SYSTEMS DESIGN AND MODELING: A VISUAL ANALYTICS APPROACH

Dimitri N. Mavris*, Olivia J. Pinon*, David Fullmer Jr.*
***Aerospace Systems Design Laboratory (ASDL)**
School of Aerospace Engineering
Georgia Institute of Technology, Atlanta, GA, 30332-0150, USA

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Abstract

The process of designing unconventional aerospace vehicle configurations is characterized by a lack of relevant data, information, and knowledge, which prevents the designer from applying traditional design methods. To address this issue, significant amount of data need to be generated, collected, and analyzed to increase the designer's knowledge about the physics of the problem and to explore the diverse spectrum of available design options. However, the amounts of data required to successfully pursue unconventional designs can rapidly become overwhelming, hence limiting the designer's ability to fully comprehend the problem to be solved. This paper presents a multidisciplinary perspective termed Visual Analytics which can be applied to address these issues in the context of the pre-conceptual/conceptual design of unconventional configurations. The paper discusses the enabling techniques essential for the visual analytics approach and illustrates that the main requirements for a successful pre-conceptual/conceptual design are to reduce the designer's cognitive burden, foster his rapid understanding of the design problem, and support informed decision making. Finally this paper discusses and demonstrates, through the design of a supersonic business jet, the importance and benefits of implementing these enablers and of integrating Visual Analytics into the design process. More importantly, this work illustrates that the benefits to the analyst and decision maker of enablers such as surrogate modeling or probability theory are limited if they are not integrated with the visualization, interaction, and analytical reasoning capabilities provided by Visual Analytics.

1 Introduction

Design is the process of defining and exploring a vast space of possibilities that requires the building up of knowledge and familiarity with the constraints and trades involved. Design is also a problem-solving activity that maps a set of requirements to a set of functions, leading to a set or series of decisions that contribute to the final description of a solution [49, 50]. These statements are particularly true for the design of conventional aircraft. The design of unconventional configurations, on the other hand, is more challenging. Indeed, while there is historical information available on which to base traditional aircraft designs, unconventional designs are plagued by a lack of relevant data and knowledge. Also, the assumptions embedded in the historical data are very often incompatible with unconventional design concepts. Hence, significant amounts of data need to be generated, gathered, and analyzed to improve the designer's knowledge about the problem and to capture the various design options and perspectives involved.

The amount of data required to successfully pursue unconventional aircraft designs can rapidly become overwhelming [18]. The analyst or decision maker, when faced with such a data overload problem, is limited in his ability to conduct any kind of trades, test hypotheses, explore the design space, and detect unexpected trends, detail or relations, as the data sets cannot be visualized [39]. Consequently, he cannot fully comprehend the problem to be solved, or understand the behavior of the system under consideration. While unprocessed data does not hold any intrinsic value [39], it can result in missed opportunities for critical actions, which may, in turn, result in poor designs and significant loss of time and money [40]. To alleviate this problem, it is necessary to move away from static representations and visualizations and develop means that enable the interaction between information, and the human cognitive and perceptual systems, while simultaneously allowing users to integrate their background, expertise, and cognitive capabilities into the analytical process. The need to address these aspects has given rise to a multidisciplinary perspective named Visual Analytics.

In the remainder of this paper we first discuss the design of conventional and unconventional configurations, identify the technical and human and challenges linked to the design of unconventional configurations, and present techniques and methods to address them. Then, we introduce Visual Analytics, describe its process, and briefly discuss the merit of implementing Visual Analytics in design. We later present an unconventional design problem to illustrate how the integration of Visual Analytics into the design process provides the designer and decision maker with the capabilities to gain the knowledge and insight needed to make informed decisions.

2 Systems Design and Modeling

This section discusses the design of conventional and unconventional configurations with a particular emphasis on the challenges associated with unconventional configurations.

2.1 Traditional Design of Conventional Configurations

Current legacy tools and design methods for conventional configurations have been developed based on the information and capabilities available at their inception. In the early 1900s, the Wright brothers initially developed their designs based on the literature of the time. After a number of failures, they set out to build a facility for wind tunnel testing. Numerous shapes (airfoil models) were tested and documented, resulting in a library of information that they could rely on [30]. Since this time, aerospace engineers have been constructing models to collect data useful for design.

Expert designers who are well versed in these information resources follow a three-phase design process comprising conceptual, preliminary, and detailed phases. During this process, "design evolves in increasing levels of detail, from high-level representations of the overall concept to the details of each and every component" [19]. In the conceptual phase of the design, a handful of design concepts are considered [61, 65]. These concepts are created using a predictive set of tools based on existing flight data documenting both aircraft configuration and characteristics. At the end of the process, a full-scale aircraft is subjected to experimentation and flight testing, thus generating data and knowledge leveraged to design the next generation of aircraft. This library of information, built through successive aircraft developments, represents the best source of information on which to base derivative design concepts.

It is often taught that design is an art or talent that is obtained and built upon over time. Daniel Raymer [61] states

> "If the designer is talented, there is a lot more than meets the eye on the drawing. A good aircraft design seems to miraculously glide through subsequent evaluations by specialists without major changes being required."

This talent described by Raymer is invaluable because it indicates a familiarity with the design and an innate understanding of the consequences of early decision making. However, as discussed in the following section, the characteristics and confidence that define great designers are lost when faced with the task of designing unconventional configurations or configurations involving radically new technologies.

2.2 Advanced Design of Unconventional Configurations

Design requires the exchange of data, information and knowledge [24]. However, the class of configurations considered for the new methods presented in this paper are configurations for which there does not exist any historical database, the designer's expertise is limited or nonexistent, and there is typically no feasible design space unless new technologies are infused. The absence of these three key features prevents the designer from applying traditional design methods. More particularly, it prevents him from conducting any kind of trades, understanding sensitivities, identifying active constraints and feasible design spaces, hence limiting the chances that these configurations be successfully developed.

The following sections describe in more detail the main human and contextual challenges associated with the pre-conceptual/conceptual design of unconventional configurations. These sections also briefly discuss the enablers and methods necessary to address these challenges and provide the designer with the knowledge and insight necessary to the successful development of unconventional configurations. These methods are further illustrated in the context of a design problem in Section 4.

2.2.1 Human Challenges and Solutions

This section provides a brief discussion on human-related challenges during the design of unconventional configurations.

- Communication

  Communicating expertise or results is essential to any decision making exercise such as design. Most of the challenges in communicating results lie in the ability to present the data with an appropriate level of detail, enable the rapid extraction of relevant information by all the parties involved, independent of their background or expertise, retain the audience's attention, and clearly articulate important information to obtain the stakeholders' buy-in. Based on the realization that abstract knowledge without representation is hard to work with, Burkhard [15] proposes to "combine different visualization types that complement one another to illustrate different levels of detail." Presenting information from various perspectives and formats is also more likely to satisfy the different thinking styles, expertise and knowledge of the stakeholders, thereby improving communication between them and reducing potential misunderstandings and conflicts.

- Collaboration

  The multi-disciplinary nature of design calls for the involvement of various people with different qualifications, background and expertise. Stakeholders may have different interpretations of the data or may contribute at different levels of the analysis [27]. In particular, differing perceptions of the design problem among the actors may lead to difficulties in reaching consensus. Consequently, there is a need, as previously discussed, to allow users to integrate their background, expertise and cognitive capabilities into the analytical process.

2.2.2 Contextual Challenges and Solutions

- Lack of Physical Data:

  As previously mentioned, the design of unconventional configurations is characterized by a lack of physical and historical data. One way to alleviate this issue is through physics-based modeling and numerical simulation. To be of value, the physics-based models need to be at the appropriate fidelity level for the physics of the problem to be captured. The lack of data also precludes the designer from observing trends that have not been observed before. Under these circumstances, there is thus a need to create the appropriate conditions so that trends and causality can be studied. In other words, the data corresponding to a particular designer's interest need to be created. This is accomplished through *data farming*, a concept coined by Brandstein and Horne [10], and described by Horne and Meyer [29] as the "study and development of methods, interfaces, and tools that make high performance computing readily available to modelers and allows analysts to explore the vast amount of data that results from exercising models."

- Sensitivity to Requirements:

  Design requirements are a direct driver of cost and, therefore, affordability. It is thus critical to understand and capture the significance of requirements' impact on the design [4, 11], as well as the sensitivity of affordability metrics to requirements. Also, the mission requirements and constraints associated with the design of a new concept are likely to change as the stakeholders learn about the design problem. Each change may result in the selection of a different design concept. Consequently, unless multiple scenarios are investigated and documented, a static approach to design will rapidly show its limitations. Additionally, decision making implies considerations beyond the technical aspects. Consequently, the final solution may be different from one decision maker's perspective to the next. There is thus a need to move from deterministic, serial, single-point designs to dynamic parametric trade environments. In particular, as advocated by De Baets [20], the designer should be provided with "a parametric model of the airplane to allow quick changes in the shape and size of the vehicle." This parametric formulation should also have the appropriate degrees of freedom to allow the decision maker to play the what-if games he is interested in.

- Integration of Multiple Disciplines:

  The design of revolutionary, unconventional configurations requires that the multiple disciplines describing the problem, as well as their interactions, be integrated. However, as mentioned by Kamdar et al. the "very large number of variables and the physics behind the system are too profound or esoteric to be fully understood" [33]. Additionally, the disciplinary interactions are so intricately coupled that a parametric environment is necessary to avoid re-iterating the design process until all requirements are met [20]. This parametric environment, depending on the level of fidelity of the disciplinary models it is composed of, may run slowly, hence limiting the designer's ability to explore the design space. Indeed, as acknowledged by Ligetti [46] et al. "speed is critical for certain cognitive tasks." A successful approach that addresses this challenge, while providing an all-encompassing model for exploring a complex design space, is surrogate modeling [20, 33]. Surrogate modeling enables virtually instantaneous analyses to be run in real-time [46] by approximating computer-intensive functions or models across the entire design space with simple mathematical/analytical models [83]. A variety of surrogate modeling techniques exists that yield insight into the relationships between design variables (x) and responses (y) and facilitate concept exploration [83, 71]. The most prevalent ones include Response Surface Methodology (RSM) [54, 9, 8], Artificial Neural Network (ANN) [75, 16], Kriging (KG) [70, 69], and Inductive Learning [43]. The reader is invited to consult [83, 73, 71, 32] for reviews and comparative studies of these different techniques. One of the most popular of these surrogate modeling techniques, RSM, is discussed in more detail in the context of an example application (Section 4.4.1).

- Uncertainty:

  The design problem is plagued with uncertainty. Uncertainty exists at all levels and is notably present in the requirements, vehicle attributes, and technologies that define the design concept. Consequently, the sensitivities of the outcomes to the assumptions need to be assessed. The need to address uncertainty can be handled, as further illustrated in Section 4, through the implementation of probability theory and probabilistic design methods. Additionally, during this phase of the design process, the designer does not know which technologies are going to be implemented in the final design. Probability theory and probabilistic design methods can support the designer in his selection of technologies by providing him with the capability to continuously and simultaneously trade between requirements, technologies and design concepts. Finally, the use of probability theory in conjunction with RSM can allow the analyst and decision maker to quantify and assess risk and to explore huge combinatorial spaces. The combination of these methods, as illustrated in Section 4, can enable the discovery and examination of new trends and solutions in a transparent, visual, and interactive manner.

- Data Overload:

  While this may seem contrary to the lack of physical data previously discussed, it is important to recognize that designers of unconventional configurations are facing a data overload problem. This problem mainly originates from the significant amounts of data that need to be generated, collected, and analyzed in order to increase the designer's knowledge about the physics of the problem. Data by itself has little value if it is not structured and visualized in a way that allows the designer to act upon it. This challenge can be addressed by enabling the interaction between the information and the human cognitive and perceptual systems.

2.2.3 Preliminary Remarks

This brief review of the challenges faced by the designer during the conceptual design phase illustrates that, independently of the methods and techniques proposed, the real requirement is to reduce the designer's cognitive burden; to foster, in a broad sense, his rapid understanding of the design problem; and to support informed decision making.

Humans deal with the world through their senses. The human visual system, in particular, provides us with the capability to quickly identify patterns and structures [82] and supports the transition from cognition, the processing of information, to perception, the obtaining of insight and knowledge. Hence, visual representations are often the preferred form of support to any human cognitive task because they amplify our cognitive ability [68] and reduce the complex cognitive work necessary to perform certain activities [38, 40]. From the early ages, when design was conducted on a piece of paper, up until today with the recent advances in Computer-Aided Design (CAD) models, design has always been conducted and communicated through visual means. As explained by Wong et al. [88], "visual representations are essential aids to human cognitive tasks and are valued to the extent that they provide stable and external reference points on which dynamic activities and thought processes may be calibrated and on which models and theories can be tested and confirmed." However, it is important to understand that "visualization of information alone does not provide new insights" [52]. In other words, information visualization without interaction between the information and the human cognitive system does little to stimulate human reasoning and enable the generation and synthesis of knowledge or the formulation of appropriate conclusions or actions [52].

A multidisciplinary perspective termed Visual Analytics has originated from the need to address this issue and reasonably appears as the common enabler to the many solutions enunciated in Section 2.2. In particular, Visual Analytics provides visualization and interaction capabilities, allowing the analyst and decision maker to be presented with the appropriate level of depiction and detail to help them make sense of the data and synthesize the knowledge necessary to make decisions.

3 Visual Analytics

3.1 Definition and Scope

Visual Analytics, as defined in the National Visualization and Analytical Center^{TM}(NVAC^{TM}) 5-year Research and Development Agenda for Visual Analytics [78], is the "science of analytical reasoning facilitated by interactive visual interfaces." While Visual Analytics initially had a strong focus on homeland security, it has since broadened to various users [37]. It has now developed into a field of study that stems from and encapsulates diverse research areas and disciplines (Figure 1) grouped into three main components: interactive visualization, analytical reasoning, and computational analysis. More particularly, Visual Analytics reduces the user's cognitive burden by combining and leveraging both human and electronic data processing strengths and capabilities (Figure 2), with the goal to "make processing data and information transparent for an analytical discourse" [39].

Visualization is essential to scientific reasoning and the scientific process as a whole. However, in order to facilitate the generation of knowledge and the formulation of informed decisions, visualization needs to be combined with analytical techniques [39] and embedded in the analysis/reasoning process, as opposed to being an end-product of it [52]. In other words, visualization should also be considered as an exploration means and not limited to communication or presentation purposes [82]. Along the same lines, John W. Tukey had recommended, in 1977, a shift from confirmatory data analysis to exploratory data analysis [81]. These aspects are further discussed and illustrated in the following sections.

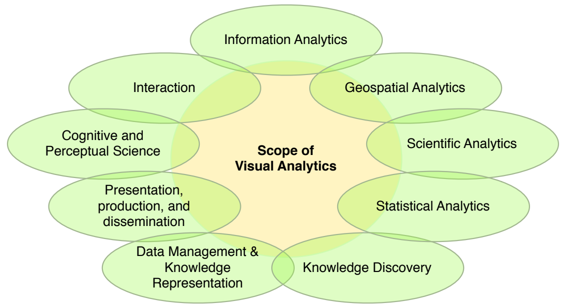

Fig. 1 The Scope of Visual Analytics (Reproduced from [40])

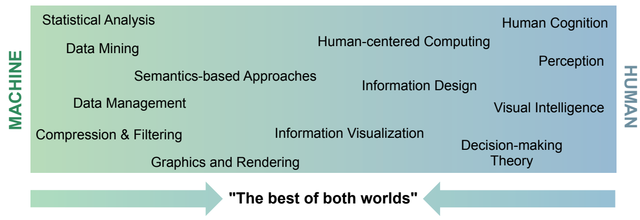

Fig. 2 Visual Analytics integrates Machine and Human Strengths (Adapted from [39])

3.2 Process

The process illustrated in Figure 3 superimposes the visually enabled reasoning process, as defined by Meyer et al. [52] and the Visual Analytics process, with the ultimate goal to support informed decision making. The Visual Analytics process is based on the visualization model proposed by Van Wijk [82] and further enhanced and formalized by Keim et al. [40] and Riveiro et al. [64]. Both processes are discussed concurrently in the following paragraphs.

3.2.1 Data Pre-processing

The nature of the data sets, as described in Section 1, requires some data pre-processing (D_W)

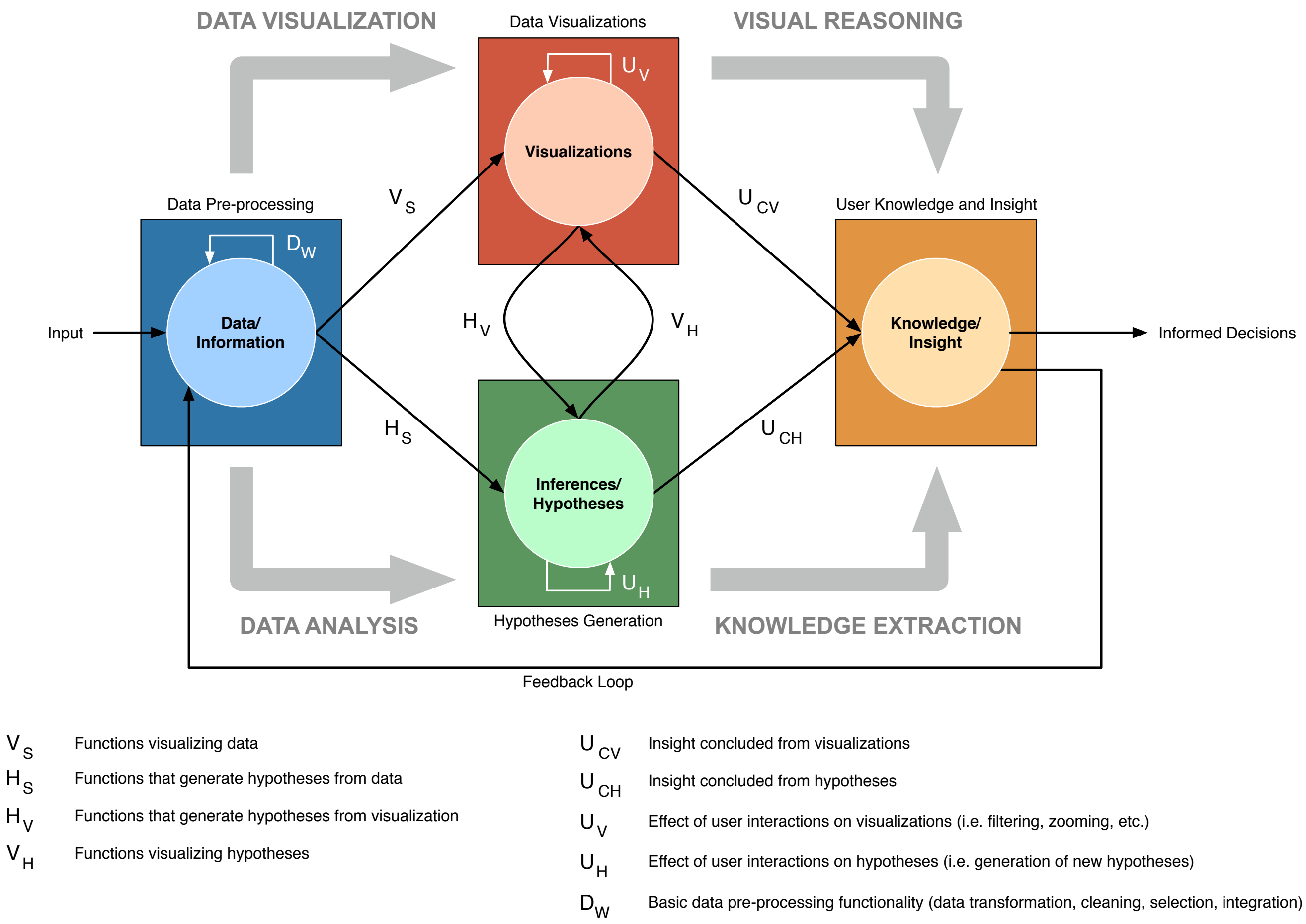

Fig. 3 The Visual Analytics and Enabled Reasoning Processes (Adapted from [40], [52] and [64])

for any type of efficient *data analysis* or *data visualization* to take place. The goal of this step, as explained by Kasik et al. [35], is to prepare the data for visual representation by "identifying higher-order characteristics in the data, such as relationships, trends, summaries, clusters and synopses" [35]. Pre-processing may include data cleaning, selection, integration, transformation, etc. [40, 35]. In particular, as explained by Russell et al. [68], data transformation "deals with transforming data into varying levels of abstraction or deriving additional data that has new semantic meaning." Data pre-processing is usually achieved through the implementation of mathematical, statistical, and linguistic techniques. More detailed information regarding existing methods can be found in [35]. Once the data have been pre-processed and transformed into efficient data representations, hypotheses can be generated (H_S) and visualizations can be created (V_S).

3.2.2 Hypotheses Generation

Hypotheses can be formulated after applying analytical and statistical methods to the data (H_S). Additionally, hypotheses can drive the type of visualization to be used (V_H) and, inversely, visualizations can help formulate new hypotheses (H_V). However, as explained by van Wijk [82], visualization should not be used to "verify the final truth" [82], as it has been advocated in previous publications, due to the subjective nature of what can be observed (different people may observe different patterns, certain parameters may better explain by a phenomenon than others). Along the same lines, visualization can be misleading, because the data used to create a particular visualization could have been subjectively manipulated by a user wishing to see a particular outcome. Consequently, it is important that the formulated hypotheses be verified afterwards [82].

3.2.3 Data Visualization

Visualization is a means to extract and present relevant information from large volumes of generated or compiled data [82] in a format that enables reasoning and analysis while allowing the user to navigate the overall space spanned by the data [35]. As explained by Kasik et al. [35], data representations obtained during the data preprocessing phase (Section 3.2.1) need to be further transformed (V_S) in order to provide the user with intelligible and effective visual representations (Figure 4). Hence, visualization methods, defined by Lengler and Eppler [45] as "a systematic, rule-based, external, permanent, and graphic representation that depicts information in a way that is conducive to acquiring insights, developing an elaborate understanding, or communicating experiences" can be applied to data representations to help the user identify patterns, trends, etc. and better disseminate results and synthesize knowledge [35].

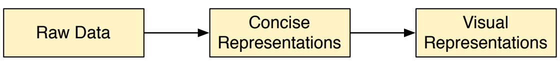

Fig. 4 The Two-Step Data Transformation and Representation Process

The resulting visual representations depend on the type of data, the task to be accomplished, and the time-frame allowed for the completion of the analysis [35, 38, 45].

3.2.4 User Knowledge and Insight

The user is a critical element of the Visual Analytics process [35] but he often knows very little about the data [38]. The knowledge or insight he may gain from visualization (U_{CV}) and visual data exploration, in particular, is enabled through *visual reasoning* and depends on the level of information and interaction provided, his level of expertise and a priori knowledge, as well as his cognition and perception capabilities.

Based on his newly acquired knowledge and exploration objectives, the user may decide to obtain additional insight both on the data and its visualization. He may recompute the data and steer the analysis in a different direction (feedback loop) or he may dynamically interact with the visualization (U_V) through analytical means and techniques like brushing and linking (connecting of two or more views of the same data), and/or panning and zooming (smoothly moving a camera across a scene while increasing or decreasing the magnification of the objects in the scene) [52] to focus on a different region or dimension of the data space. This is expressed in the *Visual Analytics Mantra* proposed by Keim et al.: "Analyze first, show the important, zoom, filter and analyze further, details on demand" [40].

Exploring and investigating the data through a different or more focussed angle can offer a new perspective on the problem, thus helping the user refine existing hypotheses and formulate new ones (U_H). As claimed by Keim, "the visual data exploration process can be viewed as a hypothesis-generation process" [38]. These new hypotheses, through the process of *knowledge extraction*, may in turn contribute to increased insight (U_{CH}) and a better understanding of the problem.

This disciplined, iterative, and interactive process [52] by means of which the user learns about the problem through data manipulation, information visualization, and hypotheses generation and testing, eventually leads to the formulation of informed decisions.

3.3 Preliminary Remarks

As discussed in Section 1, design is primarily a problem-solving activity. In the case of unconventional design, characterized by a lack of historical data and limited designer's expertise for this particular problem, this problem-solving activity requires that the data, knowledge, and insight necessary for the formulation of informed decisions be generated throughout the design process. While significant amounts of data can be created through simulation, the generation of knowledge and insight necessitates a framework with which:

- Large and complex data sets can be explored
- Initial concepts and hypotheses can be formulated and later affirmed or discarded
- Information can be synthesized and shared
- Scientific and analytical findings can be documented and communicated

Visual Analytics, the goal of which is to support the analytical reasoning process [79], is thought to provide that necessary framework through the process described above. The following section illustrates, through an unconventional design problem, how Visual Analytics and the enablers discussed in Sections 2.2.1 and 2.2.2 are integrated into the design process to address the aforementioned design challenges, and provide the means for the necessary generation of knowledge and insight.

4 Example Application

The failure of the High Speed Civil Transport (HSCT) program led by NASA in the mid 90's revealed the extreme sensitivity of commercial supersonic aircraft to both environmental and economical parameters. Using this knowledge, and motivated by favorable market studies, the aerospace community's interest shifted from supersonic airliners to supersonic business jets (SBJs) [33]. Significant amount of research has thus been conducted on the design and development of quiet SBJs capable of meeting the stringent requirements of flying overland at supersonic speeds with minimum sonic boom and acceptable levels of engine noise and emissions [11].

The following sections discuss, based on previous SBJ design studies [11, 26, 60, 12, 59, 33, 14], the early phases of the design process (pre-conceptual/conceptual phases) for this unconventional and complex vehicle, emphasizing the design challenges and enablers. In addition, these sections illustrate how the integration of Visual Analytics in the design process provides the analyst and decision maker with the capabilities to gain the knowledge and insight necessary to make informed design decisions.

4.1 Design Problem and Requirements Definition

The definition of the design problem has been recognized as a central issue in design [67]. In particular, the design of a new air vehicle is a challenging undertaking that requires a proper understanding of the mission type to be performed and the mission requirements to be met. Mission requirements describe how the system should operate for a given mission profile [4] and represent what the user needs, the ultimate goal of all systems to be acquired. However, as acknowledged by Trainor and Parnell [80], what at first appears to be the problem is rarely the real problem to be addressed due to changing requirements or ambiguous customer needs. Hence, it is important that significant amounts of time and effort be directed towards diligently capturing the voices and perspectives of all stakeholders/customers. Ultimately, the customer requirements need to be translated into engineering requirements (detailed technical specifications) for the designer to be able to effectively develop and evaluate candidate designs.

A quality system developed in the ‘60s by Yoji Akao and Shigeru Mizuno [2] called Quality Function Deployment (QFD) provides the designer with the means to truly capture the customer needs and translate those into design requirements. Its associated design tool is termed a QFD diagram or “House of Quality”. This tool also enables the ranking of requirements, the identification of synergy or conflict between the engineering requirements, and the benchmarking of other existing products, when relevant, to help establish engineering targets.

Once the iterative process of mapping customer requirements to quantifiable engineering parameters is completed, the designer needs to provide design alternatives to be tested against these requirements.

4.2 Concept Space Definition

The concept space represents all possible solutions of a design problem. The goal of defining the concept space, as described by Kirby [41], is to "identify a potential class of vehicles and provide (...) a starting point for selecting potential solutions to satisfy the customer requirements." However, there exists a multitude of combinations of different subsystems that may satisfy requirements. Different methods such as brainstorming and affinity diagramming [85] can be implemented to enumerate the variety of these subsystems and generate design alternative combinations. Morphological Analysis (MA), as discussed in the following section, has been particularly successful in defining a concept space for complex system engineering problems such as this one.

4.2.1 Morphological Analysis

MA was first developed in 1966 by Fritz Zwicky, a Swiss astronomer and astrophysicist, who used it to develop jet and rocket propulsion systems and propellants [91]. This technique has since been extensively used in a variety of scientific disciplines [47, 62, 63, 86] and successfully implemented in complex system engineering problems [7, 41]. MA is particlualry attractive for multi-dimensional, non-quantifiable, complex problems [62] because it provides a structured, functional, and intelligent means to decompose the problem and generate alternatives [41]. MA is implemented through the development of a matrix of alternatives, or morphological matrix, which is formed by "identifying the major functions or characteristics of a system on the vertical scale, and all the possible alternatives (or system attributes) for satisfying the characteristics on the horizontal scale" [41].

The concept of the Interactive Reconfigurable Matrix of Alternatives (IRMA), developed by Engler et al. [23], further extends the capability of the matrix of alternatives by incorporating new concepts such as filters, compatibility and dependency matrices as well as Multi-Attribute Decision Making (MADM) techniques into the selection of product features. An IRMA, as illustrated by Figure 5, is populated through brainstorming and includes all possible combinations of the brainstorming activity. The simplified matrices in Figure 5, for instance, include $1.8 * 10^9$ alternatives. However, by enumerating all the possible alternatives along with their dependencies and compatibilities, the IRMA helps scope an intractable problem space to a manageable one. The implementation of filtering capabilities, such as the option to eliminate alternatives with respect to technology maturity, also contributes in reducing the scope of the problem. Finally, the integration of MADM techniques such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which allows decision makers to rank alternatives according to the importance of pre-determined criteria [23], further supports experts in down-selecting the number of options to be considered.

The implementation of the aforementioned capabilities enables the exploration of a high number of options, as well as the identification of potential concepts or new technological combinations for a potential system. This process, during which both requirements and design configurations are considered, eventually supports subject matter experts in determining the baseline around which a concept space that satisfies the customer requirements may exist [11]. The chosen baseline aircraft concept, shown by the shaded boxes in Figure 5, can be further decomposed into a set of geometric and propulsive parameters that define the design space to be investigated. The IRMA thus greatly helps decision makers eliminate some alternatives and reduce the concept space to a defined region that can be further investigated.

Concept space exploration, design space exploration, and feasibility identification, as discussed further in this paper, are followed by a selection process in which the decision maker has control [5, 76]. However, in the case of revolutionary, unconventional concepts, this control

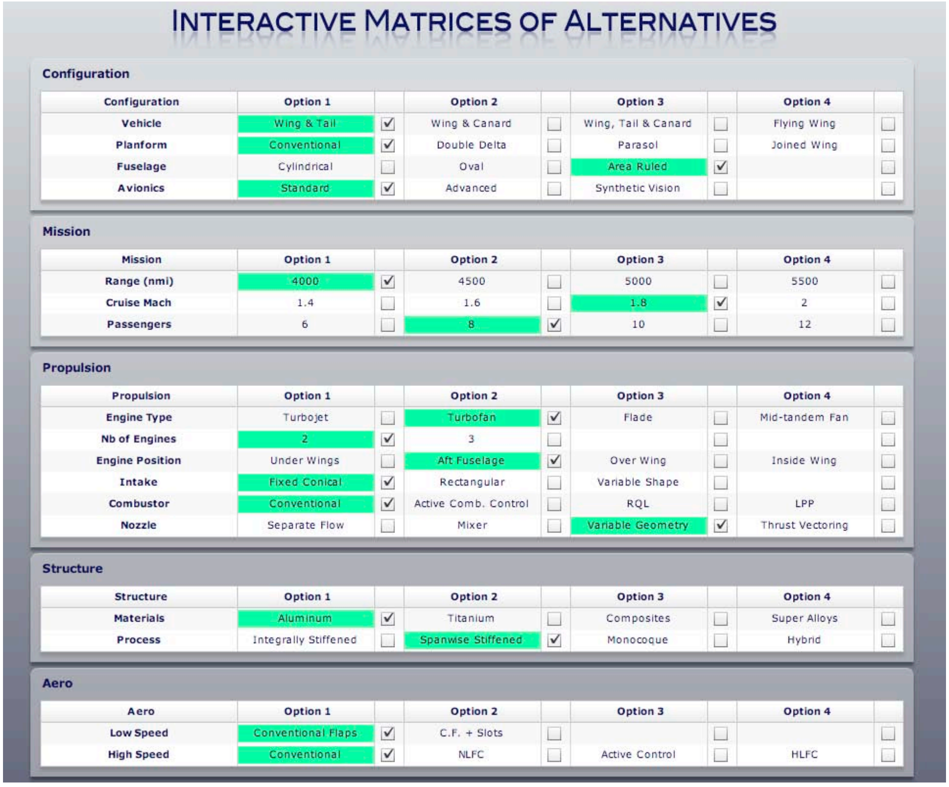

Fig. 5 Example of an Interactive Reconfigurable Matrices of Alternatives (IRMA) for a SBJ

is limited by the lack of empirical data or experience of the decision maker. Additionally, because the concepts are defined by several parameters that must be allowed to vary concurrently, the decision maker cannot mentally analyze them without the aid of graphical tools. The concepts are also often judged against multiple conflicting objectives that are sensitive to the values of the design parameters. The concept and design spaces are thus so complex that it is exceedingly difficult for the decision maker to identify a concept with confidence [51]. It also happens that multiple different concepts result in equally feasible design. Finally, as discussed by Mavris and Jimenez [51], small variations in requirements and constraints can quickly change what concept is most appropriate. To address these challenges, Genetic Algorithm (GA) [25], a search, optimization and machine learning technique that became known in the 1970s through the work of Holland [28], can be implemented. The use of Genetic Algorithms (GA) for concept generation [56], exploration [72] and selection [17] has been successfully implemented [51]. In particular, GA has shown to be very efficient in supporting trade-offs in the early definition of system taxonomy [57, 17, 14, 13, 31]. While GA can be used at different stages of the conceptual design phase (concept space exploration, design space exploration, feasibility identification, etc), this paper only illustrates its applicability to concept space exploration.

4.3 Concept Space Exploration

As previously discussed, the IRMA enables the reduction of the concept space to a reduced number of alternatives. The remaining alternatives are further decomposed into relevant geometric and propulsive parameters. These parameters and their associated ranges define the design space that will be further investigated. The ranges are chosen so as to represent the highest number of configurations possible. These alternatives and their parameters guide the designer in deciding which models and codes to integrate to explore

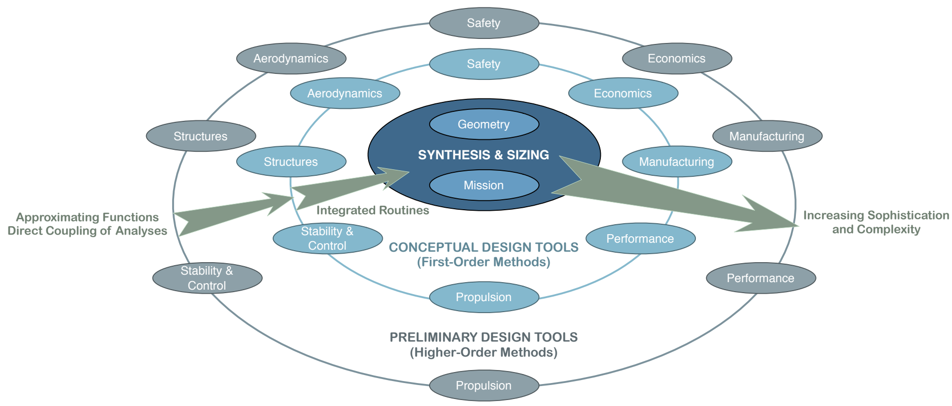

Fig. 6 Synthesis and Sizing

the concept space. The fidelity of these tools is also dictated by the parameters chosen.

Many disciplinary analyses and codes are often necessary to evaluate the feasibility and viability of the design. An efficient means to lessen the design cycle time is to study many different aspects of the design simultaneously. This is achieved through the creation of an integrated and parametric computational synthesis and sizing environment (Figure 6) in which conceptual and preliminary design tools and codes are linked together, eliminating the re-keying of information from output files to input files.

The Genetic Algorithm is then executed to help "identify the dominant designs that may confirm subject matter expert intuition or reveal unexpected trends" [51]. Through the implementation of the GA, different complete design concepts can be created in less than a minute, or up to a day, depending on the level of fidelity of the design tools and models (Figure 7). These designs are sized for the mission requirements, which are also scalable; a change in the required range, for example, will change this matrix of designs. Parametric design thus provides the user with the power to test hundreds or thousands of designs, where previously, time permitted a single design point only.

After some number of design generations, the dominant solutions become apparent, hence defining the Pareto frontier and the performance envelope of the concept space, as illustrated in Figures 8 and 9. The Pareto frontier is a trade-off curve on which designs cannot be improved in one metric category without a tradeoff in another [58]. By selecting any point on the Pareto front, the designer is also able to access all the information regarding a particular design.

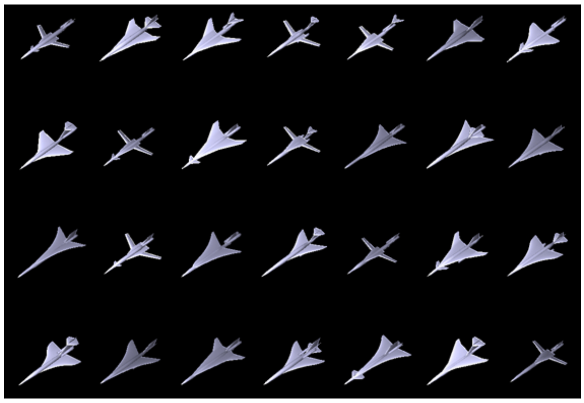

Fig. 7 Subset of SBJ Configurations

The development of a parametric, integrated modeling and simulation environment, along with the implementation of GA, allows the concept space to be quickly explored, providing the designer with additional insight and a deeper knowledge about the design problem. It allows the designer to better understand and quantify the trade-offs between metrics and concepts [22], hence leading him to the confirmation or discovery of trends that he could not have apprehended or visualized beforehand. Additionally, it enables the concept space to be reduced from a multitude of options to one family of concepts and one M&S environment.

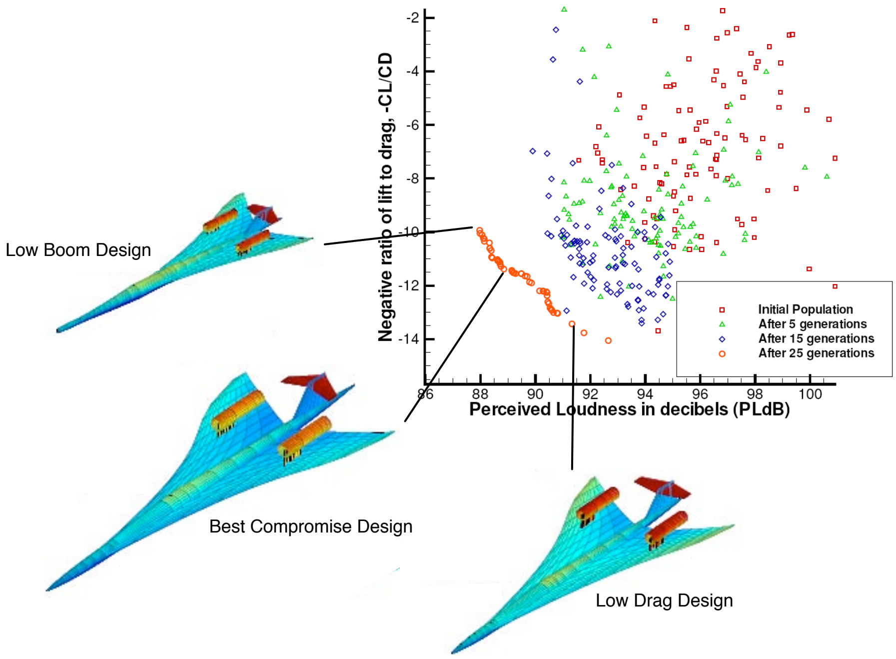

Fig. 8 -C_L/C_D as a function of PLdB for various Design Generations

This family of concepts is then further investigated, as discussed in the section below. In particular, higher fidelity tools may be integrated into the parametric M&S environment described above to evaluate the sensibility and feasibility of the chosen concepts and assess, in more detail, their corresponding design variables.

These tools or codes often appear as "black boxes" to the user. Indeed, the equations embedded in them are so complex that it is impossible for the analyst or decision maker to clearly identify or grasp the relationships between inputs and outputs. This lack of understanding prevents any sensitivity analyses to be conducted and thus limits the insight and knowledge that the decision maker could gain about the design problem [83]. To address this challenge, Wang and Shan [83], as well as other practitioners, advocate the use of surrogate modeling and visualization methods to support the decision maker's understanding of the design problem. Both enablers are discussed in the following sections.

4.4 Surrogate Modeling

As discussed in Section 2.2.2, surrogate modeling techniques, by constructing approximations of analysis codes, supports the integration of discipline-dependent and often organization-dependent codes, and represents an efficient way to lessen the time required for an integrated parametric environment to run. These techniques also yield insight into the relationships between design variables (inputs) and responses (outputs), hence facilitating concept exploration [71]. Additionally, by enabling virtually instantaneous analyses to be computed in real-time, surrogate modeling supports the use of interactive and integrative visual environments [46]. These environments, as described in Section 4.4.1, in turn facilitate the designer's understanding of the design problem. Surrogate modeling, as stated by Wang and Shan [83], thus provides "a decision support role for design engineers." Among the variety of surrogate modeling techniques that facilitate the exploration of complex design spaces [83, 71], Response Surface Methodology (RSM), first developed by Box and Wilson [9], is particularly well-accepted and suitable for Aerospace

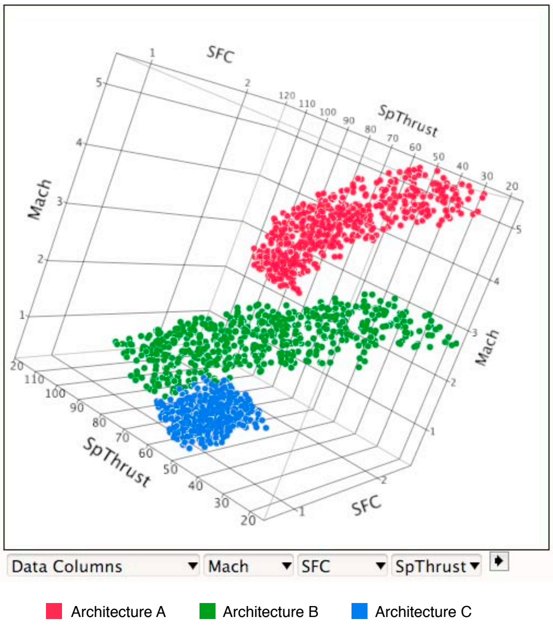

Fig. 9 3D Pareto Frontiers

and Mechanical engineering design applications [71].

4.4.1 Response Surface Methodology (RSM)

RSM [54] is a mathematical modeling technique that uses a simplified representation, called Response Surface Equation (RSE) or surrogate model, to approximate the behavior of a response (such as a disciplinary or system level metric) as a function of independent design parameters or input variables [4, 11, 85]. RSM is particularly suitable when several input variables *potentially* influence a performance measure (response), but the underlying relationship is unknown [54]. As shown in Equation 1, an RSE takes the form of a polynomial approximation of the relationships across given ranges for the input variables and usually includes linear, quadratic, and interaction terms between the design parameters [11, 33]. The philosophy behind the use of a polynomial approximation is based on the principle of Taylor series expansion.

$$R = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} b_{ii} x_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} b_{ij} x_i x_j + \varepsilon \quad (1)$$

where:
R: response of interest
b_0: intercept term
b_i: regressed coefficient for first-order terms
b_{ii}: regressed coefficient for second-order terms
b_{ij}: regressed coefficient for cross-product terms
x_i, x_j: design variables or factors
ε: error associated with second-order approximation
The reader is invited to consult [54, 53, 8] for a more detailed description of RSM developments, applications, techniques and tools.

The steps in the RSM process are as follows [11, 71]:

1. Select design variables and their ranges.

2. Execute a 2-level Design of Experiment (DOE) and conduct a Pareto analysis of the significant metrics via an analysis of variance using the results form the execution of the DOE: the Pareto analysis allows the designer to "capture and visualize requirement-attribute sensitivities and leverage trade-off analyses at any level of system decomposition" [51]. In other words, Pareto analysis reduces the dimensionality and complexity of the solution space [85] by providing, in order of priority, the variables that contribute the most to the variability of a given response (Figure 10).

3. Select an appropriate DOE for the number of significant factors and number of simulation cases. DOEs are a series of tests in which *purposeful* changes are made to input variables. By only running a limited number of cases, predictions can be made regarding the influences of variables and their interactions on the responses. DOEs provide a maximum amount of knowledge with minimal time and computational expenditures [54].

4. Run the prescribed simulation cases and collecting the appropriate response data.

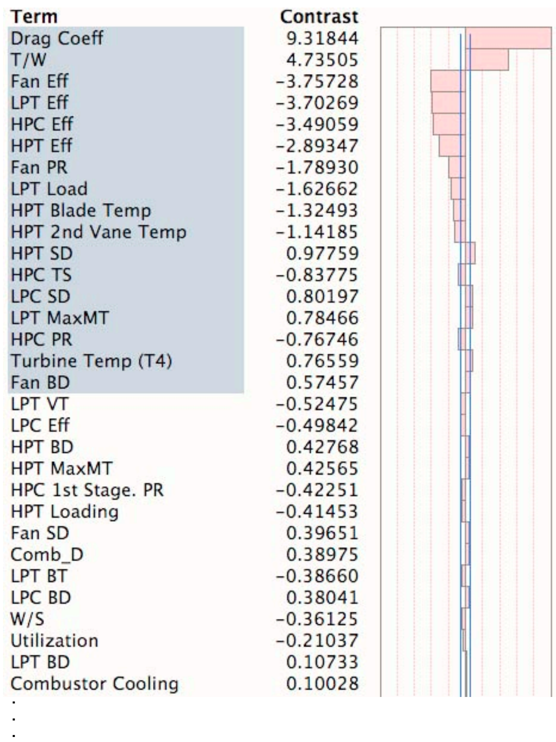

Fig. 10 Example of Pareto Analysis for CO_2 Reduction

5. Perform multivariate regression analysis to build RSEs.

6. Validate the model with a confirmation test and random sample case.

After validation, the RSEs obtained can be used to perform rapid optimization, Monte Carlo simulation, or design space exploration [11, 83], as discussed in the following section.

4.5 Design Space Exploration

As previously discussed, surrogate modeling supports the use of higher-fidelity analysis for unconventional configurations by facilitating the integration and automation of organizationally disseminated tools. In particular, the creation of physics-based approximation models (surrogate models) can replace the higher fidelity tools, which are usually described as too slow for use in the design process, cryptic in their use of inputs, interfaces and logic, and non-transparent (lack of proper documentation, legacy). The use of these approximation models also enables the integrated tools to run at a fraction of the time of original models. Consequently, surrogate modeling also empowers the designer to generate and collect larger data sets, hence allowing him to capture more of the dimensionality of the problem. However, the amounts of data generated can rapidly become overwhelming and prevent the designer from learning about the design problem any further. Alleviating this issue, as discussed in Section 1, requires that visualization capabilities be developed to help reduce the designer's cognitive burden, foster his rapid understanding of the design problem, and support informed decision making. The importance of visualization-enabled design space exploration in general, and of visualization methods for multidimensional data sets in particular, has been widely recognized as a means to support engineering design and decision making [46]. In particular, Wong and Bergeron [87] mention that such techniques have for objective the synthesis of multidimensional data sets and the identification of key trends and relationships.

Companies such as Chrysler, Boeing, Ford, Lockheed Martin or Raytheon, to name a few, have invested significant efforts in the use of visualization to speed and improve product design and development. The research community has also worked on the development and implementation of diverse design space visualization environments. Past efforts to visualize multidimensional data include programs such as XmdvTool [84], Xgobi [77], VisDB[36], and WinViz [44]. More recent work, such as the one by Marsaw et al. [48], for instance, discusses the use of an interactive visualization environment to help determine the technologies and engine point designs that meet specific performance and economic targets. In particular, this environment features a scatterplot that allows the designer to display simultaneously both design variables and responses and to filter the discrete designs to determine regions of the design space that are the most promising for further and more detailed exploration. Additional recent interactive and multidimensional design space visualization environments include, among others, the ARL Trade Space Visualizer (ATSV) [55, 76], Cloud Visualization [21], BrickViz [34], the Advanced Systems Design Suite [89, 90], the framework introduced by Ross et al. [66], and the work conducted by Simpson et al. [74]. These environments incorporate diverse visualization techniques (glyphs, parallel coordinates, scatter matrices, 3-D scatter plots, etc.) depending on the nature of the data and the end goal of the environment [76]. The reader is invited to consult [18] for a thorough review of the theory and techniques used to visualize multivariate design data.

The following paragraphs and sections discuss, in more detail, the integration of specific design methods and visualization techniques in support of the exploration of the design space and the evaluation of a feasible design.

Design space exploration is a dominant activity in conceptual design. The RSEs generated describe the overall design space and can be visualized in a dynamic design space exploration tool called a prediction profiler (Figure 11). A prediction profiler is constructed from partial derivatives and depicts the sensitivities of each response to the design parameters. In other words, a prediction profiler enables the user to evaluate how a given attribute x_i varies as the value of x_j changes. Hence, when the hairlines (dashed vertical lines in Figure 11) are moved to indicate the changing of an input variable value, the responses are automatically updated through the RSE [4].

Such capability is important to investigate the overall design space and determine which attributes have the greatest impact on the responses. By being able to explore trends and sensitivities in a highly visual, dynamic, interactive, transparent, and collaborative environment, the designers are provided with the capability to conduct and document trade-off analyses and therefore gain valuable insight and knowledge about the design problem. Such an environment also brings the world of the analyst and the world of the decision maker together by fostering communication and informed discussions between the different actors.

Baker et al. [4] and Baker and Mavris [3] have recommended partitioning the design space model into three design spaces: a mission requirement space, a vehicle space, and a technology space. The simultaneous assessment and rapid tradeoff between the three design spaces can be conducted in a Unified Trade-off Environment (UTE) to investigate the interactions among input variables, as well as the impact of the variability of the requirements, vehicle attributes, and technologies on the complex design space.

Once the major attributes have been identified and their sensitivities assessed, the following step consists of identifying if a solution exists that meets the requirements and satisfies the constraints. However, depicting a solution space requires that the uncertainty that plagued the design problem be considered. Uncertainty in design is present in the requirements, vehicle attributes, and technologies that define the design concept. The use of probability theory and probabilistic methods in conjunction with surrogate models, as described in the following section, have been particularly successful in allowing the designers to quantify and assess risk, and explore huge combinatorial spaces.

4.6 System Feasibility Evaluation

The main objective of design space exploration is the determination of feasibility [22] and the creation, when necessary, of a feasible design space. A Monte Carlo Simulation (MCS) is run on each RSE assuming a uniform distribution on the ranges of all the design variables as a means to map all the possible outcomes. This leads to the generation of Probability Density Functions (PDFs) and corresponding Cumulative Distribution Functions (CDFs). Using probability distributions along with surrogate modeling enables thousands of designs across a user-specified distribution (uniform or other) to be quickly generated and analyzed, hence allowing a designer to assess technical feasibility and economic viability.

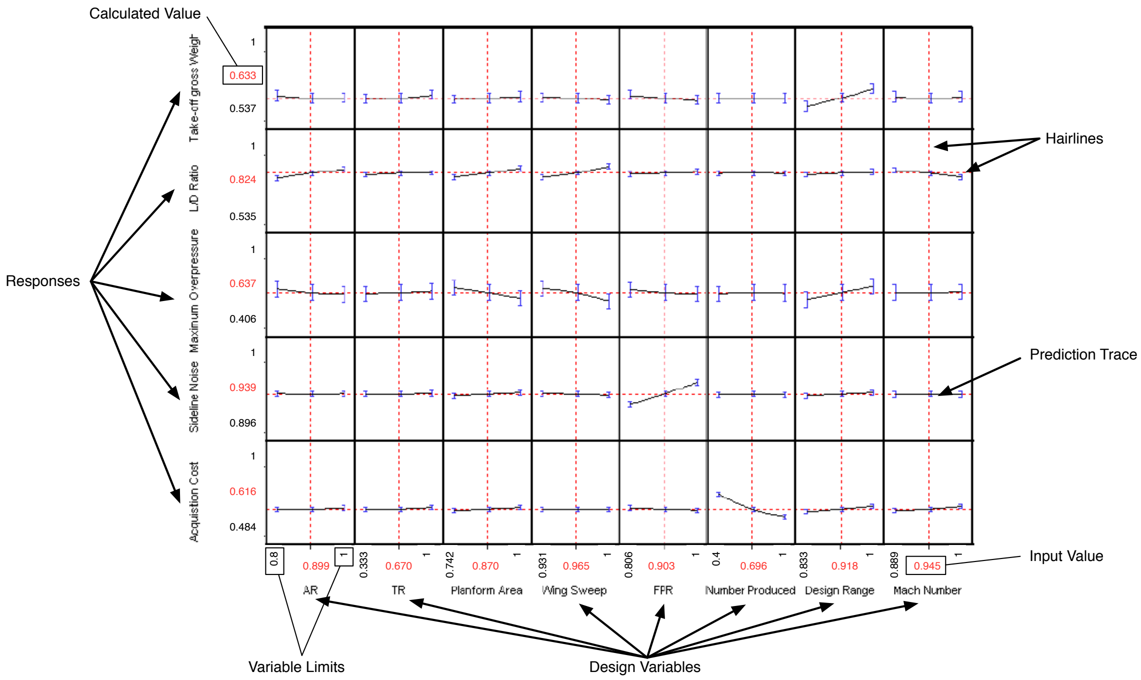

Fig. 11 Dynamic Interactive Design Space Trade-off Environment (all values have been normalized)

By simultaneously representing specific constraints and their associated CDFs in a single plot, as illustrated in Figure 12, the designer can then evaluate how feasible the design space is and quickly identify any "show-stoppers", constraints inhibiting acceptable levels of feasibility. In addition, he is provided with information regarding the magnitude and direction of the needed improvements to obtain an acceptable feasible space. However, a design is feasible if it meets all requirements concurrently. The requirements associated with two metrics of interest can be evaluated simultaneously using joint probability distributions. Joint distributions can be represented, along with both future target values and Monte Carlo Simulation data, to quickly identify any points that meet the constraints (Figure 13). Technology metric values can then be extracted for any of the points that satisfy these constraints. Finally, these points can be further queried and investigated in other dimensions, through brushing and filtering, as illustrated in Figure 14.

As stated by Marsaw et al. [48], the analyst or decision-maker, in order to explore and understand the overall design space, should be able to compare any input or response characteristic of the point design to any other input or response in the design space. This can be achieved by generating and representing multiple plots of input vs. input, input vs. output, and output vs. output combinations in a multivariate scatterplot. In particular, such visualization technique allows the designer to visualize the total variability of a response metric as a function of the collective variability of the design parameters. It can also represent the locus of boundary points of the response metrics, hence allowing the designer to quickly identify the "best" and "worst" designs achievable within the design space for each metric [48]. Additionally, different concepts or architectures can be color-coded to make their impact on the design space immediately visible, hence informing the analyst or decision maker about the effect of concepts or architectures, and specific technologies, on the available design space [48]. A multivariate scatterplot showing all the potential output vs. input plots simultaneously can also provide essential insight regarding trends and correlations, while plots of outputs vs. outputs provide covariances

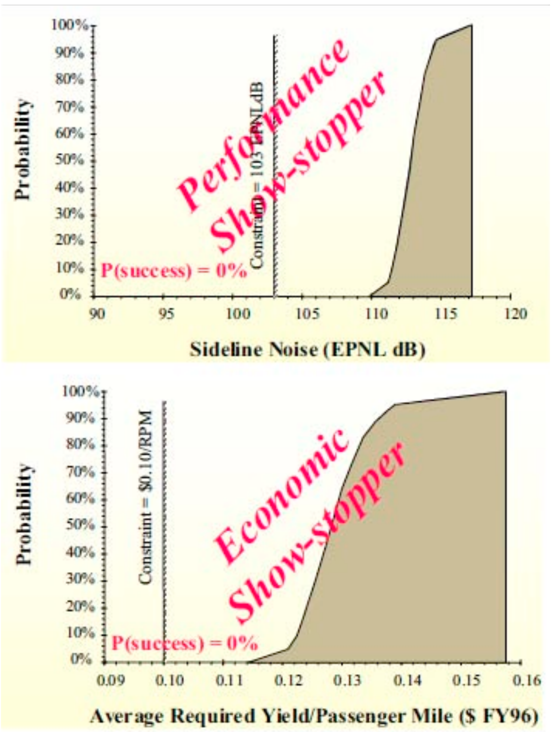

Fig. 12 Design Feasibility Assessment Enabled by Surrogate Modeling

of the relevant responses. Using a multivariate scatterplot along with filtered Monte Carlo analysis, a technique for performing "inverse design" that combines Monte Carlo simulation with surrogate models, the designer can also quickly interactively filter in all dimensions simultaneously and identify the solutions that concurrently meet all of the constraints placed on the output parameters [6]. Hence, filtered Monte Carlo, a method first introduced by Kuhne et al. [42], can help find all the design combinations that meet the constraints and thus present the decision maker and analyst with more than one feasible option. In particular, the interactive and visual capabilities illustrated in Figure 14 allows the analyst, through brushing and filtering, to query a complex, multidimensional design space graphically, reduce the number of solutions to a handful of points by excluding undesirable ones, and identify feasible concepts quickly.

A feasible design space, if it exists, can also be identified by plotting both constraint contours and design points on a bivariate graph, as illustrated in Figure 15. When no feasible design space exits, as it is often the case for unconventional designs, or if the extents of the feasible design space is unacceptable, the designer has the options to:

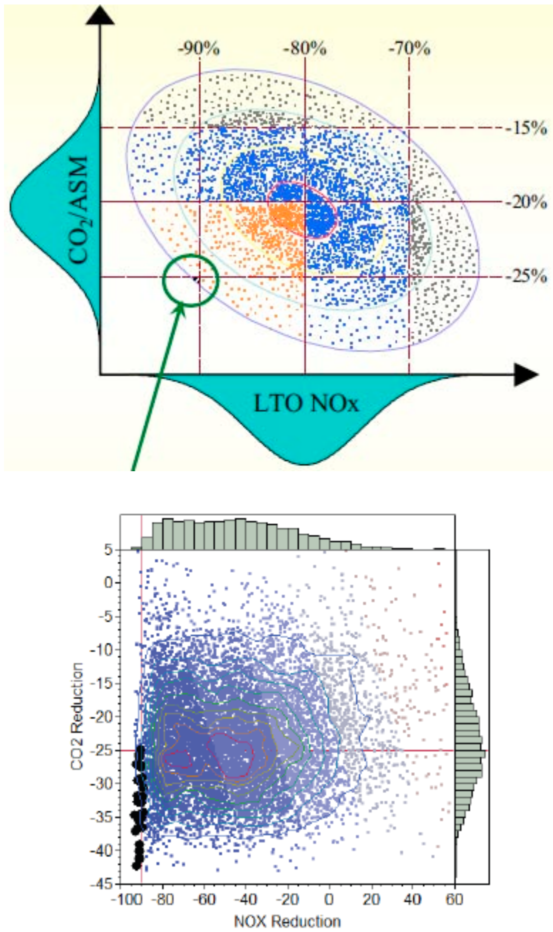

Fig. 13 Selecting Potential Solutions to Meet Future Goals

- Open design variable ranges: the ranges considered being wide, as discussed in Section 4.3, this does not represent a viable option.
- Relax constraints: this may or may not be an option, depending if the constraints are rigid or not.
- Select a different concept space: this is already investigated with the requirements aspects of the method.

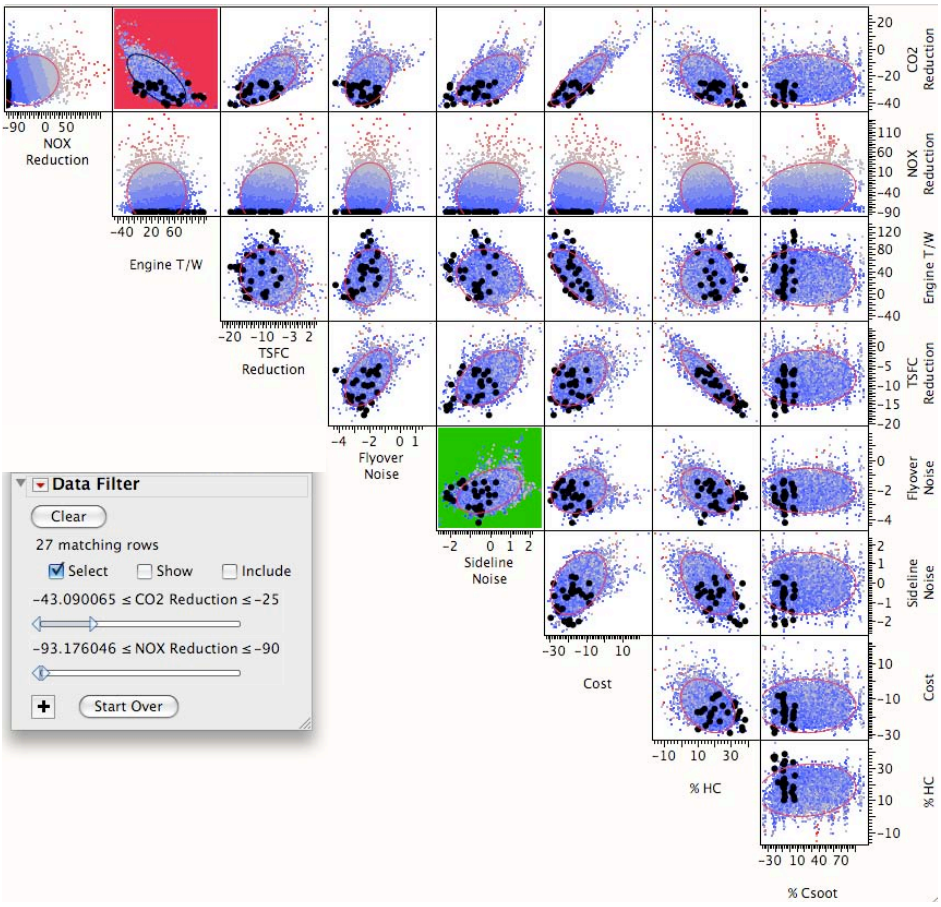

Fig. 14 Scatterplot Matrix of Outputs

- Infuse new technologies: this is discussed in more details in Section 4.7.

Being able to identify the constraints that overlap with the design space is thus paramount as it helps the designer gain valuable insight regarding the constraints to relax or the type of technology to infuse. A parametric, dynamic, and interactive environment such as the one depicted in Figure 15, hence allows the designer to rapidly explore hundreds or thousands of potential design points for multiple criteria, while giving him the freedom to change the space by moving both the design point and the constraints. The designer is thus able to visualize the active constraints and identify the ones that most prevent him from obtaining the largest feasible space possible and, consequently, from gaining the full benefits of the design concept. Additionally, the response surface equations generated from the design space exploration can also be shown as three dimensional contours to which constraints can be applied (Figure 16). Using the sliders, the surface can be reshaped in real time, hence enabling trade studies to be performed and visualized instantaneously. In fact, this capability enables the designer and decision maker to uncover trends or solutions that have never been examined in a transparent, visual, and interactive manner. This interaction between the designer and the exploration environment allows the designer to constantly reformulate constraints and variables as he gains new insight about the design problem, thereby facilitating the formulation of informed decision [68, 1].

As previously discussed, an unconventional design will likely, at first, not have a feasible design space. The creation of a feasible de-

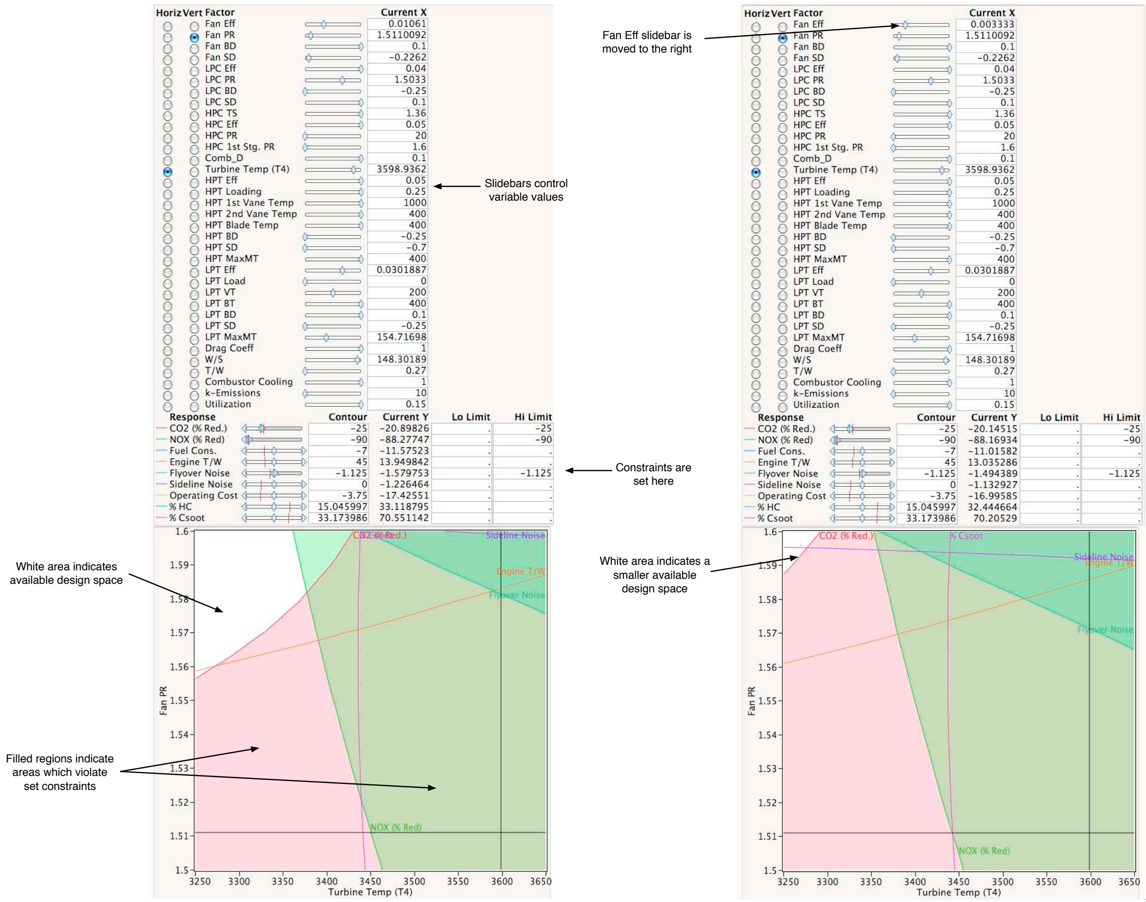

Fig. 15 Design Space Exploration

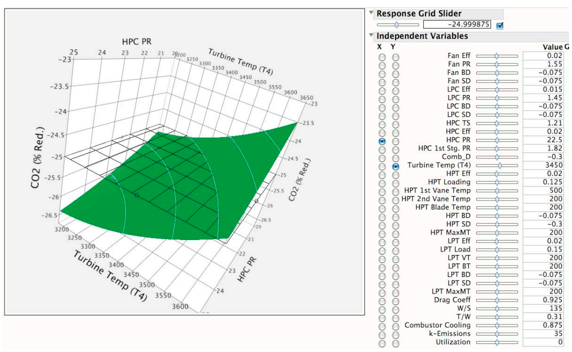

Fig. 16 Surface Plot for Percentage of CO_2

sign space is thus the main objective in the early phases of design. The techniques and visualization described above allow the designer to identify the most limiting constraints, hence guiding him in the choice of concepts or technologies to be further investigated or infused.

4.7 Refinement of the Design Space

Refining and opening the feasible space entail pushing the state-of-the-art and identifying, evaluating, and selecting technologies that are under development or close to maturity. These steps are part of methodologies such as the Technology Identification, Evaluation, and Selection (TIES) methodology [41], which provides a process by which requirements can be met and a feasible design space identified. These steps are briefly described in the following sections.

4.7.1 Identify Technologies

Technologies are identified according to their compatibility with respect to one another, as well as their effects on the system. In TIES, technology impacts are captured by k-factors and modeled as vectors of k-factors. k factors are, in essence, scale factors added within a M&S environment to model changes introduced by new technologies on particular metrics. Vectors of k-factors, or technology vectors, are then defined for each technology whose elements consist of the benefits and degradations associated with the technology

4.7.2 Evaluate Technologies

RSM is then used to create surrogate models of the responses as a function of k-factors. However, because the technologies considered are often under development, there exists some uncertainty regarding their impact on the system. In TIES, uncertainty is modeled by treating each k-factor as a random variable with a specified PDF. Monte Carlo simulation is then run for each set of k-factors sampled.

4.7.3 Technology Selection

A technology space exploration is then conducted, analogous to the design space exploration described in Section 4.5. A prediction profiler illustrating the impact of independent effect of each technology on the responses can be built. Similar filtering and visualization capabilities can be implemented to determine which technology enables a baseline that meets the requirements. However, for any multi-attribute, multi-constraint, multi-objective problem, the selection of the "best" alternative is inherently subjective. The techniques proposed by the TIES methodology are aimed at providing the decision maker with the necessary knowledge and justification for selecting the appropriate set of technologies. These techniques include:

- MADM Selection Techniques: MADM techniques, such as TOPSIS, are used to identify the best mix of technologies for the stated evaluation criteria.
- Technology Frontiers: Technology frontiers allow the analyst and decision maker to visualize the limiting threshold *effectiveness parameters* attainable from any combination of technologies (Figure 17). *Effectiveness parameters*, such as performance and economics, can be utilized to compare various technology alternatives and may be constructed from a *user defined utility function for which maximization is desired.*
- Resource Allocation: Resource allocation allows the analyst and decision maker to quickly and efficiently identify the technologies that have the strongest impact on the baseline metrics.

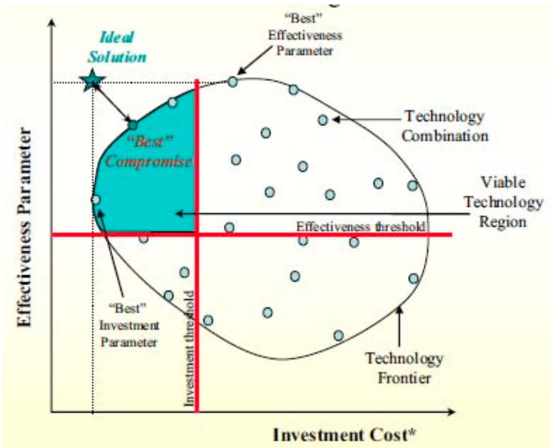

Fig. 17 Example of Technology Frontier

The selection of the final concept alternative is highly dependent on the people present in the room when a decision has to be made. To minimize this effect, one of the purposes of the techniques and capabilities described throughout this paper is to allow the analyst to run cases and conduct some analysis ahead of time to be able to provide the decision maker with the justified means of making an informed decision. In particular, providing some degrees of freedom on the variables with which the decision maker is familiar with will eventually help him gain valuable insight and optimally direct program resources.

5 Concluding Remarks

Design is a problem-solving process during which data, information, and knowledge are exchanged to foster the formulation of appropriate conclusions and actions. In the case of unconventional design, historical data are nonexistent, expertise is limited, and new technologies must be

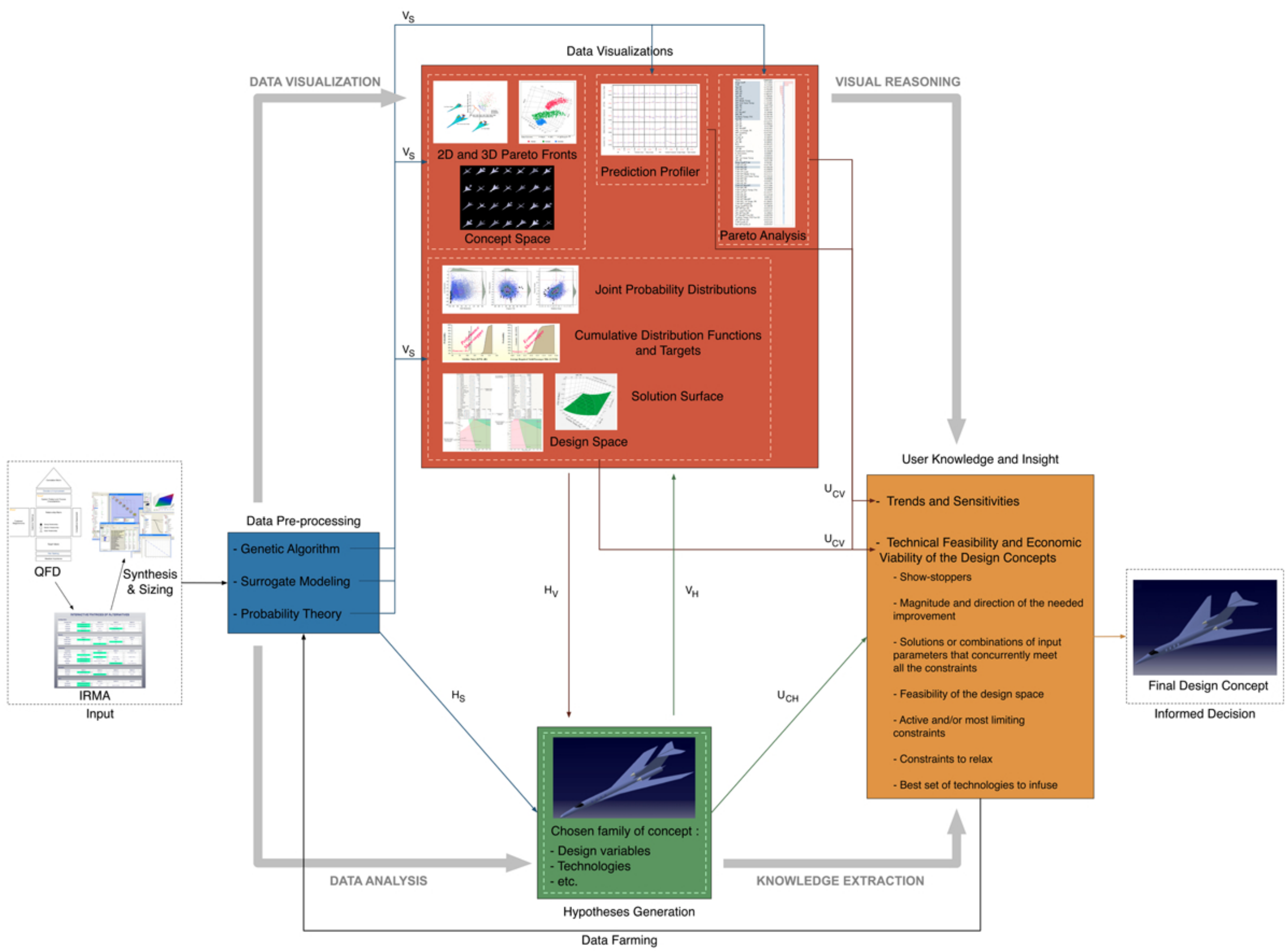

Fig. 18 The Visual Analytics Process applied to an unconventional Design Problem

considered in order to satisfy the constraints and create a feasible design space. A brief review of the challenges faced by the designer during the conceptual design phase has highlighted the fact, that, independent of the methods and techniques proposed, the real need is to reduce the designer's cognitive burden, and to support the analytical reasoning process that eventually leads to a better understanding of the design problem.

Figure 18 illustrates, in the context of the Visual Analytics and enabled reasoning processes, how the tools and methods described in Section 4 are implemented and integrated to foster knowledge and the formulation of informed decisions. This integration of Visual Analytics in the design process offers a valuable answer to the needs discussed above, while strongly supporting both qualitative exploration and quantitative decision making. In particular, it allows the analyst and decision maker to

- Rapidly explore huge combinatorial spaces,
- Identify potentially feasible concepts or technology combinations,
- Formulate and test hypotheses,
- Steer the analysis by requesting additional data as needed (data farming),
- Integrate their background, expertise and cognitive capabilities into the analytical process,
- Understand and quantify trade-offs between metrics and concepts,

- Study correlations, explore trends and sensitivities,
- Provide interactive feedback to the visualization environment,
- Synthesize and share information,
- Investigate the design space in a highly visual, dynamic, interactive, transparent and collaborative environment, and
- Document and communicate findings and decisions.

However, it is important to acknowledge that although enablers such as response surface methodology or probability theory are essential to the investigation of unconventional design problems, their benefits to the analyst and decision maker are limited if they are not integrated with the visualization, interaction, and analytical reasoning capabilities provided by Visual Analytics.

Finally, while the conceptual design phase is the most important phase of design in terms of the number of concepts to be examined, technologies to be considered, and mappings that need to occur between requirements and configurations, we believe that the design methods and solutions described in this paper could, in principle, apply to all the phases of the design process.

6 Acknowledgment

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7 Copyright Statement

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