathrm{i}}\left(\mathrm{y}_{\mathrm{i}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}}\right)^{1/\mathrm{s}} \qquad \text{(II.3.3)}$$

$$\Rightarrow \mathrm{DI}^* > \mathrm{DI}^{\mathrm{opt}}$$

This result is in contradiction with the assumption that $\mathbf{x}^{\mathrm{opt}}$ maximizes the DI. Therefore, for s>0, $\mathbf{x}^{\mathrm{opt}}$ must be Pareto optimal. For s<0, the relation (II.3.2) leads to:

$$\begin{cases} \mathrm{w}_1 \cdot d_1\left(\mathrm{y}_1 \mid \mathbf{x}^*\right)^{\mathrm{s}} \leq \mathrm{w}_1 \cdot d_1\left(\mathrm{y}_1 \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \\ \vdots \\ \mathrm{w}_{\mathrm{t}} \cdot d_{\mathrm{t}}\left(\mathrm{y}_{\mathrm{t}} \mid \mathbf{x}^*\right)^{\mathrm{s}} < \mathrm{w}_{\mathrm{t}} \cdot d_{\mathrm{t}}\left(\mathrm{y}_{\mathrm{t}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \\ \vdots \\ \mathrm{w}_{\mathrm{k}} \cdot d_{\mathrm{k}}\left(\mathrm{y}_{\mathrm{k}} \mid \mathbf{x}^*\right)^{\mathrm{s}} \leq \mathrm{w}_{\mathrm{k}} \cdot d_{\mathrm{k}}\left(\mathrm{y}_{\mathrm{k}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}} \end{cases}$$

$$\Rightarrow \left(\prod_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w}_{\mathrm{i}} \cdot d_{\mathrm{i}}\left(\mathrm{y}_{\mathrm{i}} \mid \mathbf{x}^*\right)^{\mathrm{s}}\right)^{1/\mathrm{s}} > \left(\prod_{\mathrm{i}=1}^{\mathrm{k}} \mathrm{w}_{\mathrm{i}} \cdot d_{\mathrm{i}}\left(\mathrm{y}_{\mathrm{i}} \mid \mathbf{x}^{\mathrm{opt}}\right)^{\mathrm{s}}\right)^{1/\mathrm{s}} \qquad \text{(II.3.4)}$$

$$\Rightarrow \mathrm{DI}^* > \mathrm{DI}^{\mathrm{opt}}$$

This result is also in contradiction with the assumption that $\mathbf{x}^{\mathrm{opt}}$ maximizes the DI. Therefore, for s<0, $\mathbf{x}^{\mathrm{opt}}$ must be Pareto optimal. To conclude, the maximization of the DI computed by the general weighted mean aggregation, leads to Pareto optimal solutions.

ANNEXE III Design model of two-staged flash evaporators

Transfer, dimensional, environmental and economical models contributing to the design model of the flash evaporation process are briefly described in the following, but the reader could refer to Annexe 3 and to the publications [Bouchama 2003b, Ho Kon Tiat 2008b] for further explanations.

III.1 Heat and mass transfer model

The physical model is mainly based on heat and mass transfer balances inside the evaporation chambers and condensers. This is an equilibrium model since, even with the flash phenomenon, the steam is close to saturation state in the entire system and the working fluid is cooled at this saturation temperature. The mass flow rate of the steam generated in the evaporation chambers is derived from this equilibrium hypothesis. It is calculated from the following equation, where subscripts i and o refer to the inlet and outlet of the stage being considered:

$$q_{vapor} = \frac{q_{pi} \cdot \left(Cp_{pi} \cdot T_{pi} - Cp_{po} \cdot T_{vsat}\right)}{\Delta h_{evap}} \tag{III.1.1}$$

The outlet temperature of the product is also equal to the steam saturation temperature. Therefore, this outlet temperature transferred through the flash evaporator is the saturation temperature of the vapour inside the low-pressure evaporation chamber:

$$T_{po} = T_{vsatLP} \tag{III.1.2}$$

The cooling power of the flash evaporator is derived from:

$$\mathcal{P}_{cool} = q_{pi} \cdot Cp_{pi} \cdot T_{pi} - q_{po} \cdot Cp_{po} \cdot T_{po} \tag{III.1.3}$$

The evaluation of this mass flow rate is used to estimate the mass flow rates of the condensates flowing out of the condensers. Indeed, the condensate mass flow rate depends directly on the inlet and outlet steam mass flow rates in the condenser. The outlet mass flow rate of steam flows towards the air ejector coupled with the vacuum pump and due to this configuration, the steam outlet mass flow rate is roughly constant. Consequently, the condensate mass flow rate can be expressed as a function of the steam mass flow rate, as shown in equation (III.1.4), where a and b are equal to 0.7163 and 0.0027 respectively for the high pressure stage condenser, and 0.8025 and -0.0025 for the low pressure stage one. From experimental measurements, it has been observed that the coefficients of determination corresponding to these parameters are 91% for the high pressure and 67% for the low pressure condenser:

$$q_{cdst} = a \cdot q_v + b \tag{III.1.4}$$

The mass flow rates of the condensates are used to calculate the steam side heat transfer coefficient, given by equation (III.1.5), based on Nusselt's theory. The adaptation coefficient

A has been derived from experimental measurements and is equal to 0.58 for the high pressure condenser and 0.45 for the low pressure condenser.

$$h_{cd} = A \cdot \left(0.023 \cdot Re_{cdst}^{1/4} \cdot Pr_{cdst}^{1/2}\right) \cdot \lambda_{cdst} \cdot \left(\frac{\mu_{cdst}^{2}}{\rho_{cdst} \cdot \left(\rho_{cdst} - \rho_{v}\right) \cdot g}\right)^{-1/3} \tag{III.1.5}$$

In the same way, the coolant side heat transfer coefficient is calculated using equation 6.2.2.6 derived from supplier data. In this equation, the adaptation parameter B is equal to 0.031 and 0.034 for the high pressure condenser and low pressure condensers respectively.

$$h_{cl} = B \cdot G_{cl} \cdot Cp_{cl} \cdot Re_{cl}^{-0.2} \cdot Pr_{cl}^{-2/3} \tag{III.1.6}$$

The global heat transfer coefficient is then estimated using equation (III.1.7), considering that the thermal resistance of the wall, with a thickness of about 1.5mm, is negligible compared to the two other coefficients.

$$k = \frac{h_{cd} \cdot h_{cl}}{h_{cd} + h_{cl}} \tag{III.1.7}$$

Bouchama [Bouchama 2003a] has shown that the physical behaviour of the condensers can be modelled using a NTU-Efficiency model, by considering the energy balance of a volumetric cell of condensers and heat transfer laws. This model is based on the hypothesis of laminar flow of the condensates, saturation of the steam, adiabatic heat exchange between the coolant and the steam, incomplete condensation inside the condenser (no sub-cooling) and immaterial pressure losses inside of the condensers. Thus, the global heat transfer coefficient has been introduced in equation (III.1.8)to calculate the Number of Transfer Units, and then evaluate the heat efficiency of the condensation through the following equation:

$$NTU = \frac{k \cdot N_p \cdot A_p}{q_{cl} \cdot Cp_{cl}} \tag{III.1.8}$$

In this relation, the exchange surface of the plate-type condensers has been divided into N plates, each with an exchange surface of A_p. The thermal efficiency of the condensers is derived from:

$$\varepsilon = 1 - e^{-NTU} \tag{III.1.9}$$

Finally, the outlet temperature of the working fluid is calculated using the definition equation of the thermal efficiency:

$$T_{po} = T_{vsat} = \frac{T_{clo} + (\varepsilon - 1) \cdot T_{cli}}{\varepsilon} \tag{III.1.10}$$

The outlet temperature of the coolant liquid T_{clo} is calculated through an energy balance inside the condensers, considering an adiabatic heat exchange between the coolant and the steam/condensate flow:

$$T_{clo} = T_{cli} + \frac{q_v \cdot \Delta h_{evap}}{q_{cl} \cdot Cp_{cl}} \tag{III.1.11}$$

The assumption of adiabatic heat exchange has been experimentally verified by a comparison between the vapour side and coolant side thermal powers. The pressures inside the evaporation stages are then calculated using the correlation of Clapeyron linking pressure and saturation temperature.

$$P_o = P_i \cdot \exp\left[\left(\frac{M_v \cdot \Delta h_{evapi}}{R}\right)\cdot\left(\frac{1}{T_{v.sati}} - \frac{1}{T_{vo}}\right)\right] \quad \text{(III.1.12)}$$

The design model of the flash evaporation process has been developed around this physical model, so that the global definition of the system can be adapted to the operative parameters. Dimensional, economical and environmental models complete the heat and mass transfer model.

III.2 Dimensional model

The dimensional model is used to compute the overall dimensions and mass of the system. This model is also related to the definition of the main characteristics of some components, which is equivalent to their dimensioning. The size and the mass of the evaporator are mainly calculated according to the buffer tank, evaporation chambers and condensers dimensions, which are the biggest and heaviest components of the system.

The volume of the buffer tank is calculated from the mass flow rate of the product and the filling time of the tank:

$$V_{chbbuf} = \frac{t_{fill} \cdot q_p}{\rho_p} \quad \text{(III.2.1)}$$

Since this tank is supposed to be cylindrical in shape, the height and diameter are calculated by fixing one of these two parameters and calculating the other from the volume of a cylinder. The thickness of the buffer tank is estimated using the relation given by the European directives concerning pressure equipment (CODAP). In order to limit calorific energy losses and ensure staff safety, the buffer tank is insulated. The thickness of the insulation layer is calculated from a heat transfer balance between the product and the surrounding air. The insulation layer is covered with a thin external layer of aluminium. The buffer tank is also equipped with a mixer to ensure uniform temperature throughout the product. The mass of each of these elements is considered in the mass model of the buffer tank.

The dimensions of the high and low pressure evaporation chambers are determined by considering the droplet carry-over phenomenon inside the chambers due to the flow of steam. Most of the droplets are generated by the sudden expansion of the liquid phase at the inlet of the chambers. The minimal diameter of the droplets is assessed assuming thermodynamic equilibrium between the liquid and vapour phases at the surface of the liquid inside the chambers. Minimizing droplet diameter is the most unfavourable case regarding the system dimensioning. Since the droplet generation phenomenon is extremely complex and difficult to understand, we use this minimal diameter to compute the evaporation chamber diameters and design the mist eliminator. Therefore, the droplet diameter is derived from the surface tension of the product and the pressure gradient between the saturation pressure of the product entering the chamber and the vapour inside the chamber:

$$d_{dr} = \sqrt{\frac{4.\sigma_s}{P_{sat}(T_{pi}) - P_{sat}(T_v)}} \quad \text{(III.2.2)}$$

Most of the droplets must fall to the bottom of the chambers to be extracted with the liquid phase. Therefore, the diameter of the chambers is calculated by considering the application of Newton's second law to the equilibrium between the Earth's gravity, buoyancy and friction force applied to a droplet. This gives the following equation, taking into account the properties of the vapour carrying the droplets out of the chamber and the gravity moving the droplets down to the bottom of the chamber:

$$d_{chb} = \sqrt{\frac{72 \cdot \mu_v \cdot q_v}{g \cdot \rho_v \cdot \pi \cdot d_{dr}^2 \cdot \left(\rho_v - \rho_p\right)}} \tag{III.2.3}$$

The thicknesses of the chambers are calculated using the European directives for the construction of pressure apparatus. The volumes and masses of the evaporation chambers are derived from these thicknesses and diameters. Finally, the dimensions of the float separating the evaporation stages are determined from the balance between the forces applied to this component. These forces result from the pressure difference between the two evaporation stages, buoyancy forces due to the accumulation of cooled product in the bottom of the high pressure stage and its weight.

The masses of piping, condensers and holding structure are assessed from manufacturers' data. The mass of the entire system is then determined from the masses of all the parts, including the pumps, valves and sensors for which masses are provided by suppliers.

Defining the main characteristics of some of the components is equivalent to a dimensioning process. These components are purchased and their dimensions directly derive from some of their characteristics, such as the power and flow rate of a pump. As an illustration, the vacuum pump electrical power is calculated from the downstream to upstream pressure gradient (close to 1bar), volume flow rate and efficiency:

$$\mathcal{P}_{vacp} = \frac{Qv_{vacp} \cdot \left(P_f - P_i\right)}{\eta_{vacp}} \tag{III.2.4}$$

The volume flow rate is assessed from the volume of the system (flash evaporator), initial and final concentration of air inside this volume and expected discharge time, which is 10 minutes:

$$Qv_{vacp} = \frac{V_{sys} \cdot \left(1 - W_{ai}\right)}{t_{vac} \cdot W_{ai} \cdot W_{af} \cdot \ln\left(1 - W_{ai}\right)}, \quad W_{ai} = 0.98, \quad W_{af} = 0.01, \quad t_{vac} = 600\text{ s} \tag{III.2.5}$$

III.3 Environmental model

Facing with the emergence of environmental constraints in the agricultural field, the environmental impact of the flash evaporation process must be also considered as a design objective. Two main trends have emerged from studies on the environmental impact of systems. Those centred on post-evaluation of emissions in order to highlight solutions for improving the environmental efficiency of systems a posteriori and those oriented towards knowledge management for eco-design. Several aspects are considered through eco-design analysis [Sweatman 1996]:

- Optimization of energy efficiency and reduction of impacts,
- Optimization of production techniques,
- Selection of materials with lower impacts,
- Reduction of the amount of material used,
- Optimization of the system packaging, transportation and distribution,
- Optimization of the life cycle,
- Optimization of the end-of-life and recycling phases.

Since the environmental impact of the flash evaporation process is mainly due to its high consumption of energy, materials and fluids, the main aspects of eco-design considered in this study are concerned with the optimization of energy efficiency, reduction of impacts during the system functioning, optimization of production techniques and reduction of the amount of material used.

In this study, the material consumption of the system is mainly based on the amount of materials used for manufacturing the tank, that is to say, steel sheets for the shell and Rockwool for the insulation of the buffer tank. Since the dimensions of the tank are related to the operating conditions, material consumption modelling is also adapted to the evolution of those operating conditions. Based on the EcoIndicator99 methodology [Goedkoop 2000], the relative impact corresponding to one ton of steel is quantified and the related damages coefficients (environment, human health, resources) are derived.

$$\begin{aligned} &EI_{material} = \left(a_1 + a_2 + a_3\right) \cdot M_{sys} \\ &a_1 = 1.9 \text{ (environment)},\ a_2 = 13\,233 \text{ (human health)},\ a_3 = 2.3 \text{ (ressources)} \end{aligned} \qquad \text{(III.3.1)}$$

This score characterizes the environmental impact on resources, fuels and minerals of the manufacturing process and material recycling. Similarly, we evaluate the damages coefficients associated to the consumptions of 10kWh and 1m3 of water. Finally, a global score EI is derived from the impacts of material, energy and water consumptions.

$$\begin{aligned} &EI = EI_{material} + EI_{elec} + EI_{water} \\ &\text{with}, \\ &EI_{elec} = \left(b_1 + b_2 + b_3\right) \cdot C_{elec},\ \ b_1 = 0.145,\ b_2 = 0.0139,\ b_3 = 0.0271 \\ &EI_{water} = \left(c_1 + c_2 + c_3\right) \cdot C_{water},\ \ c_1 = 0.0187,\ c_2 = 0.00204\ ,\ c_3 = 0.00607 \end{aligned} \qquad \text{(III.3.2)}$$

The energy consumption calculation is based on the power required to supply the different pumps, mixer and fan. The water consumption corresponds to the volume of water used by the cooling tower to cool the water at the outlet of the LP condenser. The mass flow rate of coolant required for the high pressure condenser is higher than the low pressure one. Nevertheless, the required coolant inlet temperature is higher in the high pressure condenser than in the low pressure one, so the system is structured so that the heated outlet coolant flow of the low pressure condenser is sent to the inlet of the high pressure condenser where additional fresh coolant is added to reach the required flow rate of the LP condenser:

$$C_f = q_{cl\,LP} + q_{cl\,+HP} \qquad \text{(III.3.3)}$$

Mechanical draft cooling towers consume water in three major ways [Leeper 1981]. Evaporation rate (C_E) is approximately 1% of the water flow rate (C_f) per each 10°F (≈5.5°C) of the cooling range. Drift (C_D) is approximately 0.2% of the water flow rate, and refers to the water which leaves the cooling tower carried out with the exiting air. In order to prevent concentration of solid and chemical particles in the cooling water resulting from the evaporation, blowdown (C_B) is the volume of water removed from the system and replaced by fresh water. It is usually 20% of the evaporation rate.

$$\begin{aligned} &C_{elec} = \left(Power_{mixer} + Power_{fan} + \sum Power_{pumps}\right) \cdot t_{op} \\ &C_{water} = \left(C_E + C_D + C_B\right) \cdot t_{op} \end{aligned} \qquad \text{(III.3.4)}$$

The electrical consumption and water consumption are respectively expressed in kWh and m3/h. They are estimated over a period (t_{op}) of 20 years with an average operating time of 10 hours a day during 2 months (duration of the harvest period).

III.4 Economical model

The development of flash détente processes in the wine area is also hampered by the initial cost of investment. The economical analysis of the flash evaporator aims at modelling manufacturing costs (material purchase and forming) of tanks, and purchasing costs of other parts of the flash evaporation system (condensers, pumps, etc.). The global purchasing cost of the system is calculated by adding these manufacturing and purchasing costs for each part of the system.

Manufacturing costs of the buffer tank, evaporation chambers and purchasing costs of the condensers, piping and mist eliminator have been estimated from mass calculation and updated prices given by manufacturers. The purchasing cost of the system is calculated by adding together these manufacturing and purchasing costs for each part of the system. This total is then multiplied by the Lang factor (L_f) taking into account installation costs, transportation costs and various costs such as insurance [Rehfeldt 1997]. The resulting cost is the investment cost of the process:

$$\overline{\mathcal{C}}_{\text{inv}} = \mathcal{L}_{\text{f}} \cdot \left(\overline{\mathcal{C}}_{\text{chb}} + \overline{\mathcal{C}}_{\text{pumps}} + \overline{\mathcal{C}}_{\text{cnd}} + \overline{\mathcal{C}}_{\text{divers}} \right) \quad \text{with} \quad \text{L}_{\text{f}} = 3.1 \tag{III.4.1}$$

and,

$$\begin{aligned} \overline{\mathcal{C}}_{\text{chb}} &= \mathcal{C}_{\text{chbHP}} + \mathcal{C}_{\text{chbBP}} + \mathcal{C}_{\text{chbbuf}} + \mathcal{C}_{\text{float}} \\ \overline{\mathcal{C}}_{\text{pum}} &= \mathcal{C}_{\text{vacp}} + \mathcal{C}_{\text{extp}} + \mathcal{C}_{\text{cdstp}} + \mathcal{C}_{\text{tankp}} \\ \overline{\mathcal{C}}_{\text{cnd}} &= \mathcal{C}_{\text{cndHP}} + \mathcal{C}_{\text{cndLP}} \\ \overline{\mathcal{C}}_{\text{div}} &= \mathcal{C}_{\text{mist}} + \mathcal{C}_{\text{tubes}} + \mathcal{C}_{\text{struct}} \end{aligned} \tag{III.4.2}$$

Some of these costs are related to components (pumps, condensers and mist eliminator) purchased and installed in the system without any modification, whereas other components must be dimensioned and manufactured from basic materials (sheets, tubes, linking elements). Costs of purchased components are calculated from some of their overall characteristics. For instance, high and low condensers are thermal exchangers (plate condensers) whose costs are assessed from their exchange surface area. Thus:

$$\mathcal{C}_{\text{cnd}}(\text{A}) = 3789 \cdot \text{A}^{0.4678} \tag{III.4.3}$$

In the same way, the main overall dimension taken into account in calculating the cost of a mist eliminator is its vapour inlet section. The cost of waved strip droplet separators is derived from:

$$\mathcal{C}_{\text{mist}}(\text{S}) = 3448 \cdot \text{S}^{0,7817} \tag{III.4.4}$$

The main overall characteristic that is relevant for assessing the purchase costs of the pumps is their electric power. The purchase cost of the liquid ring vacuum pump, for instance, is calculated from:

$$\mathcal{C}_{\text{vacp}}(\mathcal{P}) = 5779 \cdot \mathcal{P} + 228 \tag{III.4.5}$$

Other purchased components such as the tubes connecting the tank, chambers and pumps of the flash evaporator are computed from their mass. The cost of steel tubes is estimated through:

$$\mathcal{C}_{\text{tube}}(\text{M}) = 4.9521 \cdot \text{M} + 0.2482 \tag{III.4.6}$$

Some other components are more specific to the evaporator flash and must be dimensioned and design for this particular application. Therefore, we use models of material and manufacturing costs. For instance, the buffer tank is made of a rolled steel sheet, a layer of Rockwool and a thin layer of aluminium. The costs of the metals are derived from their mass:

$$\mathcal{C}_{\mathrm{sheet}}^{\mathrm{steel}}\left(\mathrm{M}\right)=4.745\cdot\mathrm{M}+4.7715,\quad \mathcal{C}_{\mathrm{sheet}}^{\mathrm{alu}}\left(\mathrm{M}\right)=20.09\cdot\mathrm{M}^{0.6605} \tag{III.4.7}$$

whereas the cost of the Rockwool layer is derived from its thickness (e) and its surface (S),

$$\mathcal{C}_{\mathrm{rockwool}}\left(\mathrm{e,S}\right)=\left(30.44\cdot\mathrm{e}+8.87\right)\cdot\mathrm{S} \tag{III.4.8}$$

From the investment cost of the system, we derive the maintenance cost which is assessed as 2.5% of the investment cost, and the total discounting cost of the system which is estimated from the coefficient of discounting evaluated over a period of twenty years:

$$\overline{\mathcal{C}}_{\mathrm{maint}}=0.025\cdot\overline{\mathcal{C}}_{\mathrm{inv}}$$

$$\overline{\mathcal{C}}_{\mathrm{disc}}=\left(\mathrm{a}+0.025\right)\cdot\overline{\mathcal{C}}_{\mathrm{inv}},\quad \mathrm{a}=\frac{1}{\left(1+\mathrm{r}\right)^{\mathrm{n}}},\quad \mathrm{n}=20 \tag{III.4.8}$$

The overall operating cost ($\overline{\mathrm{C}}_{\mathrm{op}}$) over this period is derived from the electricity and water consumption costs calculated according to the peak charges applied by EDF (0.1275€/kWh) and the average price of water distributed in France (3.39€/m^3) in 2011.

Finally, the overall cost of ownership ($\overline{\mathrm{C}}_{\mathrm{total}}$) is calculated by adding the overall costs of discounting and the operating cost of the system:

$$\overline{\mathcal{C}}_{\mathrm{tot}}=\overline{\mathcal{C}}_{\mathrm{inv}}+\overline{\mathcal{C}}_{\mathrm{op}} \tag{III.4.9}$$