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Mohamad Tout

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POUR OBTENIR LE GRADE DE
DOCTEUR DE
L'UNIVERSITÉ DE BORDEAUX

ÉCOLE DOCTORALE : Sciences Physiques pour l'Ingénieur (SPI)

SPÉCIALITÉ : Mécanique

Par Mohamad TOUT

**Conception optimisée de systèmes énergétiques
embarqués**

Sous la direction de : Patrick SEBASTIAN
(co-directeur : Jérôme PAILHES)

Soutenue le 03 décembre 2020

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﴿ اِقْرَأْ بِاسْمِ رَبِّكَ الَّذِي خَلَقَ ﴾

سورة العلق الآية ١

﴿ *Recite in the name of your Lord who created -* ﴾

Holy Qur'an, surat Al-Alaq 96:1

﴿ *Lis, au nom de ton Seigneur qui a créé,* ﴾

Le saint Quoran, sourate Al-Alaq 96:1

﴿ وَقُلْ رَبِّ زِدْنِي عِلْمًا ﴾

سورة طه الآية ١١٤

﴿ *and say, "My Lord, increase me in knowledge."* ﴾

Holy Qur'an, surat Taha 20:114

﴿ *Et dis: «O mon Seigneur, accroît mes connaissances!»* ﴾

Le saint Quoran, sourate Taha 20:114

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Résumé

La prise de décision est une étape difficile et importante dans le processus de conception. Elle vise à guider les concepteurs dans le choix des solutions de conception entre de nombreuses alternatives. Un processus spécifique, dérivé de la combinaison entre l'ingénierie des systèmes basés sur les modèles (MBSE) et l'ontologie de la morphogenèse, de l'observation, de l'interprétation, de l'agrégation (MOIA), et appliqué aux systèmes embarqués sur les véhicules, est présenté dans ce manuscrit afin de trouver la solution optimale qui répond à plusieurs objectifs demandés. Ce processus est basé sur un algorithme d'optimisation, couplant des modèles de comportements physiques et des préférences des concepteurs. Il intègre un algorithme d'apprentissage machine afin de générer des modèles de simulation réduits fonctionnant en temps réel. En utilisant ces modèles de simulation, le temps de calcul diminue. Cela améliore le processus décisionnel et introduit un processus d'optimisation dynamique qui repose sur une vision dynamique des spécifications, des scénarios, des besoins et des préférences des clients. Cette méthode est appliquée pour optimiser le groupe motopropulseur d'un véhicule électrique, qui comprend la batterie, l'onduleur, le moteur électrique et la boîte de vitesses, répondant à trois objectifs majeurs : autonomie, performance et coût.

En outre, nous développons un démonstrateur d'interface homme-machine pour le cas de conception du groupe motopropulseur d'un véhicule électrique. Cette interface représente le cadre d'optimisation de la conception à l'aide de MOIA qui fournit un moyen pratique de structurer le problème de conception. Elle est considérée comme une démonstration de concept d'un outil interactif où les différents acteurs participant au processus de conception peuvent vérifier immédiatement l'évolution du problème de conception et les conséquences de leurs décisions.

De plus, nous évaluons à travers des sessions de travail l'acceptabilité des différentes techniques d'interprétation et d'agrégation utilisées dans la méthode MOIA. Cette évaluation conduit à une meilleure compréhension de l'environnement industriel du processus de décision dans les phases de conception. Enfin, nous visons à développer un outil d'aide à la décision qui aide les décideurs à négocier des solutions probablement optimales et acceptables pour eux dans les phases de conception préliminaire. Cet outil est considéré comme un outil collaboratif visant à minimiser les échanges itératifs entre les différents acteurs participant au processus de conception.

Mots clés : Ontologie MOIA, MBSE, Optimisation, Prise de décision, Aide à la décision, Optimalité et acceptabilité.

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Abstract

Decision-making is a difficult and important step in the design process. It aims at guiding designers in the selection of design solutions between numerous alternatives. A specific process, derived from the combination between Model Based Systems Engineering (MBSE) and Morphogenesis, Observation, Interpretation, Aggregation (MOIA) ontology, and applied to vehicle embedded systems, is presented in this manuscript in order to find the optimal solution that responds to several demanded objectives. This process is based on an optimization algorithm, coupling models of both physical behaviors and designers' preferences. It integrates a machine-learning algorithm in order to generate reduced simulation models operating in real-time mode. By using these simulation models, the computation time decreases. This improves the decision-making process and introduces a dynamic optimization process that lies on a dynamic vision of specifications, scenarios, client needs and preferences. This method is applied to optimize the powertrain of an electric vehicle, which includes battery, inverter, electric motor and gearbox, responding to three major objectives: autonomy, performance and cost.

In addition, we develop a one-page user interface for the electric vehicle powertrain design case. This interface represents the design optimization framework using MOIA which provides a convenient way to structure the design problem. It is regarded as a proof of concept of an interactive tool where the different actors participating in the design process can check immediately the evolution of the design problem and the consequences of their decisions.

Moreover, we evaluate through work sessions the acceptability of the different techniques of interpretation and aggregation used in the MOIA method. This assessment leads to a better understanding of the industrial environment of the decision-making process in the design phases. We finally aim to develop a decision-support tool that helps decision-makers to negotiate solutions that are probably optimal and acceptable for them in the preliminary design phases. This tool is considered as a collaborative tool aims at minimizing the iterative exchanges between the different actors participating in the design process.

Keywords: MOIA ontology, MBSE, Optimization, Decision-making, Decision-support, Optimality and Acceptability.

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Chapter 1. General introduction

1.1. Research motivations:

1.1.1. General context

The competitiveness of a company relies on the mastery of the design and/or supervision processes of the systems as they are the most critical and complex processes of the Product Development Process (PDP). Design is one of the most critical processes in the PDP because:

- It is a phase of innovation where ideas and/or stakeholders' needs are transformed (formulated) giving rise to several decision-making choices; the misunderstanding and poor formulation of those needs at the design phase will result in a product that is different from the one requested. Yannou mentioned that the company must be efficient in design in order to innovate effectively [Yannou et al. 2008]. Indeed, innovation implies the use of new solutions and not the reuse of existing solutions. The effective evaluation of these new solutions in the preliminary phases requires an adapted approach based on numerical simulation and decision-making in a multi-objective context.
- It integrates, at early stages, all the constraints of the product life cycle [Sohlenius 1992] and defines the physical, esthetical and functional aspects of the final product. Therefore, the final product depends on the decision-making choices taken into

consideration; errors introduced in this phase will have a major impact on the final product (the product does not perform the function it was intended to perform, or it has a different shape than expected, etc.).

- It is a phase of knowledge [Tomiyama et al. 2009] and decision-making [Berliner and Brimson 1988].

1.1.2. Design process challenges

Design problems are ill-defined or ill-structured problems [Simon 1973] and fit the definition of wicked problems [Giachetti 2016]. Ill-defined problems do not have clear, defined goals or a clear path to solve the problem [Nazidizaji et al. 2015]. Rittel describes ten characteristics of wicked problems; the main points, as presented in [Rittel and Webber 1973], are:

1. There is no definitive formulation of a wicked problem: every specification of the problem is a specification of the direction in which a treatment is considered.
2. There is no stopping rule: The planner terminates work for considerations that are external to the problem like running out of time, or money, or patience. He finally says, "That's good enough," or "This is the best I can do within the limitations of the project," or "I like this solution," etc.
3. Solutions are not true-or-false, but good-or-bad: The assessments of proposed solutions are expressed as "good" or "bad" or, more likely, as "better or worse" or "satisfying" or "good enough".

Several problems can arise during the execution of the design process; most of them are related to the loss of information and waste of time. Below, some of the most repetitive problems in an industrial context:

- Quality of decisions taken: Schonberger points out that 85% of the problems encountered in the production process are related to decisions taken in the design phase [Schonberger 1982]. Berliner and Brimson show that 85% of the decisions taken in the design phase impact more than 80% of the final cost of the product [Berliner and Brimson 1988; Gautier and Giard 2000]. Backtracking, which results in additional cost and production time delay, is due to poor decisions and is significantly reduced if the design phase is well mastered and if operational considerations are taken into account early in the PDP, i.e. at the level of the design process. Indeed, the cost of a correction made at the production phase is multiplied by 500 to 1000, compared to only 3 to 6 times in the design phase [INCOSE 2015] (See Figure 1).
- Waste of time in decision-making: in a company, with a hierarchical structure, designers are not always technically capable of making the right decisions in a very short period due to the multi-level approval process. The decision is not made instantaneously because it involves several participants, and is usually dependent on several decisions that require cumulative additional time.
- Waste of time in objectives clarification: design process is a collaborative process that implicates several multidisciplinary teams, often geographically dispersed which introduces non-negligible time during their exchanges. Moreover, iterative exchanges between designers and clients constantly improve and clarify the clients' needs. These

exchanges between actors increase the complexity and difficulty of the design process, which consumes both time and cost throughout the project.

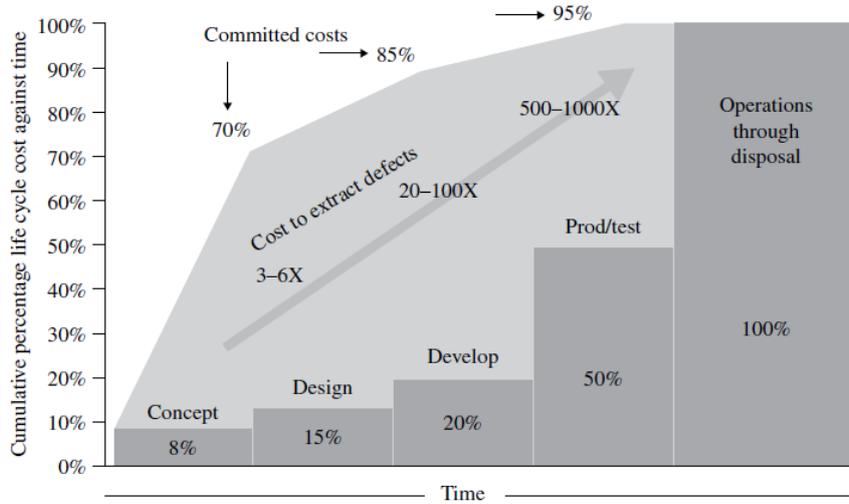


Figure 1: Committed life cycle cost against time [INCOSE 2015]

In addition, in the context of the design process, the emergence of new technologies presents significant difficulties to component manufacturers. During the preliminary design phases, the selection process, often based on existing solutions reuse, can drastically eliminate any candidate solutions that can have significant advantages compared to those selected. Re-use limits risks but stifles innovation.

For this reason, numerical solution based decision-making is recommended as the final step in the design process which focuses on the most interesting technologies and techniques. Many possibilities, derived from the design variables domains, are explored at this stage from numerical simulation and optimization techniques in order to select the most relevant solutions. The fastest is the step of numerical simulation the most efficient is the optimization process and therefore the design process.

1.2. Research Objectives

Electrification, automation and connectivity are the main trends in the automotive market. All three interconnected, they are essential to the success of car manufacturers and their suppliers. Modern vehicles integrate large amounts of electronic devices with sophisticated software - featuring about 100 million lines of programming code [Habeck et al. 2014]- that increases vehicle system design complexity. One of the ways to mitigate the problems associated with increased systems complexity is to use the most efficient systems engineering methods in order to ensure that products are delivered on time, on budget and in good quality.

Moreover, vehicles' embedded systems are constantly changing to adapt to new stakeholders' needs like the emergence of new technologies, or the evolution of existing technologies or components. These developments affect the design of all the vehicles components and in

particular the powertrain system. Design objectives of powertrain systems are related to many domains like energy consumption, noise-level control, maintenance, vehicle safety, etc.

The choice made for the architecture of the propulsion system and the available component technologies interact through the overall design objectives and constraints of the vehicle. For example, the choice of a voluminous component in a vehicle will leave less space available for the other components (Packaging constraint). Generally speaking, design objectives and constraints in correspondence with a vehicle interact through the notion of relative importance (Criticality). A safety objective, for example, is probably much less flexible, but is not necessarily more critical, than an energy performance objective. Because design is a human activity, the preference choices will depend on the points of view of actors regarding design objectives. A point of view translates to a decision about the criticality, priority, flexibility, importance level of design objectives; the latter terms will be detailed in the following manuscript.

In order to design efficiently, the steps of the design process must be clarified. In an industrial research department, the method of analysis of the information, delivered by the client for example, is ambiguous and obviously not standardized. In order to organize the design problem in an efficient way, several points must be clarified about the design process. Below some examples:

- How designers deal with the information in the specifications?
- How actors exchange and negotiate about the specifications, criteria, objectives, etc.?
- How the different points of view of actors are manipulated? How are all these points of view treated? Is there a real process of collaboration between the actors?

The answers to these questions may vary from one company, team or activity to another. It is therefore important to prepare a dedicated questionnaire to better understand the work environment and how the information are analyzed before proceeding into design process. Moreover, such a questionnaire can be a preliminary step in the creation of an acceptable methodology within industrial research departments.

The research objectives addressed in this thesis are discussed through the following points. Refer to Table 1 to see in which chapter each point is discussed.

1. In the design process, designers have to make decisions as quickly as possible. In addition, they must identify and take into account modifications of stakeholders' needs. It must be possible to integrate the continual evolution of the problem. It is a question of agility in the design process.
2. Design is an intermediate phase between stakeholders' needs and the company solution(s) proposed for product or service. Generally, those needs are decomposed in many requirements; this demand is seen as a Multi-Disciplinary and Multi-Objective problem to be solved. During the preliminary design phases, between the phase of the research of concepts and the detailed design phase, it is necessary to study the behavior of the system and verify its feasibility.

3. The modeling of the design optimization process. It is necessary to integrate a robust and low-cost methodology into the classical systems engineering process by using a digital approach based on simulation and minimizing the use of physical prototypes. The latter must be adapted for industrial perspectives. Therefore, there is a need to integrate any proposed tool or methodology into industrial processes.
4. From a practical point of view, in order to explore a large design space in the preliminary design phases, which probably allows the identification of relevant design solutions, the used tool must respond quickly to the question of feasibility of solutions. The problem here stems from the rapidity of simulation models which have high levels of accuracy and then require non-negligible computation time. Therefore, we are going to set up substitution models which have lower levels of accuracy but run faster compared to original simulation models.
5. For industrial perspective, apply the proposed methodology to a case study in order to prove its feasibility, and prove the importance of using such a methodology in the preliminary design phases. An application on electric vehicle powertrain will be treated.
6. The investigation of the acceptability and usability of the proposed methodology of a decision-support tool.

1.3. Structure of the thesis

The structure of the thesis is as follows:

- Chapter 2 provides a general research context. It provides a review of design decision-support methods, especially the Morphogenesis Observation Interpretation and Aggregation (MOIA) method, including tools for formalizing preferences and aggregating them into a single value that can be used in optimization loops.
- Chapter 3 introduces the global design framework of Model Based Systems Engineering (MBSE) and proposes the existing relation between MBSE and MOIA. First, it structures the numeric optimization process based on the information derived from the MBSE approach. Second, it mentions the importance of using reduced models instead of the heavy observation models often involved in Multi-Objective Optimization (MOO) problems.
- Chapter 4 discusses the optimization process which integrates Extreme Learning Machine (ELM) for the optimization of electric vehicle powertrain. In addition, a user interface will be presented to mention the advantages of using such an approach in the preliminary design phases. This interface also aims at supporting the decision-making process.
- Chapter 5 introduces the concepts of optimality and acceptability arising from human judgement in the design process through decision-making. Through work sessions, we investigate the choices of participants for interpretation and aggregation steps.

Table 1 presents the details of the structure of the research by relating research objectives to chapters. Some comments are added to clarify the tasks of chapters.

Research objectives	Chapters	Comments
1	Chapter 2	Introduction of MOIA ontology which adds agility to design process
2	Chapter 2	The possibility of using MOIA ontology as a multi-objective optimization tool
3	Chapter 3	The integration of MOIA ontology into the systems engineering process
4	Chapter 3	A proposition to use ELM to generate substitution models
5	Chapter 4	Application on electric vehicle powertrain. Presentation of the user interface.
6	Chapter 5	Investigation, through work sessions and questionnaire, the acceptability of using MOIA ontology

Table 1: Structure of the thesis

Chapter 2. Design: State of the art

2.1. Introduction

2.1.1. Design science

Design is a fundamental activity directed toward the fulfilment of human needs. The activity of design, which is called Designing by Matsuoka [Matsuoka 2010], can be considered as the activity of building a set of specifications, and their evaluations, for the conception of a product or system. It involves creativity and decision-making. Creativity means the generation of alternative solutions and decision-making is the selection among these alternatives.

Hubka and Eder introduced Design Science *as a system of logically related knowledge, which should contain and organize the complete knowledge about and for designing* [Hubka and Eder 1996]. Matsuoka summarized the framework of Design Science by representing the design knowledge and designing (see Figure 2) [Matsuoka 2010]. Design knowledge consists of general objective knowledge and special subjective knowledge. Objective knowledge holds generalities that are independent of human's preferences, while subjective knowledge depends on human's preferences, opinions and interpretations. Designing is defined as an action to be pursued based on design knowledge. It is represented as a scale containing four layers: design practice, design method, design methodology, and design theory. Design theory expresses the generality of phenomena found in every design. Design methodology identifies the principles of how to apply a design method while a design method signifies specific procedures to

integrate, analyze, or evaluate the phenomenon of a design object. Applying a design method produces new design ideas based on the designer's previous knowledge. Design practice consists of actual practices conducted in various design domains like product design, architectural design, graphic design, etc. Compared to the other layers, design practice can be defined as the most specific and detailed layer [Sakae et al. 2016]. In the four layers scheme, specialty and dependence on the design object increase as the layer proceeds from a lower layer to a higher layer. In contrast, generality and abstractness increase as the design proceeds from the upper layer to the lower layer [Matsuoka 2010].

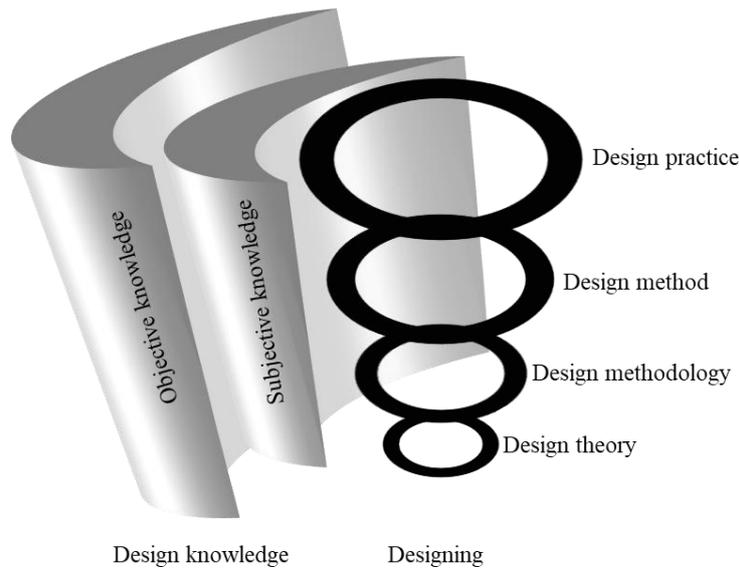


Figure 2: Framework of Design Science [Matsuoka 2010]

It may be noted that design theory considers the relationship between design elements which can be classified into two types: psychological design elements and physical design elements. The psychological design elements express the concept of a value that each user carries or a functionality and an image of a design object. The physical design elements consist of a measurable physical quantity and a physical property [Sakae et al. 2016]. For example, in the case of designing a vehicle, comfort and sense of fitting are defined as psychological design elements, whereas performance and material resistance are classified as physical design elements. Typically, in an industrial context, in the preliminary design phases, designers often interactively deal with psychological elements and physical elements, while in the late design phases, designers unidirectionally deal with physical elements [Sakae et al. 2018].

2.1.2. Design Theory and Methodology (DTM)

As an example of early Design Science, in 1946 Altshuller has introduced the Theory of Inventive Problem Solving, known as TRIZ (Teoriya Resheniya Izobretatelskikh Zadatch in Russian) [Altshuller and Altov 1996]. This theory comprises a set of sequential steps, invention support methods and tools that led to innovations in the fields of engineering [Altshuller 1999]; therefore, the TRIZ decision-making process is based on filtering non-acceptable solutions with a non-iterative process. In 1960, Herbert Simon also started a new scientific approach of design

study by considering decision-making in design through an iterative process and not an event, aiming for rational process [Simon 1960].

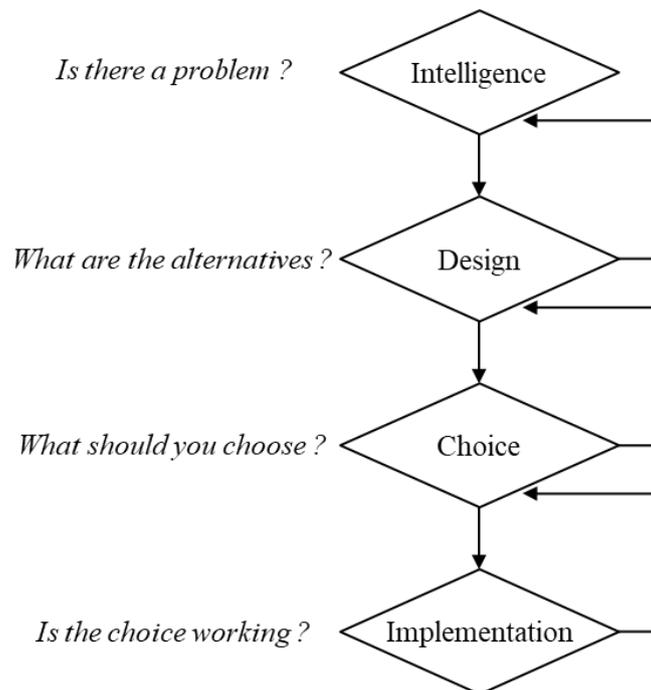


Figure 3: The decision process by Simon [Tomiyama et al. 2009]

In fact, the essence of rationality lies in the loops of the process, in the iterations and feedbacks, which must be numerous, between the three phases: Intelligence (problem finding) and Design and Choice (problem solving). Figure 3 shows Simon's proposal for this iterative process as presented in [Tomiyama et al. 2009]. Since then, many design theories and methodologies have been proposed and developed, and the field of Design Theory and Methodology (DTM), which is a part of Design Science from Matsuoka point of view, has been intensively studied.

DTM is a rich collection of advances and knowledge resulting from studies and experiments on design processes and activities. Several classifications of DTM have been proposed by researchers [Finger and Dixon 1989a, 1989b; Tomiyama 1997]. Table 2 presents an adapted classification of DTM based on the Tomiyama classification. This classification is based on the scope of applicability (concrete/abstract) and level of abstraction (general/individual) of DTM. With the exception of abstract design theories, most of these DTMs are either a generalisation of design methods, and therefore may be applicable to a wide range of products, or computational methods that are only applicable to a specific class of products.

Within the abstract and general category, the most famous theory is the General Design Theory (GDT) which is a theory of design knowledge developed by Yoshikawa [Yoshikawa 1981; Yoshikawa and Uehara 1985; Tomiyama and Yoshikawa 1986; Reich 1995]. The GDT theory is in line with 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 through mapping between the functional requirements (FRs) in the functional domain and the design parameters (DPs) of the physical domain, through proper selection of the DPs that satisfy the FRs*".

	General	Individual
Abstract	<i>Design theory</i> <ul style="list-style-type: none"> - General Design Theory (GDT) [Yoshikawa 1981; Yoshikawa and Uehara 1985], - Universal Design Theory (UDT) [Lossack and Grabowski 2000], - Abstract Design Theory (ADT) [Kakuda and Kikuchi 2001] - Concept-Knowledge (C-K) Design Theory [Hatchuel and Weil 2009] 	<i>Math-based methods</i> <ul style="list-style-type: none"> - Axiomatic Design, - Optimization, - Taguchi method [Taguchi et al. 2005], - Computer programs
Concrete	<i>Design methodology</i> <ul style="list-style-type: none"> - System design [Hansen 1974], - TRIZ [Altshuller 1984], - Mechanical design process [Ullman 1992], - Integrated Product Development [Andreasen 1994], - Design science [Hubka and Eder 1996], - Design Structure Matrix (DSM) [Browning 2001], - Emergent Synthesis [Ueda et al. 2001], - Contact and Channel Model (C&CM) [Albers et al. 2003], - Product design and development [Ulrich 2003], - Adaptable Design [Gu et al. 2004], - Characteristics-Properties Modelling (CPM) [Weber 2008], - Product-Service System (PSS) [Maussang et al. 2009], - Engineering design [Pahl and Beitz 2013], - User Experience-based (UX) design [Gothelf 2013], - Radical Innovation Design (RID) [Yannou 2015] <i>Methodology to achieve concrete goals</i> <ul style="list-style-type: none"> - Axiomatic Design (AD) [Suh 1990], - Total Design of Pugh [Pugh 1991], - Failure Mode and Effects Analysis (FMEA) [McDermott et al. 1996], - Design Decision-Making Methods [Lewis et al. 2006], - Design for X (DfX) [Eastman 2012] <i>Process methodologies</i> <ul style="list-style-type: none"> - Concurrent Engineering [Sohlenius 1992], - Big Data Team [Saltz and Shamshurin 2016] 	<i>Design methods</i>

Table 2: Classification of DTM

However, design research cannot be limited to DTM [Finger and Dixon 1989a, 1989b; Horvath 2004]. Many other practices and techniques, such as the so-called Toyota Product Development System, are used in the industry [Sobek II et al. 1999; Morgan and Liker 2006]. Nowadays, in the industrial areas, V-model of Systems Engineering (SE) (see 3.2.2) became the standard approach, especially when dealing with multidisciplinary product development.

2.1.3. Function-Behavior-Structure (FBS) ontology

From the GDT framework, descriptive models of design processes have been derived. In 1990, Gero proposed his design ontology [Gero 1990; Gero and Rosenman 1990]. This design ontology extends GDT by taking into account the interactions between the designer and its environment. Gero's aimed at unifying the whole design approaches by defining the *being* of design, the *invariant* of design or the *ontology* of design leading to a robust process. Gero's design ontology is named FBS and describes three different concepts related to system design

which are the Function (F), which corresponds to the purposes of the design being designed, Behavior (B), which are the attributes derivable from structure or expected structure, and Structure (S), which represents the elements of design and their relationships [Vermaas and Dorst 2007]. Figure 4 shows the eight elementary design steps of the FBS framework as described in [Gero and Kannengiesser 2004].

The term ontology comes from the Greek *ontos* meaning *being*, and *logos* meaning *word* [Breitman et al. 2007]. It is therefore a speech about becoming, existence and reality, in general. It has appeared in recent decades in the field of cognitive sciences and computer science. An ontology can take different forms, but it will necessarily include a vocabulary of terms and a specification of their meaning. Gruber defined ontology as an explicit specification of a conceptualization [Gruber 1993] which means that an ontology is a way of showing the properties and their relations, in a subject area, by defining a set of concepts and categories that represent the subject. According to Merrill “*ontological modeling in science is more fundamental than mathematical modeling since its result is the basic structure to which mathematical modeling is applied and on which theories are built*” [Merrill 2011].

The FBS is considered as the *ontos* or the fundamentals of design since each system has structure and functions to achieve. According to Gero, there is no direct connection between function and structure. In fact, through experience, designers link function (F) to expected behavior (B_e) by the formulation step (1). Then, the expected behavior is transformed into a solution structure (S) by a synthesis step (2). From this solution structure, an actual behavior (B_s) is derived by the analysis step (3). This actual behavior is evaluated (4) and compared to the desired behavior. If the evaluation is satisfactory, a design description D is documented (5) for manufacturing the product. Otherwise, designers have to iterate with previous steps in the sequence in order to reformulate (6, 7, and 8) structure variables, behavior variables and function variables.

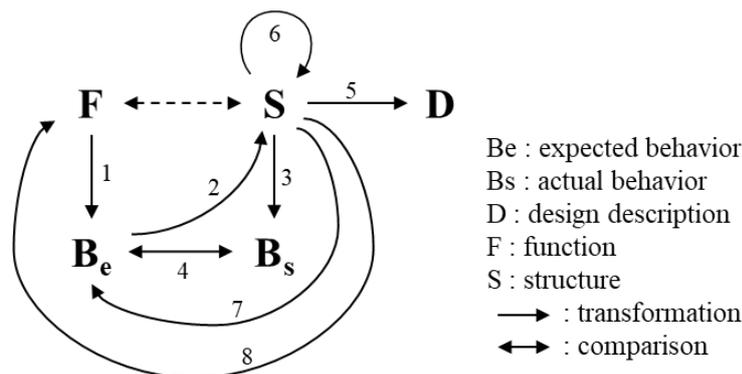


Figure 4: Gero's FBS ontology

The FBS ontology has been declined in processes (like OIA, discussed in 2.2.2.1) used in several design disciplines including engineering design [Collignan 2011; Quirante 2012], architectural design [Fontenelle and Bastos 2014] and computer aided design [Shih et al. 2017]. Yannou maps his Radical Innovation Design (RID) [Yannou 2015], which is a methodology supporting innovative design purposes, in the FBS framework [Yannou et al. 2018]. The FBS ontology has also been used to integrate and to analyze work situations during design phases [Sadeghi et al. 2017].

2.2. Decision making in engineering design process

Engineering design is a process that engineers use to identify and solve problems. This process is a difficult and mandatory activity of the conception of complex products. Engineering design uses widely scientific principles and multi-physics domain interactions for simulation. The goal of the process is mainly to find at least one acceptable solution that responds to the multiple objectives demanded by the stakeholders of the design project, whereas candidate solutions belong to the set of all conceivable solutions. Candidate solutions are extremely numerous because of the combinatorial character of the design problem in nature.

Decision-making in selection between alternatives is then a crucial aspect of the design process. According to several researchers in design decision-making methods, the principal difficulty in design lies in the selection among design alternatives and not in the generation of alternatives [Okudan and Tauhid 2008; Tomiyama et al. 2009]. This difficulty is principally related to the opposite relationship between the numerous design objectives and the inherent uncertainties in the design process [Pahl and Beitz 1996].

Design problems are always Multi-Objective Optimization (MOO) problems. Theoretically, MOO problems have many solutions that respect constraints. Generally, the main issues to choose one solution in MOO are related to the accurate modelling of decision-makers' judgments (preferences and priorities). As presented in Table 3, most MOO methodologies and techniques can be classified according to *a priori*, *interactive* or *a posteriori* preferences modelling [Korhonen et al. 1992; Marler and Arora 2004].

Articulation of preferences	Methodologies and techniques
<i>A priori</i> formulation	<ul style="list-style-type: none"> - Weighted Global Criterion method and its extensions (including utopia point method) [Le Yu 1974; Wierzbicki 1982; Vira and Haimes 1983; Miettinen 1999; Chankong and Haimes 2008; Zeleny 2012] - Weighted Sum method [Zadeh 1963; Vira and Haimes 1983; Koski 1985; Steuer 1986; Athan and Papalambros 1996; Das and Dennis 1997] - Weighted Min-Max method (or Tchebycheff method) [Miettinen 1999; Messac et al. 2000a; Messac et al. 2000b] - Weighted Product method [Bridgman 1922] - Exponential Weighted method [Athan and Papalambros 1996] - Lexicographic method [Stadler 1988] - Goal Programming method [Charnes and Cooper 1977; Tamiz et al. 1998] - Bounded objective method (ϵ-constraint approach) [Hwang and Masud 1979] - Physical Programming [Messac 1996; Messac and Ismail-Yahaya 2002]
<i>Interactive</i> formulation	<ul style="list-style-type: none"> - Bi-reference Procedure [Michalowski and Szapiro 1992] - Light Beam Search [Jaszkiewicz and Słowiński 1999] - Visual Approach [Korhonen and Laakso 1986] - Implicit Value Function [Geoffrion et al. 1972; Zionts and Wallenius 1976; Steuer and Choo 1983]
<i>A posteriori</i> formulation	<ul style="list-style-type: none"> - Physical Programming [Messac and Ismail-Yahaya 2002] - Normal Boundary Intersection (NBI) method [Das and Dennis 1998] - Normal Constraint (NC) method [Messac et al. 2003]

Table 3 : Classification of MOO methodologies and techniques

The *a priori* articulation of preferences makes it possible to solve the problem by integrating the modeling of the decision-makers' judgments into the optimization process. The *interactive* approach articulates the decision-makers' judgments during the optimization process, whereas the *a posteriori* approach integrates the decision-makers' judgments only after the generation of a set of effective solutions like Pareto frontier which is an illustration of the Pareto optimality concept. Pareto's optimality is discussed in 2.2.1.

In *a priori* formulation, preferences are introduced at different levels of the problem formulation, from the definition of objective functions to the definition of a global objective value. These new constraints reduce the number of degrees of freedom of the multi-objective problem to a single-objective problem. In addition, we aim at developing a decision-support tool which is an interactive design tool (see 4.7), where decision-makers are able to modify their preferences in order to see the consequences of their decisions directly and in an online mode. Therefore, the research work presented in this thesis falls within the scope of the *a priori* and *interactive* formulations.

2.2.1. Pareto optimality

Some problems can be formulated to correspond to a maximization (or minimization) problem of the observation variables, vector Y . In a single-objective maximization problem, the optimal solution would be the one that maximizes the single observation variable. In a multi-objective problem, the concept of optimality is therefore replaced by that of Pareto's optimality.

In the case of maximization problems, a candidate solution X^* is a non-dominated solution if there is no other solution X such as $Y \geq Y^*$ i.e. there is not at least one observation variable such as $y_i > y_i^*$. All non-dominated solutions define the Pareto frontier in the objective space. Pareto-optimal is the set of non-dominated solutions included within the feasible design space.

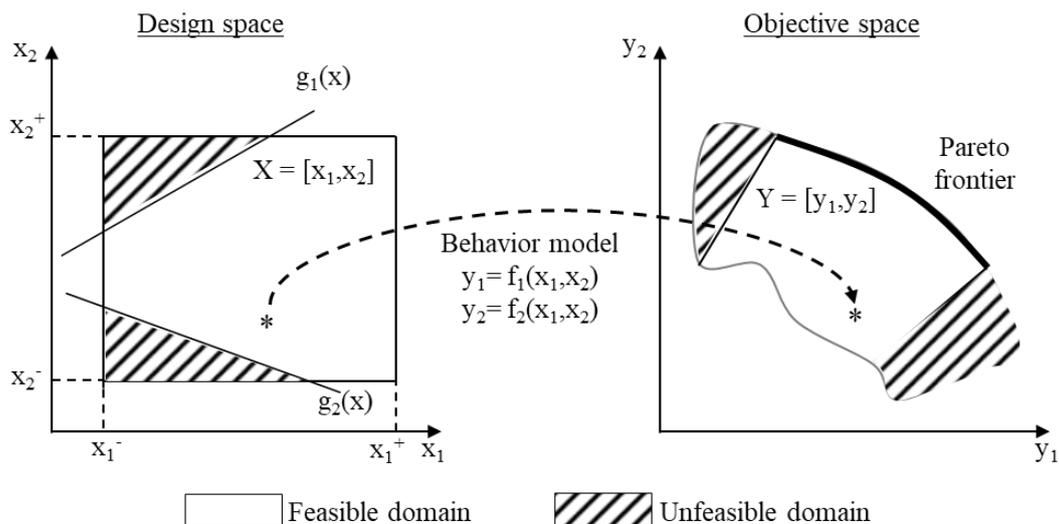


Figure 5 : Mapping between design space and objective space for a bi-objective maximization problem with two design variables (x) and two design constraints (g)

Figure 5 represents the mapping between design space - defined by the domain of values of x_1 and x_2 - and objective space for a bi-objective maximization problem with two design variables

(x) and two design constraints (g). The Pareto frontier is represented in the objective space. The determination of the Pareto frontier is technically relevant in engineering since it represents the set of the most effective solutions among all possible candidate solutions. Visualization of this set of optimal solutions allows a better understanding of the behavior of the problem. In multi-objective problems, several mathematical and numerical methods focus on the search for the Pareto frontier. The Non-dominated Sorting Genetic Algorithm (NSGA-II) [Deb et al. 2002] is a leading algorithm in the field of multi-objective evolutionary optimization.

However, in practice, it appears that Pareto's frontier is confusing to decision-makers because it contains too many solutions. More to the point, visualizing Pareto frontier is not really possible when facing problems where the number of objectives exceeds three.

2.2.2. Morphogenesis, Observation, Interpretation, Aggregation (MOIA) ontology

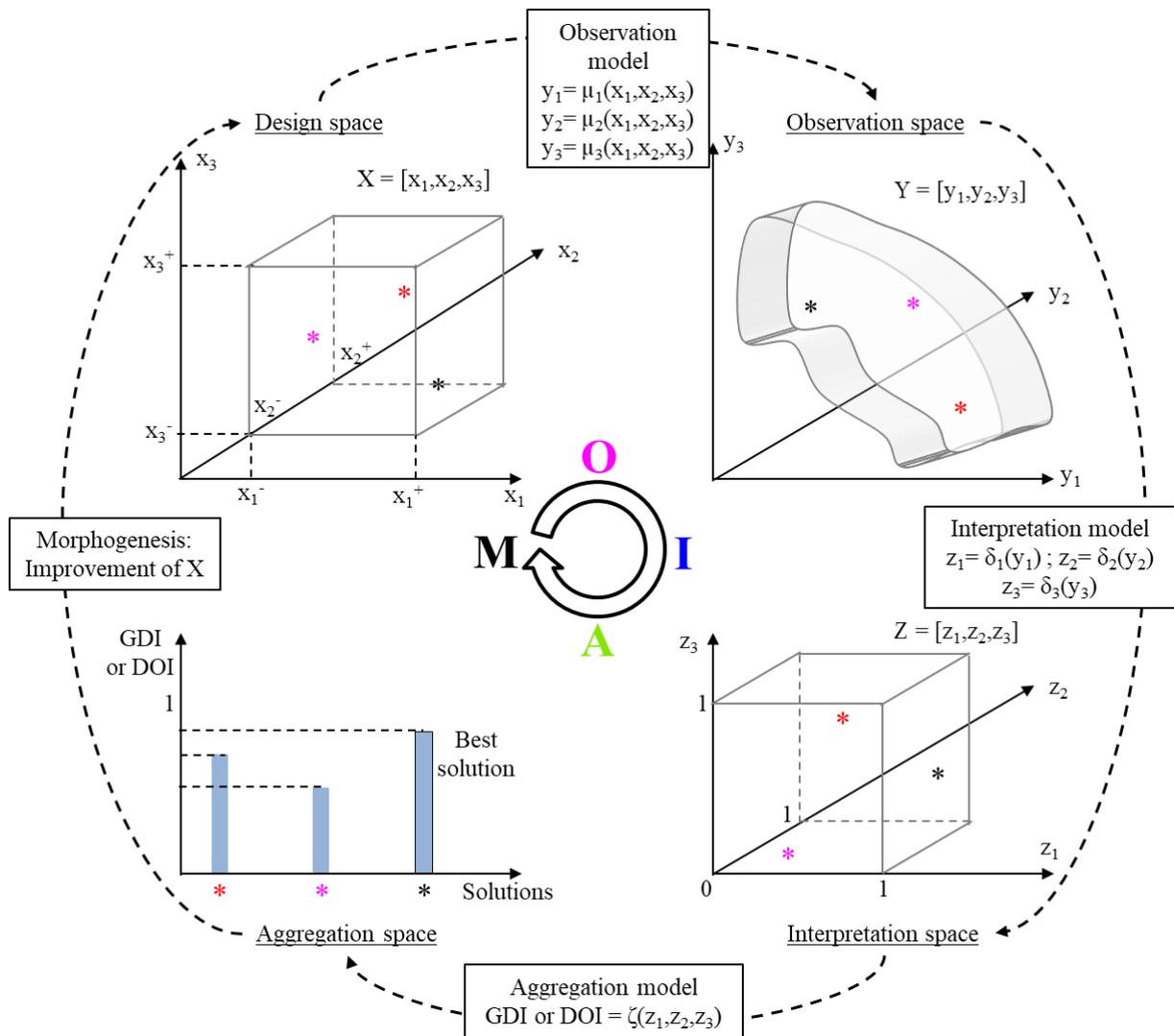


Figure 6: Mapping between MOIA models spaces

In order to illustrate the *a priori* and *interactive* formulations targeted in this manuscript, the proposed framework consists of design inputs, iterative design optimization and design output. The iterative design optimization is the core of the proposed framework, and it consists of four

models Morphogenesis, Observation, Interpretation, and Aggregation. Figure 6 shows a mapping between the design, observation, interpretation and aggregation spaces. Between these spaces, models must be defined. The observation model, interpretation model, aggregation model and morphogenesis model correspond to simulation, normalization, weighting and generation respectively. All these models are discussed in detail in the following.

2.2.2.1. Observation, Interpretation and Aggregation (OIA)

OIA is a framework for design optimization activities that can be derived from the FBS ontology. OIA has been initiated and developed by the I2M team at the University of Bordeaux [Collignan 2011; Quirante 2012]. OIA combines three kinds of models, which are the observation (μ), the interpretation (δ) and aggregation (ζ) models. Figure 7 shows those models within the FBS framework:

- The structure (S) - to be designed - is defined by a set of design variables (X). The observation model (μ) allows computing the desired observation variables (Y), which define the actual behavior (B_s), from the set of design variables (X).
- The actual behavior (B_s) must be compared to the expected behavior (B_e). The interpretation model (δ) is a satisfaction evaluation model that quantifies the degree of desirability (acceptability) of each observation variable and generates a set of interpretation variables (Z); it is based on design constraints and clients or designers' expectations.

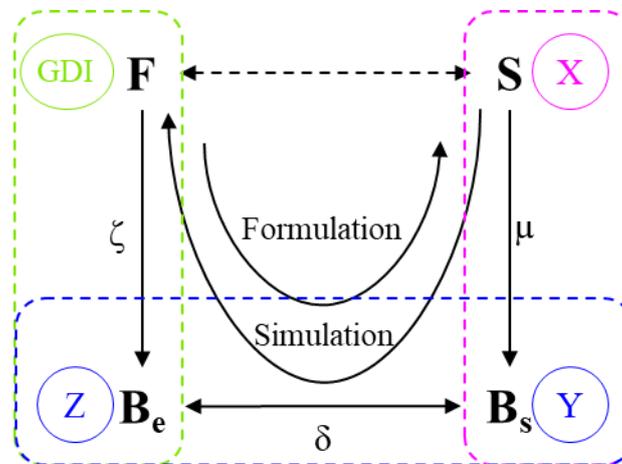


Figure 7: OIA within the FBS framework

- The design problem is always a multi-objective optimization problem. For solving this kind of problem, the optimization process passes through an aggregation of the interpretation variables (Z) in order to obtain a global desirability index (GDI) that must be maximized. The majority of multi-objective optimization methods do not use an explicit aggregation step and are satisfied with the localization of the set of optimal solutions (Pareto frontier). Faced with these confusion optimal solutions, decision-makers often make non-rational choices. The aggregation model (ζ) makes a selection rule among the set of possible solutions based on the decision makers' preferences.

Briefly, after the formulation of the observation, interpretation and aggregation models, OIA operates as a simulation/optimization/decision-support process giving a global desirability index (GDI) of a given design represented by design variables (X).

$$GDI = \zeta \circ \delta \circ \mu(X) \quad (1)$$

The GDI is therefore an objective function of X. GDI has to be maximized to perform the optimization process. To find the optimal solution, an optimization algorithm is implemented. Figure 8 shows the global optimization process. The presented aggregation model aims at aggregating all the interpretation variables to compute the design objectives indexes (DOI) and from them, the global desirability index (GDI).

It is noticeable that, using this OIA approach, designing is regarded as a mono-objective optimization problem from a mathematical point of view. Indeed, the design constraints and objectives are aggregated in a single desirability index. The formulation of the design problem takes into account the flexibility of designers' reasoning through both interpretation and aggregation functions. OIA covers many processes used by human experts in order to judge solutions and make a decision since the interpretation and aggregation functions can take many different forms.

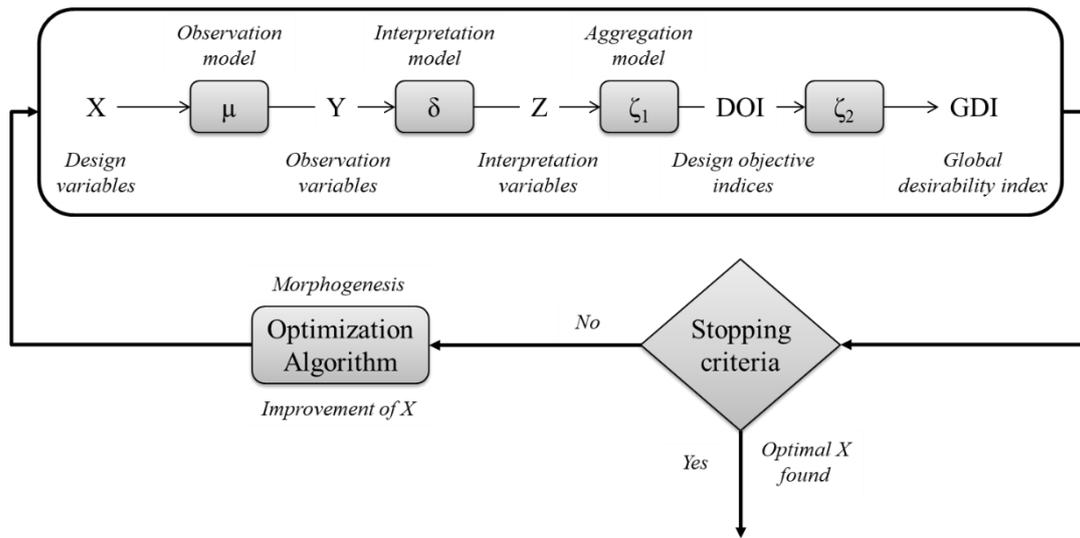


Figure 8: The global optimization process based on OIA

In order to conclude, OIA integrates the observation model which corresponds to the system behavior, the interpretation and aggregation models which formulate designers' preferences and the optimization which allows the exploration of the design space and study different design solutions (see 2.2.2.7). Each design optimization process must consider these fundamental steps; then, OIA is considered as the *ontos* or the fundamentals of optimization. For this reason, it is referred to as the OIA ontology in the following.

2.2.2.2. Observation model

In OIA, system, or candidate solution, is characterized by different values of the design variables X. The observation model (μ) is a simulation model of the system behavior that uses

operational scenarios to compute the observation variables Y . Generally, these performances derived from the client specifications. They are required to support the decision-making process. These performances can be of different orders: cost, mass, volume, etc. Operational scenarios include all the information related to the context of the design such as the environmental parameters that describe the surrounding environment of the product like operating temperature, humidity, etc. The observation model is generally composed of physical, technical and economic models that compute the observation variables using simulation. One of the challenges today is how to deduce the appropriate observation model from the system specifications and constraints. [Sohier et al. 2019] propose a tooled approach based on MBSE models for the description of the system architecture and the concept of MIC (Model Identity Card) [Sirin et al. 2015] which allows to capitalize simulation models and make them available for the construction of the adapted observation model. Sohier et al. applied MIC on an autonomous driving application [Sohier et al. 2019].

2.2.2.3. Interpretation model

Interpretation is the process of verifying how well the values obtained from observation variables match the expectations and preferences of the decision-makers. Observation variables are always of different nature and always measured on different scales. Because of this, in order to obtain a single value that represents a candidate solution, Lawson mentioned that “*Because in design there are often so many variables which cannot be measured on the same scale, value judgements seem inescapable*” [Lawson 2006].

Desirability is a preference measurement which reflects the level of satisfaction achieved by the properties of a design according to the designers’ points of view. Desirability functions are non-dimensional, monotonous, or piecewise monotone functions. They express the level of satisfaction of designers on observation variables’ values. Their values are ranged in the interval $[0, 1]$. A desirability value of 1 means that the observation variable value is fully satisfactory in relation to the decision-makers’ expectations. A desirability value of 0 corresponds to a totally unsatisfactory observation variable value. This approach has been widely used in engineering design [Derringer and Suich 1980; Derringer 1994; Kim and Lin 2000; Réthy et al. 2004; Trautmann and Mehnen 2005; Kruisselbrink et al. 2009; Trautmann and Mehnen 2009; Chen 2011]. Different forms of desirability functions exist.

2.2.2.3.1. Simon’s function

In 1956, Simon introduced the name “satisficing” for this function, made from a combination of two words: “satisfy” and “sufficient” [Simon 1956]. In a context of maximization of the benefit of an action, even if all the information required is available, Simon mentioned that the human mind is not able to process information properly because the human mind is bound by “cognitive limits”. As a result, decision-makers are often inclined to accept the action completely (Extremely satisfied) or not at all (Not at all satisfied). Simon’s satisficing functions can be expressed as presented in Table 4.

It may be noted that by using Simon’s functions, there are usually a large number of fully

satisfactory solutions or no solutions at all. The fully satisfactory solutions are not classified, then, an optimal solution is unfindable.

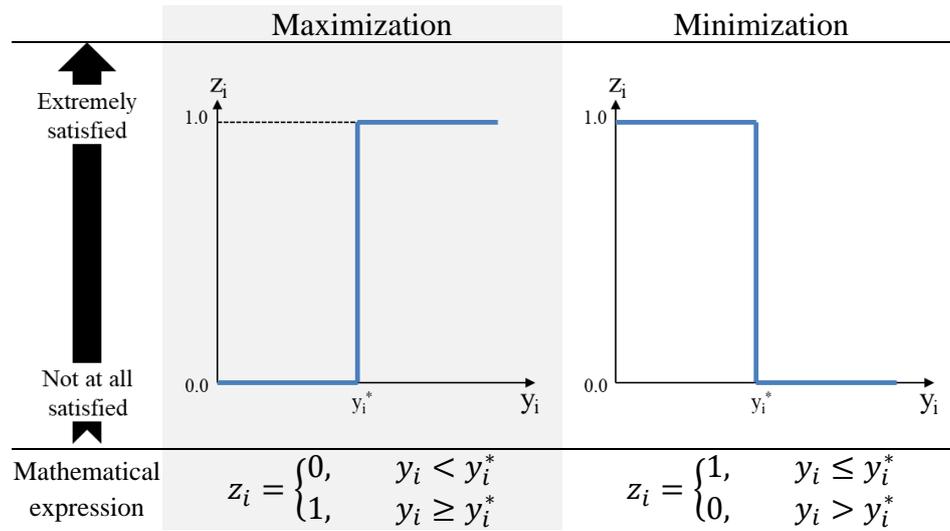


Table 4: Simon's satisficing functions

2.2.2.3.2. Harrington's function

In 1965, Harrington introduced the concept of "desirability" and "desirability functions" to deal with multi-criteria optimization in quality engineering [Harrington 1965]. Table 5 presents the three functions proposed by Harrington. They are adapted to three different decision problems: maximization, minimization and targeting.

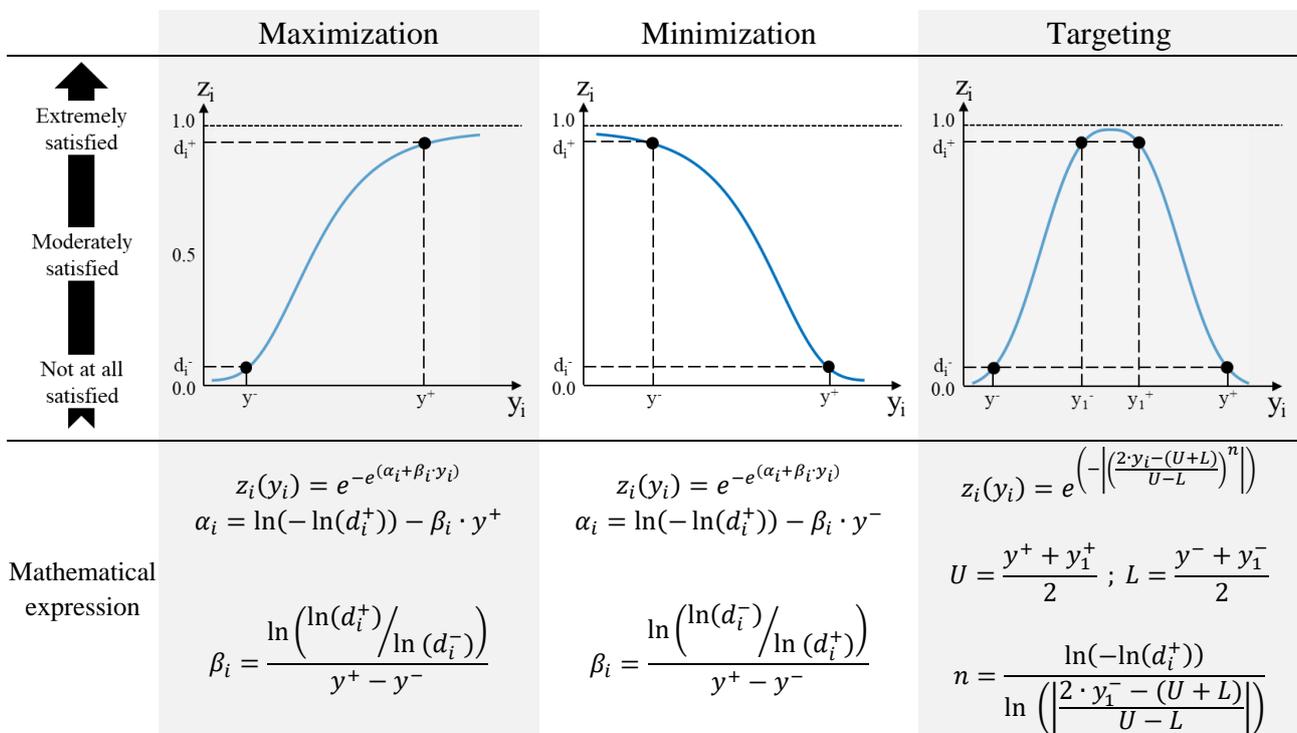


Table 5 : Harrington's desirability functions

Harrington's desirability functions have many advantages. Thanks to their exponential form, they have no discontinuities and they allow a progressive but strong variation of desirability

when approaching y^- and y^+ ; Harrington called these values the Accurate Constraint value (AC) and the Soft Limit value (SL) for the maximization problem, for example. Since the two desirability values, $z_i = 0$ and $z_i = 1$, are never reached, it becomes possible to classify all design alternatives, including acceptable and unacceptable alternatives. The range between the two control points y^- and y^+ is named satisfaction range in the following.

Harrington's desirability functions appear to be relevant functions to interpret property's values and models based on design requirements and designers' expectations.

2.2.2.3.3. Derringer's desirability function

In 1980, Derringer proposed a modified formula of Harrington's desirability functions [Derringer and Suich 1980]. Unlike Harrington's desirability functions, Derringer's desirability functions are piecewise-defined functions as presented in Table 6.

	Maximization	Minimization	Targeting
Mathematical expression	$z_i(y_i) = \begin{cases} 0 & , y_i \leq y_i^- \\ \left(\frac{y_i - y_i^-}{y_i^+ - y_i^-}\right)^r & , y_i^- \leq y_i \leq y_i^+ \\ 1 & , y_i \geq y_i^+ \end{cases}$	$z_i(y_i) = \begin{cases} 1 & , y_i \leq y_i^- \\ \left(\frac{y_i^+ - y_i}{y_i^+ - y_i^-}\right)^r & , y_i^- \leq y_i \leq y_i^+ \\ 0 & , y_i \geq y_i^+ \end{cases}$	$z_i(y_i) = \begin{cases} \left(\frac{y_i - y_i^-}{y_i^* - y_i^-}\right)^r & , y_i^- \leq y_i \leq y_i^* \\ \left(\frac{y_i - y_i^+}{y_i^* - y_i^+}\right)^r & , y_i^* \leq y_i \leq y_i^+ \\ 0, & y_i < y_i^- \text{ or } y_i > y_i^+ \end{cases}$

Table 6 : Derringer's desirability functions

The curve reflecting the designers' desire is rarely linear; this aspect is demonstrated in Chapter 5. Therefore, the adjustment parameter r is important to alter the desirability curve for a precise formalization of the preferences of the designer. The main disadvantage of Derringer's desirability functions is the discontinuity that is difficult to justify in the context of design problems. In addition, due to the threshold values, when $z_i = 1$, Derringer's formulas do not differentiate the most satisfying design solutions between them. Same when $z_i = 0$, they do not differentiate the unacceptable design solutions between them. Therefore, a ranking between the solutions having $z_i = 0$ or $z_i = 1$ cannot be established.

Other desirability functions based on the geometrical sigmoid function have been used in engineering design [Raffray et al. 2015]. These functions are centered, symmetrical and smoothly monotonous. These properties offer additional advantages over the previously

mentioned desirability functions, since they often prove to be simple and practical to implement.

2.2.2.4. Aggregation model

Aggregation is defined as the process of synthesizing all desirability values z_i into one through an aggregation function, which aims to compute a single numerical value. This value is supposed to be representative of the overall satisfaction derived from individual satisfaction levels. Hereafter, it is called Global Desirability Index (GDI). Scott [Scott and Antonsson 1998] expressed this aggregation function ζ as a function of z_i and the weighting parameters w_i .

$$GDI = \zeta((z_1, w_1), \dots, (z_n, w_n)), \quad n \in \mathbb{N}^* \quad (2)$$

Aggregation makes it possible to transform a multi-objective decision problem into a single-objective decision problem, which facilitates the discrimination process of design alternatives. Aggregation also automates the evaluation process and thus for the processing of a large number of alternative designs.

Axioms	Formulation
<i>Monotonicity</i>	$\zeta((z_1, w_1), \dots, (z_n, w_n)) \leq \zeta((z_1, w_1), \dots, (z'_n, w_n)) \quad \forall z_n \leq z'_n$ $\zeta((z_1, w_1), \dots, (z_n, w_n)) \leq \zeta((z_1, w_1), \dots, (z_n, w'_n)) \quad \forall w_n \leq w'_n; z_i \leq z_n \forall i \leq n$
<i>Commutativity</i>	$\zeta((z_1, w_1), \dots, (z_i, w_i), \dots, (z_j, w_j), \dots, (z_n, w_n))$ $\leq \zeta((z_1, w_1), \dots, (z_j, w_j), \dots, (z_i, w_i), \dots, (z_n, w_n)) \quad \forall i, j$
<i>Continuity</i>	$\zeta((z_1, w_1), \dots, (z_k, w_k), \dots, (z_n, w_n)) = \lim_{z_k \rightarrow z'_k} \zeta((z_1, w_1), \dots, (z'_k, w_k), \dots, (z_n, w_n)) \quad \forall k$ $\zeta((z_1, w_1), \dots, (z_k, w_k), \dots, (z_n, w_n)) = \lim_{w_k \rightarrow w'_k} \zeta((z_1, w_1), \dots, (z_k, w'_k), \dots, (z_n, w_n)) \quad \forall k$
<i>Idempotency</i>	$\zeta((z, w_1), \dots, (z, w_n)) = z \quad \forall w_1, \dots, w_n \geq 0; w_1 + \dots + w_n > 0$
<i>Annihilation</i>	$\zeta((z_1, w_1), \dots, (0, w), \dots, (z_n, w_n)) = 0 \quad \forall w \neq 0$
<i>Self-scaling weights</i>	$\zeta((z_1, w_1 * t), \dots, (z_n, w_n * t)) = \zeta((z_1, w_1), \dots, (z_n, w_n)) \quad \forall w_1, \dots, w_n \geq 0; w_1 + \dots + w_n > 0; t > 0$
<i>Zero weights</i>	$\zeta((z_1, w_1), \dots, (z_k, 0), \dots, (z_n, w_n))$ $= \zeta((z_1, w_1), \dots, (z_{k-1}, w_{k-1}), (z_{k+1}, w_{k+1}), \dots, (z_n, w_n)) \quad \forall w \neq 0$

Table 7 : Axioms for design appropriate aggregation functions

It is important to note that each aggregation function corresponds to a particular logic of trade-off between design objectives. This logic takes into account both the relative importance between the objectives and the compensation levels between them [Dai and Scott 2006]. In order to obtain a GDI value that effectively reflects the preferences of decision-makers, the trade-off logic of the aggregation functions must effectively reflect the intentions and preferences of the decision-makers. In this context, Scott et al. [Scott and Antonsson 1998] propose a set of axioms to verify that an aggregation function is appropriate for the design

problems of any kind of product. Table 7 illustrates the axioms for design appropriate aggregation functions, as presented in [Scott and Antonsson 1998]. These axioms form a consistent basis to guarantee the rationality of preference modelling in engineering design [Otto 1992].

Several aggregation functions have been proposed by researchers. Yager [Yager 2004] has proposed a continuum aggregation function allowing defining different aggregation functions using a parameter (s). The mathematical expression of this function is presented below:

$$GDI = \sqrt[s]{\sum_i w_i (z_i)^s} \quad \text{with} \quad \begin{cases} \sum_i w_i = 1 \\ w_i \geq 0 \\ s \in]-\infty; +\infty[\end{cases} \quad (3)$$

Figure 9 shows some generated aggregation functions while the parameter s is taking several particular values. This figure represents the values of s where the design is considered appropriate and non-appropriate.

- If $s \rightarrow +\infty$, the aggregation function is the maximum. It means that an alternative is good if one of the desirability values z_i is good, thus it is considered as non-design-appropriate.

$$GDI_{+\infty} = \max(z_i) \quad (4)$$

- If $s = 1$, the aggregation function is the weighted arithmetic mean (or weighted sum). This function is widely known and used but it is considered as non-design-appropriate because it is not respecting the annihilation axiom which is fundamental in design [Otto and Antonsson 1993].

$$GDI_1 = \sum_i (w_i \cdot z_i) \quad (5)$$

- If $s = 0$, the aggregation function is the weighted geometric mean (or weighted product). This function has been used by Derringer [Derringer 1994] in order to respect the annihilation axiom. It is a compensatory function since the highest value of z_i compensates the lower values. This function is called Derringer's aggregation function in the following.

$$GDI_0 = \prod_i z_i^{w_i} \quad (6)$$

- If $s \rightarrow -\infty$, the aggregation function is the Minimum function. It has been proposed by Kim and Lin [Kim and Lin 2000] in order to avoid problems related to the use of weights w_i . It is considered as being design appropriate.

$$GDI_{-\infty} = \min(z_i) \quad (7)$$

This function corresponds to a precautionary principle, namely a principle that values de facto the least worst design solution among the possible alternatives [Raffray et al. 2015]. This function is well known in the field of fuzzy logic [Bouchon-Meunier and Marsala 2003] but it is relatively unusual to meet him in the field of design.

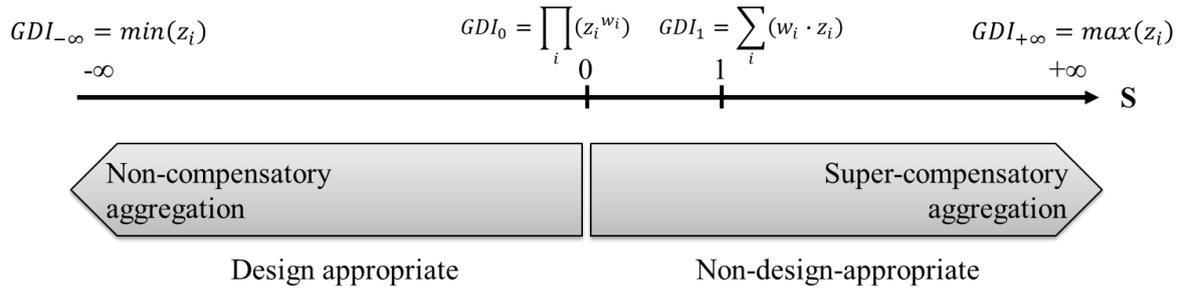


Figure 9: The space of the continuum aggregation function

It may be noted that some methods, like Promethee [Brans 1982] and Electre [Roy 1968], are able to rank (a partial or complete ranking in case of Promethee method) a set of solutions using different techniques than aggregation. Those methods are not in our scope, since we are focusing on the *a priori* formulation where each solution is noted separately using a GDI index.

2.2.2.5. About the modelling of the interpretation and aggregation

For the sake of generalization, the terms criterion (criteria) and objective(s), used in the following, correspond to:

- Objective: generally, the objective aims at applying an action or operator (how?) to an object (what?) in order to respond to a meaning (why?). In the context of this manuscript, the meaning corresponds to a client or stakeholder need (design objective or DOI). The operation corresponds to an aggregation (ζ) between several objects, satisfaction level or interpretation variables (z). For example, the performance (meaning, demanded by the client) of a vehicle is an aggregation (operator) of the maximum vehicle speed and the acceleration from 0 to 100 km/h (two objects).
- Criterion: the criterion is defined as *a standard on which a judgment or decision may be based* [Dictionary 2020c]. It aims also at answering the three questions: how? what? and why?. The meaning here corresponds to the determination of satisfaction levels (z) by applying the operation of normalization using the interpretation model (δ), on the observation variables (y). For example, the satisfaction level of the maximum vehicle speed (meaning) is an interpretation (operator) of the value of the maximum vehicle speed measured in km/h (object).

It may be noted that the meanings and the objects are defined using the Systems Engineering process (see Chapter 3). Moreover, the operations are parametrized by the actors that participate in the design process.

2.2.2.5.1. Kolmogorov complexity

In OIA ontology, the interpretation model generates a set of interpretation variables Z from a set of observation variables Y using desirability functions while the aggregation aims to transform the set of interpretation variables into one global desirability index GDI using aggregation function. GDI represents a global satisfaction note of a specific solution.

The acceptability of a design solution mainly depends on its ability in satisfying every observation variable but it also depends on human's trade-off. The level of satisfaction of an observation variable is calculated using a desirability function that is defined by the human. In addition, human's trade-off is interpreted into the aggregation step using different forms of aggregation functions. Therefore, the parameters of interpretation and aggregation models correspond to decision makers' points of view.

In an industrial context, due to the important number of actors that participate in the design process, the choices of the parameters of interpretation and aggregation models are not obvious and require fundamental studies of criteria. Those choices depend on decision-makers' points of view (see Chapter 5) and the available amount of information about the criteria.

In the following, the concept of complexity (as defined by Andrey Kolmogorov in 1963 [Li and Vitányi 2019]) is used to assess the worthiness of information of criteria; the more valuable, precise and irregular the information the higher the complexity of defining the criteria is. To simplify the concept of Kolmogorov complexity through an example, the regular set of values $[0,1,2,3,\dots,100]$ can be generated using a simple code based on a "for loop" (see Code 1). Then, there is no complexity in setting up this set. In contrast, a set of 100 irregular values requires an entry of 100 values to define this set, which is higher in the scale of complexity of defining the set than the latter example.

```
S=[]; % initialization
for i = 0:100
    S = [S , i];
end
```

Code 1: A Matlab[®] code to generate the set of values $[0,1,2,3,\dots,100]$

The number of control points or parameters used to parameterize a function determine the amount of information required to define it. This amount of information determines the level of complexity. The higher the amount of information, the higher the level of complexity. Figure 10 shows an example of the complexity of defining a criterion using a set of bits. Each set of bits defines the parameters of a criterion. In general, we can imagine that the first bit in the set corresponds to the type of problem (0 for minimization and 1 for maximization). The other bits correspond to the other information about the criterion. For a pseudo-function, which is not a real function and does not have any quantitative information; therefore, the needs behind such a function is to minimize or maximize the criterion value without any control point and any additional information. The pseudo-function corresponds to the lowest level of complexity. Simon's function requires the definition of a control point (or target value). Therefore, the number of bits required to define such a function is higher compared to the pseudo-function; then, the complexity is higher. Finally, the soft function, where each control point corresponds to a desirability value, corresponds to the highest level of information, which corresponds to the highest level of complexity. Additional information about the parametrization of desirability and aggregation functions are given in the next part.

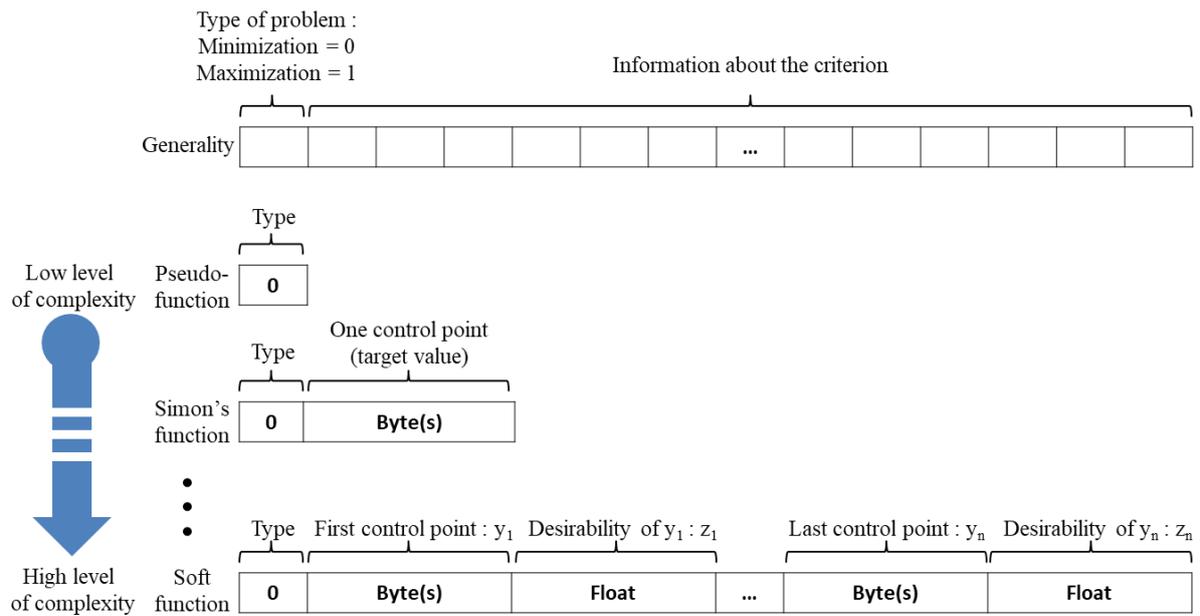


Figure 10: The complexity of defining a criterion using a set of bits

2.2.2.5.2. Ordinal and cardinal ranking

Understanding the difference between ordinal and cardinal information is critical to understand the interpretation and aggregation functions, and the consequence of choosing certain functions instead of others. In order to rank a set of values, two methods of ranking exist corresponding to ordinal and cardinal classification methods. Fiat [Fiat 2007] defined these methods as:

1. In an ordinal ranking, the value returned for each value in the set is its position in an ordered classification of the set of values. Then, the values are ranked without assigning any numerical scalar quantities. Finally, the returned value is qualitative.
2. In a cardinal ranking, the value returned for each value in the set is its real value, sometimes relative to the other values involved in the classification. Then, cardinal ranking consists in interpreting preferences in terms of value. Finally, the returned value is quantitative.

It is clear that the cardinal ranking contains more valuable information than an ordinal ranking. This means that a cardinal ranking allows an ordinal ranking; the inverse is not possible. Fiat illustrates this idea through a simple ranking method called the "card method" [Fiat 2007].

Observation variables	Cardinal		Ordinal	
	y_1	y_2	y_1	y_2
Solution A	1.00	0.50	1 st	3 rd
Solution B	0.50	1.00	3 rd	1 st
Solution C	0.51	0.51	2 nd	2 nd

Table 8: Comparison between the ordinal and the cardinal information

For a better comprehension of the consequences of choosing cardinal or ordinal method, Table 8 shows an example of comparison between these two methods. Based on the cardinal information, solution C can be regarded as a poor solution. However, based on the ordinal

information, solution C may appear as a good solution, since it seems to be a good compromise between solution A and solution B. Therefore, the ordinal information is less valuable than the cardinal information; it can be misleading.

2.2.2.5.3. Parametrization of interpretation functions

Figure 11 shows some significant interpretation functions of desirability for a maximization problem. It starts from the pseudo-function which does not have any quantitative information. More informative functions can be extended from the pseudo-function and divided into two major categories: ordinal and cardinal functions.

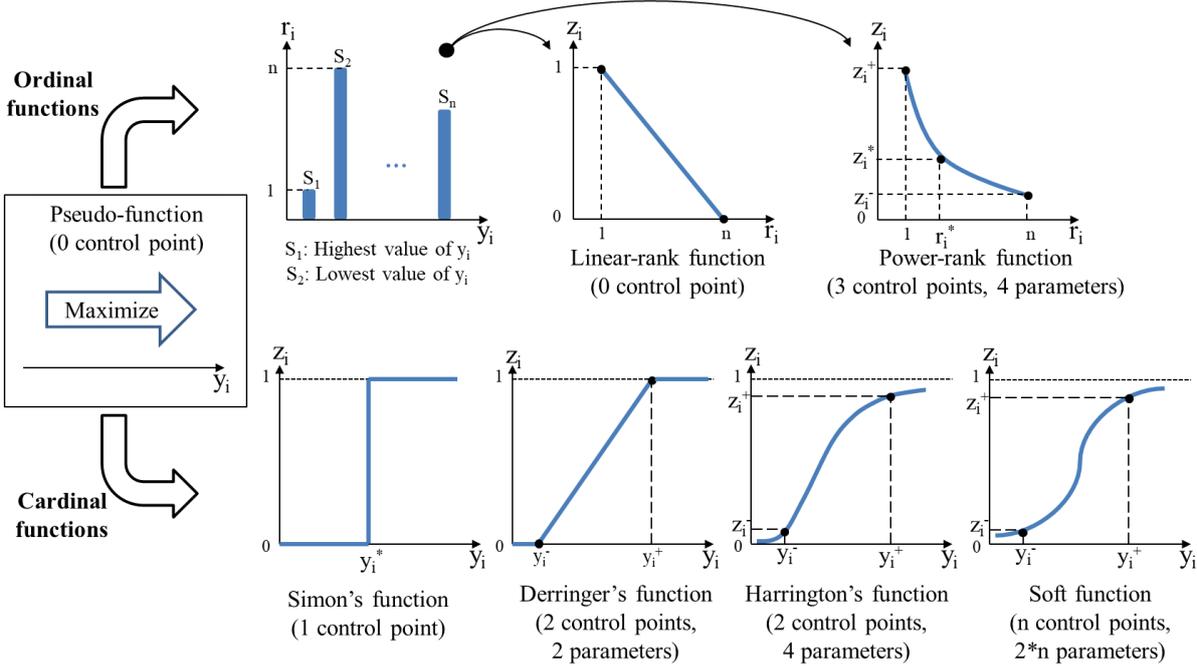


Figure 11: Ordinal and cardinal interpretation functions

The basic ordinal function is linear and assigns a desirability value to the rank r_i of the solution where the rank one has a desirability of 1 and the rank n has a desirability of 0. This function does not require any control point and parameter to be defined on the space (r_i, z_i) .

The most complex ordinal function shown is a power curve defined from three control points corresponding to the ranks 1, r_i^* and n . For those points, the corresponding values are z_i^- , z_i^* and z_i^+ and consequently, the power function requires the definition of four different parameters.

Cardinal functions compute the desirability values directly from values of y_i . The basic cardinal function is the satisfying function of Simon which has only one control point. This control point aims to express satisfaction in a minimal way by interpreting whether the value of y_i is both sufficient and satisfying. The most complex function is the Soft function which has n control points and $2*n$ parameters, between (y_i^-, z_i^-) and (y_i^+, z_i^+) . This function is able to compute a desirability value within the range $]0, 1[$ for every value of y_i . Thus, this function contains an important quantity of information.

Starting by Simon’s function, passing through Derringer’s and Harrington’s functions and ending with Soft function, Figure 11 shows these functions by highlighting some functions defined in the space (y_i, z_i) that require more and more control points and parameters, namely increasing information. It is also worth noting that their numerical ranges of sensitivities increase since these monotonic functions evolve toward continuous differentiability.

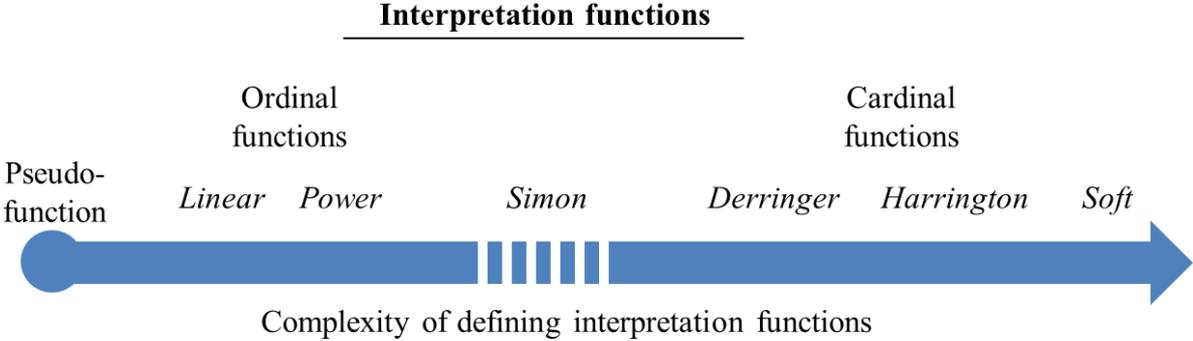


Figure 12: Classification of interpretation functions in the scale of the complexity

The worthiness of information is assessed from the concept of complexity. Figure 12 shows a classification of all interpretation functions presented above in the scale of the complexity. The number and relevance of the parameters of all of the interpretation functions, allows us to conclude that Pseudo-function has the lowest complexity and the complexity of ordinal functions is lower than cardinal functions.

Information is costly. Designers often do not have enough information to parameterize every criterion; due to scarcity of information, they are often obliged to use functions that carry out a minimum level of information. Information scarcity then be related to low-complex interpretation functions.

2.2.2.5.4. Parametrization of aggregation functions

As previously, the same analysis can be made for aggregation functions. Figure 13 shows the defined aggregation functions in the scale of complexity. It shows several possible aggregation functions from an example of two interpretation variables (z_1 and z_2). The Pseudo-function does not contain any information of how to rank the solutions; aggregation is not possible using such a function. Pareto’s function is based on the implementation of ordinal ranking. For a maximization problem, Pareto’s function is capable of classifying solutions into sets of different levels using the non-dominating strategy detailed in 2.2.1 and expressed by the rectangles outlined in Figure 13. The first level ① is called “Pareto Frontier”. Solutions in the same set are of equal optimality level. It is noticeable that each set may contain numerous solutions; thus, Pareto’s function has a low discriminatory power. Pareto’s aggregation function seems well-adapted in contexts of information scarcity since it can be computed from any ordinal or cardinal interpretation function that is consistent with a pseudo-function to result in ordinal information.

The Minimum function (see (7)) does not require any parameter to be defined. It proposes to aggregate the variables according to the “worst-case” strategy, which corresponds to a precautionary principle. This function is much more discriminative compared to Pareto’s function. This process will select solutions according to their minimal value of z_i and the best solution maximizes this minimal value. The ranking of solutions corresponds to squares expanded from the ideal solution along the median line. Solutions in the same rectangle border are of equal optimality level. Extreme solutions having a very low value of z_i will be eliminated from such a selection process. The Minimum function is well-adapted to intermediate levels of complexity and requires to be connected to suitable interpretation functions, namely cardinal satisfaction functions.

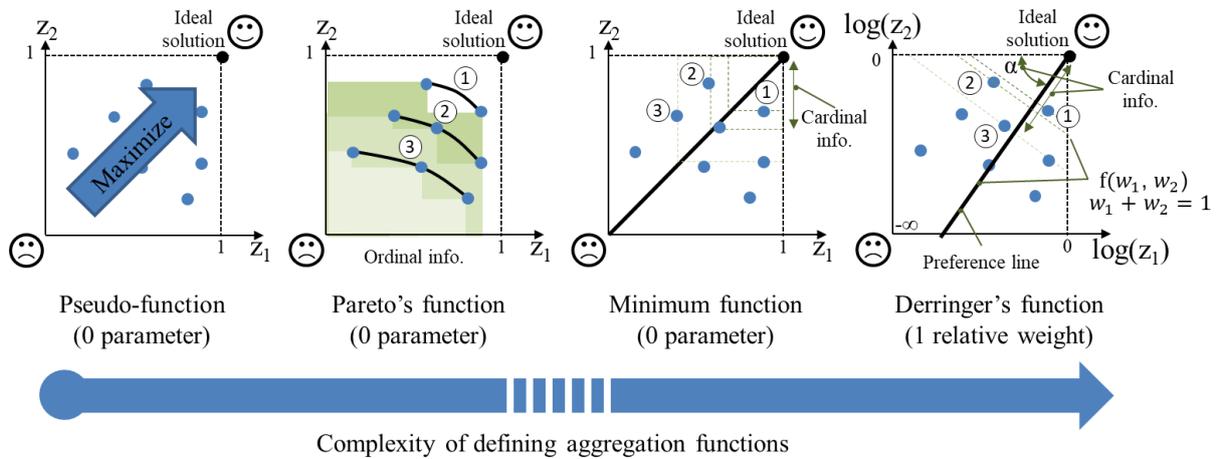


Figure 13: Classification of aggregation functions in the scale of the complexity

Derringers’ aggregation function (see (6)) also has a high discriminatory power. It is a weighted product of z_i values. For example, two variables are presented in Figure 13 with a function requiring one parameter of relative weight w_1 or w_2 to be defined. The weighted product can be interpreted from a geometrical point of view as a projection on a preference line which slope depends on relative weights. The desirability of criteria of each solution is set on a logarithmic scale and projected on the preference line; the closer the projection to the ideal solution the better the solution. For specific values of weights, each projection line corresponds to a value of the weighted product of z_i . Solutions in the same projection line are of equal optimality level. The relative weights reflect the importance of the criterion related to z_i . Geometrically, the more important the criteria z_1 , the higher the corresponding relative weights, and therefore the slope of the preference line. The angle α corresponds to that slope. α is a function of the weights values and it is calculated using the formula $\alpha = \arctan(w_1/w_2)$.

Weighting levels of importance of criteria through the aggregation process allows taking into account their criticality, namely the severity of the consequences of their possible failure. Derringer’s aggregation function is related to high levels of complexity and necessitates information resulting from cardinal functions. Relevant weight estimation techniques such as AHP (detailed in 2.2.2.6.1) can highly improve the complexity level conveyed by the optimization process provided that human judgement is rational and consistent.

For making decisions and selecting relevant optimal solutions in multi-objective optimization problems, the steps of interpretation and aggregation are mandatory. Finally, humans will make their choice. However, the interpretation and aggregation functions allow the formalization of human judgements through mathematical functions and the integration of these functions in an optimization process. These functions require a certain level of complexity in order to be defined and can lead to opposite results. In a general context, no interpretation or aggregation method can be regarded as superior to the others.

2.2.2.6. Determination of the weighting parameters

In the literature, most multi-criteria decision-support methods propose the use of numerical weights to quantify the relative importance of the criteria, and objectives. In the vast majority of cases, weights are normalized. Several authors have proposed different methods for determining these weights [Pekelman and Sen 1974; Saaty 1977; Dyer and Sarin 1979; Nutt 1980; Choo and Wedley 1985; Solymosi and Dombi 1986; Darmon and Rouzies 1991; Zhang et al. 1992; Semassou et al. 2011]. The Entropy method, initiated by [Shannon 1948] and applied in [Li et al. 2011], and the Critic method [Diakoulaki et al. 1995] are able to calculate criteria weights based on the criteria values of a set of solutions. We limit our analysis in this section to the methods that determine criteria weights for an *a priori* formulation.

2.2.2.6.1. Analytic Hierarchy Process (AHP)

Saaty's Analytic Hierarchy Process (AHP) [Saaty 1977] and its further evolution [Saaty 1990, 2008] is popular and of great interest in the field of operational research and decision theory. Its popularity arises from its global consistency. It proposes an efficient combination of concepts such as units of measurement, hierarchical structure, interdependence, consistency, identification of priorities and unicity [Jlassi 2009]. AHP is a hierarchical modeling method of design objectives aiming to weight their relative importances from a pairwise comparison process.

Saaty [Saaty 1977] has proposed a fundamental scale of the intensity of importance ranging from 1 to 9 which corresponds respectively to equal importance and absolute importance. After the determination of the design objectives by a hierarchical decomposition, a judgment matrix is defined from pairwise comparisons between the objectives. Figure 14 shows an example of judgment matrix completed by the pairwise comparison technique. The calculated weights w and consistency ratio CR are also shown.

The judgment matrix is positive and inversely symmetric. Saaty has proposed a method to determine the weights of objectives by calculating the matrices of eigenvalues and eigenvectors. Moreover, the consistency of the judgment matrix and therefore of the judgment itself can be qualified through a consistency ratio CR . According to Saaty, consistency ratio value lower than 10% corresponds to acceptable consistency and higher than 30% corresponds to low consistency. It is noticeable that judgment matrices must reflect the real human judgment. Consequently, a perfect consistency ($CR = 0\%$) is considered undesirable.

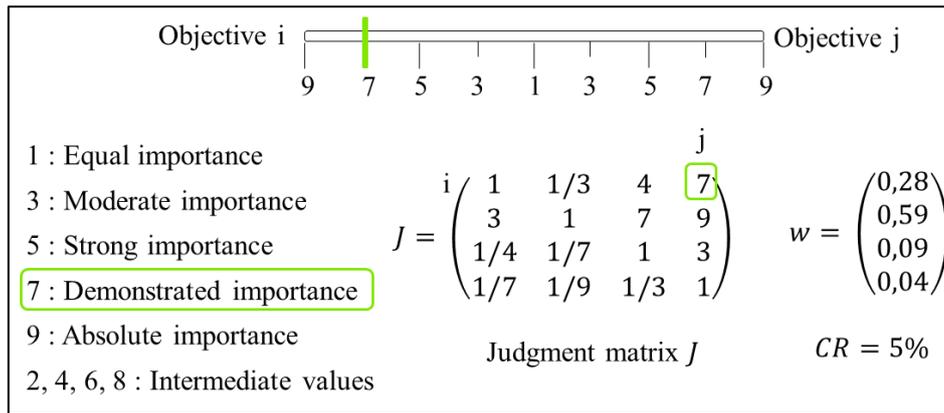


Figure 14: Example of pairwise comparison and judgment matrix

When the number of design objectives is high, the completion of the judgment matrix becomes long and difficult. In addition, it becomes difficult to maintain acceptable consistency. According to Saaty, the AHP method is not appropriate for more than 7 design objectives [Saaty and Ozdemir 2003].

2.2.2.6.2. Adapted Failure Mode Effects and Criticality Analysis (FMECA)

The importance of an objective corresponds to its relative criticality. In 2011, Semassou proposed an adapted Failure Mode Effects and Criticality Analysis (FMECA) by coupling it with the AHP [Semassou et al. 2011]. The FMECA is used to classify design objectives according to their level of criticality (C). The criticality is calculated by multiplying the three numerical subjective estimates Occurrence (O), Severity (S) and Detection (D). Occurrence estimates if the failure will occur rarely (1), frequently (5) or permanently (10). Severity estimates if the severity of failure is negligible (1), important (5) or dramatic (10). Detection estimates if the detection of failure is certain (1), possible (5) or impossible (10). The mathematical expression of the criticality is:

$$C = O \cdot S \cdot D \quad (8)$$

Finally, the weights of objectives are determined by normalizing the calculated criticality.

2.2.2.6.3. Delphi method

The Delphi method, also known as Delphi technique or Delphi forecasting, was developed by the researchers Norman Dalkey and Olaf Helmer of RAND Corporation [Helmer 1967; Dalkey 1969]. It is a forecasting or estimating method based on a discussion by a group of experts. The technique consists of several rounds of individual and anonymous questions to each expert, followed by a group discussion after every round. The latter allows participants to reflect and adjust their opinions. The process is usually repeated until a consensus is achieved; it is usually ending with three or four iterations.

While such discussion can happen in person, an alternative is to send out a series of paper or online questionnaires. In this case, a written summary of all responses is distributed to everyone

after each round, instead of a group discussion.

The Delphi technique is useful for situations that allow for a range of scenarios or opinions such as estimating the duration of tasks, identifying project risks and forecasting their probability or allocating the resources. Valerdi used the Delphi method in cost estimation models [Valerdi 2011]. Moreover, this method can be used to calculate the weights of criteria [Milosavljević et al. 2018]. This technique results in a very good estimate but it requires a non-negligible time to be completed.

2.2.2.7. Morphogenesis (Optimization algorithm)

2.2.2.7.1. Morphogenesis definition

The word morphogenesis comes from the Greek *morphê* meaning shape, and *genesis* meaning creation. Morphogenesis is the set of laws that determine the shape and structure of tissues, organs and organisms [Bard 2008]. It is a concept used in several disciplines including biology, engineering, urban studies, art and architecture. It corresponds to the evolution of shape of an organism together with the differentiation of its parts [Minarsky et al. 2018].

In engineering, computational morphogenesis is used to determine the best possible shapes and material distributions for prescribed structural objectives. The goal is to minimize structural weight while respecting mechanical constraints. Whereas efficient structures in nature generally result from slow genetic evolution, in engineering fast solutions that also consider manufacturing limitations are necessary. Aage et al. apply a 3D computational morphogenesis tool to the design of the internal structure of a full-scale aeroplane wing [Aage et al. 2017].

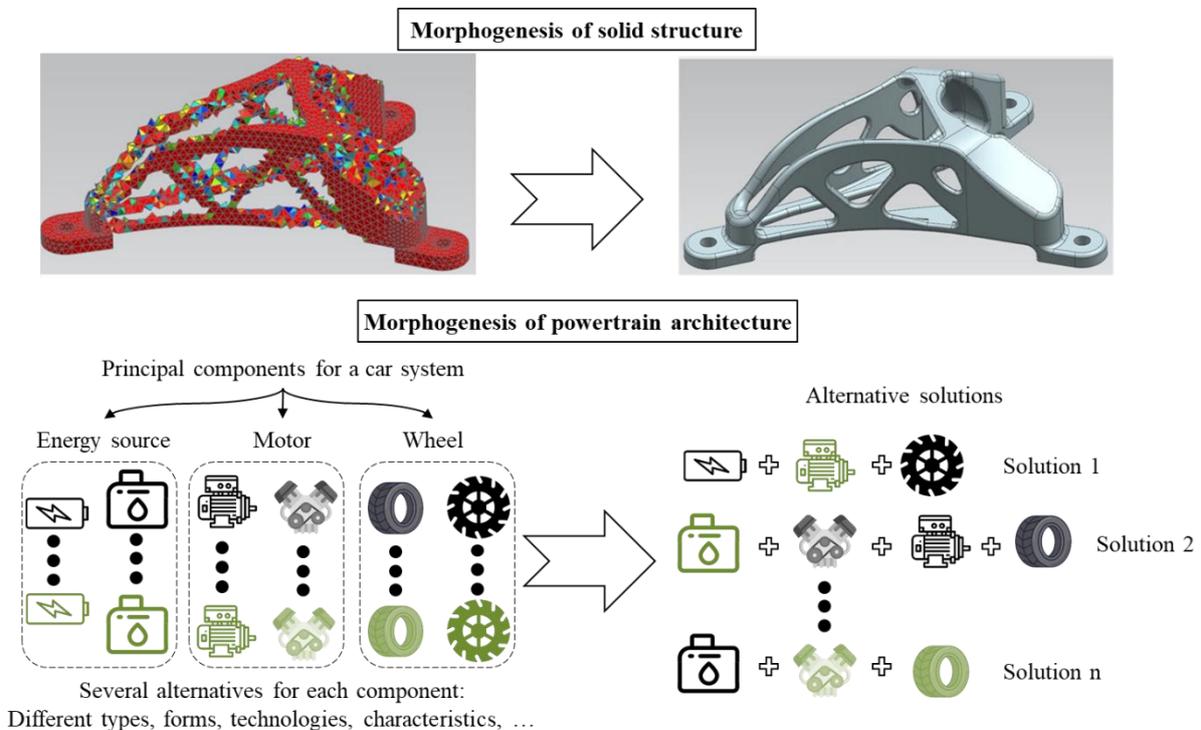


Figure 15: The morphogenesis concept of architecture

As shown in Figure 15, a solid structure can be presented as a spatial assembly of elements. In the same way, a system can be seen as an assembly of components where each of them is composed of several pieces and so on. The morphogenesis concept is introduced to express the possibility of changing the architecture of a system by changing its components, the way they are interconnected, the technology of those components, the positions, etc. For example, Figure 15 also shows the morphogenesis of powertrain architecture which contains generally three main steps: (1) the choice of the powertrain architecture, (2) the sizing (technology, dimensions, etc.) of the components imposed by the chosen powertrain architecture and (3) the control law imposed by the chosen components.

Based on OIA, the proposed framework consists of design inputs, iterative design optimization and design output. The iterative design optimization is the core of the proposed framework, and it consists of four models Morphogenesis, Observation, Interpretation, and Aggregation; this can be regarded as Morphogenesis plus OIA (MOIA). Generation and evaluation of the solutions are the two main activities that describe MOIA; the morphogenesis model performs the generation, while the other models (OIA) perform the evaluation. In conclusion, Morphogenesis is the iterative process that computes (improves and evolves) the values of design variables X , that characterize the candidate solutions, in order to maximize the GDI.

2.2.2.7.2. The targeted solutions

The iterative design optimization initially starts by using random values, or reference values if exist, of design variables and computes the GDI after passing through observation, interpretation and aggregation steps. The Morphogenesis model improves the values of design variables, by using an optimization algorithm. Hence, stopping criteria must be used to stop the algorithm (see 2.2.2.8), which results in design output.

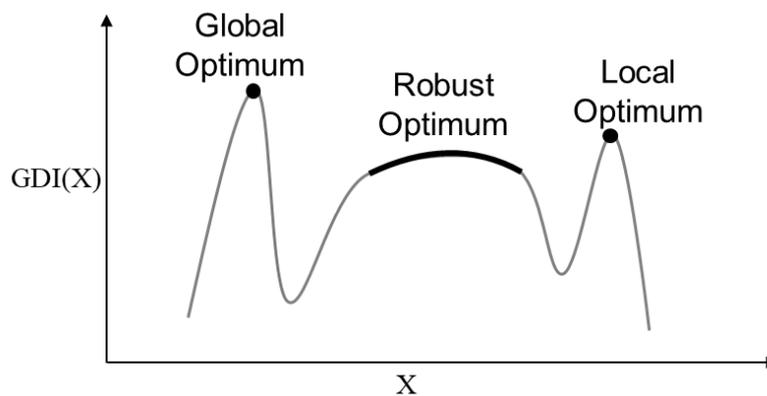


Figure 16: The local, global and robust optimums [Roy et al. 2008]

In this manuscript, we aim at investigating large design spaces in order to determine relevant acceptable and robust design solutions. A robust design solution is a solution insensitive to limited variations of the design variables. It maintains the same level of performance facing design variables variations. Moreover, the term *decisional robustness* is also used to mention the insensitivity of a solution to the variations of the preferences parameters in interpretation

and aggregation models. Figure 16 shows geometrically the difference between the local, global and robust optimums.

Several local optimums may exist. In addition, observation models are often non-differentiable. Therefore, classical optimization techniques based on gradient, for example, are not efficient for this type of optimization problem. In the following, we will focus on stochastic optimization algorithms, especially the Genetic Algorithm (GA).

2.2.2.7.3. Optimization algorithm

Many optimization algorithms are described in the available literature of optimization tools. The algorithms considered here are based on stochastic techniques and aims at finding optimal solutions for non-trivial optimization problems. Recently, also proposed a representation of the most important meta-heuristic optimization algorithms in a tree format [Yang et al. 2020] (see Table 9). However, the most used and efficient algorithms are related to two categories: Biology-based algorithms or Evolutionary Algorithms (EA) and Swarm-based algorithms or Swarm Intelligence (SI).

Evolutionary Algorithms are based on a principle of progressive modification of the set of candidate solutions, while the swarm intelligence exploits a system of communication and cooperation between candidate solutions.

In this work, we will focus on Genetic Algorithm (GA) which is widely used especially for solving MOO problems. GA is efficient to deal with most optimization problems, independently of the nature of the objective function and constraints. Holland mentioned that GA offers a good compromise between ratio of convergence (percentage of success) and convergence velocity [Holland 1992].

Biology-based algorithms	<ul style="list-style-type: none"> - Evolution Strategy (ES) [Rechenberg 1978] - Genetic Algorithms (GA) [Holland 1992] - Genetic Programming (GP) [Koza 1992] - Dolphin Echolocation (DE) [Kaveh and Farhoudi 2013]
Physics-based algorithms	<ul style="list-style-type: none"> - Big-Bang Big-Crunch (BBBC) [Erol and Eksin 2006] - Central Force Optimization (CFO) [Formato 2007] - Gravitational Search Algorithm (GSA) [Rashedi et al. 2009] - Charged System Search (CSS) [Kaveh and Talatahari 2010]
Swarm-based algorithms	<ul style="list-style-type: none"> - Particle Swarm Optimization (PSO) [Kennedy and Eberhart 1995] - Ant colony optimization (ACO) [Dorigo et al. 2006] - Cuckoo Search (CS) [Yang and Deb 2009] - Fruit fly Optimization Algorithm (FOA) [Pan 2012] - Grey Wolf Optimizer (GWO) [Mirjalili et al. 2014] - Whale Optimization Algorithm (WOA) [Mirjalili and Lewis 2016]
Sociology-based algorithms	<ul style="list-style-type: none"> - Tabu Search (TS) [Glover 1989, 1990] - Harmony Search (HS) [Geem et al. 2001] - Group Search Optimizer (GSO) [He et al. 2009] - Teaching Learning Based Optimization (TLBO) [Rao et al. 2012]

Table 9: Meta-heuristic algorithms [Yang et al. 2020]

Genetic Algorithm, proposed by Holland [Holland 1992], is one of the first methods of stochastic optimization. Its principle is to generate a population of candidate solutions, and make it evolve, mimicking natural selection as well as genetic processes. The candidate solutions are seen as individuals (sets of chromosomes), and their design variables are their genes, combined into a population (genome), (see Figure 17).

Starting from an evaluated population, the individuals are ranked in the evaluation order (maximization or minimization) and the best individual is stored. Then, the algorithm performs consecutive operations, through three operators, that are all controlled by random coefficients, in order to generate a new population. These operators are:

1. Selection and reproduction: some individuals are randomly selected by favoring the best, while leaving the possibility of selecting less good individuals. The selected individuals will be inserted in the new population.

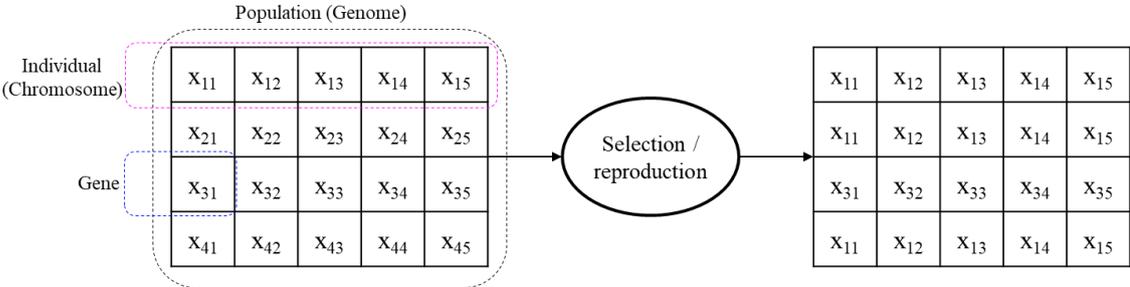


Figure 17: Selection and reproduction operator

2. Crossover: This operator aims at generating a new individual “Child” from a pair of individuals “Parents”. From the first individual, the operator selects randomly a gene that replaces a gene from the second individual in order to generate the “Child”, see Figure 17. This process is repeated for all the individuals in the population.

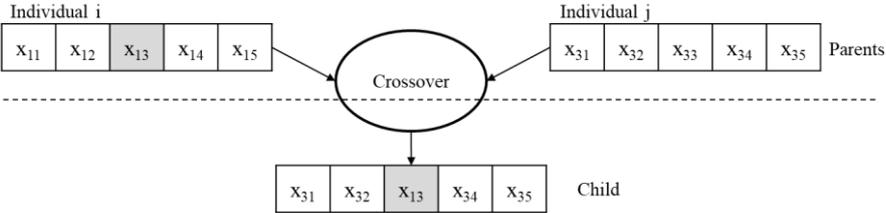


Figure 18: Crossing operator

3. Mutation: Similarly to crossover operator, the mutation operator randomly selects a gene from those of the individuals under consideration. A new value for this gene is then randomly generated from the corresponding domain of values.

2.2.2.8. Stopping criteria

In an optimization algorithm, the stopping criterion is the condition (or set of conditions) that leads to a programmed termination of the algorithm. This criterion is placed after the evaluation

phase (see Figure 8). Zielinski cites eleven different forms of stopping criteria [Zielinski and Laur 2007]. Generally speaking, three types of stopping criteria exist [Roudenko 2004]:

1. A target value for the objective function.
2. A limited number of evaluations or iterations.
3. A lack of improvement in the value of the objective function for the best solution over several consecutive iterations.

In this work, a combination between types 2 and 3 has been used. Then, the stopping criterion of the optimization algorithm is based on a limited number of iterations while an improvement in the value of the objective function is required over several consecutive iterations.

Chapter 3. Integration of MOIA ontology into Systems Engineering

3.1. Introduction

Today's systems are becoming more and more complex because of the emerging technologies such as mechatronics, artificial intelligence, Internet of Things (IoT), cybersecurity, factory 4.0, etc. Systems are now multidisciplinary or even interdisciplinary. A vehicle system, for example, is not only a combination of chassis, powertrain and electric/electronic systems, but also is a mobility type, yields to regulations of safety and comfort, has a style, and of course has a cost.

To cope with the lack in multidisciplinary specialists, the lack of a global vision for engineering and management and the difficulties in organizing the information exchanges between all professions, it is necessary to have a structured and methodical approach to design, build, produce these systems and manage complexity.

In the following, systems engineering, which becomes a standard industrial approach aims at developing (designing and validating) complex systems, is presented. The multi-physics modelling and simulation is a mandatory step in the design process. The system simulation can be considered as an early validation allowing to anticipate risks and minimize the number of design iteration loops and costly prototypes. These models are derived from the physical laws

that simulate the behavior of the system. Due to system complexity, these models are often characterized by long calculation times which lead to a difficulty to explore a large design space in the preliminary design phases. Because rapidity is central in design, the model reduction technique is proposed to create a quick tool, containing all the degrees of freedom with optimization at the core, which is efficient and simple to employ.

In addition, and in order to integrate the design optimization process into industrial processes, a relation between the MOIA and systems engineering is proposed. This relation aims to organize the design problem from a multi-objective optimization problem point of view, to organize the trade-off analysis and to assist decision-making in the preliminary design phases.

3.2. Systems Engineering (SE)

A system is a combination of interacting elements organized to achieve one or more stated purposes [ISO 2015]. Then, a system is composed of a set of components, also called system elements, that are organized in synergy, and meet specific needs in a multidisciplinary environment [Mhenni 2014; Crowder et al. 2016]. Generally, design processes in the early stages are based on imprecise knowledge, whereas design decisions have many economical and technical consequences [Berliner and Brimson 1988; INCOSE 2015]. In order to improve the performances of the design process, industrial actors generally rely on Systems Engineering (SE) approach that has management advantages of complexity. The International Council on Systems Engineering (INCOSE) defines Systems Engineering as an interdisciplinary approach aiming at formalizing the design and validation of complex and innovative systems successfully. It focuses on defining client and stakeholders' needs and ensuring their satisfactions in a high quality, trustworthy, cost efficient and schedule compliant manner throughout a system's entire life cycle [INCOSE 2015]. Systems Engineering also aggregates a set of activities (excluding the production activity) in order to transform the information from needs into technical instructions for its manufacturing [Fiorèse and Meinadier 2012].

In addition, Systems Engineering is an integrative approach in which the contributions of mechanical engineers, electrical engineers, human factors engineers and many other disciplines are evaluated to produce a coherent system that is often not dominated by a single discipline. The challenge of Systems Engineering is to manage the complexity, communication among disciplines and systems integrations. Moreover, Systems Engineering allows a trade study analysis for component selection.

3.2.1. Model Based Systems Engineering (MBSE)

Systems Engineering has been extensively used to facilitate the design process particularly in automotive, space and railway transportation industries [Romanovsky and Thomas 2013]. The main disadvantage of Systems Engineering is that it historically relies on a document-centric approach which produces a large amount of documents with various types and increases the difficulty to update and ensure overall consistency in case of changes. Therefore, when coordinating the work of a complex system, several manual tasks, like updating the documentation when client requests change, still required a huge effort. In order to increase

productivity by minimizing unnecessary manual transcription of concepts, the INCOSE proposed a more specific approach called Model-Based Systems Engineering (MBSE) to refer to information management between engineers throughout the design process using modeling. MBSE is defined as the “*formalized application of modelling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycles phases*” [INCOSE 2007]. *Applying MBSE is expected to provide significant benefits over the document centric approach by enhancing productivity and quality, reducing risk, and providing improved communications among the system development team* [OMG 2020].

In addition, the MBSE with Object Management Group System Modeling (OMG SysML), which now is a de facto in various industries practicing MBSE, is capable of solving the complexity, communications, and integrations issues [Friedenthal et al. 2014]. The OMG SysML is a standard graphical modeling language *that supports the specification, design, analysis, and verification of systems that may include hardware and equipment, software, data, personnel, procedures, and facilities* [Friedenthal et al. 2014].

3.2.2. Global V-model

The global V-model represents graphically the classical SE process or the system’s development lifecycle (see Figure 19). It is composed of two main branches: the design and the physical validation branch. The design branch mainly contains needs analysis, system specification (Blackbox), architectural design (Whitebox) and system elements specification. The physical validation branch contains also three main steps which correspond to system integration, system verification and system validation. In a system containing several components, the V-model steps are repeated recursively for all the components. Moreover, the V-model is also repeated iteratively several times along the product development cycle, in order to progressively improve the maturity of the design. Generally, after the final system validation step, the production starts.

The step of needs analysis describes the market needs, requirements, and constraints which are derived from stakeholders’ expectations, project and enterprise constraints, external constraints due to the physical context, and higher-level system requirements. These are documented in a requirements baseline. The requirements baseline guides the remaining activities of the SE process and represents the definition of the problem to be solved. The IEEE 1220 standard defines a requirements analysis sub-process for the purpose of establishing [IEEE-Std-1220 2007]:

- What the system will be capable of accomplishing;
- How well system products are to perform in quantitative, measurable terms;
- The environments in which system products operate;
- The requirements of the human/system interfaces;
- The physical/aesthetic characteristics;
- Constraints that affect design solutions.

In addition, the standard defines the following concepts (see 3.3 for the homogeneity of these concepts with MOIA):

- Requirement: A statement that identifies a need related to a product or process operational, functional, or design characteristic or constraint, necessary for product or process acceptability (by consumers or internal quality assurance guidelines), which is unambiguous and verifiable.

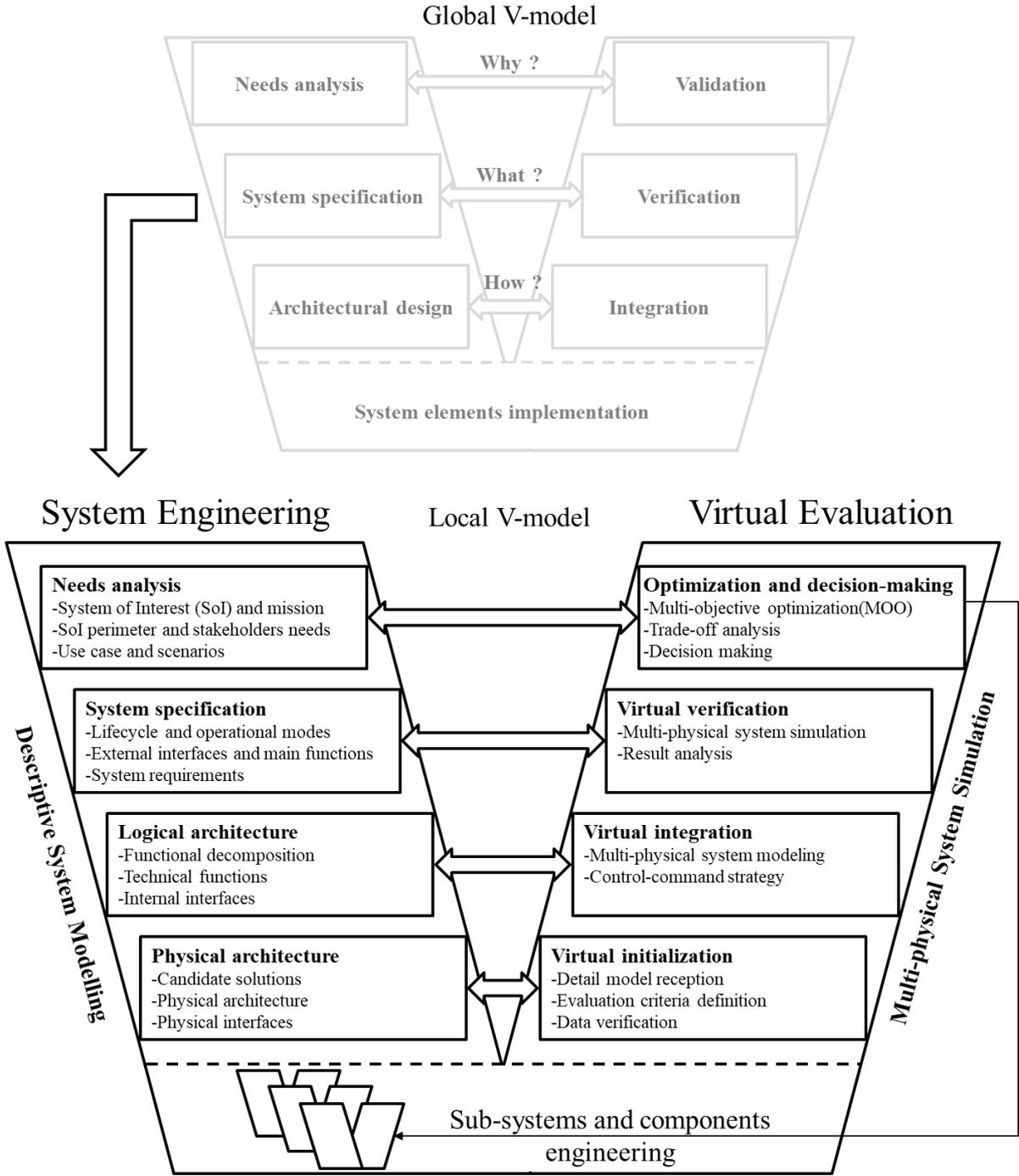


Figure 19: MBSE approach with local V-model proposed by Yang [Yang et al. 2017]

- Specification: A document that fully describes a design element or its interfaces in terms of requirements (functional, performance, constraints, and design characteristics) and the qualification conditions and procedures for each requirement.
- Measure of Effectiveness (MoE) [from end-user perspective]: The metrics by which an acquirer will measure satisfaction with products produced by the technical effort.
- Measure of Performance (MoP) [from designer perspective]: An engineering performance measure that provides design requirements that are necessary to satisfy a MoE (There are generally several measures of performance for each MoE).
- System architecture: The organizational structure of a system or component; the organizational structure of a system and its implementation guidelines [ISO 2010].
- Technical Property Measures (TPM): Quantitative measure of a physical design characteristic.
- Trade-off analysis: An analytical evaluation of design options/alternatives against performance, design-to-cost objectives, and life cycle quality factors.

3.2.3. Local V-model

In context of the Valeo company and in order to implement the MBSE approach, Piques has introduced a methodology called SysCARS (System Core Analyses for Robustness and Safety) which is inspired from automotive particular constraints and international standards (ISO 15288 [IEC 2008], IEEE 1220 [Doran 2006], EIA 632 [EIA 2003], etc.); it was adapted to Valeo's engineers mindset and usages. Piques defines SysCARS as *a methodology which provides a practical help for system designers on how to perform the sequence of system modeling activities with SysML* [Piques 2014]. A modeling tool providing automated documentation generation and traceability supports the SysCARS methodology.

Even if the MBSE approach can be an efficient way to generate simulation models [Yang et al. 2017; Brunet et al. 2019; Sohier et al. 2019], insufficient training on SE as well as the complexity and non-ergonomic design of numerical SE tools, still result in serious problems of operational implementation [Góngora et al. 2012; Doufene 2013; Yang et al. 2017]. Several researches lead to the development of software solutions that generate automatically executable simulation models from SysML behavioral diagrams and automatically update SysML models based on simulation results [MagicDraw; ModelCenter; Phisystem; Syndeia; WindchillModeler]. As example, Kaslow et al. used MagicDraw, Matlab and ModelCenter [Kaslow et al. 2014] in order to develop a CubeSat MBSE reference model [Kaslow et al. 2015].

Yang has proposed an adapted MBSE approach integrated in conceptual and preliminary design phases, with a focus on energetic system applications, that represents a local V-model (see Figure 19) into the global V-model [Yang et al. 2017]. This method is expected to assist decision-making in the early system design phases. This model is made of two main branches:

- The design branch (descending branch) consists in describing the SE approach by decomposing the System of Interest (SoI) starting from a high-level needs analysis, then specifying and defining the system more and more precisely, up to the choice of physical architecture. It contains four main steps which correspond to needs analysis (stakeholder

requirements definition), system specifications (system requirements) and system logical and physical architecture (architectural design).

- The virtual evaluation branch (ascending branch) consists in going through the evaluation and optimization activities by using multi-physical system simulation and multi-objective optimization methods, up to decision-making. It contains also four main steps which correspond to virtual initialization, virtual integration, virtual verification and a final step called optimization and decision-making.

This proposal relates the descriptive system modelling and multi-physical simulation. Through simulation, this relation allows engineers to manage and integrate multiple criteria in the preliminary design phases.

3.2.4. SCTO method

Following Yang proposition; the Source, Converter, Transmitter, operator (SCTO) method [Sallaou 2008; Pailhès et al. 2011] is used to organize the functional and physical architecture analysis. SCTO is the energetic view of the law of completeness of system parts [Savransky 2000]. This system is composed of sub-system components having different functionalities. From MBSE perspective, the SCTO elements provide mechanics oriented functional patterns to guide the elaboration of the logical system architecture. Figure 20 shows SCTO method as presented in [Pailhès et al. 2011]:

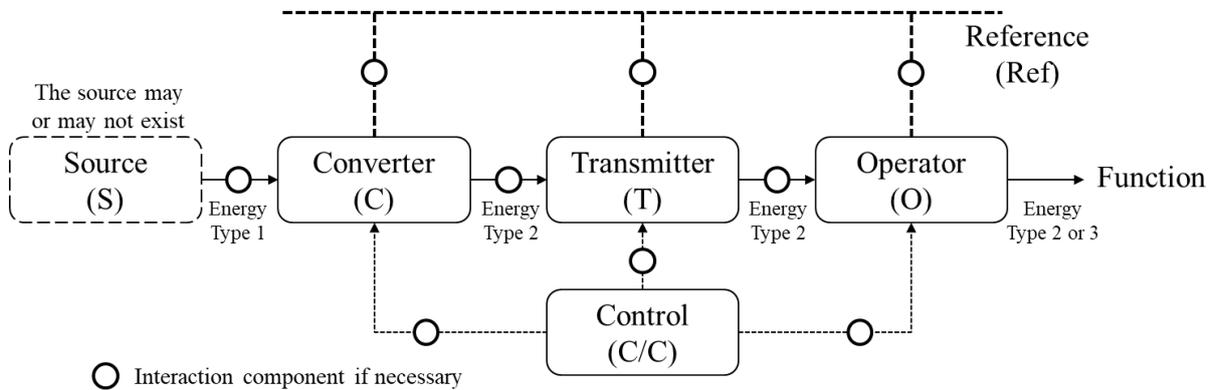


Figure 20: SCTO method – decomposition of a system and energy types

- Source (S): supplies and stores energy. It can be external or internal to the system.
- Converter (C): converts source energy into other types of energy usable by other components.
- Transmitter (T): transmits energy without changing its initial type.
- Operator (O): performs the action required by the system. It can be either a converter or a transmitter.
- Reference (Ref): Allows positioning the different components in relation to the reference.
- Control-command (C/C): ensures the functions of the system's components.

SCTO method is enriched by a new concept called Converter, Transmitter, Operator (CTO) database, presented as a database matrix (See Figure 21). From MBSE perspective, the CTO

database consists in assisting the transition from logical architecture to physical architecture by supporting the allocation of system internal technical functions to system physical components. The matrix presents a large component base containing different existing technical solutions with their proper characteristics.

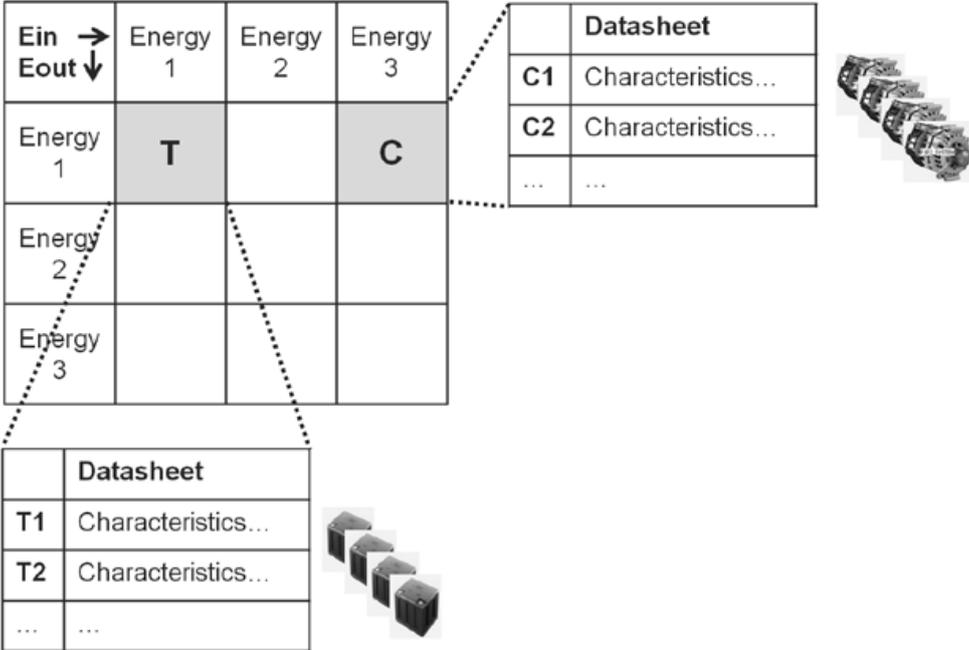


Figure 21: CTO Database matrix [Yang et al. 2017]

Moreover, simulation allows connecting the local V-model to an optimization and decision-making tool in order to assist early-phase decision-making. For example, designers will be able to make decisions between system candidate solutions in a level N (system) before passing to the detailed system design step in a level N-1 (sub-system), see Figure 22.

The optimization and decision-making tool used is based on MOIA ontology. MOIA aims at helping designers in taking rational decisions when they face a combinatorial number of candidate solutions in a multi-objective optimization problem. MOIA ontology plays the role of a design framework for optimization in MBSE. The integration of MOIA ontology into Systems Engineering process is explained in 3.3.

3.3. Integration of MOIA into MBSE

The MBSE approach is related to interdisciplinary management and coordination in the design process. According to MOIA, designers’ preferences are expressed through interpretation and aggregation models to link physical behavior, functional constraints and design objectives. As shown in Figure 22 and Figure 23, a close relation exists between the MBSE approach and MOIA ontology. In addition to the design problem organization advantage, explained in the following, and because of the standardization aspect of MBSE, the mentioned relation will boost the acceptability of using MOIA as an optimization and decision-making tool.

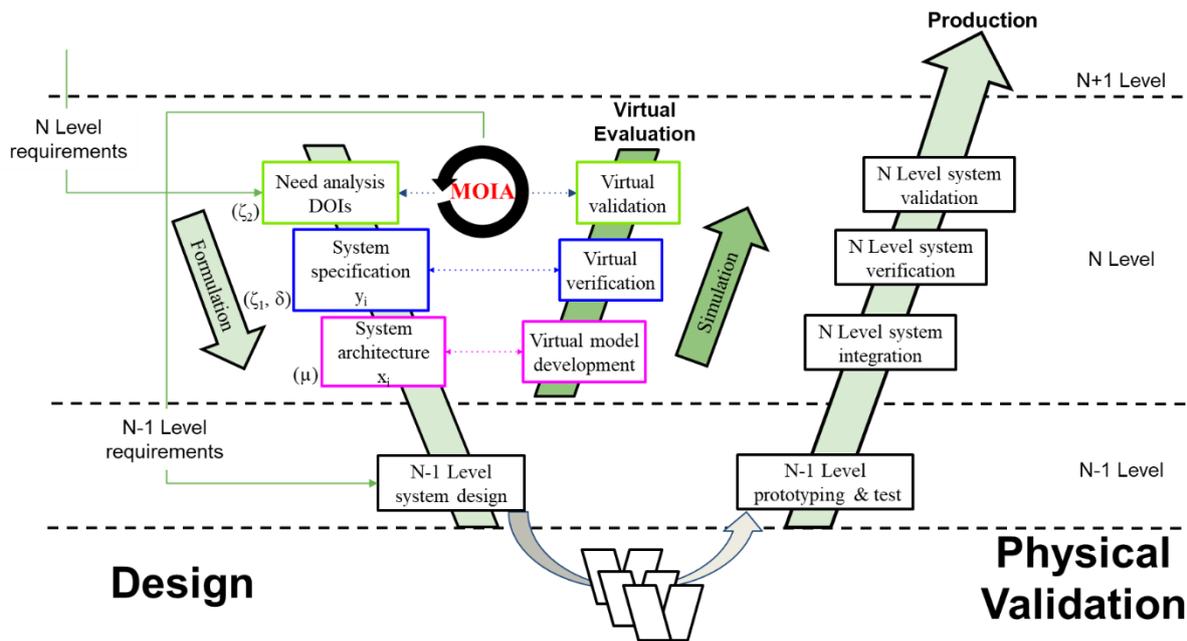


Figure 22: Integration of MOIA into MBSE local V-model

As mentioned before, MOIA combines three kinds of models which are the observation (μ), the interpretation (δ) and aggregation (ζ) models. The observation model allows computing the desired observation variables (Y) from a set of design variables (X) of the system. The interpretation model is a satisfaction evaluation model that quantifies the degree of acceptability of each observation variable and generates a set of interpretation variables (Z); it is based on design constraints and clients or designers' expectations. The aggregation model aims at aggregating all the interpretation variables to compute the global design objectives (DOIs) and from them, a global satisfaction index called global desirability index (GDI). GDI has to be maximized to perform the optimization process.

The client, which is the main stakeholder, provides the system specifications in form of many kinds of requirements; thus, the problem of design is seen as a Multi-Objective problem to be solved. Needs analysis is the first step in the V-model. It aims at defining the main objectives or services, the use cases and scenarios expected from the system. These main objectives are specially demanded by stakeholders. The indexes of these objectives are known as Measures of Effectiveness (MoEs) in SE wording and can be expressed as DOIs on the MOIA side. In an innovation context, marketing engineers have to approximate the main objectives of a product based on market forecast study.

The second step aims at deriving the system requirements and main functions from the first step. The calculable requirements are the Observations variables Y , also called criteria or Measures of Performance (MoPs) in SE wording. All the operational scenarios that allow the calculation/verification of Y must be provided in the statement of the design scope. These Y are normalized by the desirability functions δ , which results in a set of interpretation variables Z ; each Y_m variable is then interpreted into one or several Z_m . Desirability functions contain the available information of observation variables. This information can be negotiated between

client, marketing engineer, and design experts. These actors are in charge of providing the minimum level of information in order to build desirability functions (see 2.2.2.5.3 for the parametrization of desirability functions). Changing this information can drastically change the characteristics of the optimal solution.

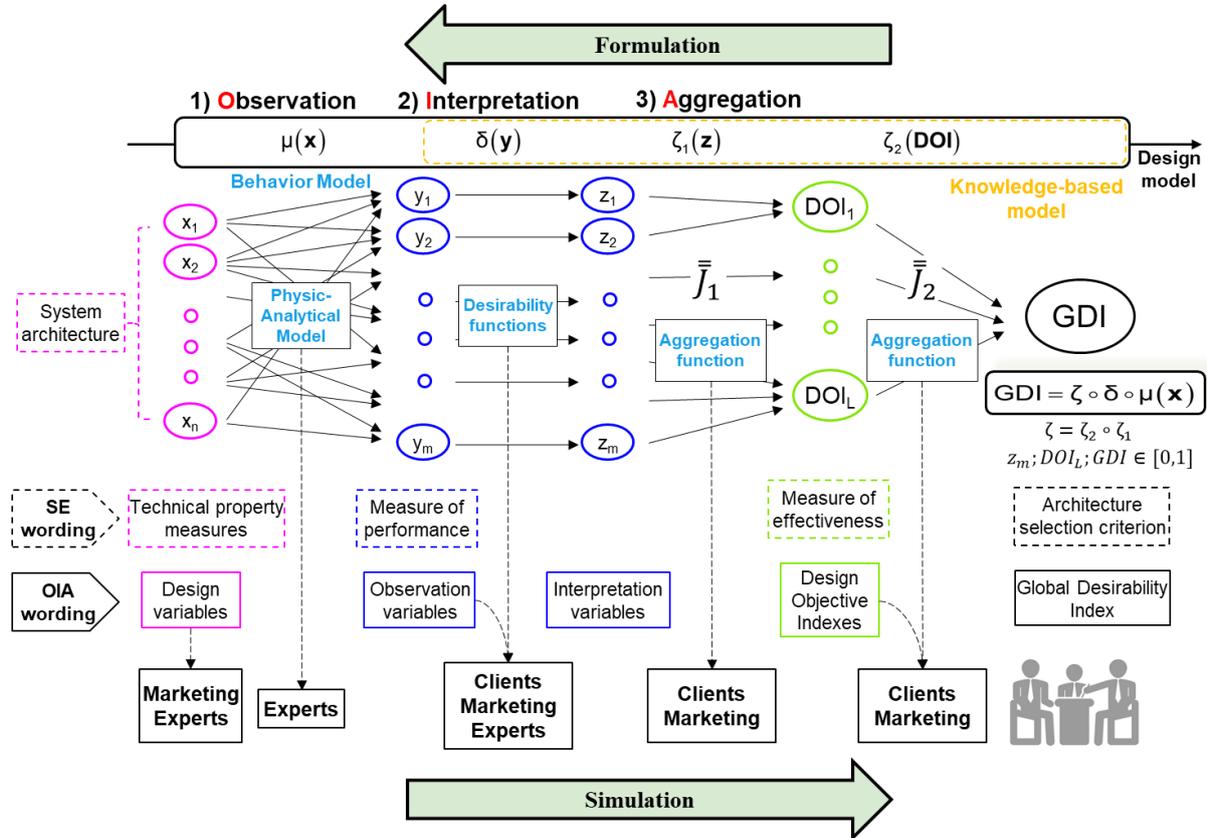


Figure 23: Illustration of the MOIA ontology

The third step aims, first, at describing the functional architecture of the main functions. These functional architectures are then declined in physical architectures using a functional decomposition process like SCTO. From this functional decomposition, all the Physic-Analytical (PA) simulation models are created by experts to compute Y from X. X represents the physical architecture in terms of *design variables* (in OIA wording) or *design characteristic* (in SE wording). Marketing engineers and design experts also define the domains of values of the design variables.

Two aggregation steps are carried out during the MOIA process: the first one aggregates the Z_m into DOIs and the second aggregates the DOIs into one GDI which represents the *architecture selection criterion* in SE wording. Aggregation is a way to combine several indicators into one, taking into account the importance level of each. It is based on aggregation functions ζ_1 and ζ_2 that can be parameterized using judgment matrices \bar{J}_1 and \bar{J}_2 defined from pairwise comparisons of the criteria (see 2.2.2.6.1). All these functions are selected and parameterized by the client or marketing engineers (see 2.2.2.5.4 for the parametrization of aggregation functions). In SE wording, an aggregation step corresponds to what is called trade-off analysis.

In conclusion, a strong relation exists between MBSE and MOIA ontology. This relation, constructs a tool, aimed at supporting decision-making in complex design problems which are regarded as multi-objective optimization problems. GDI is considered as the unique selection criterion that results from a package of information derived from the different levels of the design process and implicates the right actors in the decision-making process. In addition to the objective of optimization, the MOIA facilitates the management of multiple points of view, using the interpretation and aggregation steps, in order to confront and optimize architecture choices based on the evaluation of critical elements and the search for compromises. Table 10 illustrates the contributions given by MBSE to enrich MOIA and the inverse.

MBSE to MOIA	<ul style="list-style-type: none"> - Definition of the design objectives, observation variables and design variables (system physical architecture(s)). - Definition of the principle functions and scenarios in order to prepare the observation model. - Identification of actors and allocation of activities to specialist teams.
MOIA to MBSE	<ul style="list-style-type: none"> - Organization of the multi-objective design problem: Ensure the virtual integration, verification and validation of the system. - Simplification of the multi-objective optimization design problem into single-objective optimization design problem. - Manipulation of different points of view using the steps of interpretation and aggregation functions.

Table 10: The contributions given by MBSE to MOIA and the inverse

3.4. Substitution models

Generally, facing complex physical phenomena, numerical simulation consumes most of the CPU time of the optimization process. This can be quite critical depending on the design space to be explored, that is to say the number of design variables X and the extent of their own domain of values. As mentioned before, a very accurate simulation model, characterized by long calculation times, forces designers to limit the design space by treating a small number of design solutions in the preliminary design phases. Moreover, using such models will force designers to limit the flexibility of design specifications and the study of the different decision-makers' points of view. At the end, this leads to an absence of a fully satisfactory solution.

Substitution model aims to replace an initial model with another model that is faster, but often less accurate. To do this, it generally requires a set of data (Inputs: design variables X and outputs: observation variables Y) derived from simulations by the initial model that we want to reduce. The simulation data can be combined with experiment measurements. This hybrid approach is widely explored in the literature today [Chinesta et al. 2018; Sancarlos et al. 2020].

A widely used methodology for approximating a model is the Response Surface Methodology (RSM). Two of the most known techniques in RSM are probably the polynomial surface response [Box and Wilson 1951; Draper and Guttman 1986; Kleijnen 2009] and the Artificial Neural Networks (ANN) first developed by neurologists [Anderson et al. 1988].

In addition, by using methods like the Principal Components Analysis (PCA) [Hotelling 1992; Lee and Verleysen 2007] and Bayesian Network [Pearl 1985; Neal 2012], there is a possibility to identify the most significant variables of a design problem and the relationship between them.

Generally, those methods are used as a first step in the approximation of a model. After the identification of the significant variables, the model can be approximated by using only these variables, which allows the minimization of the computation time.

Below we cite two of the most used methods. Those methods correspond to two categories under “black box” model type which requires no prior knowledge of relationships between input and output variables:

- Polynomial surface response:

In traditional RSM, it is typically assumed that the function to be modeled can be adequately approximated by a polynomial model in the region of interest [Box and Wilson 1951]. Box and Wilson assume that the response Y at any point $(x_1, \dots, x_t, \dots, x_n)$ in the region of interest can be represented by a regression equation of the form:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_{11} x_1^2 + \dots + \beta_{12} x_1 x_2 + \dots + \beta_{111} x_1^3 + \dots \quad (9)$$

The approximation is viewed as a linear combination of monomials. The coefficients β are calculated based on observed data. β can be calculated using the Analysis of Variance (ANOVA) [Gelman 2005]. Using such a method, the most important variables X that affect the response Y can be identified. However, the main disadvantage of the polynomial model is that the capture of local non-linearities requires very high order polynomials which are expensive in terms of computing time [Moustapha 2016].

- Artificial Neural Networks (ANN):

Artificial Neural Networks, inspired by the biological neural networks, mimic the way the brain processes information to memorize complex data sets and predict new situations [Moustapha 2016]. An ANN is a set of neurons (non-linear functions) which can be used to process information from inputs to outputs from their inter-connections in a given architecture.

Extreme Learning Machine (ELM), initiated by [Huang et al. 2006; Huang 2020], corresponds to a particular form of ANN for classification and regression. According to Huang, the main advantage of the ELM algorithm is that it can be quickly parametrized and has better generalization performances than the traditional classic gradient-based learning algorithms such as backpropagation [Rumelhart et al. 1986]. Figure 24 shows a three-layer ELM function. The mathematical expression of the ELM function is presented in (10) where W , b , f and β are the input weights matrix, input biases matrix, activation function, and output weights matrix respectively. W and b depend on the number of hidden neurons N that must be chosen in advance.

$$Y = \beta \cdot H \quad ; \quad H = f(W \cdot X + b) \quad (10)$$

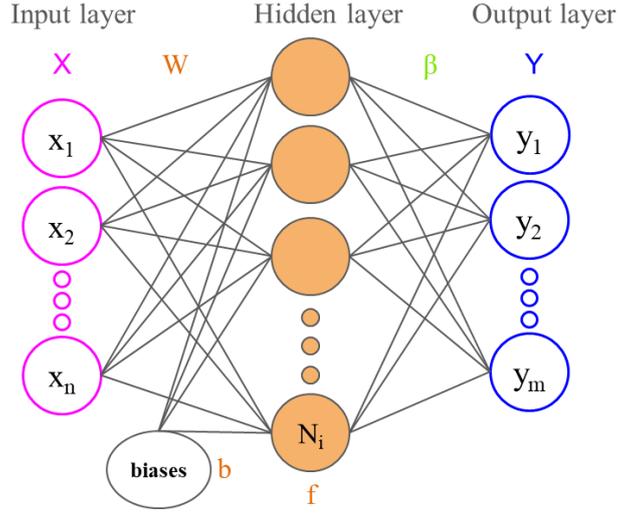


Figure 24: Three-layer Extreme Learning Machine as a function $Y(X)$

The seminal ELM learning algorithm is based on the computation of β after selecting the values of W , b , f and N from a random choice. The values of W and b must be chosen in the range of -1 to 1. Several types of activation functions exist and it is difficult to recommend a function that works in all cases. The computation of β is regarded as a learning phase, and uses a learning set of values of X and Y . The values of X and Y must be normalized by projecting the numerical values of the data set onto a common scale.

$$\beta = Y \cdot H^+ \quad (11)$$

Computing the Moore-Penrose generalized inverse H^+ of the hidden layer output matrix H requires most of the learning time [Huang et al. 2006]. Then, during the testing phase, a testing set is evaluated and the ELM approximation error is calculated. The approximation error generally used is the Root Mean Square Error (RMSE); RMSE represents also the level of accuracy. It can be calculated using the formula below where Y^t represents the testing set values, Y^e represents the evaluated values using ELM and k is the number of elements of the testing set.

$$\text{RMSE} = \sqrt{\frac{\sum_k (Y_k^t - Y_k^e)^2}{k}} \quad (12)$$

Due to the random selection of W , b , f and N , the ELM function may be improved by optimizing the value of these parameters. Therefore, in the following, we distinguish two types of ELM called *random-ELM* and *optimized-ELM* corresponding to the original and GA-optimization based algorithm of ELM respectively.

3.5. The optimization of ELM

The backpropagation algorithm aims at optimizing the matrices W and b while specifying a number of hidden neurons N and a differentiable activation function f . Huang proves that the

matrices W and b can be randomly assigned if the right number of hidden neurons and activation function are chosen [Huang et al. 2006]. Because design problems are evolutive in essence, and in order to adapt continuously the ELM parameters choices, we developed an *optimized-ELM* algorithm that optimizes the choices of the number of hidden neurons and the activation function; as a reminder, the matrices W and b will also be optimized because they depend on the number of hidden neurons.

In terms of precision, it can be noted that the approximation error of the *random-ELM*, in comparison with the PA model, can be very large due to an inappropriate choice of the activation function f and/or the number of neurons N in the hidden layers of the network. The aim of the *optimized-ELM* is to minimize the approximation error compared to the *random-ELM*, by optimizing these choices.

3.5.1. Optimized-ELM algorithm

The *optimized-ELM* is found using the algorithm presented in Figure 25. The first step consists of defining the design space by choosing the domains of the values of the design variables X . The second step is to prepare the learning and testing sets. It starts by choosing randomly a set of X values and then calculates Y using the PA model. In the third step, an optimization algorithm is used to optimize the ELM parameters f and N ; this algorithm is limited by a number of iterations «Limit_I». Seventeen activation functions have been identified [contributors 2020].

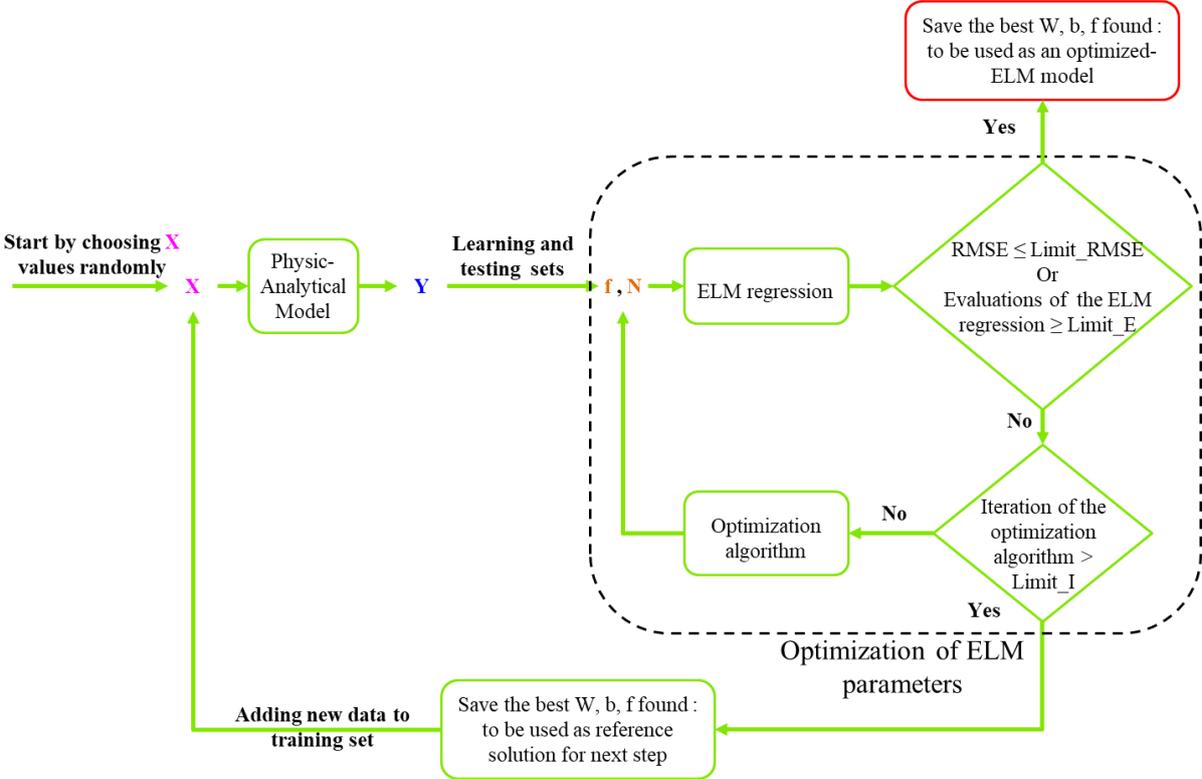


Figure 25: Optimized-ELM algorithm

The stopping criteria of the *optimized-ELM* algorithm are the RMSE of the ELM model and a limit number of evaluations of the ELM regression block. If the RMSE is higher than the expected limit “Limit_RMSE” and the number of evaluations of the ELM regression block is lower than the expected limit “Limit_E”, the *Optimized-ELM* algorithm will enrich the learning set, and will save the best ELM parameters in order to be used as a reference solution for the next iteration. When one of the stop criteria is satisfied, the ELM parameters are saved and used as an *optimized-ELM* model.

3.5.2. Test functions

To evaluate the precision of the *optimized-ELM* as substitution models, we use two test functions representative of the PA models complexity: The Sphere and the Ackley functions. The 2D versions of these functions are presented in Table 11. The objective is to find the global minimum of each of them.

To make the optimization problem complex, the number of design variables is chosen equal to 6 which represents the dimension of these functions. The domain of values chosen is [-3 ; 3] for each of the six design variables with a discretization step of 0.01. This means that the optimization algorithm has to find the optimum solution (the minimum) among 601^6 ($>10^{16}$) solutions. The GA is used to find the minimum of the test functions with the same parameters in all cases.

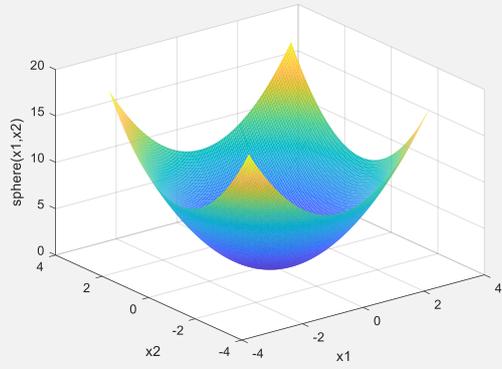
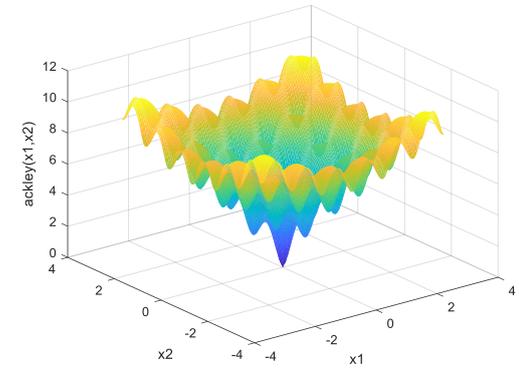
	Sphere function	Ackley function
2D representation		
Mathematical expression	$f(x) = \sum_{i=1}^d x_i^2$	$f(x) = -20 \cdot \exp \left(-0.2 \cdot \sqrt{\frac{1}{d} \sum_{i=1}^d x_i^2} \right) - \exp \left(\frac{1}{d} \sum_{i=1}^d \cos(2\pi \cdot x_i) \right) + 20 + \exp(1)$
Number of design variables	d = 6	
Domain of values	[-3 ; 3] with 0.01 of discretization step $\rightarrow \sim 5 \cdot 10^{16}$ possible solution	
Global optimum	[0,0,0,0,0,0]	

Table 11: Sphere and Ackley test functions

3.5.3. Optimized-ELM vs random-ELM

If we use the RMSE as a precision indicator, we find that, in some cases, the *random-ELM* can generate very large RMSE values. To adopt a statistical point of view, Table 12 shows the arithmetic average of 100 RMSEs computed from the *random-ELM* and the *optimized-ELM* for the test functions. Table 12 also shows the number of test function evaluations. The initial number of test function evaluations, which represents the calculation done to initiate the learning and testing sets, is the same for the *random-ELM* and the *optimized-ELM*. It is remarkable that the number of test function evaluations is higher for the *optimized-ELM* since the *optimized-ELM* algorithm has a loop aiming at adding new data to the learning set.

Test functions	<i>Random-ELM</i>				<i>Optimized-ELM</i>			
	Number of test function evaluations	RMSE		Number of test function evaluations	RMSE			
	Average	Average [%]	Standard deviation [%]	Average	Standard deviation	Average [%]	Standard deviation [%]	
Sphere	1200	12	20	1215	86	0.035	0.024	
Ackley	5200	4	8	6170	119	2.63	0.13	

Table 12: Random vs Optimized ELM comparison

We can see that the *optimized-ELM* is much more precise than *random-ELM* while the number of test function evaluations is not much higher. This means that the *optimized-ELM* can be estimated as a low-cost algorithm in terms of computation time, with much more precise results than *random-ELM*. It may be noted that the accuracy of the *optimized-ELM* can be improved by increasing the number of iterations of the *optimized-ELM* algorithm and then the computation time.

3.5.4. Optimized-ELM vs test functions for the minimum search

We use a GA to find the minimum of both test functions and the *optimized-ELMs* that approximate the test functions. The stopping criterion of the GA is the number of iterations. To adopt a statistical point of view, we run the optimization 100 times for each case.

Table 13 shows the optimization results. Globally, the time saved using the *optimized-ELM* corresponds to the reduced number of evaluations of the test functions.

First, the search for the minimum is done on the test functions. On average, the GA requires 28862 evaluations on the *Sphere function* and 28684 evaluations on the *Ackley function* in order to find the global minimum. Second, the search for the minimum is done using the *optimized-ELM*. In this case, the test functions are only evaluated by the *optimized-ELM* algorithm and 1215 evaluations of the *Sphere function* and 6170 evaluations of the *Ackley function* are necessary to generate the *optimized-ELM* models used for the minimum search. It is clear that the number of evaluations of the test functions is much higher in the case of optimization using the test functions than the case of optimization using *optimized-ELM*. Then, the optimization using *optimized-ELM* models is much faster. In addition, in both cases, the minimums found with the *optimized-ELMs* are similar to the minimums found with the test functions.

Optimization using		Number of evaluations of the test function		Convergence accuracy	
		Average	Standard deviation	Average	Standard deviation
Test functions	Sphere function	28862	13071	The solution found is the global minimum [0, 0, 0, 0, 0, 0]	
	Ackley function	28684	13760		
Optimized-ELM	Sphere function	1215	86	[0, 0, 0, 0, 0, 0]	[0.01, 0.01, 0.01, 0.01, 0.01, 0.01]
	Ackley function	6170	119	[-0.02, -0.05, 0, -0.01, -0.04, 0.02]	[0.06, 0.06, 0.06, 0.07, 0.08, 0.06]

Table 13: Application of optimized-ELM on test functions

In order to conclude, compared to the test functions, the *random-ELM* model is fast both in learning and in calculation but not very precise. The *optimized-ELM* model is also fast in calculation but the learning phase requires additional computation times. The *optimized-ELM* model can be considered as an intermediate model, with a good balance between computation times and precision.

Finally, due to their speed and precision, *optimized-ELM* models are good candidates to replace the complex PA models (substitution model) used in multiphysics simulation. In addition, it may be noted that once the *optimized-ELM* models are found, they are usable for further applications.

3.6. Integration of ELM into MOIA

3.6.1. Dynamic optimization process

Generally, the development and the computation times required by the observation models (Physic-Analytical model) limit designers' capability to investigate a large design space and to treat flexible design specifications. In order to reduce computation time and improve decision-making, this section introduces a dynamic optimization process, which adds flexibility to design approaches in several different ways. This process lies on a dynamic vision of specifications, scenarios, client needs and preferences; it aims at integrating a machine-learning algorithm in a global evolutionary optimization algorithm generating reduced models directly in an online mode.

Figure 26 shows the flowchart of the proposed dynamic optimization process; it is based on the *optimized-ELM* algorithm presented in Figure 25. It may be noted that Y is often composed of several observation variables Y_m ; then, the *optimized-ELM* algorithm will run for each Y_m . After finding the *optimized-ELM* models, these models will be used into the red optimization loop, which represents the main design optimization process.

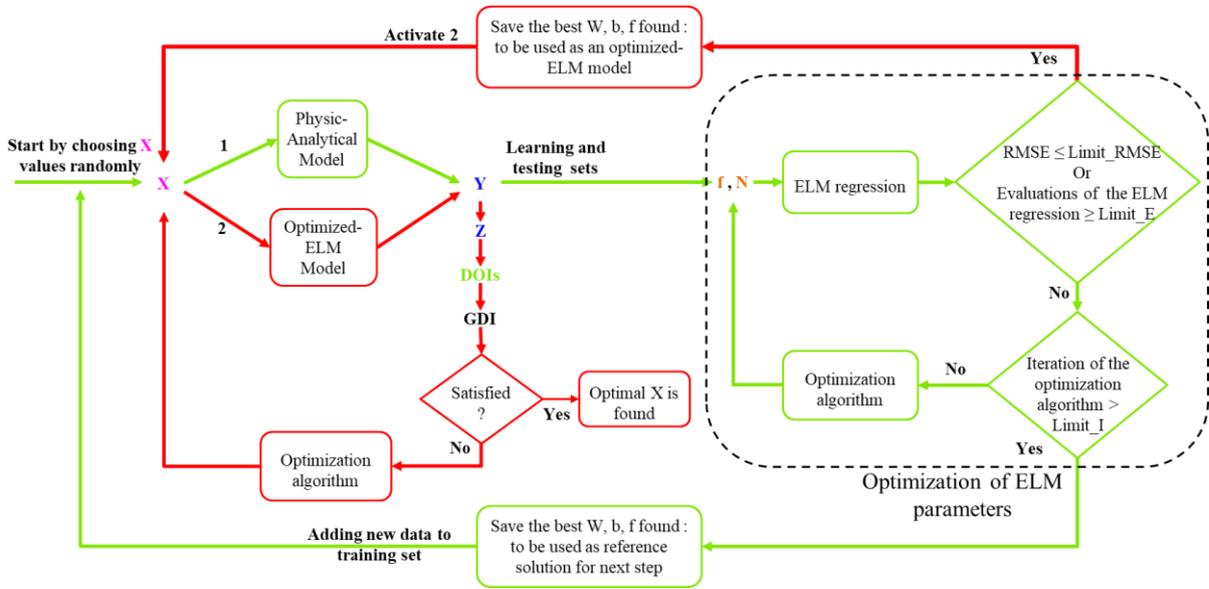


Figure 26: Flowchart of the dynamic optimization process

Figure 27 shows a schematic comparison between the CPU times required for the classical process, based on the use of the PA model, and the dynamic optimization process proposed in this thesis. Theoretically, the CPU time in the original process can be represented as a straight line function of the number of iterations of the optimization algorithm. The slope of this line is a function of the parameters of the optimization algorithm used. For the dynamic optimization process, the CPU time can be divided into 3 main phases:

1. Linear phase: prepares the learning and testing sets using PA model. It is superimposed with the line of the original process.
2. Rapid growth phase: the optimization of ELM parameters requires CPU time in order to compute the *optimized-ELM* model of Y .
3. Saturation phase: the optimization of X is based on the use of the *optimized-ELM* model. The slope of the line becomes lower than the first line, because the *optimized-ELM* model runs much faster compared to PA model.

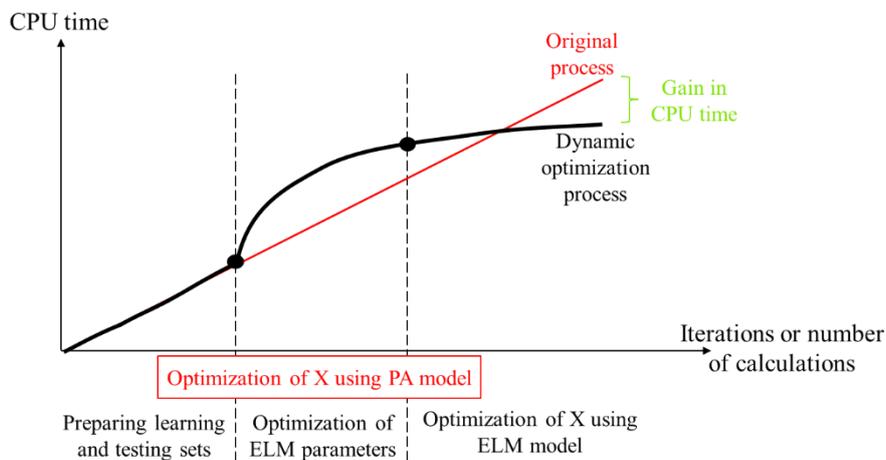


Figure 27: Comparison between the original process and the dynamic optimization process

As a result of the process presented above, it is possible to overcome the difficulty arising from the high CPU time of the PA model by using the *optimized-ELM* model. The model can calculate results instantaneously, which highly improves the computation performances and the decision-making process flexibility. Therefore, there is a possibility to study different decision-makers' points of view by changing the parameters of the interpretation and aggregation models.

3.6.2. The practical perspective

Once the specifications are formalized using the MBSE approach, the design problem becomes an optimization problem with specified design variables, criteria and objectives. Then, MOIA ontology plays the role of optimization. The dynamic optimization is supported by the replacement of the PA model in MOIA with the *optimized-ELM* model (see Figure 28).

Following this process, decision-makers are capable to explore a large design space by evaluating a huge number of solutions. The optimal solutions are visualized in real time by decision-makers.

Interpretation and aggregation parameters are not formalized during the MBSE approach. They characterize the decision-makers' points of view that characterize the optimal solutions. By modifying the MOIA parameters of interpretation and aggregation, they are also able to check immediately the evolution of the problem and the consequences of their decisions.

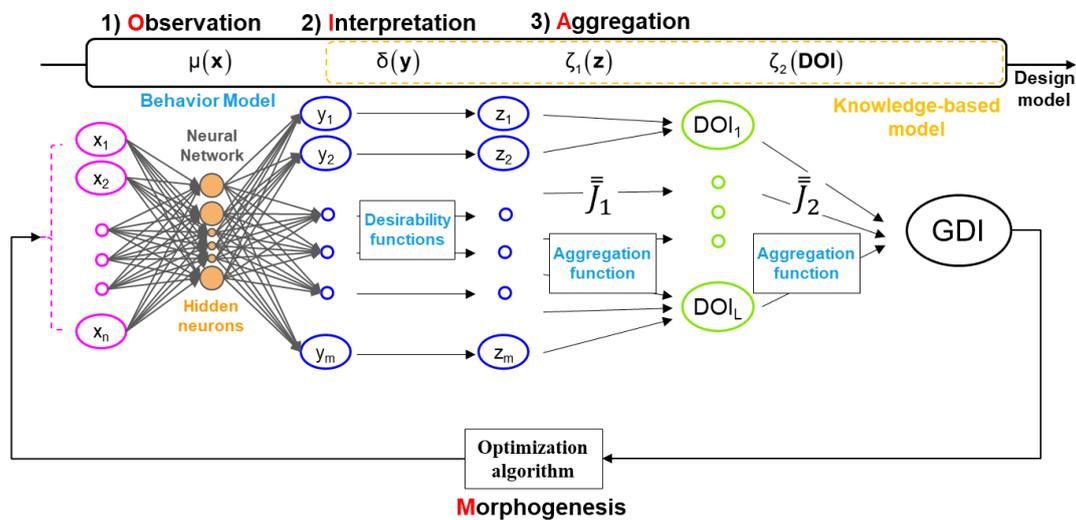


Figure 28: MOIA ontology with Neural Network

Based on the method explained above, a graphic interface, based on the MOIA ontology, has been created in order to illustrate how to support decision-making in complex design problems. Figure 36 shows this interface for Electric Vehicle (EV) case study that is described in Chapter 4.

Chapter 4. Use cases

4.1. Studied cases

Within the framework of the PhD thesis, two use cases have been investigated:

1. Electric vehicle powertrain: This project aimed at computing optimal powertrains for an electric vehicle considering the vehicle autonomy, the powertrain cost and the vehicle performance criteria. This case illustrates the integration of the ELM into the MOIA (see 3.6). Additional information is presented in part 4.3.
2. Drone taxi: This project addressed the process of dimensioning the propulsion system of a MAV (Manned Aerial Vehicle) taxi with a typical mission of transporting passengers between business areas and airports. The purpose of the approach is the specification of electric propulsion motors. This case illustrates the integration of the MOIA in the MBSE (see 3.3). Additional information is presented in Appendix I.

Table 14 shows an overview for the projects cited before. Three main categories are identified: MBSE, MOIA and the Human-Machine Interface (HMI) as a decision-support tool (see 4.7). System Modelling SysML was performed using Artisan Studio© for the Electric Vehicle project [Yang et al. 2017] and using Enterprise Architect© for the Drone taxi project. The observation models of all the projects are coded using Matlab. An ELM code is also implemented in Matlab for the substitution models.

		Electric Vehicle	Drone taxi
MBSE	System Modelling (SysML)	✓	✓
	Observation model	✓	✓
MOIA	Substitution models with ELM	✓	✗
	Interpretation and aggregation modelling	✓	✓
	Optimization	✓	✓
HMI	User interface for decision-support	✓	✗

Table 14: Use cases studied during the PhD

4.2. Introduction

In order to prove the efficiency of the proposed methodology (see Chapter 3) in the preliminary design phases, this chapter studies an application to the electric vehicle powertrain design which is a current real industrial problem. In the following, we will identify components of the electric vehicle powertrain and their design variables, the demanded objectives and their observation variables. In addition, we aim at studying this design problem from different decision-makers' points of view by modifying the interpretation and aggregation variables.

In an agile process, during the design phase, iterative exchanges between designers and clients constantly improve and clarify the clients' needs. In the preliminary design phases, it will be an advantage to propose and negotiate, between actors, solutions which probably interest both designers and clients. For this purpose, in 4.7, a graphic user interface created for the design of electric vehicle powertrain will be presented. This tool can be used to support the negotiation and the interactions between the stakeholders. It is based on MOIA ontology while ELM is used as an observation model. It allows the modification of all MOIA parameters. Then, different stakeholders can use it to find optimal solutions, based on their points of view, in real time mode.

4.3. Electric vehicle powertrain case study

In a context of strong urbanization, the environmental impacts of vehicles have become an important societal issue. In particular, the issue of Zero-Emissions Vehicles (ZEVs) has become central due to growing environmental concerns, the rising of fossil fuel prices and high mediatization of Electric Vehicles (EVs). In addition, for several years now, many governments have made EV a priority by setting up support schemes such as the bonus-malus system in France.

The development of EV projects is explained by the environmental objectives, which aim in particular to reduce CO₂ emissions. Since 2000, advances in the field of lithium-ion batteries have revealed the possibility of considering EVs as a relevant mobility solution. Compared to internal combustion engine (ICE) and hybrid vehicles, EV offers some advantages regarding the problems of high urbanization and a rapidly growing population, such as air and noise pollution [Ajanovic and Haas 2016].

4.3.1. Main objective

Our study considers an electric vehicle as the System of Interest. We analyze the relevance of integrating a multi-ratios transmission system in the electric powertrain in order to optimize the vehicle autonomy and the powertrain cost while satisfying the vehicle performance criteria.

Ren confirms that the gains of energy consumption when using a gearbox with two or more ratios are higher than 2.7% [Ren et al. 2009; Zhu et al. 2013]. It is noticeable that the latter percentage depends on the vehicle characteristics and the driving cycle used to compute the energy consumption. This low gain is generally insufficient compared to the extra cost generated by the gearbox; however, the use of a gearbox also influences some vehicle performances like the maximum speed for example. A common point of view consists in considering the price of the vehicle as the most relevant criterion of design. In the following, our analysis aims at finding the optimal solutions related to different points of view using the dynamic optimization process discussed in Chapter 3.

The study starts with the EV level requirements definition and ends with the powertrain components specifications. The needs analysis and the system specifications are performed at the electric vehicle system level. The logical and physical architecture analysis and the virtual evaluation is performed at the powertrain system level in order to define components specifications. In this manuscript, we will focus on the optimization of the powertrain components.

4.3.2. Powertrain system specifications

Beginning by the needs analysis, the demanded objectives, DOIs, are the autonomy, the performance and the cost of the vehicle powertrain. In order to define the powertrain specifications, each objective is decomposed into several observation variable Y; each Y is attached to a particular calculation scenario (see Table 15). Autonomy scenarios are standardized driving cycles corresponding to series of vehicle speeds versus time. Vehicle performance corresponds to the time required for vehicle acceleration on a 0% gradient road. The cost represents the total cost indicator of the vehicle's powertrain. Target values are extracted from the specifications given by, and discussed with, the client.

DOIs	Scenarios	Observation variables (Y)	Unit	Target
Autonomy	MCC	Autonomy	km	100
	NEDC-90	Autonomy	km	100
	WLTC-C1	Autonomy	km	100
Performance	0 to 50 km/h	Time	s	9.6
	0 to 100 km/h	Time	s	40
	30 to 60 km/h	Time	s	8
	50 to 80 km/h	Time	s	12.9
	50 to 100 km/h	Time	s	30.4
	0 to 400 m	Time	s	25
	0 to 1000 m	Time	s	50
Cost	-	Cost indicator	€	C

Table 15: DOIs, observations variables, scenarios and target values

4.3.3. Powertrain system architecture

Away from the cost, the calculation of the Y related to autonomy and performance require the generation of a propulsive force in order to transport the EV. In addition, the driving cycles scenario, used to calculate the autonomy, contain some braking phases which require the generation of a braking force.

Using the SCTO method, two principal functions, “generate propulsive force” and “generate braking force”, are used to decompose the EV powertrain into physical components contributing to the realization of internal technical functions [Yang et al. 2017]. The “generate braking force” function is decomposed into two functions which correspond to “regenerative braking” and “mechanical braking”. Figure 29 shows the logical and physical decomposition of the “generate propulsive force”. The “regenerative braking” function can be broken down in the same way as the “propulsive force generation” function with a force in the opposite direction. Based on the CTO database and considering that the source of energy should be electric, the battery is selected as a physical component to store electric energy. From Valeo’s product portfolio, the Electric Motor (EM) is selected as the converter component transforming electric power to mechanical power. The inverter is an interaction component between the nested battery and the EM; it transforms direct current (DC) into alternating current (AC). The gearbox corresponds to the transmitter; our analysis is focused on the problem of computing the characteristics of the gearbox and mainly its number of ratios.

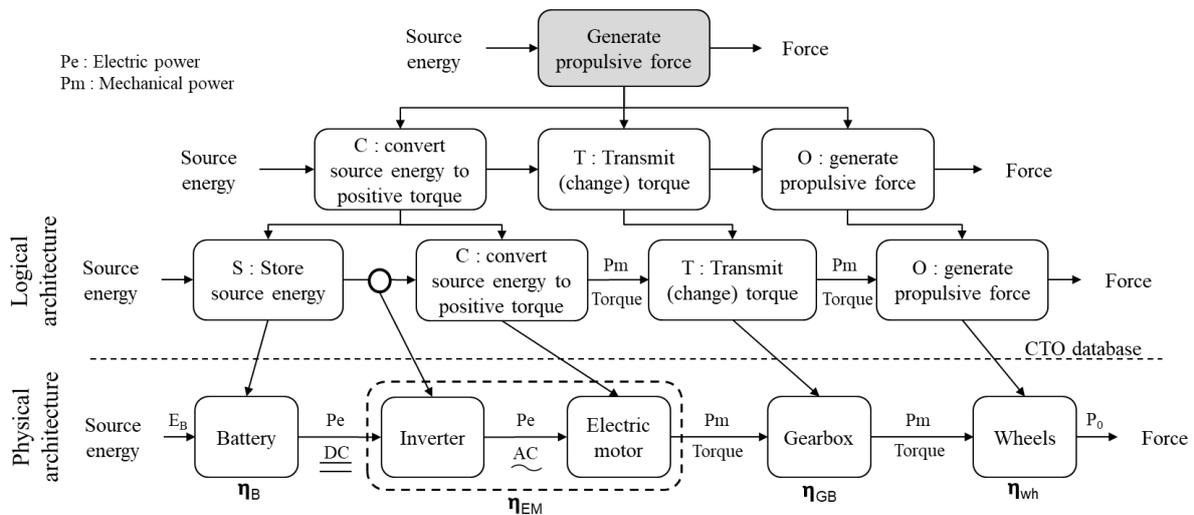


Figure 29: EV powertrain logical and physical SCTO architecture

Figure 29 shows the EV powertrain architecture. The propulsive or braking force mentioned before corresponds to the external force applied by the environment to the system at the wheels, in reaction to the force applied by the system to the environment. Using Newton’s Second Law, these forces can be deduced from the velocity scenario imposed on the system, namely the driving cycles in the case of the autonomy requirements (backward approach). In the case of the performance requirements we adopt a forward approach in considering the velocity as the consequence of these forces. The characteristics of the wheels being fixed, no design variables

are related to the wheels. It is noticeable that most often, EV gearboxes are composed of a single reducer, if we put aside the mechanical differential which also allows for a reduction.

Thanks to simulation models, the observation variables Y are derived from the design variables X. Following the MOIA ontology, the models of powertrain components are discussed in the next parts.

4.3.3.1. Battery

Several kinds of technologies exist for the EV battery. Each technology involves compromises between cost, energy storage capability, maximal power, durability and safety.

Thanks to their high energy density, lithium-ion batteries have become the standard for electric and hybrid vehicles, replacing the nickel-metal hydride (NiMH) batteries used in the 1990s and early 2000s.

The development of Li-ion batteries is fast: Renault-Nissan Alliance has announced a doubling of battery capacity in 2017 [Caillard 2015]. Other technologies such as Li-Sulfur and Li-Air are being investigated to further increase the energy density (see Figure 30); these batteries could be used by 2030 according to Toyota.

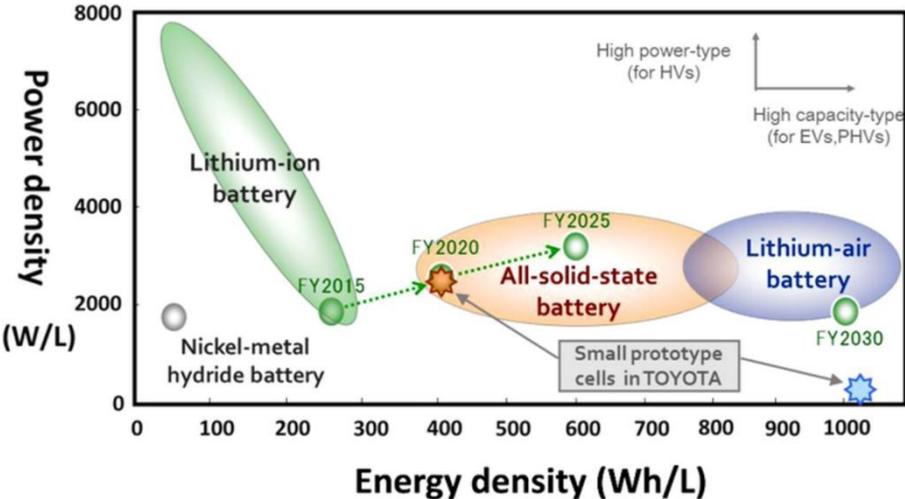


Figure 30: Ragone diagram for batteries [Yada et al. 2015]

Due to the requirement to use cutting-edge technology in the project, we selected a Lithium-ion (Li-ion) battery and only the capacity of the battery in kWh is used as a design variable.

4.3.3.2. Inverter and electric motor

Three EM technologies are discussed in the preliminary design phase (see Table 16). Based on the objectives of the project and more especially the requirement of maximum speed of the vehicle, it is obvious that the permanent magnet synchronous motor (PMSM) must be used because of their high efficiency at relatively low rotation speeds.

	Induction motor (IM) asynchronous	Permanent magnet synchronous motor (PMSM)	Electrically excited synchronous motor (EESM)
(+) : pros (-) : cons			
Power Density	(-)	(+) high magnetic density	(+) high magnetic density
Performance	(-) strong disadvantage	(+)	(+) excellent performances
Efficiency	(-)	(+) at low speeds	(+) at high speeds
Robustness	(+)	(+)	(-) brushes aging
Costs	(+) cost advantage negligible	(-) magnet price volatility	(-) brushes needed
Safety	(+)	(-) magnet centrifugal limits	(-) rotor excitation
Control	(-) complex	(+)	(-) rotor excitation control

Table 16: Pros and cons of three different electric motor technologies

At Valeo, a PMSM motor called GMG is under production. The inverter is already integrated into this motor. The performances of the GMG are synthesized through an efficiency map, which is a contour plot of the EM efficiency on axes of torque and speed. It takes into account the power losses in both inverter and EM which are estimated as a function of the maximum power. Based on GMG data, a normalized efficiency map, limited by a maximum torque of 1 Nm and a maximum rotation speed of 1 rpm (see Code 2), will be used to create a model that extend the motor efficiency map using the values of the EM design variables (see Code 3); this efficiency map follows an homothetic transformation.

<u>GMG parameters:</u>	<u>Comments:</u>
$T_{GMG} = [-T_{max}, \dots, 0, \dots, T_{max}]$	Torque vector of the GMG
$N_{GMG} = [0, \dots, N_{max}]$	Rotation speed vector of the GMG
$P_{max} ; P_{Losses} = f(T, N)$	Maximum power ; Losses power matrix
<u>Normalization:</u>	
$T_N = T/T_{max} = [-1, \dots, 0, \dots, 1]$	Normalized torque vector
$N_N = N/N_{max} = [0, \dots, 1]$	Normalized speed vector
$P_{Losses-N} = P_{Losses}/P_{max}$	Normalized losses power matrix

Code 2: Normalization code of the GMG

Figure 31 shows the efficiency map and the design variables of the EM. The EM model is related to an efficiency map characterized by the variables “Torque max”, “Speed max” and “C_b”. “Torque max” and “speed max” corresponding to the maximum torque and the maximum rotation speed delivered by the EM. “C_b” is the coefficient that characterizes the base speed of the EM from the “speed max” (13).

$$Base\ speed = Speed\ max \cdot C_b \quad (13)$$

Theoretically, from a null speed to the base speed, the EM is capable of delivering a continuous maximum torque. In addition, the base speed is used to calculate the maximum power of the electric motor (14).

$$Power\ max = Base\ speed \cdot Torque\ max \quad (14)$$

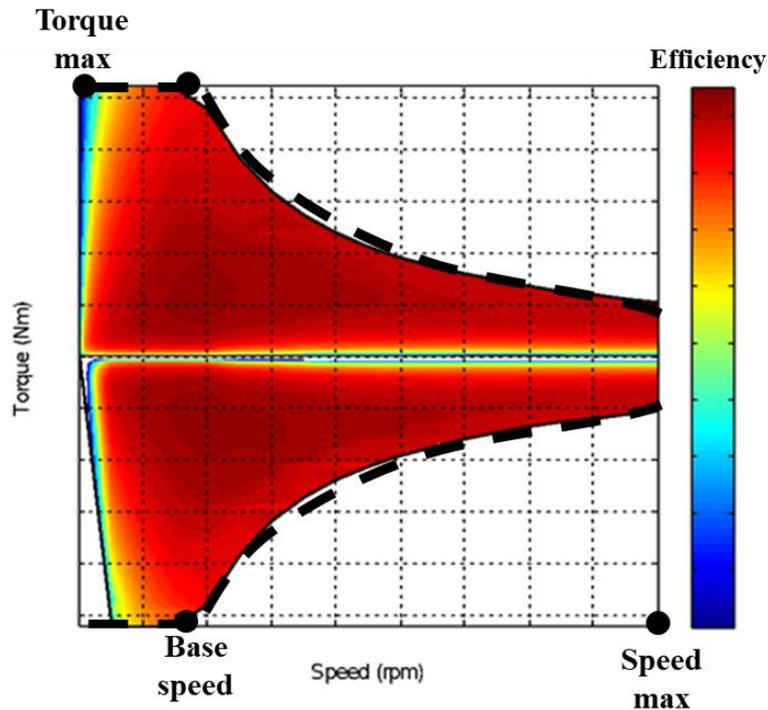


Figure 31: Reference EM efficiency map

This EM model makes it possible to modify the maximal torque of the EM. A torque reduction can lead to a reduction in costs by reducing either the active length of the EM or the maximum phase current of the inverter. In addition, the reduction in torque obviously results in a more compact motor (downsizing).

<p><u>Design variables of the EM:</u> Torque max ; Speed max ; C_b <u>Generation of the EM efficiency map:</u> $T_{EM} = T_N * \text{Torque max} = [-\text{Torque max}, \dots, 0, \dots, \text{Torque max}]$ $N_{EM} = N_N * \text{Speed max} = [0, \dots, \text{Speed max}]$ Base speed = $C_b * \text{Speed max}$ Power max = Base speed * Torque max $P_{Losses-EM} = P_{Losses-N} * \text{Power max}$</p>	<p><u>Comments:</u> Design variables Torque vector of the EM Rotation speed vector of the EM Base speed of the EM Maximum power of the EM Losses power matrix of the EM</p>
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Code 3: Electric motor model

4.3.3.3. Gearbox

Generally, the transmission of an electric vehicle consists of a single reducer gearbox incorporating a mechanical differential. The interest of this reducer is to adapt the speed and torque supplied by the motor to the speed and torque required for the wheels.

A multi-ratio transmission mainly aims at using the EM in its zone of best efficiency, but it also reduce the maximal torque of the EM. In this work, we focus on Dual-clutch transmission (DCT) technology with multiple ratios which is known to be suitable for electric drive applications by improving both powertrain efficiency and shifting comfort [Zhu et al. 2013].

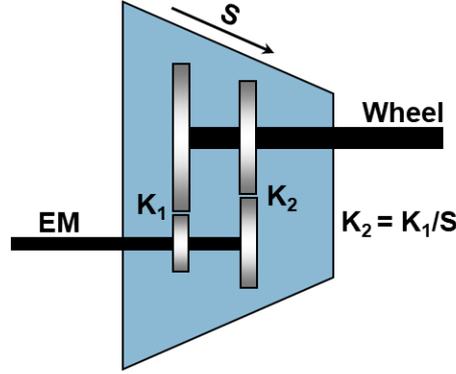


Figure 32: Gearbox model

The gearbox model is taking first gear ratio “ K_1 ”, spread “ S ” and ratios number “ N ” as design variables (see (15) and Figure 32). This allows taking into account different ratio values. When the gearbox spread is equal to 1, the gearbox is a reducer of ratio K_1 . When the gearbox spread “ S ” is higher than 1 and the ratios number is equal to 2, the gearbox is a DCT with two ratios K_1 and K_2 .

$$K_i = f(K_1, S, N) = \frac{K_1}{N^{-1}\sqrt{S^{i-1}}} \begin{cases} K_1 = \text{First gear ratio} \\ K_i = i^{\text{th}} \text{ gear ratio} \\ S = \text{Spread} \\ N = \text{Ratios number} \end{cases} \quad (15)$$

4.3.4. Global EV simulation model

The EM characteristics and gearbox ratios are the inputs of the EV simulation model; the model computes the electric consumption on a specific driving cycle and several other performance indicators of the vehicle. The cost indicator model, which is not detailed in this manuscript due to confidentiality matters, is also integrated into the PA model. The outputs of the EV simulation model are the autonomy, which is directly calculated from the battery capacity, for different driving cycles, the performance indicators and the cost indicator of the vehicle powertrain. For the calculation of autonomy, Figure 33 schematizes a backward energy calculation flow, which starts by the power needed by the wheels to move the vehicle, namely a specific driving cycle characterized by P_0 . It ends by the energy required by the battery, namely E_B . Each component has an efficiency η . It may be noted that the driving cycle ends after a known distance d . Therefore, by using the required energy E_B , the battery capacity and d , we can calculate the autonomy using simply the Rule of Three.

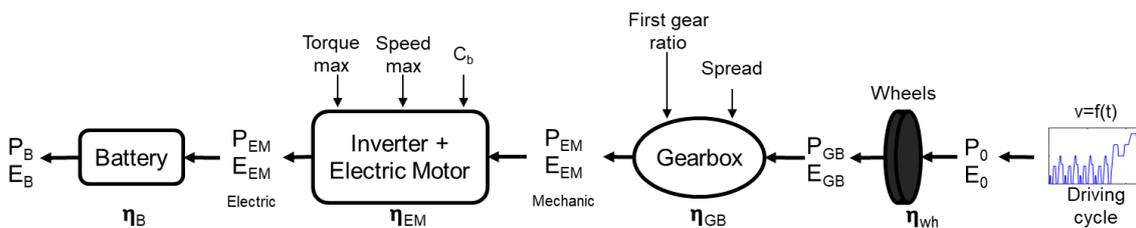


Figure 33: Backward energy flow for the calculation of autonomy

Similarly, the calculation of performances uses the same decomposition but in a forward energy flow. It aims at using the full power of the EM in order to calculate the identified accelerations.

4.3.5. Design variables

In the following, we summarize the global information needed for the parameterization of MOIA. Table 17 shows the design variables X and their domain of values. These values are determined by Valeo’s experts on the basis of their knowledge of each component considered independently. For example, for the gearbox, a ratio higher than 19 requires an additional shaft, which increases the complexity, the volume and the cost. Therefore, the first gear ratio is limited to 19. For the EM, the maximum rotational speed is limited to 20000 rpm due to the limitation of the rolling-element bearing. The range of values of “Torque max” have been estimated between 50 and 85 Nm with a discretization step of 5 Nm.

Components	Design variables (X)	Unit	Domain of values	Discretization step
Gearbox	First gear ratio	-	[8 ; 19]	0.5
	Spread	-	[1 ; 3]	0.1
Electric motor	Torque max	Nm	[50 ; 85]	5
	Speed max	rpm	[15000 ; 20000]	500
	C_b	-	[0.1 ; 0.25]	0.01
Battery	Capacity	kWh	[8 ; 10]	0.5

Table 17: Design variables X

4.3.6. Interpretation parameters

The target values of the observation variables presented in Table 15 allows only the parametrization of Simon’s desirability functions. As mentioned before, using Simon’s satisficing function, optimal solutions are generally difficult to discriminate; all acceptable solutions are of the same level of optimality, i.e. 100%. In order to add some flexibility to the design problem inside the interpretation model, desirability functions are parametrized by using the two control points called “CP_1” and “CP_2” in Table 18. For the autonomies, which have to be maximized, “CP_1” values are fixed to their target values and for the cost and other variables related to performance, “CP_2” values are also fixed to their target values. The rest “CP_1” and “CP_2” values are fixed based on the knowledge derived from the discussions with the client and marketing engineers. Harrington’s functions are used as desirability functions because of their flexibility. To illustrate this choice, an example of autonomy is explained. Autonomy is a critical (important) objective for such a design problem; this information is demonstrated in Chapter 5. A value of autonomy lower than the “CP_1” is theoretically unacceptable. However, using Harrington’s functions, this value of autonomy corresponds to a desirability value higher than 0. This allows maintaining under review solutions that have lower desirability values (even if their observation variables values are outside the theoretical satisfaction ranges) on certain criteria but have bright desirability values on other criteria.

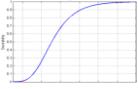
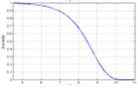
DOIs	Scenarios	Observation variables	Unit	Desirability functions (Interpretation model)		
				CP_1	CP_2	Form
Autonomy	MCC	Autonomy	km	100	150	Maximization 
	NEDC-90	Autonomy	km	100	150	
	WLTC-C1	Autonomy	km	100	150	
Performance	0 to 50 km/h	Time	s	5	9.6	Minimization 
	0 to 100 km/h	Time	s	20	40	
	30 to 60 km/h	Time	s	4	8	
	50 to 80 km/h	Time	s	6	12.9	
	50 to 100 km/h	Time	s	15	30.4	
	0 to 400 m	Time	s	20	25	
	0 to 1000 m	Time	s	40	50	
Cost	-	Cost indicator	€	C_{min}	C_{max}	

Table 18: DOIs, observations variables, scenarios and desirability parameters

4.3.7. Aggregation parameters

As aggregation functions, we then use the Minimum function and the Derringer’s aggregation function that are both design appropriate. These functions satisfy in particular the constraint of annihilation [Scott and Antonsson 1998], i.e. they result in a null value if any variable Z_i is null, which guarantees that no objective can be violated. In order to observe the influence of the weighting parameters of the design objectives, the final aggregation function ζ_2 will be defined as the Minimum function, which results in balanced solutions between the objectives satisfaction, or the Derringer’s aggregation function, weighted with different values of W_i . For the sake of simplicity, the ζ_1 aggregation function is defined as the “minimum” function. We do not vary this choice.

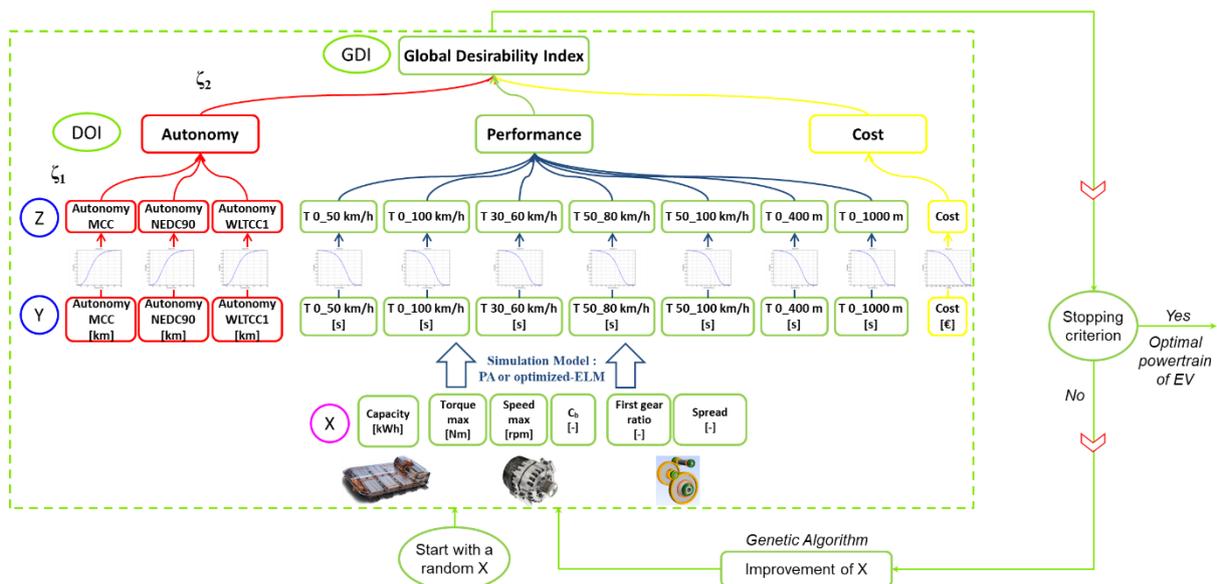


Figure 34: Illustration of MOIA method for EV powertrain case

Figure 34 shows all the parameters and variables discussed above from the X_i to the GDI. It illustrates the connections between variables and Genetic Algorithm, and the hierarchy of

objectives and criteria for the powertrain.

4.4. A comparison with the sequential approach

As a significant comparison example, we present here a simulation study performed in the frame of Veloce, a collaborative funded project dedicated to the design of 48V powertrain for EV [Patrick 2018; ADEME 2020]. The objectives presented before are the same as those used for the Veloce project.

The chosen EM model corresponds to two different types of EM produced at Valeo: GMG15kW and GMG25kW. Several physical architectures are studied: one or two EMs + a gearbox with a single ratio or two ratios. It is interesting to note that they use in the Veloce project, a sequential approach filtering, a priori, the non-acceptable solutions, i.e. the solutions that do not satisfy one of the defined criteria (see Figure 35). In a first step, filtering is based on the performance criteria. Secondly, the filtered solutions are compared based on their cost values and their consumption on different driving cycles. The consumptions are transformed into battery cost on iso-autonomy. In the third step, the low-cost architectural solution is chosen. The fourth step consists at finding the optimal ratio(s) for each driving cycle and finally a ratio is recommended.

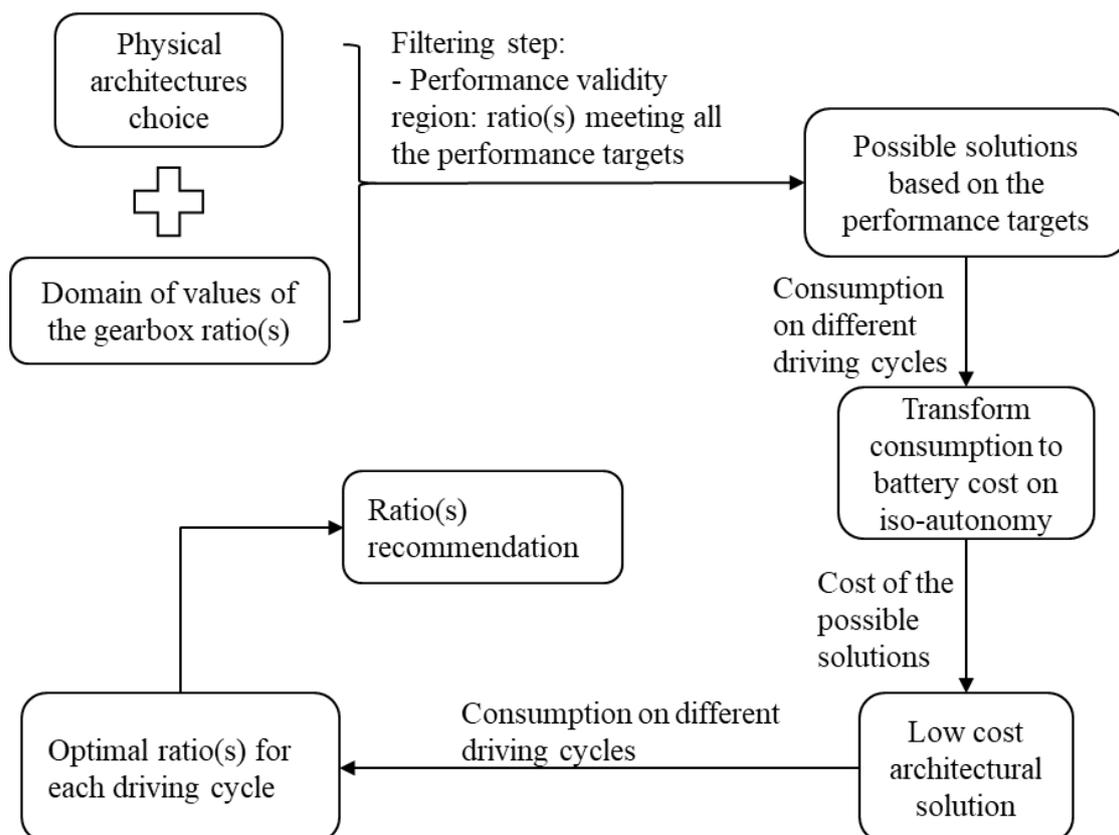


Figure 35: The Veloce project sequential approach

Using such an approach, at each step of the filtering process, engineers face many acceptable solutions that all must be studied and filtered. This risks filtering solutions, at earlier steps, that may be preferable later. This process requires interactions after each step which limit its

possibility of being an automatic process. Finally, this process is considered as *a posteriori* process; solutions are first generated and then evaluated.

The point of view adopted in the Veloce project is mainly based on the cost considered as the critical objective; the optimal solution is then the lowest-cost solution that respects the performance criteria. In MOIA approach, the Veloce point of view corresponds to Simon’s desirability functions for the autonomy and the performance and to a minimization Pseudo-function for the cost. Therefore, the optimization problem is a single objective (the cost) optimization and no aggregation function is then required. This point of view was evaluated using MOIA approach and the same solution was found while MOIA approach requires 10 times less calculation time than the sequential approach. It may be noted that this estimation is concluded after a discussion with the simulation team. In both cases, this point of view leads to an optimal solution composed of one EM and a gearbox with single ratio (see Table 19).

Optimization approach	Interpretation	Optimal solution
Veloce project	- Searching for the lowest-cost solution	GMG25kW + single ratio (10)
MOIA	- Simon’s functions for performance and autonomy - Minimization Pseudo-function for the cost	GMG25kW + single ratio (10.4)

Table 19: Solutions found using Veloce project and MOIA approaches

The above result mentions the advantage of using the MOIA approach, which is automatic, compared to the sequential approach. The automation of the MOIA approach has an advantage to non-limit the components parameters allowing to explore more design parameters. Moreover, it may be noted that evaluating different points of view has an advantage of finding different technological solutions. In contrast, this exercise is costly when using the sequential approach due to the sequential steps that may be switched if the point of view of the problem changed. Using the MOIA approach, the point of view is changing by modifying the interpretation and aggregation parameters.

Simulation model	Solutions	Design variables						Aggregation (ζ_2)				CPU optimization time [min]	
		First gear ratio [-]	Spread [-]	Torque max [Nm]	Speed max [rpm]	C_b [-]	Capacity [kWh]	Min	W_A	W_P	W_C		GDI
PA	S_1	11.5	2.7	85	16500	0.1	10	✓	-	-	-	0.732	344
	S_2	8.5	1.0	80	20000	0.1	10	-	0.2	0.2	0.6	0.851	295

Table 20: Solutions derived from two different points of view

Table 20 shows the optimization results for two different points of view. The optimization process is running using the PA model that requires around 6 seconds to compute the observation variables from the design variables. The interpretation model used is presented in Table 18. Two aggregation functions for ζ_2 are tested. The first function is the Minimum function which does not require any additional parameters to set it up, and the second function is the Derringer’s aggregation function which requires weights parametrization. By comparing the solutions S_1 and S_2 , we observe that changing the parameters of the aggregation functions leads to two different technological solutions: gearbox with single reducer and the other with

two ratios. These results confirm that in multi-objective problems, there is no absolute optimal solution. In contrast, the so-called optimal solutions are related to decision-makers' points of view.

4.5. ELM models

Using the process discussed in 3.6, we identify the *optimized-ELM* model for each observation variable. Table 21 shows that most of the RMSE computed for the *optimized-ELM* models are lower than 1%. For the majority of them, it is even lower than 0.1% which can be considered as a very good accuracy level. For information, Table 21 also shows the number of hidden neurons and activation functions chosen by the *optimized-ELM* algorithm. It may be noted that the RMSE value also depends on the values chosen in the input weights matrix and the input biases matrix. Those matrices, depending on the number of hidden neurons, are very large and cannot be presented here.

Observation variables	<i>Optimized-ELM</i>		
	Number of hidden neurons (N)	Activation function (f)	Root Mean Square Error (RMSE [%])
Autonomy _ MCC	665	Sinusoid	0.09
Autonomy _ NEDC90	160	Sinusoid	0.1
Autonomy _ WLTC1	195	Softplus	0.12
T 0-50 km/h	315	Sinusoid	0.05
T 0-100 km/h	175	Softplus	0.86
T 30-60 km/h	305	Sigmoid	0.06
T 50-80 km/h	140	Softplus	0.1
T 50-100 km/h	155	Softplus	1.2
T 0 - 400 m	105	Tanh	0.08
T 0 - 1000 m	135	Bent identity	0.07
Cost	965	Sinusoid	0.39

Table 21: RMSE of *optimized-ELM* models

4.6. Numerical results using ELM

The *optimized-ELM* models found in 4.5 are substituted here for the PA model in the optimization process. By comparing the solutions S_1 to S_3 and S_2 to S_4 , results highlight that the Genetic Algorithm converges to approximately the same solutions when using PA or the *optimized-ELM* models (see Table 22). It is clear that the *optimized-ELM* model runs much faster than PA model allowing exploration of large design spaces.

Another combination of weights is evaluated in order to compare the difference between solutions found. By choosing autonomy as the critical objective (S_5), the optimal powertrain solution will be equipped with a gearbox with two ratios; because, this solution will mainly reduce the losses in the electric motor and then will give a higher powertrain efficiency. Moreover, when focusing on performance and choosing it as a critical objective (S_6), we found that the optimal solution will be equipped also with a gearbox with two ratios but the first gear ratio is high; this can be explained by the fact that when performance is needed, a higher torque applied on wheels is also needed. Then, it is clear that the *optimized-ELM* model gives the

possibility to explore more points of view in very short time. This option allows designers to propose different solutions to clients with different purposes, for example.

Simulation model	Solutions	Design variables						Aggregation (ζ_2)				CPU optimization time [min]	
		First gear ratio [-]	Spread [-]	Torque max [Nm]	Speed max [rpm]	C_b [-]	Capacity [kWh]	Min	W_A	W_P	W_C		GDI
Optimized-ELM	S_3	11.5	2.7	85	16500	0.1	10	✓	-	-	-	0.756	1
	S_4	9.5	1.0	80	20000	0.1	10	-	0.2	0.2	0.6	0.807	1
	S_5	12	2.7	85	20000	0.1	10	-	0.6	0.2	0.2	0.774	1
	S_6	15	2.8	85	20000	0.1	10	-	0.2	0.6	0.2	0.854	1

Table 22: Solutions derived from different points of view using the optimized-ELM model

As a conclusion of these preliminary results, we can observe that our dynamic optimization approach is functional in a realistic and significant industrial problem. Compared to classical optimization methods based on PA models computations, our approach is more flexible because (1) simulation does not limit the computing process and (2) the MOIA ontology is a framework well adapted to design complex environments and requirements of flexibility of both information and processes. At the end, this approach makes it possible to explore both large design spaces and different points of view on the design.

4.7. User interface

As definition, the Human-Machine Interface (HMI) is a set of hardware and software devices enabling a human user to interact with an interactive system. In fact, interface and interaction are Latin vocabularies. Interface is composed of *inter* meaning *between*, and *facies* meaning *aspect*, and interaction is composed of *inter* and *actio* meaning *ability to act*. Therefore, HMI can also be defined as Human-Machine Interactions which corresponds to a set of actions allowing communication between an interactive system and its human user.

From the Guide Matlab[®] environment, a specific interface has been developed to support the decision-making process for the electric vehicle powertrain (see Figure 36). It is regarded as a proof of concept that will be updated and generalized for other applications. This one-page interface represents the design optimization framework using MOIA ontology. This interface is regarded as an interactive tool where actors - like designers, marketing, client, etc. - can participate in the activity of design. It allows changing the different parameters of the MOIA models and checking immediately the evolution of the design problem and the consequences of their decisions.

The interface shows mainly two main frames called “Candidate solutions” and “Optimal solution”. The “Candidate solutions” frame represents MOIA parameters for the EV powertrain. Starting from the left, the design variables X of the three main components EM, battery and gearbox are listed. The table of the domains of values of design variables are completed with the minimum values, discretization steps and maximum values. Observation variables with corresponding scenarios have been identified. These scenarios can be visualized

by clicking on the buttons under “Scenarios”; for example, the NEDC90 driving cycle scenario, which is used to calculate autonomy, is presented.

Under “Desirability Functions”, desirability parameters for all observation variables are completed. Maximization and minimization functions forms are used for three different types of desirability functions: Derringer’s, Simon’s and Harrington’s functions. The chosen desirability functions can also be visualized by clicking on bottoms under “Interpretation variables”.

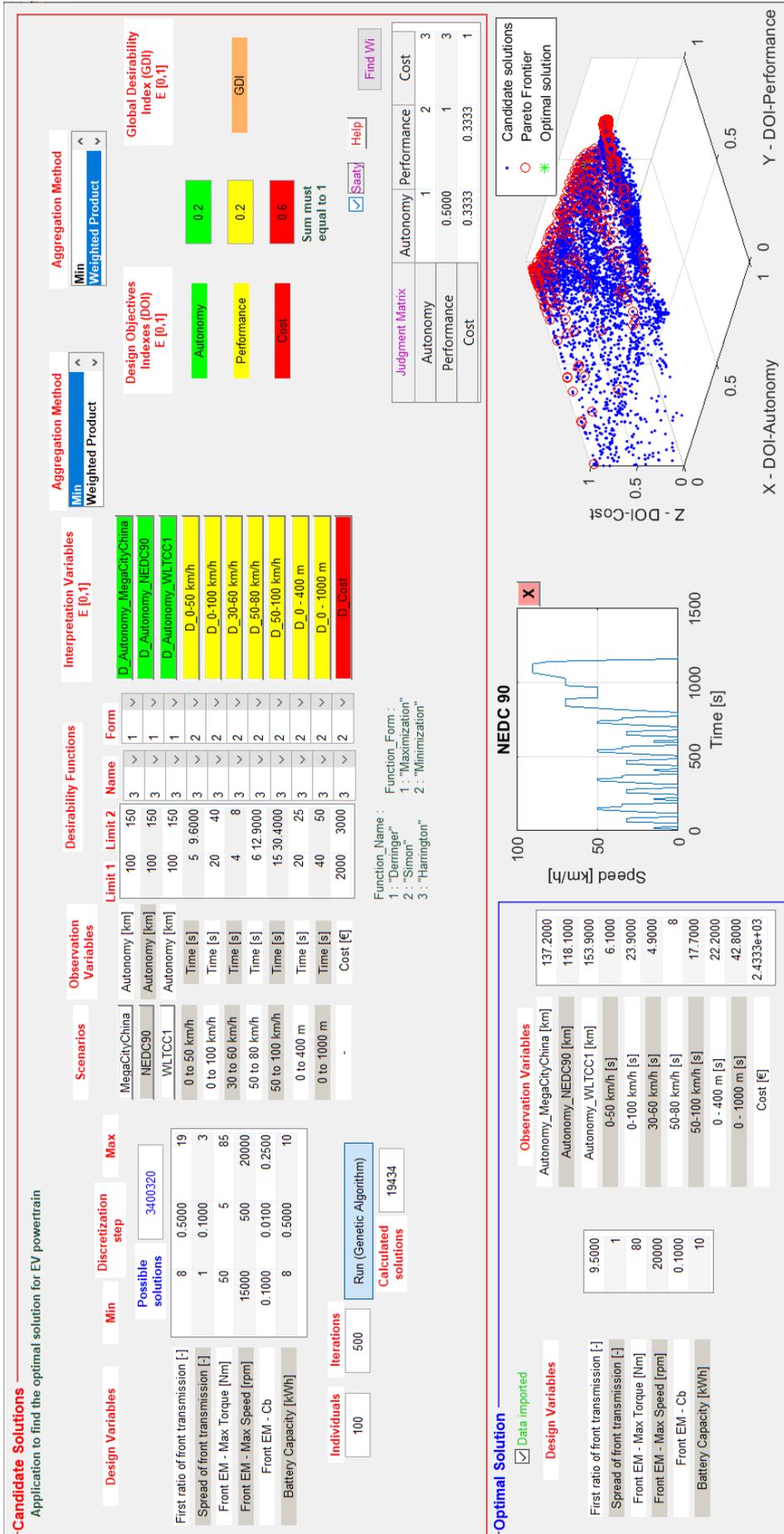
Finally, the aggregation methods are chosen from the lists under “Aggregation method”. For the Minimum aggregation function “Min”, no other parameter is required. For the Derringer’s aggregation function, here called “Weighted Product”, the weights can be entered directly, and separately, for each interpretation variable or indirectly, by completing the judgment matrix using the pairwise comparison technique and the calculating weights (see 2.2.2.6.1). For the indirectly method, “Saaty” checkbox must be checked in order to visualize the judgment matrix. Then, by clicking on “Find Wi” bottom, the different weights will be filled automatically. It may be noted that the weights presented in Figure 36 are chosen using the direct method.

The number of “Individuals” in each population and the number of “Iterations” of the Genetic Algorithm are indicated before running the optimization process. Once clicking on “Run (Genetic Algorithm)”, the number of possible solutions, which is a function of the domains of values and discretization steps of design variables, is computed. In addition, the number of calculated solutions is also visualized and updated after each iteration.

The “Optimal solution” frame shows the design and observation values of the optimal solution. A message box is shown if the algorithm has found several different optimal solutions with the same GDI value. Design, observation, interpretation and DOI values of these solutions can be visualized in a table in the workspace of Matlab® for comparison. Moreover, the interface visualizes graphically the evaluated solutions and generates Pareto optimal solutions while focusing on the optimal solution(s) chosen.

Thanks to the implementation of ELM model into MOIA ontology, this interface can be used as a tool to formalize:

1. The design decision: it is possible to explore directly both large design spaces and different decision-makers’ points of view on the design by changing the interpretation and aggregation parameters. Therefore, facing a complex design problem, where a combinatorial number of candidate solutions exist, decision-makers are able to evaluate different points of view in a large design space and see the consequences of their decisions. This can help decision-makers make rational decisions.
2. The negotiations in the preliminary design phases: it is possible to minimize the iterative exchanges between a designer and client. In addition, this tool aims at negotiating possible solutions that have advantages for both designer and client. For example, a solution, that minimizes 10% the cost when decreasing 1% of the efficiency of a component, may be acceptable or negotiable for the client.



X - DOI-Cost Y - DOI-Autonomy Z - DOI-Performance

NEDC 90

Figure 36: User interface for EV powertrain case study

Chapter 5. Acceptability of optimization

5.1. Introduction

Solving design problems involve subjective judgments and objective knowledge of the problem characteristics. Subjective judgments make design problems irreducible to purely mathematical expressions and remains the gap between numerical optimality and human acceptability in optimization used for design purposes. In many cases, optimum design solutions are not acceptable because of the decision-makers' subjective judgments. The concepts of optimality and acceptability, arising from human judgments, are thus clearly identified and contained in the design process through decision-making.

The word acceptability consists of two parts accept-ability, which means the ability to accept; it is derived from Latin *acceptabilis* “*worthy of acceptance*” [Dictionary 2020a]. Optimality etymologically means “*most favorable*” [Dictionary 2020b]. It reflects the optimization process that aims to find the best design solution while satisfying a set of criteria. Therefore, optimality concerns the computation of numerical variables based on mathematical simulation models. Hence, in multi-objective problems, optimization alone is not able to determine the acceptable design solutions from the decision-makers' points of view. The acceptability concerns human perceptions. To assess design acceptability, decision-makers' preferences should be the center

of reasoning and judgments. Through optimality, it is possible to process objective judgments and through acceptability, it is possible to process subjective judgments.

It is crucial to state that a successful design process has to consider both the optimality and acceptability in order to build a computational path that leads to optimal and acceptable solutions. However, integrating optimality and acceptability requires a deep understanding of the design process. While optimality can be calculated, it is not so easy to ensure acceptability in the design process. The MOIA method is capable of integrating acceptability by allowing decision-makers to express their preferences inside the design optimization process. The MOIA method can increase the probability of generating solutions that are optimized mathematically and acceptable by humans.

The acceptability of a design solution depends first, on the acceptability of the design process and second, on the acceptability of the solution itself. In Chapter 4, we presented the decision-support tool for the EV powertrain which is developed based on the MOIA method and considered as a proof of concept. In this chapter, we will focus on the acceptability of the MOIA method by the potential users.

In particular, we investigate the acceptability of the different techniques of interpretation and aggregation used in the MOIA method through work sessions performed with a group of Valeo employees. These work sessions also aim for a better understanding of Valeo's decision-making process at different levels of the design phases. We aim finally to create a generic decision-support tool taking into account the different acceptable techniques of interpretation and aggregation in order to be effectively used by the potential users. The work session includes three main parts:

1. An initial presentation explaining to the participants the purpose of the session and some useful concepts and terms used in the questionnaire without mentioning the MOIA method (see 5.3.1).
2. A questionnaire composed of nine parts. Participation in this questionnaire requires approximately 40 minutes (see 5.3.2).
3. A final presentation to conclude by presenting the MOIA method, the user interface developed for the EV powertrain (see Figure 36) and the targeted decision-support tool (see 5.3.3).

5.2. Participants

The work sessions consist of face-to-face work sessions including a total of 20 persons. General information about the participants are detailed in Table 23. The participants, mainly young engineers, have some experience in the automotive domain and not much experience in optimization. Only 30% of them frequently use multi-criteria design optimization while 45% have never used it.

Table 23 also shows that the participants have experience in several fields. In particular, more than 70% have more than 5 years of automotive experience, which is not surprising in the

environment of the society Valeo. Surprisingly, 60% have no experience in the field of optimization which is nevertheless an important skill in design.

Specialty		Age		Frequency of use of Multi-criteria design optimization	
Categories	Percentage	Age groups	Percentage	Frequency	Percentage
Engineering	70%	< 25	5%	Never	45%
Marketing	15%	26 – 35	65%	Rarely	20%
Computer science	5%	36 – 45	20%	Sometimes	5%
Innovation	5%	46 – 55	0%	Usually	30%
Simulation/Statistical calculation	5%	> 55	10%	Always	0%

Professional experience					
Area of experience	No experience	1-2 years	3-5 years	5-10 years	> 10 years
Automotive	5%	10%	15%	40%	30%
Energetic systems	25%	20%	20%	20%	15%
Simulation	30%	20%	20%	20%	10%
Optimization	60%	10%	25%	0%	5%
Programming	35%	15%	35%	5%	10%

Table 23: Participants general information

5.3. Materials and methods

5.3.1. Initial presentation

The working session starts by a general presentation (see Appendix II.1) on the objectives of the session and the concepts and terms used in the questionnaire, in particular the notion of design *criteria*, *flexibility* of these criteria and *relative* importance or *criticality* of these criteria.

The *flexibility* of criteria corresponds to adding / removing criteria, modifying the specified satisfaction ranges of criteria and modifying the hierarchy between the criteria (relative importance or criticality). As a consequence, *flexibility* has a strong influence on the final solution and has to be considered in the design process.

The case study on the EV presented in Chapter 4 is used for the questionnaire. The criteria are the autonomy, the cost, the maximum velocity and the accelerations from 0 to 50 km/h and from 0 to 100 km/h. In addition, different desirability functions are presented: Pseudo-function, Simon's function, Linear Derringer's function and Soft function. We explain how those functions are parametrized to reflect the satisfaction of the criteria.

Dispersion and *tolerance* are two important technical terms in the production process. Therefore, these terms are explained using an example of the autonomy of EV and another example of geometric *dispersion*. The *dispersion* corresponds to a deviation from a desired central value and the *tolerance* is a permissible limit(s) of variation in a physical dimension. The *tolerance* can be defined as a desirability of the *dispersion* where permissible limit(s) correspond(s) to the control point(s).

Finally, the *exchange rate* which is a ratio between the control points' values of two criteria, is defined. It represents a reference value that can be used to compare two different products, for example: the cost per autonomy unit [€/km], the cost per mass unit [€/kg], the gram of CO₂ per mass unit [gCO₂/kg], etc. Examples of *exchange rates* are presented for two EVs.

5.3.2. Questionnaire

After the initial presentation, we propose the questionnaire (see Appendix II.2) accompanied with a document (see Appendix II.3) providing additional information related to specific questions. The questionnaire is composed of nine parts presented in Table 24. The first two parts, related to information about the participants, are discussed in 5.2. The results of the other parts are discussed in 5.4.

Questionnaire parts	Comments
Personal information about the participants	- Background of the participants.
General information about the participants	- Experience of the participants.
Specifications and flexibility	- Questions on the interaction of the participants with the client specifications and the technical specifications. - Questions on the negotiations and evolutions of the specifications.
Criteria	- Questions on the determination and evolutions of the criteria. - Questions on the decision-makers of the flexibility of the criteria.
Dispersion and tolerance	- Asking if dispersion criteria are taken into account in the preliminary design phases. - Questions on the decision-makers of the dispersion criteria.
Satisfaction ranges of criteria	- Questions on the decision-makers of the satisfaction ranges. - Questions on the negotiations and modifications of the satisfaction ranges. - Questions on the forms used for the satisfaction (desirability) functions.
Satisfaction values	- Asking for the satisfaction values of autonomy and cost values for several EVs.
Exchange rates	- Asking if the criteria and their satisfaction ranges are obtained using the exchange rates technique.
Trade-off	- Evaluation of the importance weights using the techniques of direct weights and pairwise comparison
Solutions ranking	- Ranking of several EVs based on their performance while using different desirability functions.

Table 24: Questionnaire parts

5.3.3. Final presentation

Finally, we conclude the session by presenting the MOIA method as a framework integrating the participants' preferences, the idea of the targeted decision-support tool and its integration into the preliminary design phases, and the user interface developed for the EV powertrain (see Figure 36) as a proof of concept of the targeted tool (see II.4). The user interface allows the participants to imagine how all design actors are capable of negotiating solutions facing a one-

page tool that integrates both physical and preference data. The targeted decision-support tool is detailed at the end of this chapter.

5.4. Questionnaire results

- Specifications and flexibility:

The majority of the participants are users of technical specifications that, theoretically, are derived from an analysis of the specifications provided by the client; From the specifications provided by the client, the technical specifications are allocated to different technical teams. The majority of them have also participated in the translation of specifications into technical specifications. In addition, more than 50% of them have participated in the definition of specifications transformed to suppliers. Responses also mention that the participants are more in relation with specifications and technical specifications in the design and validation phases than in the fabrication phase.

Finally, about 70% of the participants confirm that the specifications and the technical specifications can evolve even those coming from the clients.

- Criteria:

The participants indicate that the criteria are mainly determined by the specifications while some criteria appear after the starting phase of the design process, especially from discussions between designers and clients. In addition, all the participants report that the design actors accept to negotiate the flexibility of some criteria.

Regarding the flexibility of the criteria, the participants mention that the decision mainly comes from the clients and the regulation and more rarely from actors like Valeo marketing, Valeo development and Valeo manufacturing. These results confirm that the design process is a collaboration process where the point of view of each actor must be taken into account.

- Dispersion and tolerance:

The participants are asked if dispersion criteria are taken into account in the preliminary design phases. The participants pointed out that dispersion criteria are rather taken into account in the fabrication phases. They mention also the importance to consider these criteria in the preliminary design phases.

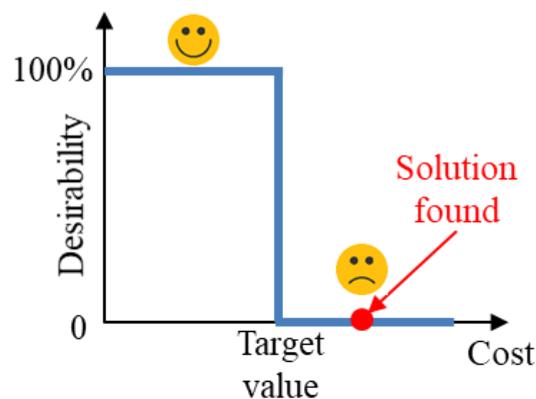
The participants also mention that Valeo manufacturing and clients have mainly the power to define the dispersion criteria but sometimes regulations, Valeo development and sub-contractors may decide these criteria.

- Satisfaction ranges of criteria:

Regarding the satisfaction ranges of the criteria, the participants mention that Valeo marketing, Valeo development, Valeo manufacturing, subcontractors and regulations sometimes have the capacity to propose these ranges while the client has always the effective power to propose such

ranges. In addition, the participants confirm that these ranges can be modified, for most of the criteria, after negotiations between actors. Moreover, the participants declare that:

- Usually, one target value is specified for each criterion; then, the associated function is the Simon's function.
- Sometimes, the satisfaction ranges are not explicit for several criteria; then, the associated function is the Pseudo-function.
- Occasionally, a satisfaction range with two control points is specified; Linear Derringer's function is probably used in this case as well as sometimes, the Soft function. This is quite logical since these functions are complex (see 2.2.2.5.1) and require more effort to be defined. The participants declare that it should be preferable to negotiate with actors, especially the client, two values instead of one for many criteria. They also comment that most of the time a target value is written down and however, orally, two values can be communicated during meetings with the client.



As the cost is often seen as a critical criterion, a general question is asked about the possibility of negotiating the cost or to redesigning, in order to meet the target cost value as shown in the figure above. Even if the participants' priority is to redesign, almost all the participants mention that a 10% of cost negotiation is sometimes possible. These responses confirm that the flexibility exists and is acceptable for almost all the criteria. That is why the integration of the flexibility in a decision-support tool, that can be used as a negotiation tool, is always interesting.

• Satisfaction values:

The concept of satisfaction values is specifically addressed in the questionnaire through the case of the electric vehicle. In order to determine the form of desirability functions that are acceptable to participants, we ask them to grade autonomy, which is always a criterion to be maximized, and cost, which is always a criterion to be minimized, for different electric vehicles. Two methods of grading are proposed: *pairwise comparison* and *absolute grading*. The *pairwise comparison* aims at comparing autonomy and cost of a reference electric vehicle S1 to other proposed vehicles; As a reference, the autonomy and cost grades of S1 are imposed to 50%. Each participant has to grade the autonomy/cost of each vehicle in comparison with the reference vehicle autonomy/cost. The *absolute grading* aims at giving a direct grade of the values of autonomy and cost to each vehicle. Figure 37 shows the average values of each

autonomy/cost, given by the participants for the two methods. It may be noted that the function forms found, from the average of participants' responses, are similar to a Hyperbolic Derringer's function ($r < 1$ for autonomy and $r > 1$ for cost) and not simply to a Linear Derringer's function.

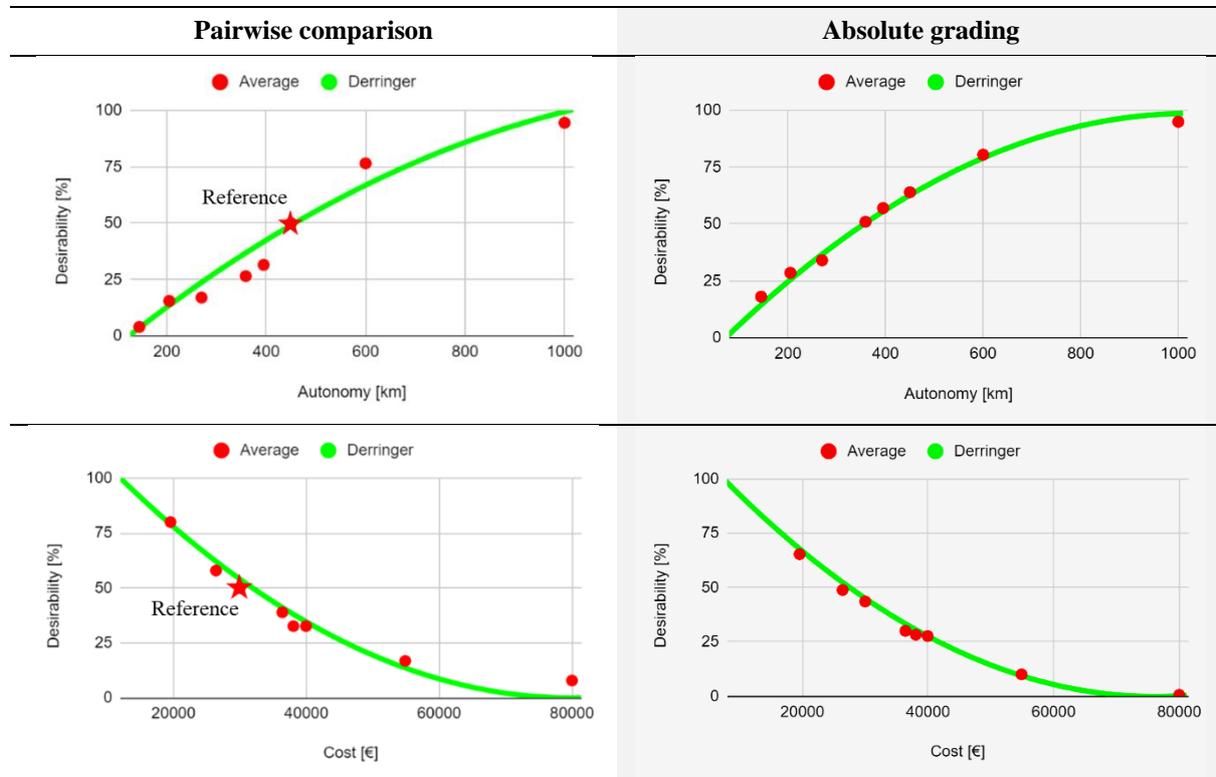


Figure 37: Results derived from absolute grading and pairwise comparison for autonomy and cost

Figure 38 shows that *pairwise comparison* gives a higher desirability level than *absolute grading* in the maximization case (autonomy) while the reverse is true in the minimization case (cost). From two different methods, two different functions are derived for one criterion while the participants are the same. Since these approaches are different, it is not surprising to find different results. This shows the importance of choosing the appropriate approach to define the desirability functions.

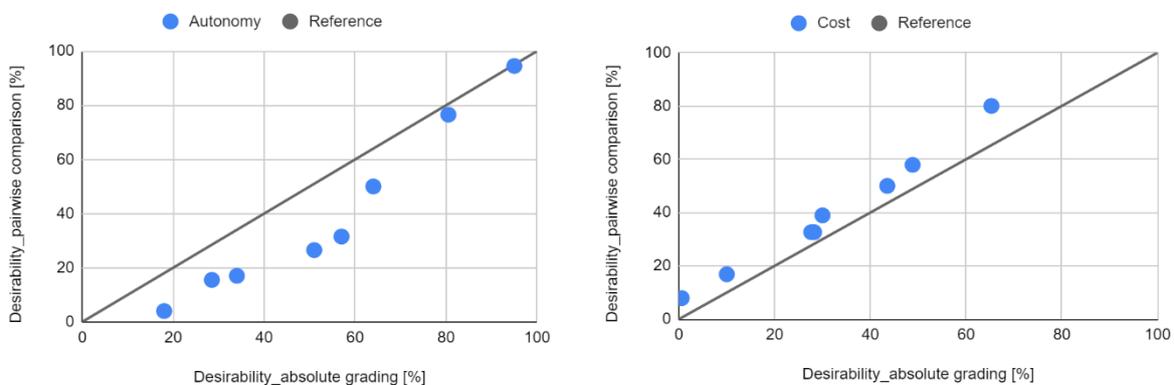


Figure 38: Pairwise comparison values function of absolute grading values

This result can help in determining if the chosen solution is robust in terms of *decisional robustness*. This can be done by testing first the function derived from the *absolute grading* and second the other function derived from the *pairwise comparison*. At the end, if the chosen solution is not changing, then, this solution is insensitive to those variations of desirability parameters and is robust in terms of *decisional robustness*.

- Exchange rate:

The participants, especially those from marketing, comment that they use ratios like the exchange rate. The majority of participants declare that the control points of the desirability functions of criteria are determined based on exchange rates, especially for innovation purposes when designers have to proceed based on, and compared to, existing solutions or competitors' data. In addition, they mention that the exchange rates can be used to negotiate the modification of the control points.

Continuing with the electric vehicle case study, using the exchange rates deriving from several vehicles data, we have succeeded to determine Soft desirability functions for criteria by fixing the value of one criterion. For example, Figure 39 shows the desirability function of autonomy for an electric vehicle cost of 40000 €; this function represents an average of values determined based on the minimum, maximum and average values of the exchange rates between the cost and autonomy of all the studied vehicles.

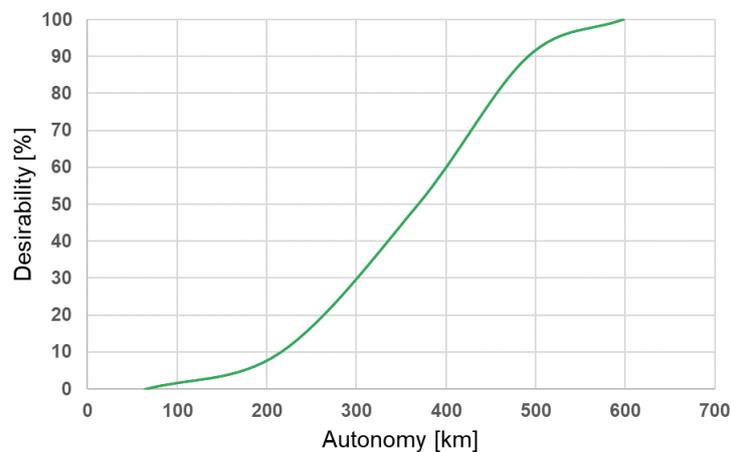


Figure 39: Autonomy's Soft desirability function derived from the cost criterion

We ask the participants to estimate/give what would be an acceptable value of autonomy for an electric vehicle with a cost of 40000 €; the estimated reference vehicle, BMW, has a cost of 39500 € and an autonomy of 395 km. 95% of them accept a value higher than or equal to the estimated reference value of 395 km. Figure 40 shows the reference desirability and the desirability of all participants' responses calculated using the function shown in Figure 39. These results mention the acceptability of the exchange rate technique for determining desirability functions because almost all the autonomy values, chosen by the participants, are higher than or equal to the reference value which corresponds to 50% of desirability in this case.

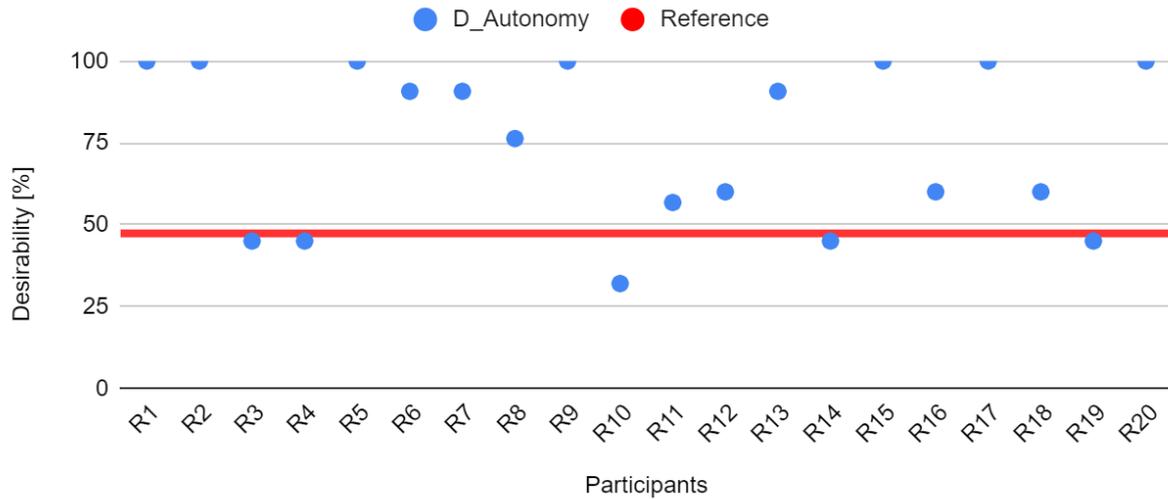


Figure 40: Autonomy desirability values of participants' responses versus the reference value

Similarly, the participants were asked to estimate the cost of an electric vehicle with an autonomy of 400 km. Figure 41 shows that the acceptable values proposed by the participants logically correspond to desirabilities greater than 50% according to the curve of desirability of the cost (see II.3), which again legitimizes the use of this curve.

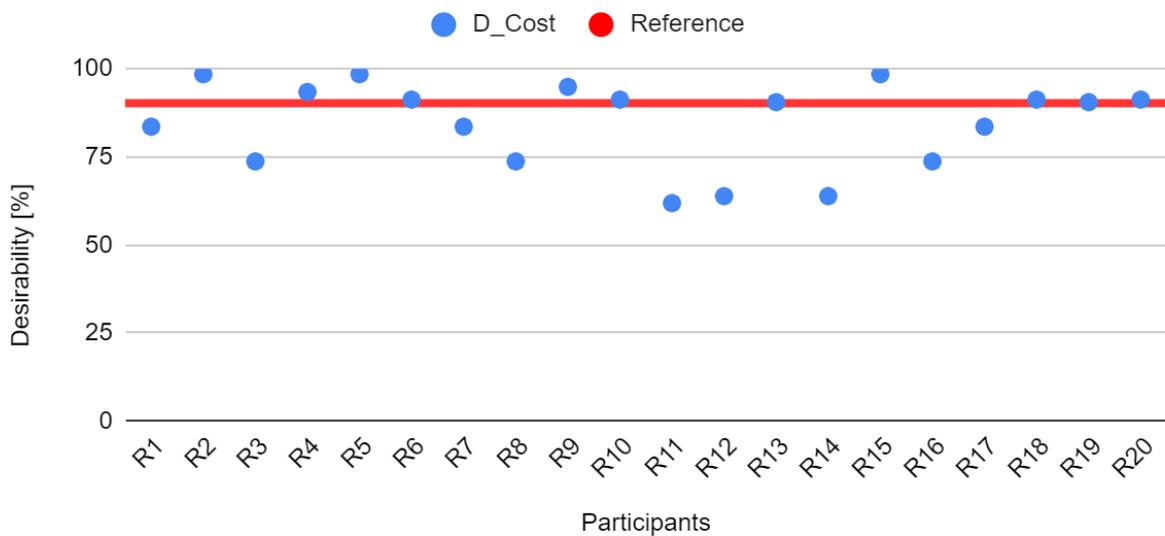


Figure 41: Cost desirability values of participants' responses versus the reference value

Based on these results, we conclude that the exchange rate can be manipulated to add some flexibility to the criteria. This makes it possible to exploit the exchange rate in the benchmarking carried out especially by the marketing team.

• Trade-off weights:

Always with the electric vehicle case study, the participants are first asked to give *direct weights* (relative weights or levels of importance) between 0 and 100% with a total of 100%, for five

criteria: autonomy [km], cost [€], maximum speed [km/h], acceleration times from 0 to 50 km/h [s] and from 0 to 100 km/h [s]. Next, they are asked to make a *pairwise comparison* between each possible combination of two criteria. If n is the number of criteria, the number of combinations is $(n^2-n)/2$; here, with 5 criteria, the number of combinations equals 10. The 10 comparisons are made from graduation scales with 11 levels; redundant information exists in pairwise comparisons. Unlike the *direct weights*' evaluation, due to the multiple combined questions, the *pairwise comparison* gives redundant and sometimes inconsistent information.

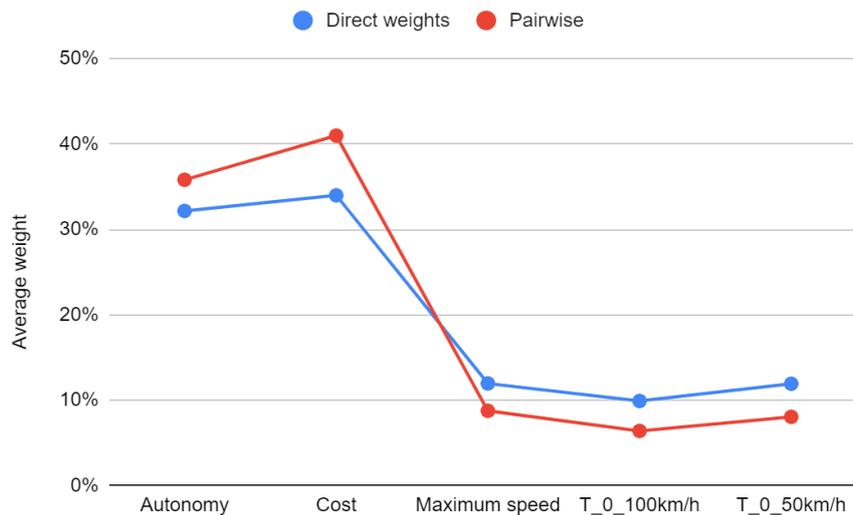


Figure 42: Average weights derived from direct weights and pairwise comparison of the five criteria

Figure 42 shows the average of the participants' responses derived from the *direct weights* and *pairwise comparison*. It may be noted that the results deriving from these evaluations could be different since the approaches are different. However, Figure 42 highlights that, on average, both evaluations lead to very close weight values. Without surprise, the cost and the autonomy result in the highest weight values, which means that these criteria are more critical compared to the three other criteria. In addition, it is remarkable that *pairwise comparison* is severe compared to *direct weights* evaluation and results of weights are major for highest weight values and minor for lowest weight values.

However, Figure 42 does not prove the consistency of the pairwise evaluations. While the average of all participants is consistent as shown in Figure 42, the pairwise comparison of each participant can be inconsistent. Figure 43 presents the consistency ratios computed from the pairwise comparison of each participant. It shows that only eight participants (40%) attained a consistency ratio lower than 10% which is usually regarded as an acceptable consistency ratio. Two other participants attained a consistency ratio higher than 30% which is very low and even implausible (random responses). The most significant result is that nine of the participants (45%) are between acceptable and very low consistency. Therefore, whereas on average the participants' responses to pairwise evaluation are equivalent to direct evaluation of the weights (regarded as perfectly consistent), individual responses are rather lowly consistent.

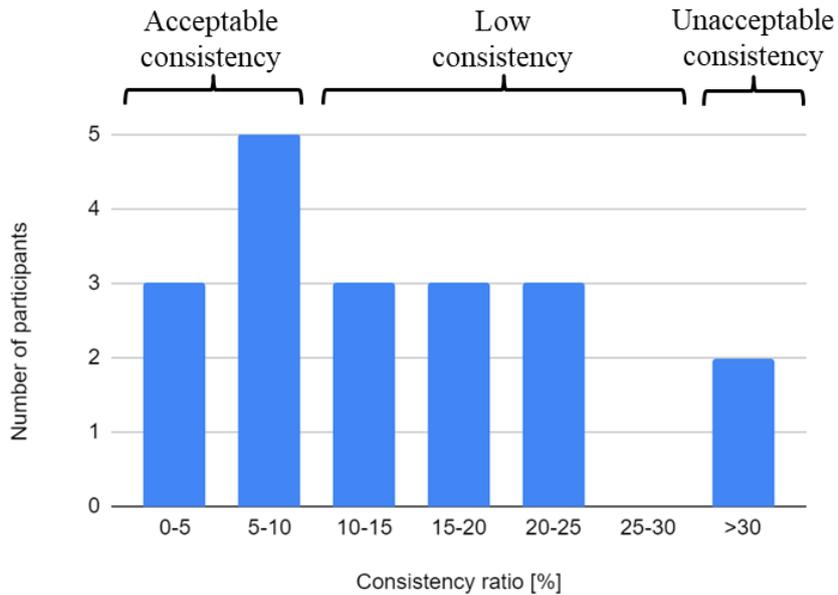


Figure 43: Consistency ratios of the participants performing the pairwise comparison of five criteria

This remarkable result has consequences putting into question the use of weighting aggregation functions (such as Derringer’s aggregation function). In addition, all consistent participants are right in their choices. Since the choice between black and white cannot be grey, a solution to encounter the average result could be to infer the set of every consistent series of weights. The weighting evaluation will therefore result in a set of series of weights rather than a unique series of weights; Each series of weights represents a point of view of one participant. The set of design solutions computed from such a set would then be a set of clusters of solutions. However, this method will lead to an additional number of generated solutions; then, it will increase the difficulty of manipulating design solutions and will affect decision-makers’ judgments. In contrast, this method can help in determining if the solution chosen is robust in terms of decisional robustness. This can be done by testing the weight values according to the consistent series of weights. If the chosen solution is not changing, then, this solution is insensitive to those variations of aggregation parameters and is robust in terms of decisional robustness.

In order to confirm the result of the severity of the pairwise comparison method compared to the direct weights method, we asked the participants to compare the five autonomy values, presented in the table below. Autonomy normalized weights are not presented to the participants; it was calculated to be compared to the weights derived from the pairwise comparison.

As shown in Figure 44, when comparing the weights that derived from the pairwise comparison to the normalized weights, we found that the weight of the autonomy of the solution “Tesla”, which has the maximum autonomy value, is inflated while the other autonomy values are deflated. This result shows that the participants, which are the decision-makers here, can be influenced by the value of a criterion and major it. This can lead to a confusion, or mixing, between the value of a criterion and the level of criticality of this criterion. As result, the interpretation and aggregation steps will be mixed; this may lead to a misunderstanding of the organization of the decision-making process and may lead to non-acceptable solutions.

Solutions	Autonomy [km]	Normalized weights [%]	Weights derived from the pairwise comparison [%]
S1	250	14%	7%
Renault	395	23%	16%
Smart	145	8%	3%
BMW	359	21%	16%
Tesla	600	34%	58%

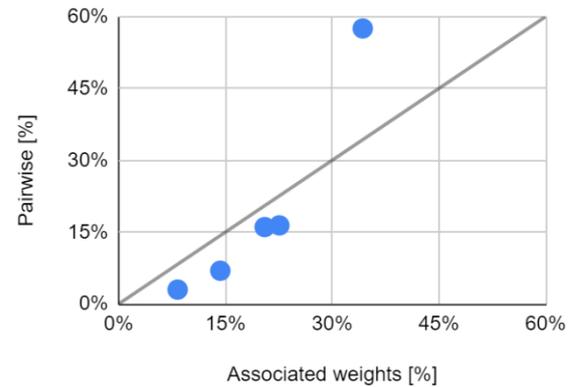


Figure 44: Weights derived from pairwise versus the associated weights of autonomy

• Solutions ranking:

Giving Table 25 (without the exchange rate column), the participants are first asked to rank the five solutions based on five criteria. Theoretically, in this example, the five solutions are not acceptable: each of them has a criterion that does not respect the threshold target value; the chosen desirability functions correspond to the Simon’s function. For example, a cost lower than or equal to 40000€ is highly desirable and a cost higher than 40000€ are not desirable.

Not desirable	Cost [€]	Autonomy [km]	Maximal speed [km/h]	T_0_100km/h [s]	T_0_50km/h [s]	Exchange rate [€/km]
Highly desirable						
Renault	26400	395	135	13.2	4.9	67
Smart	19550	145	125	11.5	4.5	135
BMW	39950	359	150	7.3	5.2	111
Tesla	54900	600	225	5.4	2.7	92
S1	30000	250	115	7	3.5	120
Target values	40000	200	120	13	5	

Table 25: Criteria and target values for five electric vehicles

Since the five solutions are not acceptable, participants are obliged to rank solutions based on criteria criticality (or priority) level. We estimate that ranking “Smart” as the best solution means that the autonomy, which is not acceptable for this solution, is regarded as a criterion with low criticality level. This question aims first at confirming the previous results of weights evaluation and second at showing the importance of using desirability functions with satisfaction ranges instead of one control point.

Figure 45 shows the ranking of the five criteria derived from the vehicle ranking. It is remarkable that on average the autonomy and the cost are ranked 1st and 2nd respectively, while the T_0_100km/h is ranked 5th; these results are in line with the results found in Figure 42. This confirms that autonomy and cost are the most critical criteria, and the T_0_50km/h is more critical than the T_0_100km/h and the maximal speed when choosing an electric vehicle.

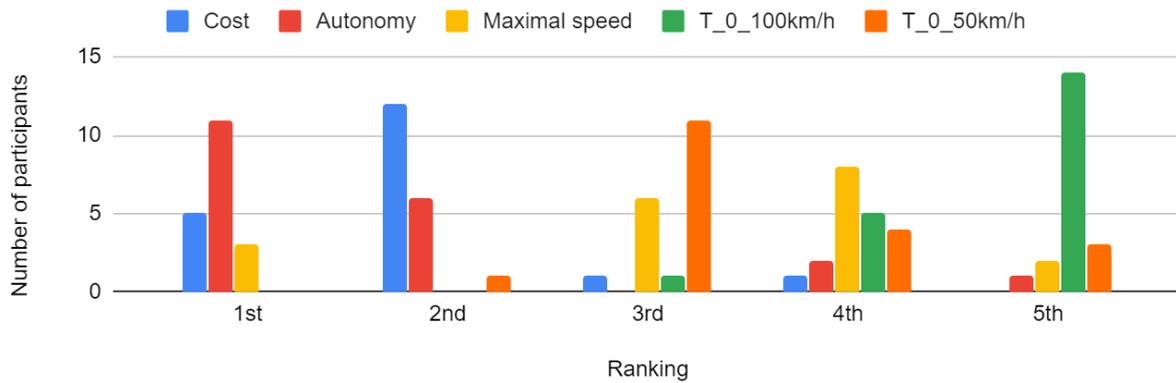


Figure 45: Ranking of five criteria based on solutions ranking

The ranking given by the participants for the five solutions shows that even if the solutions are theoretically not acceptable (because of the desirability functions chosen!), the participants create their own desirability functions or judgments for all, or some of, the criteria. Finally, the ranking is based somewhat on non-Simon's desirability functions but on other desirability functions with satisfaction ranges; those desirability functions are in the decision-makers' thoughts but often are not formalized.

From Pareto's point of view, the five solutions presented above are of equal optimality level. In contrast, the participants do not agree with this equality since all of them propose different ranking of the solutions based on their points of view. This means that a specific aggregation method, more informative, with a certain level of complexity, was used to determine the ranking of solutions. This confirms that Pareto is not a mandatory step in decision-making and can be dispensable.

Second, the same question was asked while considering Linear Derringer's desirability functions. This question aims at verifying that the form of desirability functions influences the participants choices. Table 26 is presented to participants; it contains the desirability values, with a color scale, of all criteria for all solutions. These values are determined based on the satisfaction ranges of the Linear Derringer's functions used.

Not desirable	Cost [€]	Autonomy [km]	Maximal speed [km/h]	T_0_100km/h [s]	T_0_50km/h [s]
Highly desirable					
Renault	95	98	36	11	33
Smart	100	2	21	36	45
BMW	52	84	57	96	24
Tesla	4	100	100	100	100
S1	84	42	7	100	76

Table 26: Desirability values using Linear Derringer's functions

Results highlight that 85% of the participants have made changes in the ranking of solutions. This confirms the influence of desirability functions on participants' choices. Referring to Figure 46, we found that on average, the ranking goes to 1st: Renault, 2nd: BMW, 3rd: S1, 4th: Tesla and 5th: Smart. It may be noted that the ranking could be based first on the two more

critical criteria (Cost and autonomy) since the ranking of the exchange rate of these criteria, presented in Table 25, respects the ranking of solutions especially for the 1st and the 5th solutions.

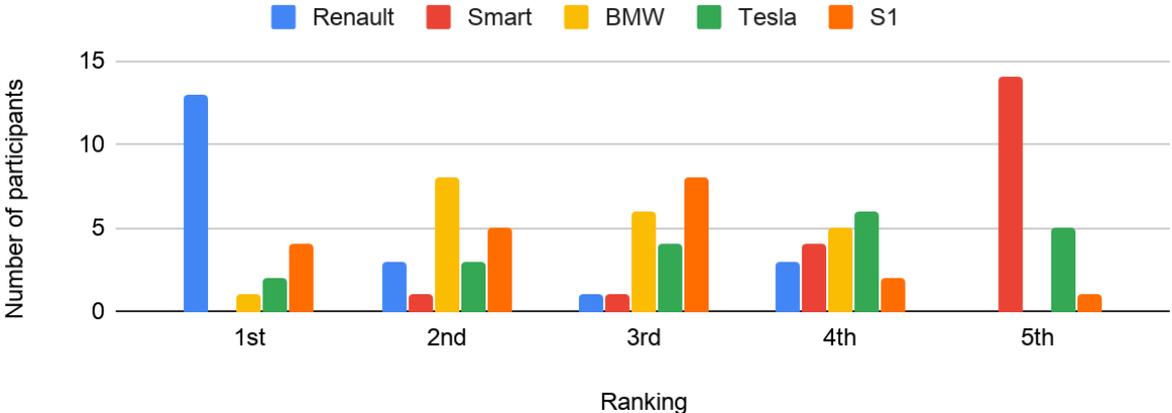


Figure 46: Ranking of solutions based on Linear Derringer's functions

In order to understand the ranking made by the participants, we tried to aggregate the desirability values using the Derringer's aggregation function and the direct weights previously found (see Figure 42). As presented in Table 27, we found that the ranking of solutions is similar to the ranking shown in Figure 46. These results confirm that participants can accept, even prefer, to work with decision-making tools containing interpretation and aggregation steps; these steps allow participants, which are decision-makers in this test, to formalize their preferences.

	GDI	Ranking
Renault	61%	1 st
Smart	18%	5 th
BMW	60%	2 nd
Tesla	34%	4 th
S1	50%	3 rd

Table 27: GDI calculated using the Derringer's aggregation function

5.5. Conclusion

In this chapter, we take a step towards the acceptability of techniques of interpretation and aggregation used in the MOIA method. From the previous results, we conclude that there is no recognized decision-making process applied at Valeo. These results also confirm that the techniques of interpretation and aggregation used in the MOIA seems acceptable to the participants which are probably the potential decision-support tool users. Client specifications, criteria and satisfaction ranges are always modifiable, negotiable and flexible. This flexibility urges humans to accept the MOIA approach and uses it as a design optimization framework.

In an industrial context, decisions are usually distributed among different departments (design, validation, materials, manufacturing, marketing, commercial, etc.) each with a different point

of view. Therefore, working on a method aiming at preference gathering during the design process can give advantages to the decision-making process. This may conclude on the constitution of a questionnaire specified for each case study. This questionnaire aims at merging all the preferences in order to converge toward a solution or set of solutions to be compared. Nowadays, the questionnaire is performed with a group of Valeo employees', but there is a necessity to integrate other actors like clients, sub-contractors, etc.

Participants are satisfied with the proposed user interface tool that presents the organization of the optimization problem and the integration of actors into the design optimization process. This tool also allows actors to differentiate between satisfaction in the interpretation model and criticality in the aggregation model. The mandatory further step is to study the acceptability of the MOIA method itself using this tool by letting the participants solve a specified design problem. This allows us to analyze how participants interact with such a tool and if they are able to generate better solutions in less time than with the current approach.

Chapter 6. Conclusion and perspectives

6.1. Conclusion

The work presented in this manuscript is part of strong industrial needs. It aims at developing methods and tools dealing with **Multi-Disciplinary Optimization** problems and helping make rational decisions in **complex design processes**.

Scientific prospects concern the development of a global design process with an optimal integration of the industrial real working environment into the decision-making process. Actually, in order to choose a design solution, designers focus on satisfying critical criteria using a filtering sequential approach: once a criterion is satisfied, designers search to satisfy the next criterion and so on. This sequential approach generates time delays, which involve desynchronizations and delays in industrial processes, while increasing costs that are proportional to the time spent. The design solution finally obtained is generally acceptable but not optimal. Furthermore, solutions are always designed based on existing components re-use which limits risks but stifles innovation. The desired approach is one that leads to better understanding, rationalization, optimality and acceptability of the solution found by designers. In this context, our work responds to the need of creating tools that organize design problems, which are always multi-objective problems, formalize decision-makers' preferences and find optimal solutions under industrial constraints like time, cost and simplicity.

After providing a review of design decision-support methods, we have introduced the **MOIA** (Morphogenesis, Observation, Interpretation, Aggregation) method that formalizes the integration of stakeholders' preferences in the design process. This method returns a single value, as a level of satisfaction for a specific point of view of the designed product. It is divided into four models: the morphogenesis model, which generates solutions, the observation model, which simulates the behavior of the product, the interpretation model, which normalizes the simulated result, and the aggregation model, which converts the multi-objective problem to a single-objective problem. The MOIA method has been used in several engineering design applications but never directly in an industrial research department which is, of necessity, moving towards technologies that are not currently being considered; this reveals the necessity of answering the **agility**, collaborative and team work problems.

From practical point of view, it is important to associate our study to the known Systems Engineering design process which becomes the standard approach when dealing with Multi-Disciplinary product development. In this manuscript, we have proposed and discussed the close relation existing between **MBSE**, presented by the **V-model**, and MOIA. On a specific scale, MBSE is used to parametrize the observation, interpretation and aggregation models of the MOIA method. Then, MOIA can operate as a simulation/optimization/decision-support process calculating the Global Desirability Indexes of generated solutions characterized by their design variables.

The projects (Electric vehicle powertrain and Drone taxi) are studied in a context constrained by the realities of research department that has to fit innovation purposes and take rational decisions while different actors (client, designer, marketing, etc.) participate into the decision-making process. It is then important to develop a global methodology that fit innovation purposes while taking human, which represent the decision-makers, into consideration; the collaborative work between actors emerges more constructed and interesting concepts than if they work separately. In order to activate this collaboration and to support the decision-making process, we start developing a conceptual HMI (Human-Machine Interface) that structure the design problem based on MOIA method. This tool computes and visualizes solutions and generates Pareto optimal solutions. It also allows the possibility to modify the interpretation and aggregation parameters and to use different forms of desirability and aggregation functions. AHP (Analytic Hierarchy Process) has also been added in order to compute the importance weights of objectives using pairwise comparison technique. This tool can then be used to concretely investigate the impact of human point of view on the solution. It can also be used as an internal and external tool for exchanges/communications and negotiations. In addition, we show the importance of replacing conventional observation models, which are always heavy and require important time to evaluate a sufficient number of solutions, with very fast substitution models for the exploration of large design spaces. A process based on Extreme Learning Machine was introduced and applied to the case study of electric vehicle powertrain. This process ensures the rapidity and the accuracy of the observation models.

To analyze the acceptability of this new approach at Valeo, we organized internal working sessions with a presentation of the main concepts followed by a questionnaire. These sessions

allow us to study the concepts of optimality and acceptability arising from human judgment through decision-making. Questions related to specifications, criteria, interpretation and aggregation were evaluated. Based on the work sessions results, we conclude that:

- The client specifications are generally flexible: those specifications can evolve during the design process. Different actors can participate to the negotiation and modification of the specifications.
- The criteria are generally flexible: the criteria, mainly determined by the specifications, can be modified after negotiations between actors. Some criteria are added after the starting phase of the design process. The interpretation functions and satisfaction ranges of criteria are also negotiable; it is a collaboration process where the point of view of each actor must be taken into account.
- The aggregation is a technique aims at ranking the generated solutions. It seems obvious for decision-makers to use further the aggregation techniques that filter the maximum of solutions, like the Minimum and the Derringer's aggregation function, instead of using the aggregation techniques that cluster the solutions, like the Pareto optimality.
- Always, several actors negotiate the same subject. The negotiation is often a complex activity because the decision emerges from the process of construction of necessity. The decision-making power is distributed between the actors.

Then, the developed tool is considered as a beta version of the aimed collaborative tool. This tool may be used by humans to implement a dynamic approach to systems knowledge development. It will represent a design environment associating the emerging intelligence of machines and the intelligence of humans in order to provide relevant knowledge or information from the point of view of optimizing the design of a system.

6.2. Perspectives: Towards Intelligence Augmentation

The invention of the computer was a big move that changed the history of the machine. The concept of Artificial Intelligence (AI), introduced by John McCarthy in 1955 [McCarthy et al. 1955], and information technology (IT) started growing very fast allowing the machine to be a competitor to humans by replacing them in several jobs. In 1997, the first supercomputer chess-playing system “Deep Blue” defeated Garry Kasparov, world’s chess champion [McCorduck 2004]. Recently, in 2016, “AlphaGo” won a Go match against Go champion Lee Sedol [BBC 2016]. It may be noted that “AlphaGo” used a power of 1MW [Mattheij 2020], while Lee Sedol used about 20W of power, which is an estimation of a human brain power [Elert 2020], to operate. This means that, in such well-defined or well-structured problems, nowadays machines require much more energy in order to replace humans and be the only decision-maker.

Because design problems are ill-defined problems, humans must be integrated inside the definition of the problem’s structure. Kasparov spoke about a collaboration between the human and the machines in order to augment human intelligence [Kasparov 2017]; the human can benefit from the machine, while the machine can learn from the human. Based on an online chess tournament, between supercomputers, human grandmasters, and computer assisted human (using AI), Kasparov concluded that *“weak human + machine + better process was*

superior to a strong computer alone and, more remarkably, superior to a strong human + machine + inferior process”. Developing a better process that integrates both machines and humans is highly recommended to improve decision-making.

From the previous parts, we conclude that humans are the real decision-makers but they need to be assisted by tools, during the design process, to move towards the best acceptable solutions. The acceptability here combines the design method, specifications, criteria, satisfaction ranges, etc. The global approach proposed in this manuscript is in line with the concept of Intelligence Augmentation (IA) which is more suitable for solving design problems as it puts humans in the optimization loop.

We can finally say that an inexperienced designer with the right process and tool can be better than an experienced designer or a powerful machine with AI tools. This combination between human and machine is less expensive than the powerful machine and better in taking decisions than experienced humans. We can imagine that the future decision-support will consist of a digital assistant tool that will assist designers during the design process.

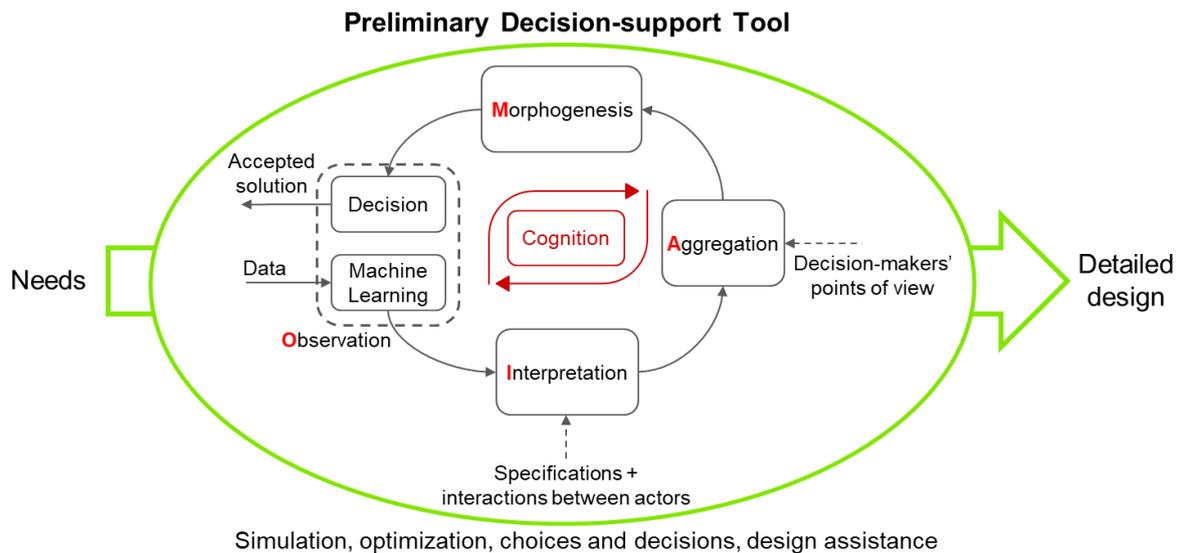


Figure 47: Learning based MOIA decision-support tool

The concept of Intelligence Augmentation (IA) in design leads to Learning, Interpretation, Aggregation and Optimization decision-support tool which is based on MOIA ontology; MOIA intrinsically carries out an IA concept. Figure 47 shows how this preliminary decision-support tool can play the role of an intermediate step between the needs and the detailed design. The needs correspond to a new idea of product or a development of an old product. Then, design assistance in the preliminary design phases using this tool is proposed. The tool is a combination between machine learning, MOIA ontology and decision-makers. The tool steps are as follows:

1. **Machine Learning:** this step corresponds to the **observation** model where inputs correspond to measured or simulated data from the studied physical system and the outputs correspond to the criteria derived from the specifications and discussed between

actors. These criteria are flexible/modifiable based on the case studied and actors' decisions.

2. **Interpretation:** it corresponds to a model composed from a set of **desirability functions**. Each function corresponds to a criterion. The forms and parameters of those functions are always under review and modification by actors.
3. **Aggregation:** it corresponds to one or several aggregation models where decision-makers can study different points of view by changing the aggregation function and the importance weights (if applicable). Weights can be calculated using a tool containing several calculation methods presented before.
4. **Optimization:** one or several optimization algorithms run in order to generate solutions corresponding to a maximum value of satisfaction that represents the optimality.
5. **Decision:** this step aims at choosing an acceptable solution. It may be noted here that the optimization can run several times. Each running time, decision-makers can acquire more knowledge of the design problem while generating solutions. Therefore, they can continuously modify their preferences and points of view by modifying interpretation and aggregation parameters in order to finally choose an acceptable solution.
6. **Cognition:** the design process is sequential and the actors who define the problem act in bounded rationality. Therefore, studying the sequential movement of the decisions made by designers becomes a challenge to better understand these decisions. The proposed tool will allow to monitor designers in a design situation in order to observe the trajectories followed by their decisions and show how the obtained solutions influence the designers' decisions. Then, this will allow the study of cognitive biases and heuristics in judgment.

Finally, this tool can be considered as an IA tool allowing humans to be inside the definition of the design problem. It integrates both optimality (machine) and acceptability (human). Such a tool can increase the probability of generating solutions that are optimized mathematically and are accepted by humans.

As Kasparov points out, the relevance and effectiveness of human-machine collaboration lies in the procedures that bring them together. The general perspectives of our work tend to develop and validate this vision of IA in the field of engineering design (see Figure 48). The aim is to increase the design optimization capabilities by acting on the procedures that link the computer and the user of a system (such as a vehicle or a vehicle component). The computer dialogues with humans through the MOIA ontological framework, which guarantees the relevance of the dialogue, i.e. its clarity, coherence, minimalism and generality. Our goal is to explore this increase in capacity by developing tools while testing their validity with design experts and ultimately with users of the artifacts they design.

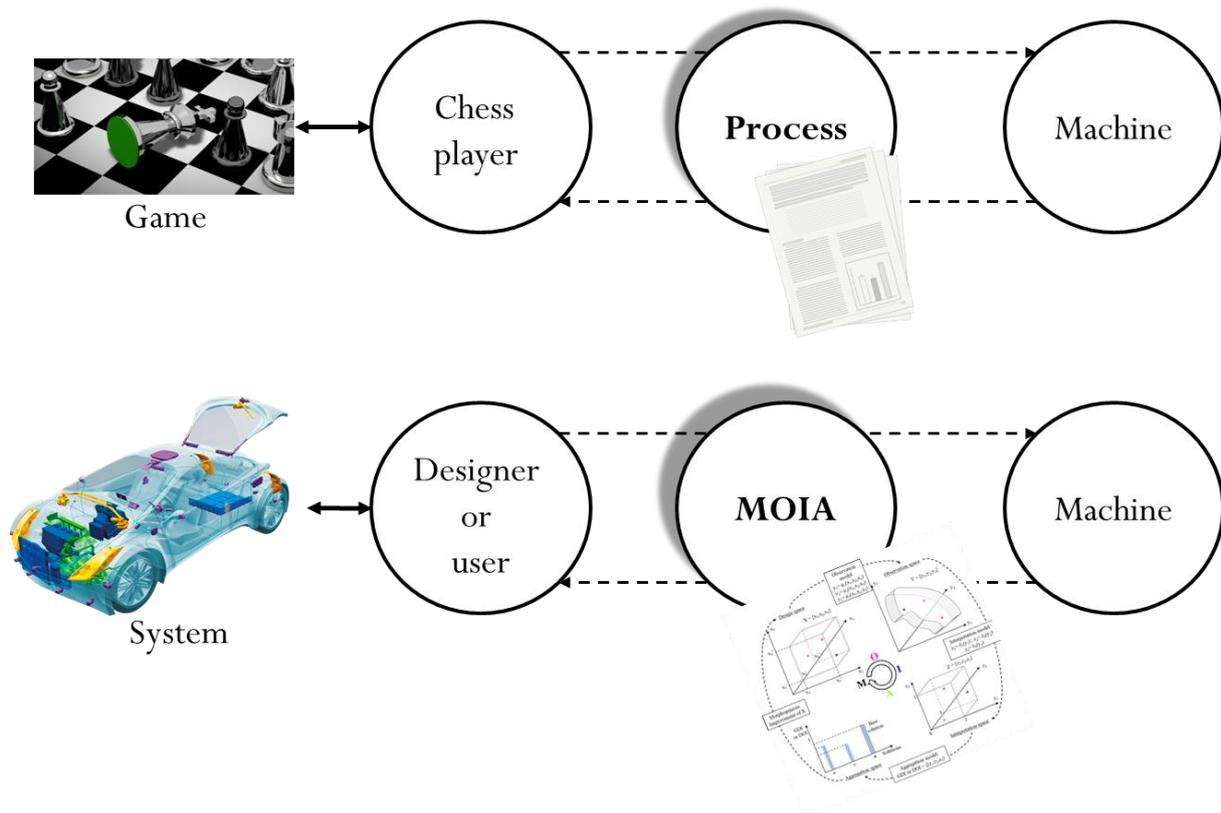


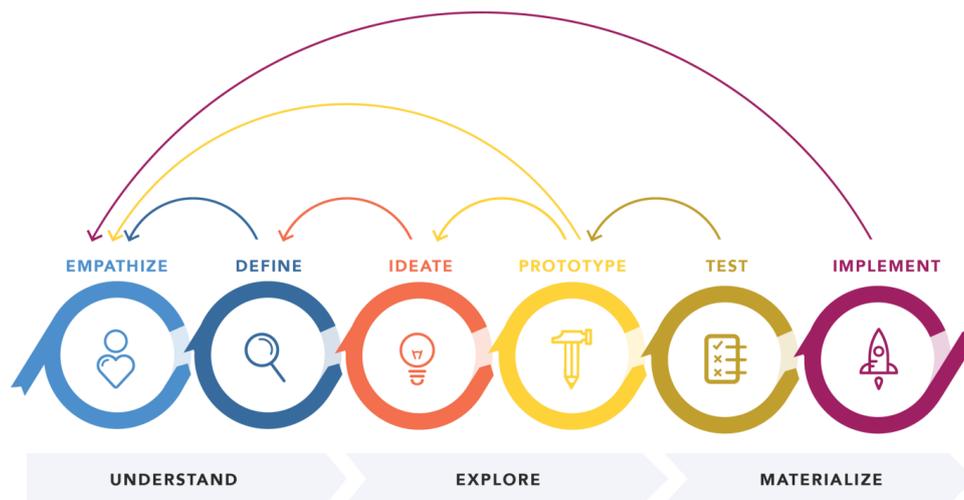
Figure 48: Human-machine collaboration in system design

The level of integration of the end-users in the design process has an advantage of increasing the possibility of generating acceptable solutions. This logic follows the Human Centered Design (HCD) [Boy 2017] which correspond to a mindset to be applied alongside human-centered approaches like the Design Thinking. Design Thinking is an approach for creative problem solving that encourages designers to integrate the end-users into the thinking process which leads to better products, services and internal processes. Design Thinking is considered as an efficient and rapid way of development of a design. For example, Tesla Inc. uses Design Thinking approach for its Autopilot application [Fridman 2018].

The work in this manuscript can be used to support general approaches like the Design Thinking. The 6 stages of Design Thinking are discussed as follows [Rowe 1987; Miller 2020]; we tried to introduce a preliminary connection between these stages and the work done in this manuscript.

- Empathize: learn from the end-users for whom you are designing. This step can be done using a questionnaire specified for each case study like the one discussed in Chapter 5.
- Define: construct a point of view that is based on end-users' needs and insights. This point of view can be translated into interpretation and aggregation parameters that enrich the learning based MOIA decision-support tool.
- Ideate: brainstorm to generate creative solutions. The ideation can be derived from the SE approach by generating different possible architectures of the design using methods like SCTO.

- Prototype: build a representation of the generated solutions. Our approach privileges numerical prototypes using the learning based MOIA decision-support tool that is capable of generating optimal solutions, based on the constructed point of view, in short time.
- Test: return to the users for feedback on the accepted solutions. This step can be done according to the previous step while the testing and the selection processes are based on optimization.
- Implementation: Put the selected solution into effect. After selecting a solution, the detailed design process starts.



In this Design Thinking approach, our vision is to develop a collaborative decision-support tool between human and machine that enriches the experience of engineering design. This tool connects machine learning (observation model) with a rule-based network (interpretation and aggregation models) in order to evaluate high-level indicators that are constructed through the interpretation and aggregation phases.

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Appendix I. Drone taxi

- Scientific objective:

In this part, we will study the integration of the MOIA in the MBSE for a MAV (Manned Aerial Vehicle) drone taxi application, illustrated in the powertrain system. The aim is to demonstrate how the MBSE will support the MOIA in order to:

- Organize the optimization problem by defining the design variables, observation variables, design objectives, etc. used in the MOIA method.
- Define the observation model based on the scenarios and principal functions demanded from the system.
- Indicate the actors that participate to the design problem.

Below, we give the main modeling steps and associated diagrams.

- Analysis steps:

The increasing urbanization of populations coupled with traffic problems and ecological concerns has recently led to a multiplication of air mobility projects based on electric vertical take-off aircraft (eVTOL: electric Vertical Take Off and Landing).

The case study considers an electric drone-taxi, called drone in the following, top-level requirements definition, followed by powertrain system specification and architectural design and ends with component specifications.

Figure 49 shows the different phases of the drone system during its life cycle in the form of a state diagram, from the design phases to the destruction or recycling phase passing through the manufacturing, the operation and the maintenance phases. In the following, we will focus on the operational phase (operating).

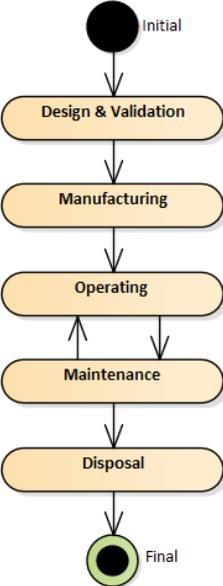


Figure 49: Drone life cycle state diagram

The needs analysis and the system specification are performed at the electric drone system level. The logical and physical architecture analysis and the virtual evaluation is performed allowing the achievement of global electric drone design objectives.

- Needs analysis:

Needs analysis is the first step in MBSE. It aims at defining the expectations of stakeholders on the service provided by the system of interest; the needs at this level are often expressed in an informal way and usually not measurable. Stakeholders represent the end-user and any external actor that has an impact on the system of interest. Needs concern an eVTOL flying system, for one or several passengers, performing a mission between two points with an advantage of time and cost per mission, which correspond to the Measure of Effectiveness (MoE), compared to other transportation systems.

Figure 50 shows the system interacting with the different actors of its environment in the operational phase. All the interactions are commented on with the acts of the actors. Physical actors are the passenger, the operator and the neighborhood.

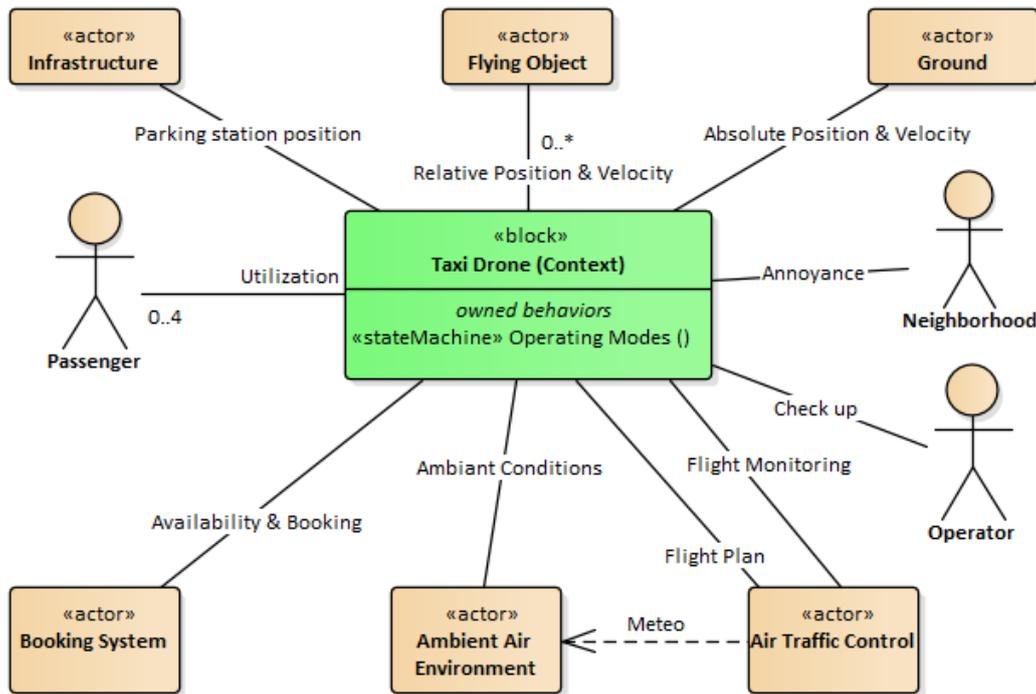


Figure 50: Drone operational context diagram

In a second step, the context use cases and scenarios are analyzed. Use case diagram is used to illustrate the stakeholder expectations by representing the different scenarios where the user interacts with the system. Figure 51 shows the operational context use cases which are Book, Travel and Check-up.

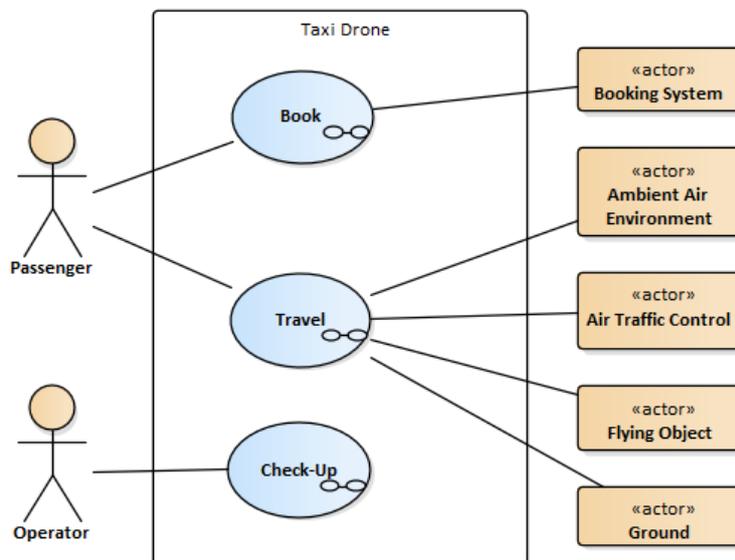


Figure 51: Drone operational context use cases

• System specification:

System specification is the second step in MBSE. It aims at translating the informal stakeholders' needs into formal and quantified system requirements. Focusing on the use case

“Travel”, Figure 51 shows the related actors to this use case which are the passenger, the ground, the air traffic control and the ambient air environment. The next step consists in determining the principal functions that the drone should perform depending on the analyses of system use cases and scenarios. The scenario of “Travel” considered (see Figure 52), corresponds to a passenger mission from a point A to a point D with a vertical climb phase (A-B), a horizontal cruise phase (B-C) and a vertical descent phase (C-D). This scenario is configured through height (m), climb speed (km/h) or time (s), length (km) and cruise speed (km/h) and descent speed (m) or time (s). Ambient air environment is also parametrized by the wind speed (km/h) and the air density (kg/m^3).

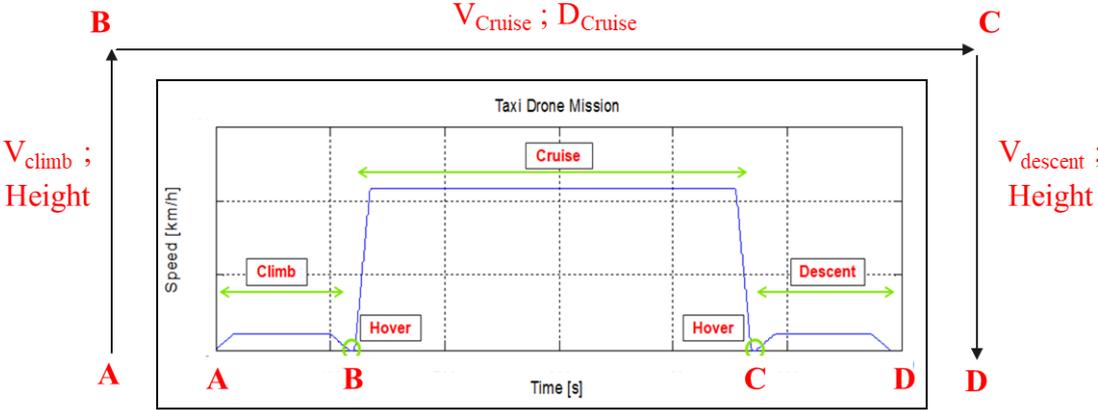


Figure 52: Typical Drone mission

A sequence diagram of the use case “Travel” is then proposed (see Figure 53). On the right side, the main functions, which reflect the role played by the system in the interaction between two elements of its environment, are shown. Three main functions are identified: MF01-Transport, which corresponds to the drone transportation from point A to point B, B to C, and C to D, MF02-Communicate, which is related to the information communicated between the drone and the “Air Traffic Control”, and MF03-Navigate, is related to the navigation data referenced by the “Ground”.

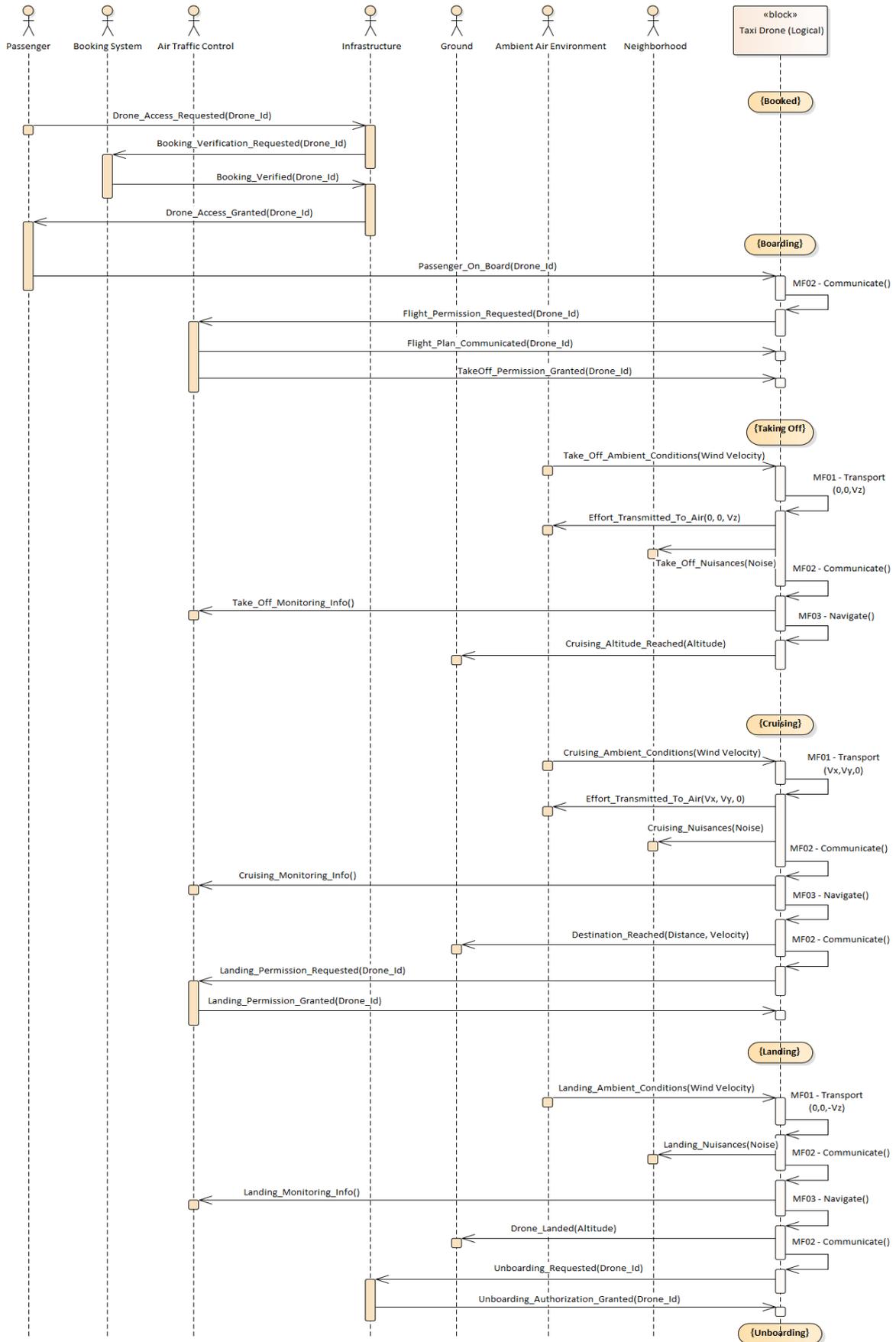


Figure 53: Sequence diagram of the use case “Travel”

• Logical architecture analysis:

By decomposing the principal function into internal technical functions, logical architecture analysis describes how system expected behaviors would be fulfilled. This step represents the passage from a black box to white box. Figure 54 shows the decomposition of the principal function MF01-Transport into three main functions: Board, Move and Disembark. The function Move is also decomposed into three internal functions which are IF01-Pilot, IF02-GeneratePropulsiveForce and IF03-OrientPropulsiveForce.

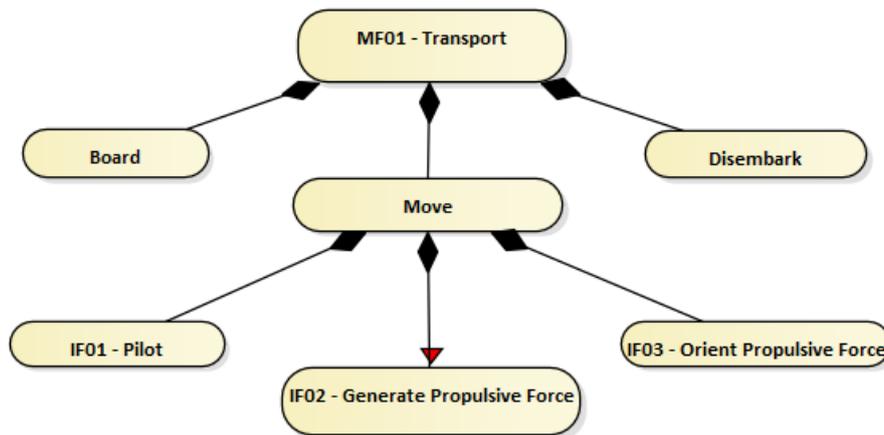


Figure 54: Decomposition of the principal function MF01-Transport

Then, the internal function IF02-GeneratePropulsiveForce is described with energetic functional flows and internal components (see Figure 55). This decomposition is based on the SCTO method.

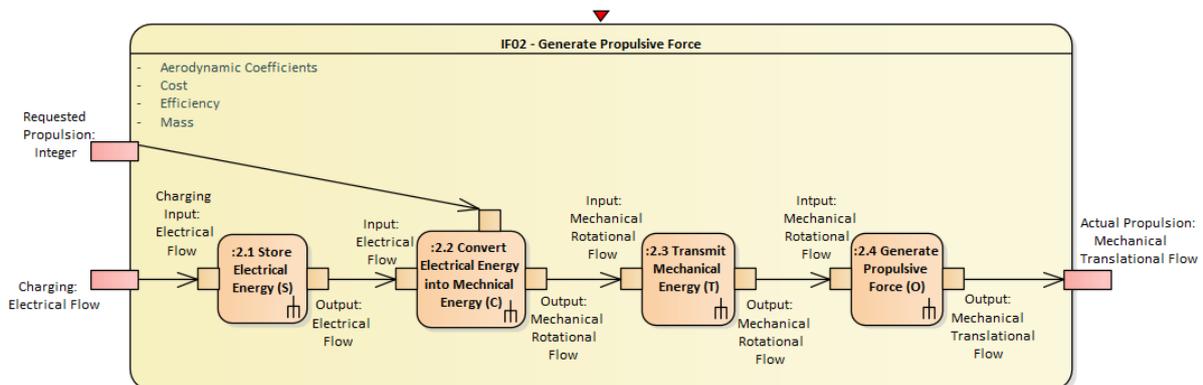


Figure 55: Logical architecture with functional flows

• Physical architecture analysis:

Two drone architectures, corresponding to several aerodynamic vertical mobility concepts, have been identified. Figure 56 shows these architectures as presented in [Grandl et al. 2018]; a multirotor is similar to a helicopter with several propellers and without a tail propeller; Tilt-x has several propellers which lift and cruise the drone.

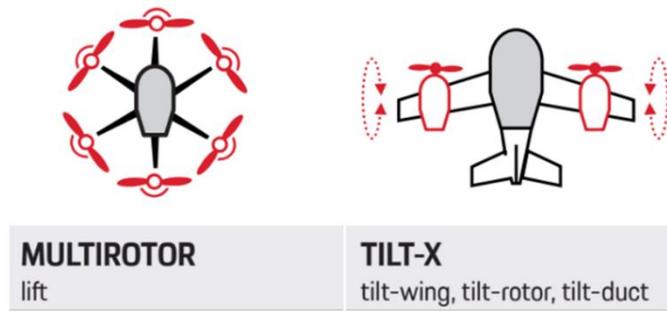


Figure 56: drone architectures

Based on these architectures, two alternative powertrain solutions are identified, with and without wings. Figure 57, Figure 58 and Figure 59 show the different blocks decompositions in order to arrive at the alternative solution with wings.

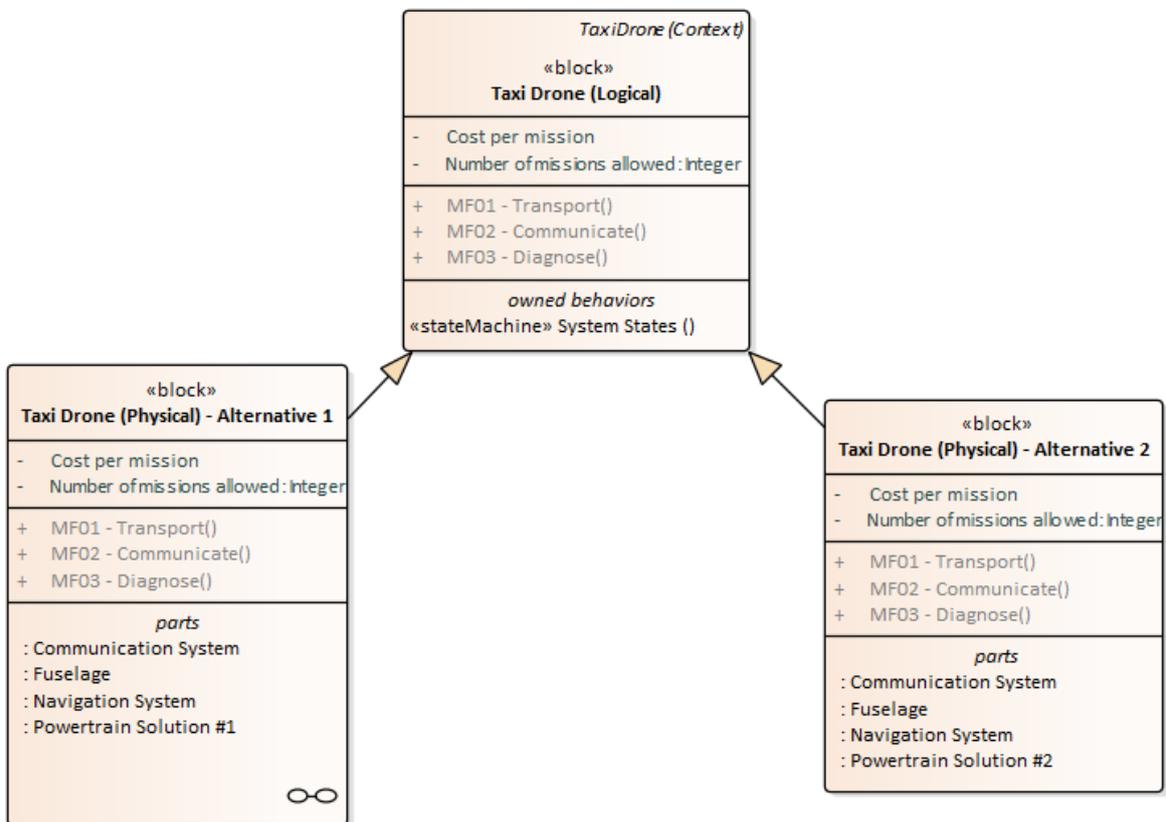


Figure 57: Two alternative solutions

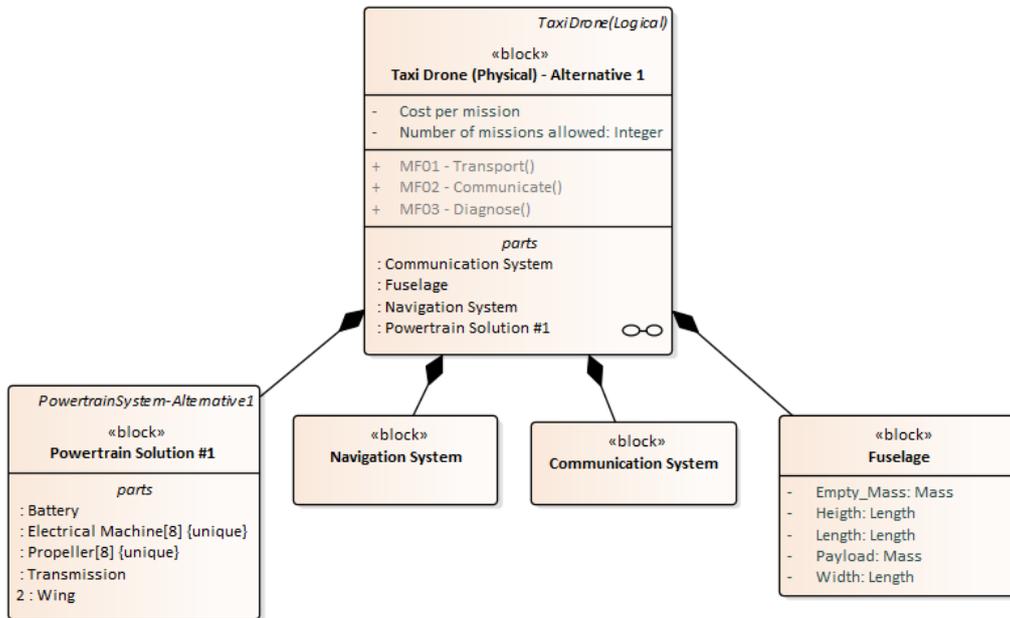


Figure 58: Block decomposition of the first alternative solution

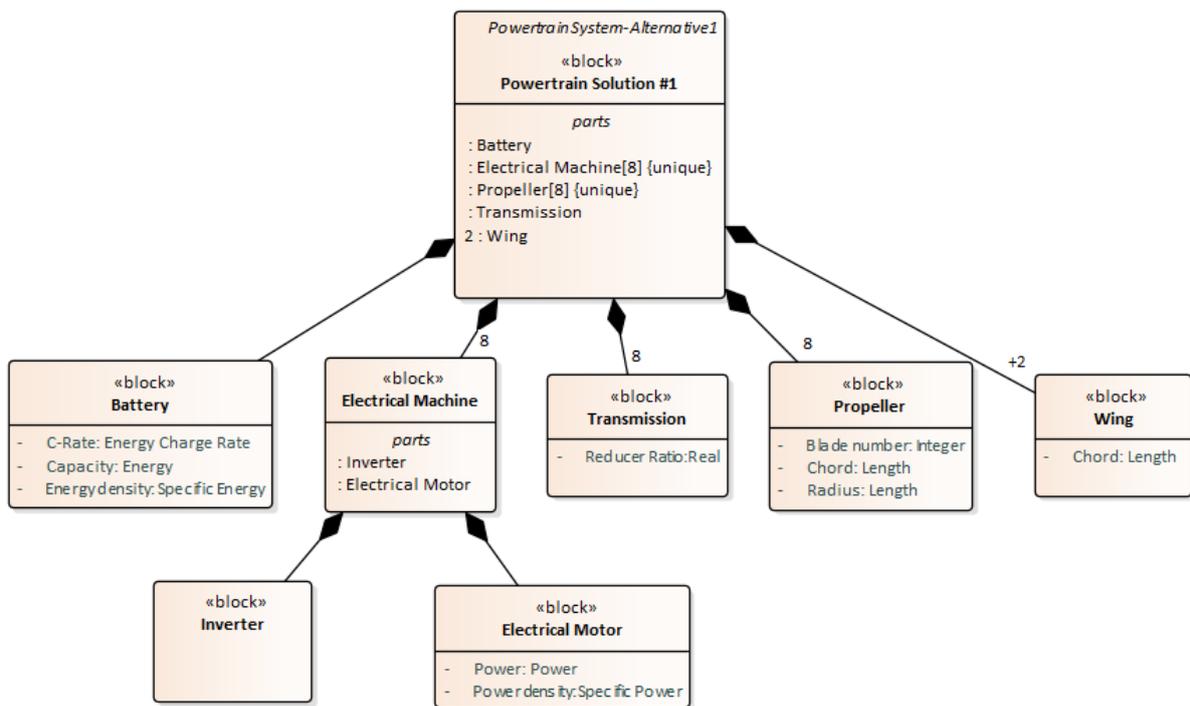


Figure 59: Physical architecture of the powertrain for the first alternation solution

In a physical architecture phase, each internal function is then allocated to a single physical system element. Here, the electric propulsion constraint, brought by the context, imposes the electric battery as an energy storage component (S), which then imposes the electric motor as an energy converter (C). A reducer-type transmission element is used for the transmission function (T). Finally, a propeller is considered as operator (O) for the generation of the propulsive force. These components are generally associated with their own parameter sets as well as the parameters of the interface elements (vehicle and ambient air). The design variables,

or Technical Property Measures (TPM), taken into account are as follows: Battery: Capacity (kWh), Energy density (Wh/kg), C-rate (kW/kWh); Electric motors: Number (-), Power (kW), Power density (kW/kg); Propellers: number (-), radius (m), number of blades (-), chord (m); Fuselage: frontal drag coefficient; Transmission: reduction ratio; Wings: chord (m).

Figure 60 shows the global optimization process based on MOIA method starting from the design variables X and ending with the global desirability index GDI passing through the observation, interpretation and aggregation models. In addition to the cost per mission, the observation model aims at calculating the drone power required for the climb, cruise and descent phases in order to find the energy needed to complete a specified mission. The calculation of the cost per mission, which is not detailed in this manuscript, is based on Vahana open source project [Vahana 2017]. The calculation of drone power is based on helicopter dynamics [Venkatesan 2014]. The energy equations that determine the operating points in terms of power, torque and propeller speed are implemented.

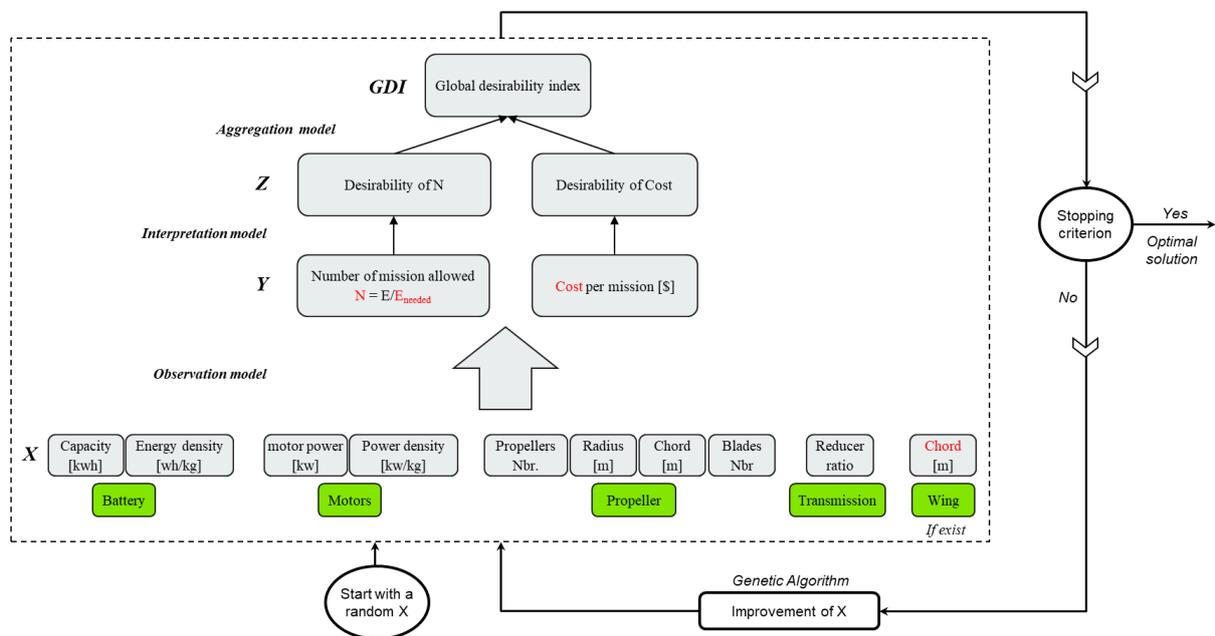
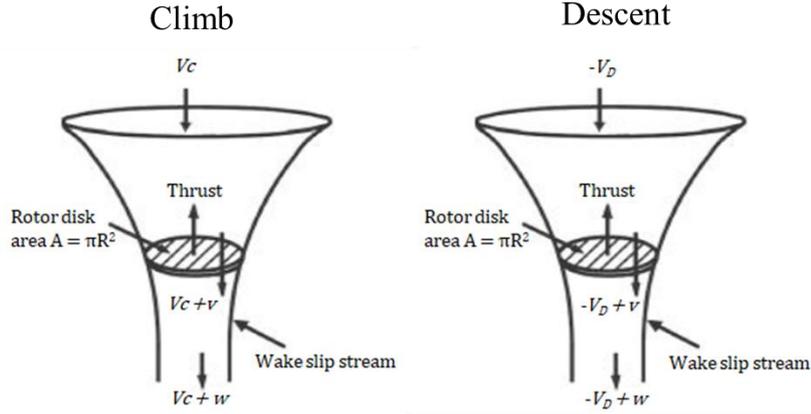


Figure 60: Drone MOIA method

Below, we detail the observation model that calculates the E_{needed} expressed by a set of energetic equations for vertical (climb and descent) and horizontal (drone without and with wings) phases:

- Vertical phase, Climb and descent:

Figure 61 shows the direction of the thrust and air speeds in climb and descent. It also describes all the variables used in the vertical phase equations listed in the following.



T_p : Propeller thrust [N]	g : Gravitational acceleration [m/s^2]
N_p : Number of propellers [-]	C_{df} : Fuselage lateral drag coefficient [-]
T : Total thrust = $N_p \cdot T_p$ [N]	S_f : Fuselage lateral surface [m^2]
R : Propeller radius [m]	F_p : Parasite force [N]
A : Propeller area (πR^2) [m^2]	ρ : Air density [kg/m^3]
V_C : Drone climb speed [m/s]	k : Effective disk area factor [-]
V_D : Drone descent speed [m/s]	N : Number of propeller blades [-]
v : Air induced speed [m/s]	C : Propeller blade chord [m]
w : Air far field wake-induced speed [m/s]	C_d : Blade drag coefficient [-]
M : Drone total mass [kg]	C_L : Blade lift coefficient [-]
a : Drone acceleration [m/s^2]	σ : Propeller blade solidity ($N \cdot C / \pi R$)
	Ω : propeller revolution speed [rd/s]

Figure 61: Thrust and speeds in Climb and descent

As inputs, climb speed (V_C) or descent speed (V_D) and the drone acceleration (a) are determined from the mission profile (scenario). The total mass (M) contains the masses of EMs, battery, passengers, propellers, transmission and fuselage. Fuselage parameters are given as functions of the number of passengers and the drone architecture. The parasite force corresponds to drone profile drag losses and can be expressed as follow:

$$F_p = 0.5 \cdot \rho \cdot S_f \cdot C_{df} \cdot V_C^2 \quad (16)$$

1. From, Newton's laws of motion, the thrust of each propeller is calculated :

$$T - M \cdot g - F_p = M \cdot a ; T = N_p \cdot T_p \Rightarrow T_p = \frac{M \cdot (a + g) + F_p}{N_p} \quad (17)$$

2. From momentum and energy conservation, we determine the induced speed :

$$T_p = 2 \cdot \rho \cdot A \cdot v \cdot (V_C + v) \Rightarrow v = -\frac{V_C}{2} + \sqrt{\left(\frac{V_C}{2}\right)^2 + \frac{T_p}{2 \cdot \rho \cdot A}} \quad (18)$$

3. Then, power (Induced, Climb, Parasite and Acceleration) is determined as follow; the effective disk area factor (K) is estimated to 1.15 :

$$P = k \cdot T \cdot (V_C + v) \quad (19)$$

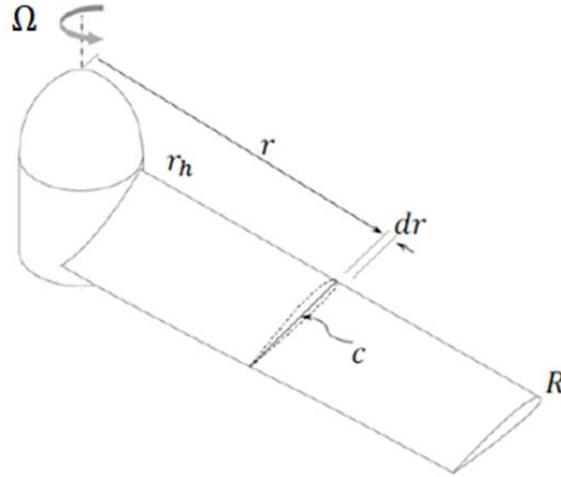


Figure 62: Propeller blade representation

4. Thrust power and blade drag power are functions of the propeller revolution speed Ω , equation that determine the revolution speed and the blade drag power are presented below :

$$dT = 0.5 \cdot \rho \cdot C_L \cdot (R \cdot \Omega)^2 \cdot dS ; dS = N \cdot C \cdot dr \quad (20)$$

$$dP_{\text{Blade Drag}} = 0.5 \cdot \rho \cdot C_d \cdot (R \cdot \Omega)^3 \cdot dS \quad (21)$$

5. By integration over r ($0 \rightarrow R$):

$$T = \rho \cdot A \cdot (R \cdot \Omega)^2 \cdot \left(\frac{\sigma \cdot C_L}{6} \right) \Rightarrow \Omega = \sqrt{\frac{6 \cdot T}{\sigma \cdot C_L \cdot \rho \cdot A \cdot R^2}} \quad (22)$$

$$P_{\text{Blade Drag}} = \rho \cdot A \cdot (R \cdot \Omega)^3 \cdot \left(\frac{\sigma \cdot C_d}{8} \right) \quad (23)$$

6. Then the total power (Induced, Climb, Parasite, Acceleration and blade drag) is:

$$P_{\text{Total}} = P + P_{\text{Blade Drag}} \quad (24)$$

For descent, replace the climb speed V_C with $-V_D$ which is the negative value of the drone descent speed.

• Horizontal phase:

a. Cruise, wingless drone:

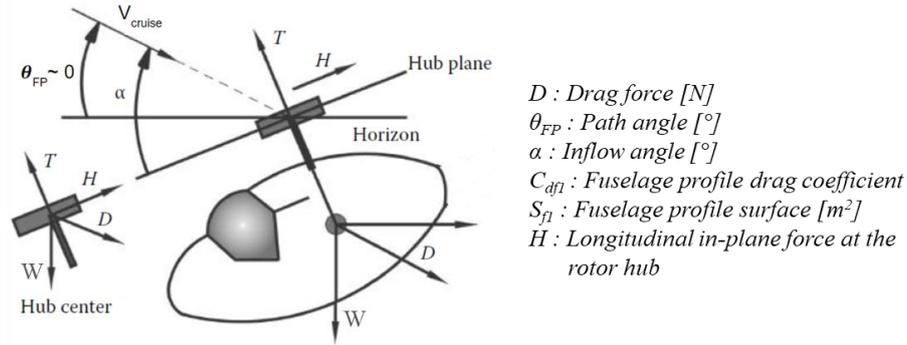


Figure 63: Representation of propeller loads in the longitudinal direction

For the wingless architecture, we took an assumption that there is a small inflow angle (α) and the drag force (D) is negligible compared to the drone weight (W); then, the longitudinal in-plane force at the rotor hub (H) is neglected. The path angle (θ_{FP}), which is the angle between the horizon and the speed direction of the drone, is neglected.

$$D = 0.5 \cdot \rho \cdot S_{f1} \cdot C_{df1} \cdot V_{cruise}^2 \quad (25)$$

1. From Newton's laws of motion on the vertical and horizontal axes, the inflow angle is determined :

$$\text{On the vertical axe : } T \approx W \quad (26)$$

$$\text{On the horizontal axe : } T \cdot \alpha = M \cdot a + D \Rightarrow \alpha = \frac{M \cdot a + D}{W} \quad (27)$$

2. From the equation of thrust in forward flight, the equation of the induced flow (v) is determined; v is solved by iteration:

$$T = 2 \cdot \rho \cdot A \cdot v \cdot \sqrt{(V_{cruise} \cdot \cos \alpha)^2 + (V_{cruise} \cdot \sin \alpha + v)^2}$$

$$v = \frac{T}{2 \cdot \rho \cdot A \cdot \sqrt{(V_{cruise} \cdot \cos \alpha)^2 + (V_{cruise} \cdot \sin \alpha + v)^2}} \quad (28)$$

3. The non-dimensional forward speed (μ) is expressed as follow:

$$\Omega = \sqrt{\frac{6 \cdot T}{\sigma \cdot C_L \cdot \rho \cdot A \cdot R^2}} \quad ; \quad \mu = \frac{V_{cruise} \cdot \cos \alpha}{R \cdot \Omega} \quad (29)$$

4. Then, the total power (Induced, Parasite, Acceleration and blade drag) is calculated; the coefficient 4.65 is obtained based on several references approximations [Johnson 1980; Venkatesan 2014] :

$$P_{\text{Cruise}} = k \cdot T \cdot (V_{\text{cruise}} \cdot \sin \alpha + v) + \rho \cdot A \cdot (R \cdot \Omega)^3 \cdot \left(\sigma \cdot \frac{C_d}{8}\right) \cdot (1 + 4.65 \cdot \mu^2) \quad (30)$$

b. Cruise, winged drone:

Figure 64 shows a representation of winged drone's forces in cruise; propellers are hidden.

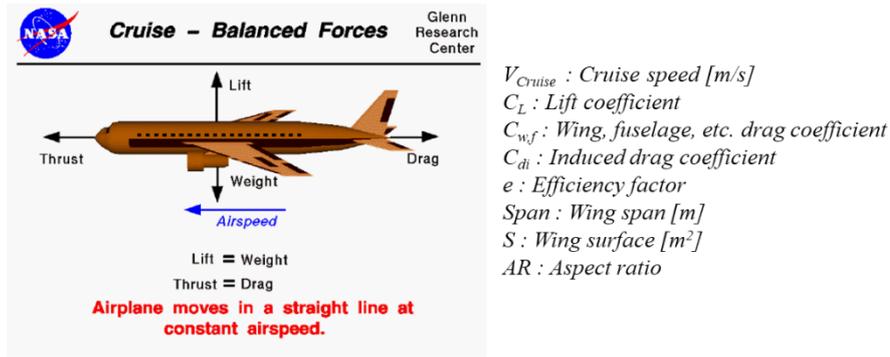


Figure 64: Representation of different forces in cruise

1. For a wing, the total drag coefficient (C_d) is equal to the base drag coefficient at zero lift ($C_{w,f}$) plus the induced drag coefficient (C_{di}). The efficiency factor (e) is assumed to 0.7.

$$C_d = C_{w,f} + C_{di}$$

$$C_{di} = \frac{C_L^2}{\pi \cdot AR \cdot e} ; AR = \frac{Span^2}{S} \quad (31)$$

2. Then drag force (Skin, form and induced) can be expressed as follow :

$$F_d = 0.5 \cdot \rho \cdot V_{\text{cruise}}^2 \cdot S \cdot C_d \quad (32)$$

3. From Newton's laws of motion :

$$T - F_d = M \cdot a \Rightarrow T = M \cdot a + F_d \quad (33)$$

4. Total power (Drone and blade drags):

$$P_{\text{cruise}} = T \cdot V_{\text{cruise}} + P_{\text{Blade Drag}} \quad (34)$$

5. The stall condition is calculated using the equation below; Cruise speed must be higher than stall speed in order to maintain the cruise :

$$V_{\text{stall}} = \sqrt{\frac{W}{0.5 \cdot \rho \cdot S \cdot C_{Lmax}}} \leq V_{\text{cruise}} \quad (35)$$

The power needed from the battery is obtained by multiplying the total power calculated by the efficiency of the transmission and the EM; then, E_{needed} is calculated by integrating the power over mission time.

In order to illustrate, MOIA method can be used in different ways depending on the issues involved:

- Verification: by imposing a set of parameters and checking that the objectives are in line with expectations.
- Sensitivity study: some parameters are set while others are varied in order to clarify their influence.
- Optimization: As presented in Figure 60, the GDI must be maximized using a stochastic algorithm in order to find the optimal solution defined by a set of X.

In the following, we present a conclusion of main results obtained without entering into details.

• Results:

The global process is coded in Matlab. In addition, an Excel sheet, with the maximum allowable simplification, has also been implemented in order to compute the estimated power required for the different flight phases. One of the first issues discussed was the possibility of using a 48V electric motor for air mobility; the study is focused on a Valeo electric motor called GMG-25kW. The study is focus on typical missions:

- For wingless architecture:
 - o Climb: 240 m, 3.5 m/s
 - o Cruise: 10.5 km, 72 km/h
 - o Descent: 240 m, 4.5 m/s
- For winged architecture:
 - o Climb: 240 m, 3.5 m/s
 - o Cruise: 10.5 km, 144 km/h
 - o Descent: 240 m, 4.5 m/s

As results, we found that the GMG is capable of propelling a multi rotor drone with 8 propellers (8 GMGs) for wingless and 10 propellers (10 GMGs) for winged architectures. More propellers are required in winged architecture because of the additional mass of wings compared to wingless architecture. It may be noted that the wingless architecture is adapted to local mission while the winged architecture is more adapted for extended mission since the cruise phase in winged architecture has a low energy consumption.

In conclusion, a wingless architecture with 8 GMGs can complete its typical mission using a battery of 26.5 kWh while the winged architecture with 10 GMGs can complete a mission of 40 km using the same battery size.

A comparison with Hacker electric motor [Hacker], which is more adapted to this type of application, has also performed but not detailed in this manuscript.

Appendix II. Questionnaire

II.1 Initial presentation:

BUT

- Analyse préalable afin de réaliser un **outil** qui aide à la formalisation:
 - *de la décision en conception*
 - *des échanges internes*
 - *des négociations en phase amont de conception*

ANALYSE

- Interroger autour des cahiers des charges afin de clarifier:
 - les **critères** de conception
 - la **flexibilité** de ces critères
 - l'**importance** relative de ces critères
- Nécessité d'intégrer tous les acteurs (Valeo, clients, sous-traitants, etc.)



3

The Valeo logo, consisting of the word "Valeo" in a bold, sans-serif font with a green checkmark integrated into the letter 'o'.

FLEXIBILITÉ

- Ajouter / éliminer des critères
- Modifier les critères
- Modifier la hiérarchie entre les critères

L'influence de cette flexibilité sera ensuite exploitée dans
la démarche de conception.

4

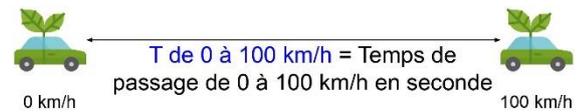
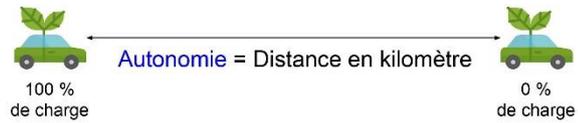
The Valeo logo, consisting of the word "Valeo" in a bold, sans-serif font with a green checkmark integrated into the letter 'o'.



EXEMPLE DE CONCEPTION

- Un véhicule électrique
- Les critères :

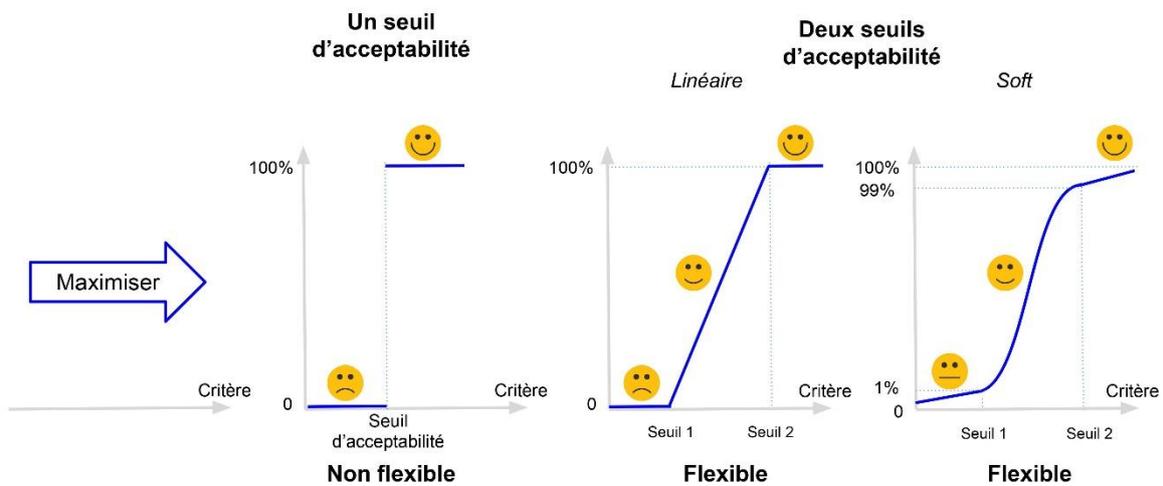
Critères	Unités
Autonomie	km
Temps de 0 à 50 km/h	s
Temps de 0 à 100 km/h	s
Vitesse maximale	km/h
Coût	€



5

Valeo

DÉSIRABILITÉ

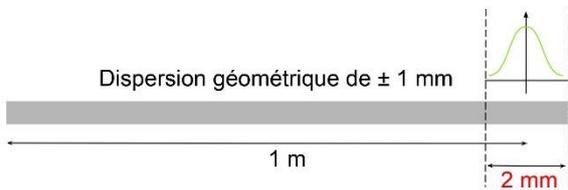


6

Valeo

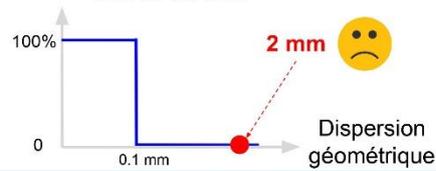
DISPERSION ET TOLÉRANCE

Dispersion



Autonomie : 200 km
Dispersion : ± 10 km

Tolérance



7

Valeo

TAUX D'ÉCHANGE

Smart Fortwo 2

19550 €
145 km
125 km/h



Prix / Autonomie **135 € / km**
Prix / Vitesse max **156 € / km/h**

Renault Zoe R110

26400 €
395 km
135 km/h



67 € / km
196 € / km/h

Autres exemples : g_{CO_2} / kg , € / kg , ...

8

Valeo

II.2 Questionnaire:

Informations personnelles

1. Monsieur Madame
2. Âge:
 < 25 ans 25-35 35-45 45-55 > 55 ans
3. Êtes-vous salarié(e) de Valeo ?
 Oui, de quel pôle ?
 - PTS
 - THS
 - CDA
 - VIS Non, quel est votre statut ?
 - Salarié
 - Travailleur indépendant
 - Chef d'entreprise
 - Etudiant (Master)
 - Etudiant (Doctorant)
 - Professeur
 - Autre : _____
4. Quelle est votre domaine d'expertise?

Préciser

 Ingénierie
 Informatique
 Marketing
 Commerce
Autre : _____

Informations générales

1. Avez-vous déjà utilisé l'optimisation multi-critères?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						

2. Quelle est votre niveau d'expérience dans les domaines suivants:

	Pas d'expérience	1-2 ans	2-4 ans	5-10 ans	>10 ans
Automobile	<input type="checkbox"/>				
Systèmes énergétiques	<input type="checkbox"/>				
Simulation	<input type="checkbox"/>				
Optimisation	<input type="checkbox"/>				
Programmation informatique	<input type="checkbox"/>				

Cahiers des charges et flexibilité

1. Avez-vous déjà participé à la définition de cahiers des charges?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Très souvent						

2. Avez-vous déjà participé à la traduction de cahiers des charges client en spécifications techniques produit?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Très souvent						

3. Êtes-vous déjà utilisateur de spécifications techniques?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Très souvent						

Cahiers des charges et flexibilité

4. Êtes-vous en relation avec des cahiers des charges dans le domaine de:

a. Conception et validation:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

b. Fabrication:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

c. Marketing:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

d. Autre (préciser):

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

5. Êtes-vous en relation avec des spécifications techniques dans le domaine de:

a. Conception et validation:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

b. Fabrication:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

c. Marketing:

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

d. Autre (préciser):

Jamais	1	2	3	Parfois	5	6	7	Très souvent
	<input type="checkbox"/>							

Cahiers des charges et flexibilité

6. Avez-vous déjà participé à des négociations visant à faire évoluer des cahiers des charges?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Très souvent						

7. Avez-vous déjà été amené à faire évoluer des spécifications techniques?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Très souvent						

Critères

1. Les critères sont déterminés par le cahier des charges?

Jamais	1	2	3	Parfois	5	6	7	Toujours
	<input type="checkbox"/>							
Aucun critères				Certains				Tous les critères
	<input type="checkbox"/>							

Commentaires

2. Les critères sont déterminés par les spécifications techniques?

Jamais	1	2	3	Parfois	5	6	7	Toujours
	<input type="checkbox"/>							
Aucun critères				Certains				Tous les critères
	<input type="checkbox"/>							

3. Les critères peuvent évoluer par des échanges entre acteurs?

Jamais	1	2	3	Parfois	5	6	7	Toujours
	<input type="checkbox"/>							

Critères

4. Quels acteurs décident de la flexibilité des critères?

	Jamais	2	3	Parfois	5	6	Toujours
Valeo marketing et commerce	<input type="checkbox"/>						
Valeo développement	<input type="checkbox"/>						
Valeo fabrication	<input type="checkbox"/>						
Client	<input type="checkbox"/>						
Sous-traitant	<input type="checkbox"/>						
Réglementation	<input type="checkbox"/>						

Dispersion et tolérance

(Voir le document page 1)

1. Est-ce que les critères de dispersion sont pris en compte dès les phases amont du processus de conception?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						

2. Selon vous, est-ce que les critères de dispersion devraient être pris en compte dès les phases amont du processus de conception?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						

3. Quels acteurs définissent les critères de dispersion?

	Jamais	2	3	Parfois	5	6	Toujours
Valeo marketing et commerce	<input type="checkbox"/>						
Valeo développement	<input type="checkbox"/>						
Valeo fabrication	<input type="checkbox"/>						
Client	<input type="checkbox"/>						
Sous-traitant	<input type="checkbox"/>						
Réglementation	<input type="checkbox"/>						

4. Si les critères de dispersion ne sont pas définis par le client, comment sont-ils définis par les autres acteurs?

Seuils et plages d'acceptabilités

1. Quels acteurs sont forces de proposition pour fixer les seuils d'acceptabilités des critères?

	Jamais	2	3	Parfois	5	6	Toujours
Valeo marketing et commerce	<input type="checkbox"/>						
Valeo développement	<input type="checkbox"/>						
Valeo fabrication	<input type="checkbox"/>						
Client	<input type="checkbox"/>						
Sous-traitant	<input type="checkbox"/>						
Réglementation	<input type="checkbox"/>						

2. Les seuils d'acceptabilités des critères peuvent se modifier par des échanges entre acteurs?

	1	2	3	4	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						
Peu de critères	<input type="checkbox"/>	Beaucoup de critères						

Seuils et plages d'acceptabilités

(Voir le document page 2)

3. Les critères des cahiers des charges se présentent sous la forme ou sous une forme proche de:

	Jamais	2	3	Parfois	5	6	Toujours
Aucun seuil d'acceptabilité	<input type="checkbox"/>						
Un seuil d'acceptabilité	<input type="checkbox"/>						
Deux seuils d'acceptabilités - Linéaire	<input type="checkbox"/>						
Deux seuils d'acceptabilités - Soft	<input type="checkbox"/>						

Commentaires

Seuils et plages d'acceptabilités

4. Dans un contexte de négociation avec tout type d'acteurs, est-il plus envisageable de négocier deux seuils d'acceptabilités (plage d'acceptabilité) plutôt qu'un seul?

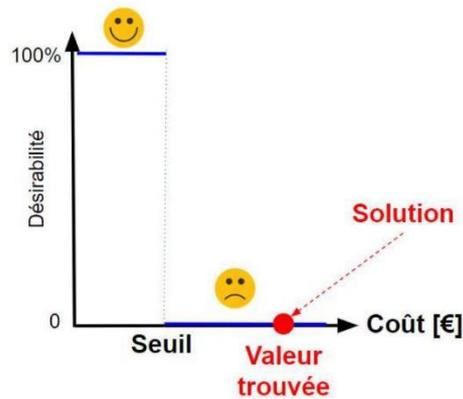
Jamais	1	2	3	Parfois	5	6	7	Toujours
	<input type="checkbox"/>							
Peu de critères	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Certains	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Beaucoup de critères

5. Dans un contexte de négociation avec un client, est-il plus envisageable de négocier deux seuils d'acceptabilités (plage d'acceptabilité) plutôt qu'un seul?

Jamais	1	2	3	Parfois	5	6	7	Toujours
	<input type="checkbox"/>							
Peu de critères	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Certains	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	Beaucoup de critères

Seuils et plages d'acceptabilités

Prenons un exemple où une solution satisfait tous les critères sauf le coût.



6. Est-il plus envisageable de renégocier le coût ou de revoir la conception pour être conforme au coût imposé?

	1	2	3	Neutre	5	6	7	
Reconcevoir	<input type="checkbox"/>	Renégocier						

7. Quel taux de renégociation est envisageable pour le coût?

0%	1%	5%	10%	20%	50%	100%	>100%
<input type="checkbox"/>							

Commentaires

Seuils et plages d'acceptabilités

8. Quel taux de renégociation est envisageable pour les critères suivants?

a. Autonomie:

?	0%	1%	5%	10%	20%	50%	100%	>100%
<input type="checkbox"/>								

b. Vitesse maximale:

?	0%	1%	5%	10%	20%	50%	100%	>100%
<input type="checkbox"/>								

c. Temps de 0 à 100 km/h:

?	0%	1%	5%	10%	20%	50%	100%	>100%
<input type="checkbox"/>								

d. Temps de 0 à 50 km/h:

?	0%	1%	5%	10%	20%	50%	100%	>100%
<input type="checkbox"/>								

Satisfaction

(Voir le document page 3)

	S1	Renault	Smart	Nissan	BMW	Honda	Tesla	EVC1000
Autonomie [km]	450	395	145	270	359	205	600	1000

1. Selon votre point de vue, veuillez situer ci-dessous l'autonomie de S1 par rapport à l'autonomie des autres véhicules:

	Élevée	4	3	2	1	Identique	1	2	3	4	Élevée	
S1	<input type="checkbox"/>	Renault										
S1	<input type="checkbox"/>	Smart										
S1	<input type="checkbox"/>	Nissan										
S1	<input type="checkbox"/>	BMW										
S1	<input type="checkbox"/>	Honda										
S1	<input type="checkbox"/>	Tesla										
S1	<input type="checkbox"/>	EVC1000										

2. Noter l'autonomie des véhicules:

	Non acceptable	-4	-3	-2	-1	Neutre	1	2	3	4	Au-delà des attentes
S1	<input type="checkbox"/>										
Renault	<input type="checkbox"/>										
Smart	<input type="checkbox"/>										
Nissan	<input type="checkbox"/>										
BMW	<input type="checkbox"/>										
Honda	<input type="checkbox"/>										
Tesla	<input type="checkbox"/>										
EVC1000	<input type="checkbox"/>										

Satisfaction

(Voir le document page 3)

	S1	Renault	Smart	Nissan	BMW	Honda	Tesla	EVC1000
Coût [€]	30000	26400	19550	36400	39950	38060	54900	80000

3. Selon votre point de vue, veuillez situer ci-dessous le coût de S1 par rapport au coût des autres véhicules:

	Élevée	4	3	2	1	Identique	1	2	3	4	Élevée	
S1	<input type="checkbox"/>	Renault										
S1	<input type="checkbox"/>	Smart										
S1	<input type="checkbox"/>	Nissan										
S1	<input type="checkbox"/>	BMW										
S1	<input type="checkbox"/>	Honda										
S1	<input type="checkbox"/>	Tesla										
S1	<input type="checkbox"/>	EVC1000										

4. Noter le coût des véhicules:

	Non acceptable	-4	-3	-2	-1	Neutre	1	2	3	4	Au-delà des attentes
S1	<input type="checkbox"/>										
Renault	<input type="checkbox"/>										
Smart	<input type="checkbox"/>										
Nissan	<input type="checkbox"/>										
BMW	<input type="checkbox"/>										
Honda	<input type="checkbox"/>										
Tesla	<input type="checkbox"/>										
EVC1000	<input type="checkbox"/>										

Taux d'échanges

(Voir le document page 4)

1. Les critères et leurs seuils d'acceptabilité sont-ils déduits des taux d'échanges?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						

2. Les taux d'échanges peuvent-ils être exploités pour négocier entre les acteurs?

	1	2	3	Parfois	5	6	7	
Jamais	<input type="checkbox"/>	Toujours						

Commentaires (exemples?)

Taux d'échanges

(Voir le document page 5)

3. Pour un véhicule électrique ayant un coût de 40000 €, veuillez indiquer une valeur acceptable pour chacun des 3 critères ci-dessous:

	Autonomie [km]	Vitesse maximale [km/h]	T de 0 à 100 km/h [s]
Valeur acceptable			

Commentaires

Taux d'échanges

(Voir le document page 6)

4. Pour un véhicule électrique ayant une autonomie de 400 km, veuillez indiquer une valeur acceptable pour chacun des 3 critères ci-dessous:

	Coût [€]	Vitesse maximale [km/h]	T de 0 à 100 km/h [s]
Valeur acceptable			

Commentaires

Pondération

1. Indiquez le poids de chaque critère entre 0 et 100 (0 = négligeable et 100 = prépondérant).

Critères					
Autonomie	Coût	Vitesse max.	T de 0 à 100 km/h	T de 0 à 50 km/h	Total
					100

2. Comparer ces critères deux à deux en terme d'importance.

	Important	4	3	2	1	Neutre	1	2	3	4	Important	
Autonomie	<input type="checkbox"/>	Coût										
Autonomie	<input type="checkbox"/>	Vitesse max.										
Autonomie	<input type="checkbox"/>	T de 0 à 100 km/h										
Autonomie	<input type="checkbox"/>	T de 0 à 50 km/h										
Coût	<input type="checkbox"/>	Vitesse max.										
Coût	<input type="checkbox"/>	T de 0 à 100 km/h										
Coût	<input type="checkbox"/>	T de 0 à 50 km/h										
Vitesse max.	<input type="checkbox"/>	T de 0 à 100 km/h										
Vitesse max.	<input type="checkbox"/>	T de 0 à 50 km/h										
T de 0 à 100 km/h	<input type="checkbox"/>	T de 0 à 50 km/h										

Classement des solutions

(Voir le document page 7)

Ci-dessous un exemple sur le choix d'un véhicule électrique selon 5 critères.

	Coût [€]	Autonomie [km]	Vitesse maximale [km/h]	T de 0 à 100 km/h [s]	T de 0 à 50 km/h [s]
Renault	26400	395	135	13.2	4.9
Smart	19550	145	125	11.5	4.5
BMW	39950	359	150	7.3	5.2
Tesla	54900	600	225	5.4	2.7
S1	30000	250	115	7	3.5
Seuils d'acceptabilités	40000	200	120	13	5

	0 = non désirable			100 = fortement désirable	
	Coût	Autonomie	Vitesse maximale	T de 0 à 100 km/h	T de 0 à 50 km/h
Renault	100	100	100	0	100
Smart	100	0	100	100	100
BMW	100	100	100	100	0
Tesla	0	100	100	100	100
S1	100	100	0	100	100

1. Veuillez classer, selon votre point de vue, ces véhicules par ordre (Le premier est le plus intéressant).

1 ^{er}	2 ^{ème}	3 ^{ème}	4 ^{ème}	5 ^{ème}

Commentaires

Classement des solutions

(Voir le document page 8)

Ci-dessous un exemple sur le choix d'un véhicule électrique selon 5 critères.

	Coût [€]	Autonomie [km]	Vitesse maximale [km/h]	T de 0 à 100 km/h [s]	T de 0 à 50 km/h [s]
Renault	26400	395	135	13.2	4.9
Smart	19550	145	125	11.5	4.5
BMW	39950	359	150	7.3	5.2
Tesla	54900	600	225	5.4	2.7
S1	30000	250	115	7	3.5

0 = non désirable

100 = fortement désirable

	Coût	Autonomie	Vitesse maximale	T de 0 à 100 km/h	T de 0 à 50 km/h
Renault	95	98	36	11	33
Smart	100	2	21	36	45
BMW	52	84	57	96	24
Tesla	4	100	100	100	100
S1	84	42	7	100	76

2. Veuillez classer, selon votre point de vue, ces véhicules par ordre (Le premier est le plus intéressant).

1 ^{er}	2 ^{ème}	3 ^{ème}	4 ^{ème}	5 ^{ème}

Commentaires

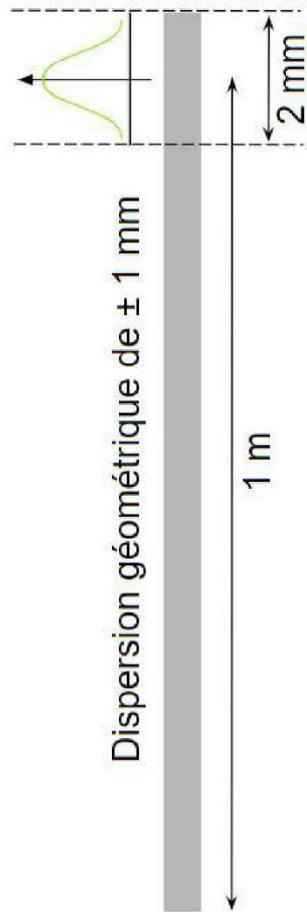
Classement des solutions

	S1	Renault	Smart	BMW	Tesla
Autonomie [km]	250	395	145	359	600

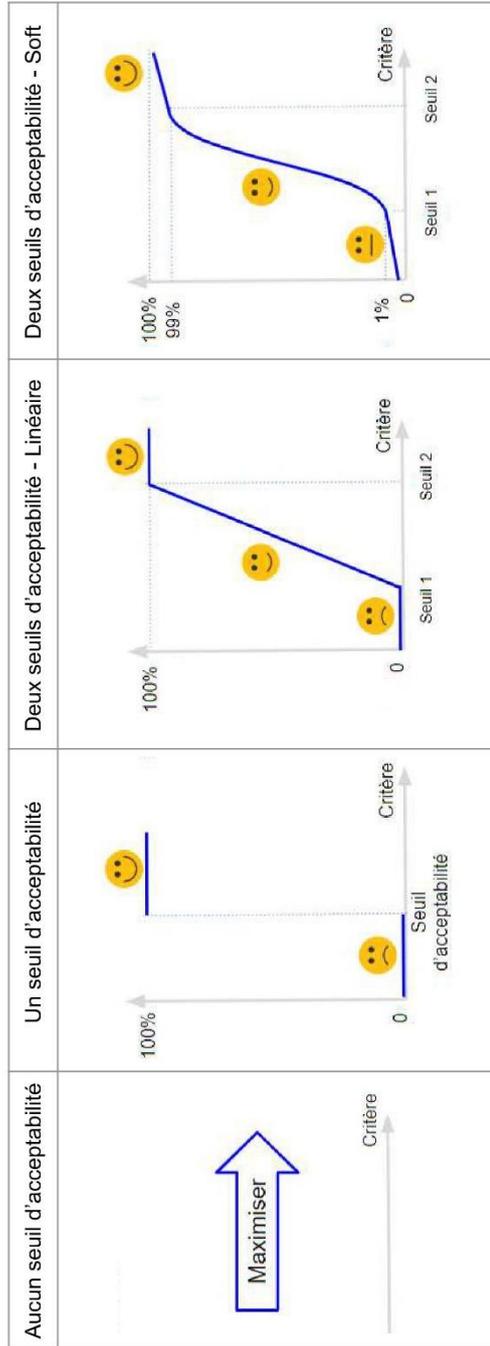
3. Comparer ces cinq véhicules selon le critère d'autonomie:

	Élevée	4	3	2	1	Identique	1	2	3	4	Élevée	
S1	<input type="checkbox"/>	Renault										
S1	<input type="checkbox"/>	Smart										
S1	<input type="checkbox"/>	BMW										
S1	<input type="checkbox"/>	Tesla										
Renault	<input type="checkbox"/>	Smart										
Renault	<input type="checkbox"/>	BMW										
Renault	<input type="checkbox"/>	Tesla										
Smart	<input type="checkbox"/>	BMW										
Smart	<input type="checkbox"/>	Tesla										
BMW	<input type="checkbox"/>	Tesla										

II.3 Document:



Autonomie : 200 km
Dispersion : ± 10 km



	Renault	Smart	Nissan	BMW	Honda	Tesla	EVC1000
							
Puissance [ch]	108	75	150	170	153	306	145
Coût [€]	26400	19550	36400	39950	38060	54900	80000
Autonomie [km]	395	145	270	359	205	600	1000
Vitesse max. [km/h]	135	125	144	150	145	225	140
T de 0 à 100 km/h [s]	13.2	11.5	7.9	7.3	8.3	5.4	8
T de 0 à 50 km/h [s]	4.9	4.5	5.6	5.2	5.5	2.7	4

Exemples des taux d'échanges :

Smart Fortwo 2



19550 €

145 km

125 km/h

Prix / Autonomie

135 € / km

Prix / Vitesse max

156 € / km/h

Renault Zoe R110



26400 €

395 km

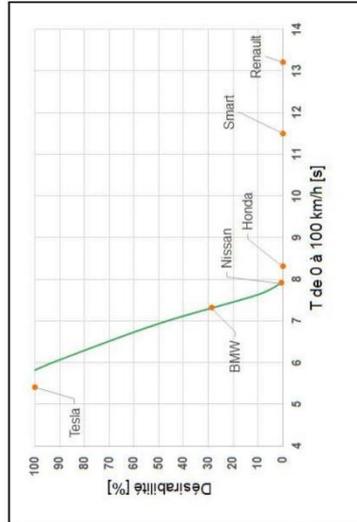
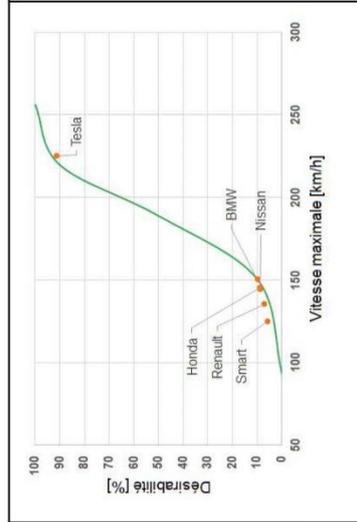
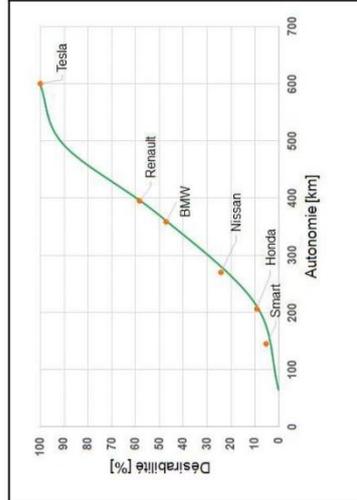
135 km/h

67 € / km

196 € / km/h

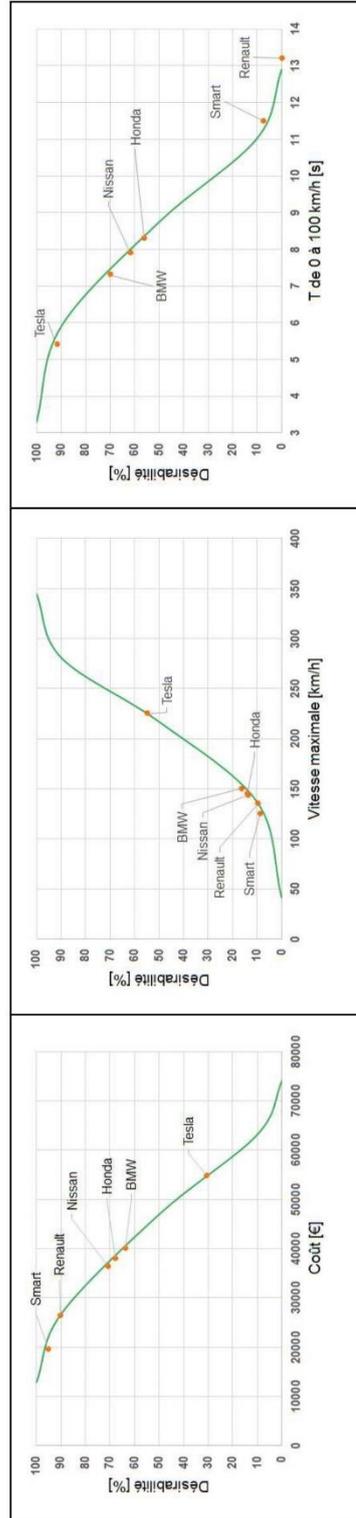
	Renault	Smart	Nissan	BMW	Honda	Tesla
						
Coût [€]	26400	19550	36400	39950	38060	54900
Autonomie [km]	395	145	270	359	205	600
Vitesse max. [km/h]	135	125	144	150	145	225
T de 0 à 100 km/h [s]	13.2	11.5	7.9	7.3	8.3	5.4

Les fonctions de désirabilité des critères pour un véhicule électrique qui coût 40000 € :

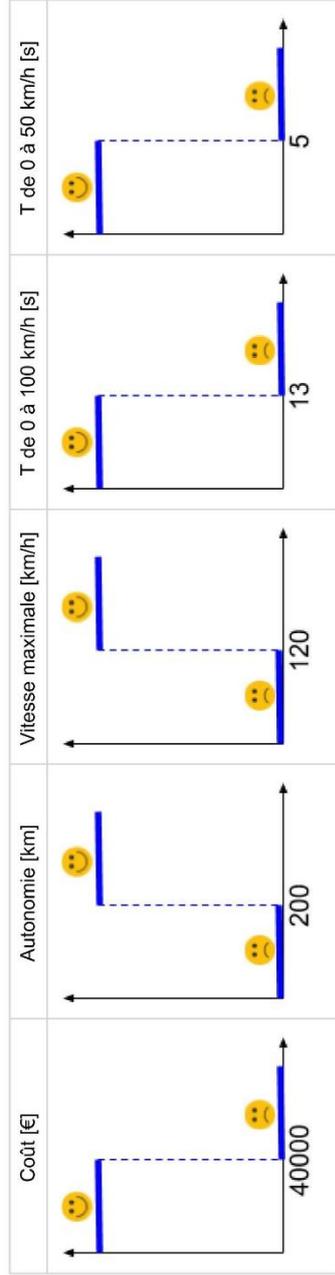


	Renault	Smart	Nissan	BMW	Honda	Tesla
						
Coût [€]	26400	19550	36400	39950	38060	54900
Autonomie [km]	395	145	270	359	205	600
Vitesse max. [km/h]	135	125	144	150	145	225
T de 0 à 100 km/h [s]	13.2	11.5	7.9	7.3	8.3	5.4

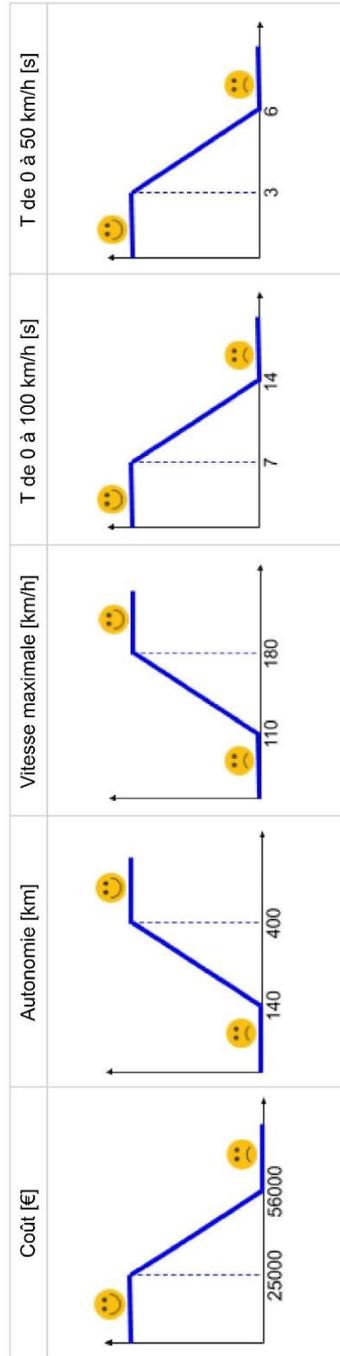
Les fonctions de désirabilité des critères pour un véhicule électrique ayant une autonomie de 400 km:



Les fonctions de désirabilité des critères:

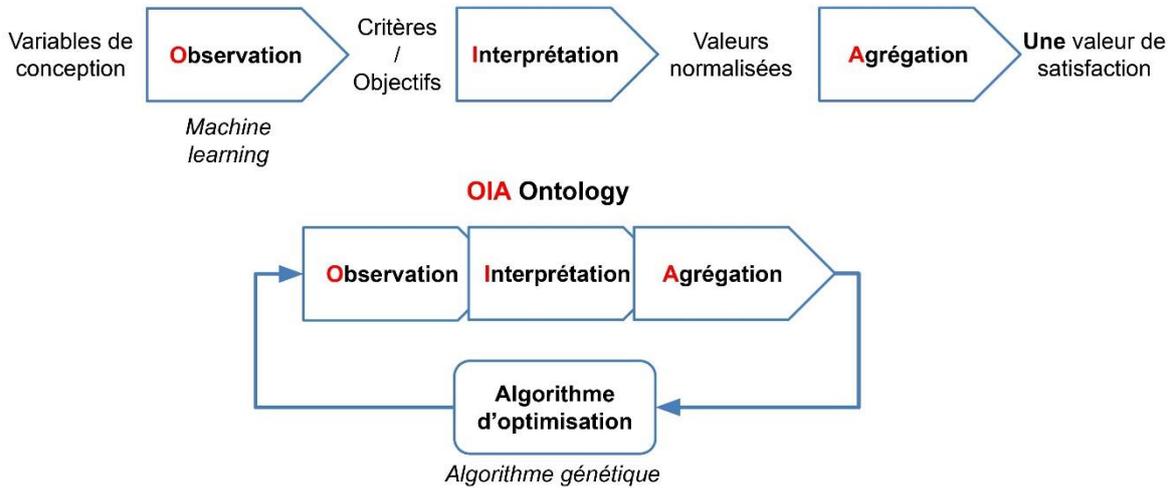


Les fonctions de désirabilité des critères:



II.4 Final presentation:

OIA

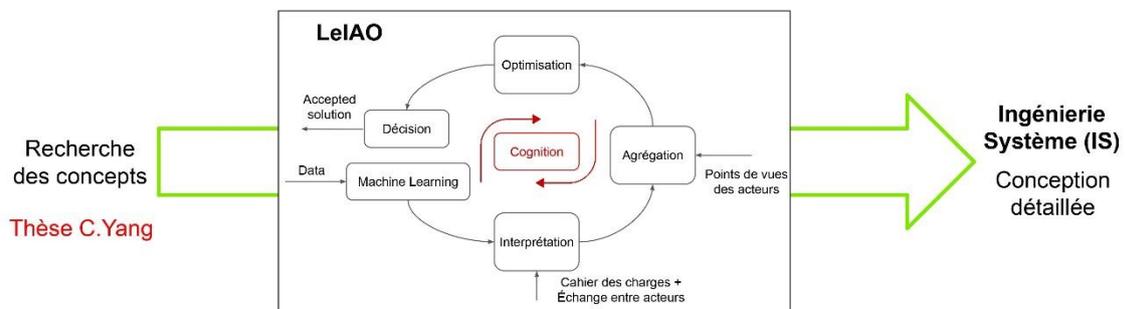


10

CONFIDENTIAL

Valeo

LeIAO



Recherche des concepts
Thèse C. Yang

Ingénierie Système (IS)
Conception détaillée

- Simulation
- Optimisation
- Choix et décision
- Aide à la conception

Cognition située

11

CONFIDENTIAL

Valeo

Espace de conception

Paramètres de désirabilité

Paramètres d'agrégation

Algorithme d'optimisation

Solution optimale

Visualiser les scénarios et les fonctions de désirabilité

Visualiser les solutions alternatives, front de pareto et le positionnement de la solution optimale

Comparaison pair à pair entre les objectifs : Pour calculer les poids (hiérarchisation)

The screenshot shows the 'Candidate Solutions' software interface. It is divided into several sections:

- Design Variables:** A table with columns for 'Min', 'Discretization step', and 'Max'. It lists variables like 'First ratio of front transmission', 'Spread of front transmission', 'Front EM - Max Torque', 'Front EM - Max Speed', 'Front EM - Cb', and 'Battery Capacity'.
- Observation Variables:** A table with columns for 'Limit 1', 'Desirability Type', and 'Limit 2'. It lists variables like 'Autonomy_MegaCityChina', 'Autonomy_NEDC90', 'Autonomy_WLTCCL', and various speed ranges (0-50 km/h, 0-100 km/h, etc.).
- Interpretation Variables:** A table with columns for 'D_Autonomy_MegaCityChina', 'D_Autonomy_NEDC90', 'D_Autonomy_WLTCCL', and various speed ranges.
- Aggregation Method:** A section for 'Design Objectives Indexes (DOI)' and 'Global Desirability Index (GDI)'. It includes a 'Judgment Matrix' table.
- Optimal Solution:** A section showing the results of the optimization, including 'Design Variables' and 'Observation Variables'.

Callouts with arrows point to these sections, providing labels in French. The 'Judgment Matrix' table is as follows:

Judgment Matrix	Autonomy	Performance	Cost
Autonomy	1	2	3
Performance	0.5000	1	3
Cost	0.3333	0.3333	1