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SOLUTION SPACE EXPLORATION IN MODEL-BASED REALIZATION OF ENGINEERED SYSTEMS

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SOLUTION SPACE EXPLORATION IN MODEL-BASED REALIZATION OF ENGINEERED SYSTEMS

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To my unbelievably supportive husband

who never failed to encourage me, to challenge me, and to support me.

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I conclude with a saying from Imam Ali, the first Imam of Shia Muslims:

'I am the slave of whoever teaches me a single letter[1]*'.*

[1] *Collection of Essays in Discussing Ahadis* by Kafi (In Farsi), Volume 1, Page. 322

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Glossary

Solution Space Exploration: Solution space exploration refers to investigating or exploring the solutions related to various design scenarios from different perspectives.

Weight Sensitivity Analysis: Weight sensitivity analysis involves exploring various design preferences associated with objective weights. In the cDSP, weights are associated with deviation variables of the deviation function.

Constraint Sensitivity Analysis: Constraint sensitivity analysis refers to exploring design constraints which involves exploring the solution space by analyzing the active and inactive constraints.

Active Constraint: In Linear Programing, an active constraint is a constraint that is satisfied at equality. For example, if the constraint is $x + y >= z$, the constraint is active when $x + y = z$.

Inactive Constraint: Any constraint that is not active is called inactive. For example, if the constraint is $x + y >= z$, the constraint is active when $x + y = z$, and inactive when $x + y > z$.

Feasibility Robustness: Feasibility robustness involves determining the relative insensitivity of the solution to incompleteness of the mathematical representation of phenomena and aspirations modeled as constraints in the cDSP.

Abstract

With growing interest in the model-based realization of engineered systems there is a need for developing methods to explore the solution space that is defined by models that approximate reality and are typically incomplete, inaccurate with different fidelities. These characteristics of model-based engineered systems manifest as uncertainties in the projected outcomes and it requires good understanding, insight and analysis of the designs/solutions in order to support the designer in the process of decision making. Therefore, a significant and desirable step in any model-based realization of engineered systems is to explore the solution space and find desired and robust designs insensitive to variations of different sources.

In this thesis a method is proposed to conduct solution space exploration in model-based realization of engineered systems. The construct that is adapted to develop the models is the compromise Decision Support Problem (cDSP). The solutions that form the solution space in the compromise DSP comprises the space defined by the constraints and variable bounds, and the achieved and aspiration space defined by the goals.

The main components of the proposed method are:

- ✓ exploring design goals through goal ordering and weight sensitivity analysis
- ✓ exploring constraints through constraint sensitivity analysis
- ✓ incorporating feasibility robustness

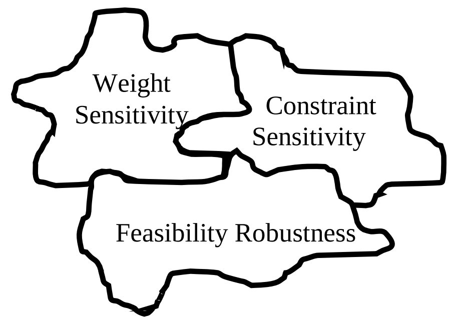
The proposed method in this thesis is illustrated in three different design examples namely a small power plant, shell and tube heat exchanger and continuous casting of steel. The emphasis is on the method rather than the results *per se*.

To generalize the method, the post solution analysis template is proposed to facilitate executability and reusability of the solution space exploration method in a computer.

CHAPTER 1 REALIZATION OF MODEL-BASED ENGINEERED SYSTEMS: FOUNDATION FOR SOLUTION SPACE EXPLORATION

What is needed in model-based system realization to increase design knowledge in order to support decision making given that the models are not complete and accurate? One answer is exploration of the solution space. It is important to realize that the design of engineered systems is based on mathematical modeling of the physical world. In developing these models, especially dealing with complex systems, a designer makes simplifications and approximations, and also deals with knowledge and solver limitations. That is why George Box a British mathematician and professor of statistics, wrote that "*essentially, all models are wrong, but some are useful*" (Box and co-authors, 1987). Therefore in model-based systems design, an essential step is the exploration of the solution space to provide knowledge and insight to the decision maker. The next obvious question is: *how is solution space explored so as to allow a system realization team to obtain useful knowledge in the process of decision making?* And the answer to this question is not simple. The intent in this thesis is to lay a foundation for a method suitable for solution space exploration which is rooted in Decision-Based Design (Mistree and co-authors, 1990b). The proposed method employs several mathematical tools and constructs to facilitate decision making in model-based realization of engineered systems. As a demonesteration, the method is applied to three design examples, namely, a small power plant, shell and tube heat exchnager, and continuous casting of steel.

In this chapter, the foundation for the thesis is laid. It starts with background and motivation for model-based engineered systems and solution space exploration. In Section 1.1, the general characteristics of a system are presented along with the definition and characteristics of model-based design. Moreover different aspects of solution space exploration, e.g., design preference exploration through weight sensitivity analysis, design constraint exploration through constraint sensitivity analysis, and incorporating feasibility robustness are described. In Section 1.2, the framwork for solution space exploration, i.e., Decision-Based Design, is introduced, and the Decision Support Problem (Mistree and co-authors, 1990b) an implementation of Decision-Based Design, is described. The objective for this thesis is discussed in Section 1.3 and research questions are posed. Finally, Chapter 1 is concluded by outlining the organization of the thesis in Section 1.4.



1.1 Background and Motivation for Solution Space Exploration

With growing interest in the model-based realization of engineered systems there is a need for developing methods to explore the solution space that is defined by models that approximates reality and are typically incomplete, inaccurate with different fidelities. These characteristics of model-based engineered systems requires good understanding and analysis of the designs/solutions in order to support the designer in the process of decision making. In Section 1.1.1, the background and examples of model-based engineered systems are discussed, followed by a discussion on solution space exploration background in Section 1.1.2.

1.1.1 Background and Examples of Model-Based Engineered Systems

Interest in model-based design and development of supportive computer environments has increased recently. There are several reasons to this such as the need for larger number of people to access applications for different purposes (Paterno, 2012). To further discuss model-based system design, it is necessary to first answer this question: What is a system? There are many different definitions of "system". According to Wikipedia, "*system is a set of interacting or interdependent entities, real or abstract, forming an integrated whole*". Based on Encyclopedia (Danbury, 1997), system is an aggregation or assemblage of things so combined by nature or man as to form an integral or complex whole. In Electronic Terms of IEEE (Blanchard and co-authors, 1992), system is defined as *"combination of components that act together to perform a function not possible with any individual parts".* Shupe (Shupe and co-authors, 1988) define system as a *grouping of associated entities characterized by a mental construct.* These definitions have the same common characteristics which is what system means in this thesis:

- A system works as a whole entity and has specific functions;
- A system has different components, which interact with each other;
- A system has a structure.

Systems are either complex, complicated or simple. According to system theory, a system can be very complicated but not complex. Complex systems are the one in which "*tightly coupled interacting phenomena yield a collective behavior that cannot be derived by the simple summation of the behavior of the parts*" (Bloebaum and co-authors, 2010), which means emergent properties is a main characteristics of a complex system. However, simple and complicated systems are fully predictable, and are often engineered. Engineered systems are the systems made by people such as medical devices, naval architectures and thermal systems. In this thesis complicated engineered systems are considered.

When the system is defined, the next definition to be discussed is the model-based or simulated-based system design. According to Wikipedia, "*model-based design is a mathematical and virtual method of addressing the problems*". "*It is transforming the way engineers and scientists work by moving design tasks from the lab and field to the desktop*" in which models are at the center of the development process, starting from requirements development to design, implementation and analysis ("Model-Based Design," 2015b). These built models used with simulation tools can lead to rapid prototyping, testing and verification. "*Simulation based design focuses on computational simulation tools and techniques to evaluate the performance of a design or design alternatives, starting at earliest conceptual design phases to help architects to make informed design decisions*" ("Advanced Environmental Systems," 2010)

All these definitions are convey the same principles about model-based design which is true in the case of this thesis:

- Mathematical modeling of the physical world;
- Implementing and testing the models using computer environments;
- Analyzing, evaluate and synthesizing to create value.

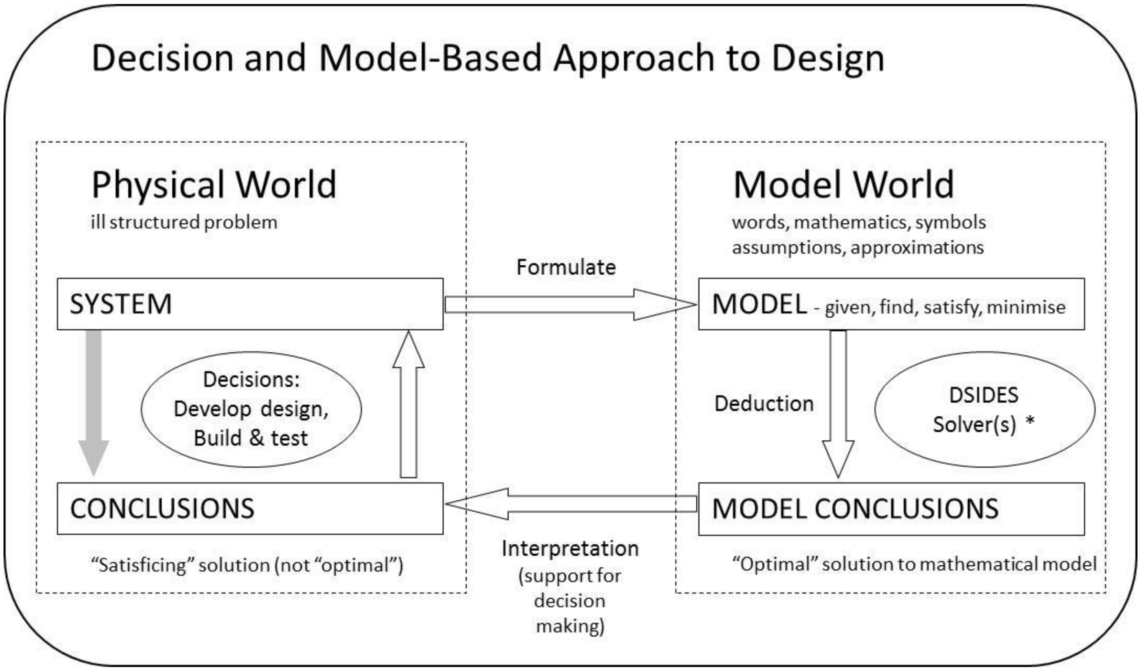


Figure 1.1: Decision and model-based approach to design, modified from (Xie and co-authors, 2002)

The nature of a decision and model-based approach to designing through modelling the physical world is portrayed in Figure 1.1. Typically in model-based design, a limited amount of information and knowledge is captured from the physical world and, based on that, a mathematical model is formulated which is an approximation of reality. Fortunately, nowadays, access to simulation tools and super computers is improved dramatically, however, in making the models and simulations, people widely use approximations, simplification, and they have to deal with method and solver limitations in addition to knowledge limitations which manifest as uncertainty. For the aforementioned limitations of model-based design, decision making requires high amount of analysis, evaluations and interpretation. This is required especially for the end user to understand and use the outcome in achieving their desired goals (Paterno, 2012). It is thus important to develop structured methods to support a decision maker to manage such complexity.

There is sometimes negative reaction to a model-based approach, and people may think it is rather theoretical and far from reality, however, even in the practical world when dealing with a complex problem, people try to find the main aspect of the problem to take into account. Therefore, even in the practical world models are built to find a way of interaction (Paterno, 2012).

Despite the limitations, there are many advantages in model-based design such as:

- Decreasing cost and time of prototyping, analyzing and evaluating, especially due to error identifications and corrections in the early stages of design and in the design timeline; as time passes, the knowledge and confidence of the designer should increase through exploration and analysis which results of completeness and utility of the outcome;
- Providing a common design environment which facilitate data documentation, analysis and visualization, model verification and multidisciplinary communication between the groups;
- Reusability of the design to upgrade and modifications to expand capabilities.

In this thesis, the compromise Decision Support Problem (cDSP) is used to mathematically model decisions associated with the design of different engineered systems used as examples, namely, a small power plant, shell and tube heat exchanger, and continuous casting of slab to test the method on solution space exploration proposed in Chapter 3. In the next section the background for solution space exploration is discussed.

1.1.2 Background for Solution Space Exploration

In keeping with George Box's observation in model-based realization of engineered systems, the decision maker must be able to work constructively with decision models that are typically incomplete and inaccurate ("Model-Based Design," 2015a) in order to make defendable decisions under uncertainty. The analysis embodied in a decision model does not represent the physical world completely and accurately, making it virtually impossible to predict the future state exactly. The models, and the search algorithms that use these models, will never be perfect and the inherent inaccuracy and incompleteness of analysis models and solvers manifest as uncertainties in the projected outcomes. A designer is able to work around this limitation by exploring and visualizing design and solution space and identifying robust solutions, these are solutions that are relatively insensitive to inaccuracies embodied in the analyses models; see (Triantaphyllou and co-authors, 1997).

To discuss more about the case of solution space exploration, the notion of multi-objective formulation in model-based design is explained. Multi-objective formulation originated in understanding that almost every problem is defined by a number of different performance criteria. These criteria typically represent conflicting goals which is the reason that a decision maker should deal with satisficing (Simon, 1996). However in single objective or mono-criterion approach, the solution depends only on the agreed criterion of choice and therefore, there is not much disagreement on the solution. This is why considering multiple objectives, can add a significant amount of complexity in decision making. The difficulty comes to satisfying multiple conflicting objectives when different decision makers have different sets of priorities (Sen and co-authors, 2012). Pahl and Beitz have introduced a linear approach of the design process with certain steps that a design passes through (Pahl and co-authors, 2013). However, a great amount of iteration is needed in refining a product to satisfy designer expectations which suggests dynamic priorities, subject to performance. In this approach, as a design progresses, satisfying the customer wishes and demands is reflected in requirement list. Any change in this document reflects a change in priorities. The multi-objective approach is appropriate in design because it offers the highest promise in satisfying the demands of a dynamic and unpredictable market. Multi-objective approach is chosen in this method to fit any multidisciplinary area of decision making with different preferences. The compromise DSP (Mistree and co-authors, 1993a), utilized in this thesis to model decisions associated with multi-objective engineered systems, discussed in detail in Chapter 2, is a hybrid of traditional optimization and goal programming and is based on the notion of satisficing rather than optimizing. The objective in the cDSP is to minimize the deviation function in which deviation variables are associated with different goals.

The notion of satisficing solutions, or solutions that are ‘good enough’ was first introduced by Herbert Simon in his book, *Sciences of the Artificial* (Simon, 1981), where he claims:

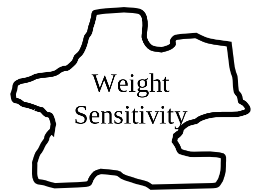
> "The decision that is optimal in the simplified model will seldom be optimal in the real world. The decision maker has a choice between an optimal decision from an imaginary simplified world, or decisions that are 'good enough', that satisfice, for a world approximating the complex real one more closely."

This idea was expanded by Gaithen where he compared executives with operations managers; he states that "executives tend to establish a set of goals and objectives that are satisfying (or satisficing) rather than optimizing" unlike operations managers who are concerned with, "a smaller set of objectives that are intended to be near optimal (Gaithen, 1980).

Due to the incompleteness of the mathematical models, an essential step in multi-objective approach in model-based design is to conduct post-solution sensitivity analysis and identify solutions that are relatively insensitive to input variations; inputs such as design parameters, design variables, deign targets and weights associated with the objectives (goals in the cDSP) (design preferences). Sensitivity analysis test the robustness of the final outcome against small changes in the input data through systematic evaluation of uncertainties (Chen and co-authors, 2009). Various approaches of sensitivity analysis are used and discussed in the literature ranges from physics to economics such as differential to Monte Carlo analysis, measures of importance to sensitivity indices, regression or correlation methods to variance based techniques (Archer and co-authors, 1997; Crosetto and co-authors, 2000). In the solution space exploration method proposed in Chapter 3, design preferences and design constraints – feasibility robustness are explored through weight sensitivity analysis and constraints sensitivity analysis respectively to develop an attention directing tool for the designers in the process of decision making. Weight sensitivity analysis involves exploring various design preferences associated with objective weights (Crosetto and co-authors, 2000; Sage, 1977; Tribus, 2013). In the cDSP, objective is to minimize the deviation function (discussed in Section 2.1), and weights are associated with deviation variables of the deviation function. Constraint sensitivity analysis involves exploring the solution space by analyzing the active and inactive constraints. Feasibility robustness involves determining the relative insensitivity of the solution to incompleteness of the mathematical representation of phenomena and aspirations modeled as constraints and goals in the cDSP, respectively; modified from (Archer and co-authors, 1997; Gunawan and co-authors, 2004).

One input parameter that can be assessed as an uncertainty to ensure robustness is the weights assigned to the objectives. To learn about model behavior, one of the most common approach is based on changing objective weights which is an input parameter (Chen and co-authors, 2009). Weight sensitivity analysis allows the designer to evaluate the importance of different design alternatives (e.g. costly high efficiency design or inexpensive low efficiency design) in line of subjectively weighted decision objectives (Li and co-authors, 2006).

In the decision making process, different stakeholders having different perspectives need strategies that results meeting all decision participants (Feick and co-authors, 2004). To model decision especially in goal programming, the major challenge is in the determination of the weights to assign to the deviations in the objective function (deviation function) (Neely and co-authors, 1980). Different method has been used for weight sensitivity such as pairwise comparison to determine set of weights for the goal programming model (Gass, 1986; Kahraman and co-authors, 2008; Li and co-authors, 2009; Wey and co-authors, 2007), penalty structures (Chang and co-authors, 2009; Jones and co-authors, 1995), and the Promethee method (Martel and co-authors, 1990). Kettani (Kettani and co-authors, 2004) have mentioned about two weighting components to be normalizing component and preferential component which reflect decision maker's preference structure. In this thesis, weight is used to reflect preferential component of the weighting term used in the compromise DSP. Perhaps the most critical shortcoming of weight sensitivity analysis found in the literature is lack of visualization which facilitates rapid adjustment in decision making when appropriate.



In the weight sensitivity analysis of the solution space exploration method proposed in Chapter 3, the need for identifying desired solutions that satisfies different goals is considered, the need for compromise and satisficing is recognized, a tool for managing preferences of different groups of decision makers is provided, and a mechanism to visualize and negotiate sound solutions is proposed. The outcome of using the method is set of weights associated with each deviation variable that guarantees the desired solutions of all the goals. The effect is not only from the value of the objective (goal) but also from the changing the weight of the deviation variables.

Another important design factor that can be affected by input variations is design constraints. To account for variation associated with the constraints in traditional design, past experiment-based experiences were used to define a safety factor instead of dealing with the ideal case. This is done to insure extra capacity of the system in presence of uncertainty. However there is not a straightforward method to properly define the safety factor (Yao and co-authors, 2011). Larger safety factor causes over capacity in the solution which results giving up of the system performance, on the other hand lower safety factor leads to risk on system reliability. To overcome the limitations dealing with the aforementioned traditional methods, constraints sensitivity analysis of the proposed method on solution space exploration is presented.

The impact of the variations in the constraints is on feasibility robustness of the design shown in Figure 1.2. Robust design which is first proposed by Taguchi (Taguchi and co-authors, 1993), is a method to improve the quality of a product by reducing the effect of the variations without eliminating the cause.

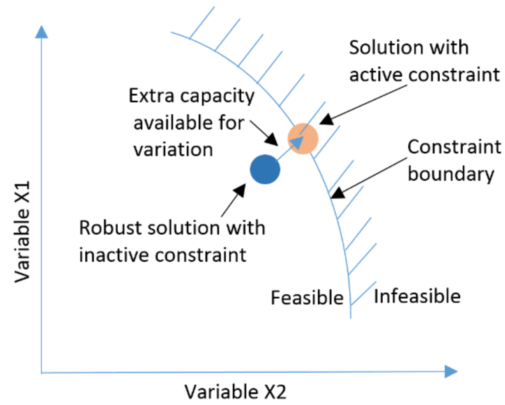
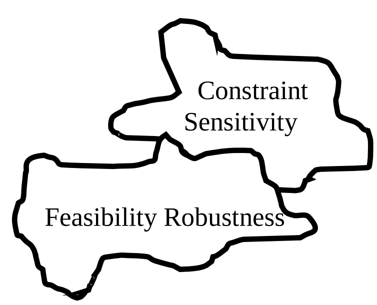
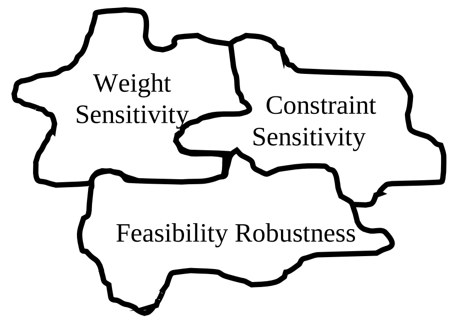


Figure 1.2: Feasibility robustness

Chen has expanded on Taguchi method through Robust Concept Exploration Method (RCEM) (Chen and co-authors, 1997b). RCEM brings robustness to the solution from variations in controllable (control factor) and uncontrollable (noise factor) parameters. However, those variations might also effect feasibility robustness through constraints violation. Therefore, a significant step in post solution analysis is constraint sensitivity measurements to ensure feasibility robustness (Li and co-authors, 2006). Alternative methods have been used in feasibility robustness issue such as the probabilistic feasibility analysis (Eggert, 1991), the moment matching method (Parkinson and co-authors, 1993), the worst case analysis (Parkinson and co-authors, 1993; Sundaresan and co-authors, 1995), the method of corner space evaluation (Sundaresan and co-authors, 1995), the variation patterns method (Yu and co-authors, 1998), and design indices consideration (Choi and co-authors, 2008a; Li and co-authors, 2006).



In the constraint sensitivity analysis of the solution space exploration method proposed in Chapter 3, the need for identifying active and inactive constraints is considered, the need for identifying and analyzing extra available capacity of each constraint for different solutions is recognized, and the need for incorporating feasibility robustness to the constraints with zero or limited capacity is addressed.



The highlight of the method proposed in this thesis which is not found in the literature is the connection between the three main aspects: weight sensitivity analysis, constraints sensitivity analysis and feasibility robustness. In the solution space exploration method proposed in Chapter 3, first desired solutions are found through weight sensitivity analysis then design constraints of those solutions are explored and analyzed to incorporate and ensure feasibility robustness in face of variations. In this thesis, the focus is on incorporating and testing robustness through solution space exploration to support a designer in the process of decision making.

In the next section, a framework including decision-based design and Decision Support Problem Technique is outlined as foundations for solution space exploration.

1.2 Foundations for Solution Space Exploration

There are many different approaches to model reality and many design and exploration methods can be applied to them, but the question is: *what is at the center of all these model-based design and exploration methods, processes, and procedures?* The answer is the human being. A human as a designer is at the center of decision making who uses those processes and methods to decide which variable settings are best, which design parameters to 'tweak', which concepts are most-likely-to succeed, etc.

Development of design methods and procedures, in general, provides attention directing tools to improve human judgment to make educated and knowledge-based decision. Computers and processes are capabilities to increase designer ability, and are often utilized to support designers in designing complex engineered systems such as aircraft. In mechanical engineering in particular, the important role of designer is increasingly highlighted as a key element in the development of design methods which facilitates design, and improve concurrency in the process. Suh, Whitney and Finger are the examples who emphasis this notion (Finger, 1990; Suh, 1990; Whitney and co-authors, 1988).

Therefore the foundation to design is in decision making and human judgment which provides the framework for development of solution space exploration, namely, Decision-Based Design.

1.2.1 Decision-Based Design

The common element in design and manufacturing processes is decision making; and that is the reason Decision-Based Design is developed. Decision-Based Design (DBD) is based on the notion that the principal role of a designer is to make decisions (Mistree and co-authors, 1990a; Mistree and co-authors, 1989; Mistree and co-authors, 1990b; Mistree and co-authors, 1993b). Design is a matter of making rational decisions about the available alternatives that fulfills one’s preference (Bloebaum and co-authors, 2010). Moreover others also thought of design as a decision making process (De Neufville, 1990; Hazelrigg, 1998; Sage, 1977; Tribus, 2013). Accepting this role of a designer provides a starting point for developing design methods based on paradigms that spring from the perspective of decisions made by designers that may employ computers as opposed to the perspective that computers are in the core of design. The role of a decision maker is to bridge the gap between the idea and reality using the information from wide range of sources and disciplines. Decisions have two components: domain-dependent and domain-independent, however they are both controlled by features of the design of physical engineering systems. Decision characteristics are outlined as:

- Decisions in design are invariably multileveled and multidimensional in nature.
- Decisions involve information that comes from different sources and disciplines.
- Decisions are governed by multiple measures of merit and performance.
- All the information required to make a decision may not be available.
- Some of the information used in making a decision may be hard (analysis-based) and some information may be soft (insight-based).
- The problem for which a decision is being made is invariably loosely defined and open. Virtually none of the decisions are characterized by a singular, unique solution. The decision solutions are less than optimal and are called satisficing solutions.

Decision-Based Design can be implemented in variety of forms, one of which is the Decision Support Problem (DSP) Technique which is outlined in the next section.

1.2.2 Frame of Reference: The Decision Support Problem Technique

The Decision Support Problem Technique (Mistree and co-authors, 1989) is developed by Mistree and co-authors to support human judgment in designing systems that can be manufactured, maintained, and retired. There are three principal components involved in DSP Technique: a design philosophy expressed in terms of paradigms, an approach for identifying and formulating Decision Support Problems, and the software necessary for solution. These components are embodied in part by the following:

- Methods for modeling, evaluating and improving design processes (Mistree and co-authors, 1990b)
- A formal structure for representing and formulating decisions as Decision Support Problems (DSPs) (Mistree and co-authors, 1991a)
- Computer software for **D**ecision **S**upport **i**n **D**esigning **E**ngineering **S**ystems, DSIDES, which solves Decision Support Problems (Mistree and co-authors, 1993a)
- A holistic computer environment that fosters concurrent engineering called the DSP Workbook (Muster and co-authors, 1989).

Two phases of implementation are involved in DSP Technique: Phase I (meta-design) and Phase II (design). During meta-design, the design process itself is designed wherein the problem is partitioned into its elemental Decision Support Problems (DSPs) and a plan of execution is devised. In Phase II, the design process is implemented and the DSPs identified in Phase I are formulated, solved, and validated.

Decision Support Problems provide a means for modeling decisions encountered in design, and the domain specific mathematical models that can be implemented on a computer are called *templates*.

Multiple objectives (goals), quantified using analysis-based 'hard' and insight-based 'soft' information, can be modeled in the DSPs. For physical world systems, all of the information for modeling systems comprehensively and accurately in the early stages of the project, may not be available. Therefore, the solution to the problem, even if one is obtained using optimization techniques, cannot be optimum with respect to the physical world due to the inherent approximations in the model. However, this solution can be used to support a designer's quest for a superior solution. In a computer-assisted environment this support is provided in the form of optimal solutions for DSPs. Formulation and solution of DSPs provide a means for making the following types of decisions:

- *Selection* - the indication of a preference, based on multiple attributes, for one among several alternatives (Kuppuraju and co-authors, 1985; Mistree and co-authors, 1994a; Mistree and co-authors, 1988).
- *Compromise* - the improvement of an alternative through modification (Fuchs and co-authors, 1990; Marinopoulos and co-authors, 1987; Mistree and co-authors, 1993a; Vadde and co-authors, 1994).
- *Coupled or hierarchical* - decisions that are linked together; selection/selection, compromise/compromise and selection/compromise decisions may be coupled (Bascaran, 1990; Bascaran and co-authors, 1989; Karandikar, 1989; Smith, 1985).

These types of decisions may also be implemented in an uncertain or conditional environment where decisions account for the risk and uncertainty of the outcome (Allen and co-authors, 1992; Allen and co-authors, 1989; Bhattacharya, 1990; Zhou, 1988), or by a rule base or heuristic approach where reasoning and rules of thumb are used (Kamal, 1990). Applications of DSPs include the design of ships, damage tolerant structural and mechanical systems, the design of aircraft, mechanisms, thermal energy systems, design using composite materials and data compression. A detailed set of references to these applications is presented in (Mistree and co-authors, 1990a). These constructs have been used to study interaction between design and manufacture (Karandikar, 1989) and between various events in the conceptual phase of the design process (Bascaran, 1990).

A critical review of the compromise DSP is provided in Section 2.1.2, and usefulness of the cDSP in solution space exploration is discussed in Section 2.1.3.

In previous sections up to this point the foundation for solution space exploration in realization of model-based engineered systems is outlined. In the remaining sections, several research questions for investigation are presented along with the objective for this thesis. Following Section 1.3 is an organization of the thesis.

1.3 Research Questions and Objectives

In the previous sections, different aspects of solution space exploration are addressed and a framework for exploration approach is discussed, i.e., Decision-Based Design and the Decision Support Problem Technique. The principal question for this thesis, namely,

> *What is needed in model-based system realization to increase design knowledge in order to support decision making given that the models are not complete and accurate?*

has already begun to be addressed. Exploring the solution space from different perspectives provides design knowledge and brings confidence to decision makers. But, in doing so *what are the characteristics of solution space exploration, i.e.,*

> *How is solution space explored so as to allow system realization team to obtain useful knowledge in the process of decision making?*

Different aspects of solution space exploration, e.g., design preference exploration through weight sensitivity analysis, design constraint exploration through constraints sensitivity analysis, and incorporating feasibility robustness are described which enable designer to make relatively robust decisions. Exploring design tradeoffs is also addressed by considering the compromise DSP. But, now the question is how these aspects are conducted and incorporated in the solution space exploration. Additional research questions for investigation are posed in the next section.

1.3.1 Research Questions to be Investigated

The following research/motivational questions are to be considered throughout this thesis. The reasoning behind each is as follows.

1. How can a design decision be modeled? Modeling is an important factor when it comes to decision making. Rather than making expensive prototypes and run complicated practical-world experiments, designers often formulate models and test different scenarios to improve judgment in the process of decision making. Although the mathematical models cannot represent the exact reality, however exercising and exploring those models from different aspects can bring insight to support human as a decision maker. The compromise DSP is used in this thesis to formulate different design examples in Chapter 4, 5 and 6.

2. What is the process to explore design tradeoffs in model-based system design? Conflicting design goals are always of paramount concern to designers as decision makers. There are different ways in which design decisions associated with design goals can be modeled. Using the compromise DSP, two different approaches are taken to explore design tradeoffs: goal ordering and weighted sum. Both approaches are explored in this thesis through different design examples. The process and the mathematics behind each is proposed in Chapter 3. Design priorities are explored through goal ordering of a small power plan presented in Chapter 4 to demonstrate and visualize the compromise that the decision maker should deal with. In Chapter 5 and 6, design tradeoffs are explored through weighted sum approach using two different examples.

3. What is the process to identify design preferences that guarantees a desired solution in which different and conflicting goals are satisfied? In the weighted sum approach of formulating deviation function, weights assigned to different deviation variables represent designer preferences. Design preferences are explored through solution space visualization and weight sensitivity analysis to identify goals that are especially sensitive to weight changes, identify weight ranges that satisfy each goal independently, and also to identify weight range that guarantee common desired solutions that satisfy all the goals. Visualization of the solution space makes it easier for a decision maker to understand the tradeoffs and provides a mechanism to explore the decision problem by learning how changes in weights affect the solution. The process underlying this part of the method is discussed in Chapter 3 and tested through design examples in Chapter 5 and 6.

4. What kinds of modification are needed if desired solutions that satisfy different and conflicting goal preferences are not found? There might be cases where the goals are in high conflicts that identifying common desired solutions to meet all the goals is not possible. In the other word, there is no overlap between solution spaces of different goals. In such cases the model should be modified through changing the targets associated with each goal. Using the compromise DSP, one input parameter is the target value of each goal which directly affect the solutions. By changing the target value of one or more goals in a sense a designer is compromising to obtain the common desired solutions which is insensitive to changes of design preferences.

5. What is the process to explore feasibility robustness under the effect of variations? Feasibility robustness is a concept related to design constraints and any variations that cause changes in boundary of feasible region. Feasibility robustness can be explored through constraint sensitivity analysis to identify desired boundary solutions. This process is done by identifying active and inactive constraints and exploring available extra capacity of the desired solutions in face of variations. The process involved in this part of the method is presented in Chapter 3, and tested through design examples in Chapter 5 and 6.

6. How can design constraint exploration be beneficial to incorporate feasibility robustness in the model? Conducting constraints sensitivity analysis of the desired solutions provide insight to the designer to incorporate feasibility robustness in the design constraints with limited capacity. Solutions with zero or limited capacity are subject to modification in this process. The modification is done by adding uncertainty in the constraints formulation of those constraints. This is done to ensure feasibility robustness of all desired solutions. This process is discussed in Chapter 3, and tested through a design example in Chapter 6.

7. How can design selections be modeled and explored? According to DSP, one of the main components of decision making is selection. Selection is about choosing from already exist alternatives e.g., from a catalog, however different attributes involved in each alternative can play a significant role in selection. In this thesis, selection DSP is adapted to formulate selection in design, and an example of a selection DSP is presented in Chapter 5.

The relevant sections for each question are outlined by chapter in Table 1.1. For example, in Section 4.2, three questions are investigated, namely, how to explore tradeoffs, how to explore design preferences, and how to modify model if desired solutions to meet all goals are not found.

As each of these questions is answered, a better understanding of the principal research question is achieved along with a better understanding of the philosophy behind and motivation for solution space exploration in model-based realization of engineered systems (refer to Section 1.1). Remember, as George Box wrote, “essentially, all models are wrong, but some are useful”. Accepting the notion that models are not representing the exact reality, it comes to the case for exploration in order to bring insight to the decision maker. Based on this, the objective for this thesis can be formulated and discussed in the next section.

Table 1.1: Relevant sections for investigating thesis research questions

Relevant Sections:	Chapter 2				Chapter 3				Chapter 4		Chapter 5			Chapter 6	
Intellectual Questions	2.1	2.2	2.3	2.4	3.1	3.2	3.3	3.4	4.1	4.2	5.1	5.2	5.3	6.1	6.2
How can an engineered system be modeled?	√	√	√	√	√	√	√		√		√			√	
What is the process to explore design tradeoffs in model-based system design?	√			√		√	√			√		√			√
What is the process to identify design preferences that guarantees a desired solution in which different and conflicting objectives are satisfied?	√			√			√			√		√			√
What kinds of modification are needed if desired solutions that satisfy different and conflicting objective preferences are not found?	√			√			√			√		√			√
What is the process to explore feasibility robustness under the effect of variations?	√							√				√			√
How can design constraint exploration be beneficial to incorporate feasibility robustness in the model?		√		√				√				√			√
What is the process to explore design selections in model-based system design?					√								√		

1.3.2 Objective for the Thesis

The primary objective for this thesis is to develop a method to explore the solution space in model-based realization of engineered systems. This method is developed to increase design knowledge in order to support designer as a decision maker by providing valuable information related to design. This is done through use of different constructs and tools such as the compromise DSP, RSM (Response Surface Method) and DSIDES. In particular, robust design techniques are employed to obtain relatively robust solutions insensitive to variations. The method is then tested through the use of different example problems, namely, the design of small power plant, shell and tube heat exchanger, and continuous casting of steel. These design examples, presented in Chapters 4, 5 and 6, provide an opportunity to demonstrate the use of several tools and constructs which are suitable for solution space exploration. Motivation and elaboration of the example problems including problem statement, design variables, goals, constraints, etc. are presented in Sections 4.1, 5.1 and 6.1 related to each example. Although the focus and examples for this thesis are in the field of engineering, the proposed method is domain independent and extensible that can be used in any field where mathematical models are used such as economy, psychology, etc.

In general, the objective for this thesis is to propose a method which involves:

- Exploring design priorities and tradeoffs through goal ordering,
- Explore design preferences through weight sensitivity analysis,
- Explore design constraints through constraints sensitivity analysis,
- Incorporating feasibility robustness

All this is done to provide a tool to support designer in the process of decision making. To validate and verify the method on solution space exploration, Validation Square is adapted and discussed in the next section.

1.4 Validation Strategy – Validation Square

Usually, engineering research is based on formal, quantitative validation through logical induction and/or deduction. However, this approach is problematic for the validation of engineering design methods because a method is not only based on mathematical modeling but also on subjective statements. The Validation Square which is published by (Seepersad and co-authors, 2006b) is a framework for validating design methods based on a relativistic notion of epistemology in which “knowledge validation becomes a process of building confidence in its usefulness with respect to a purpose” and is utilized in this thesis. In this framework, usefulness of a design method is associated with whether the method provides design solutions correctly (effectiveness), and whether it provides design solutions efficiently with acceptable operational performance. The Validation Square consists of two main constructs: structural validity and performance validity, and these are shown in Figure 1.3.

Both structural and performance validity is further divided into theoretical and empirical validity which leads to the four quadrants discussed in the following sections.

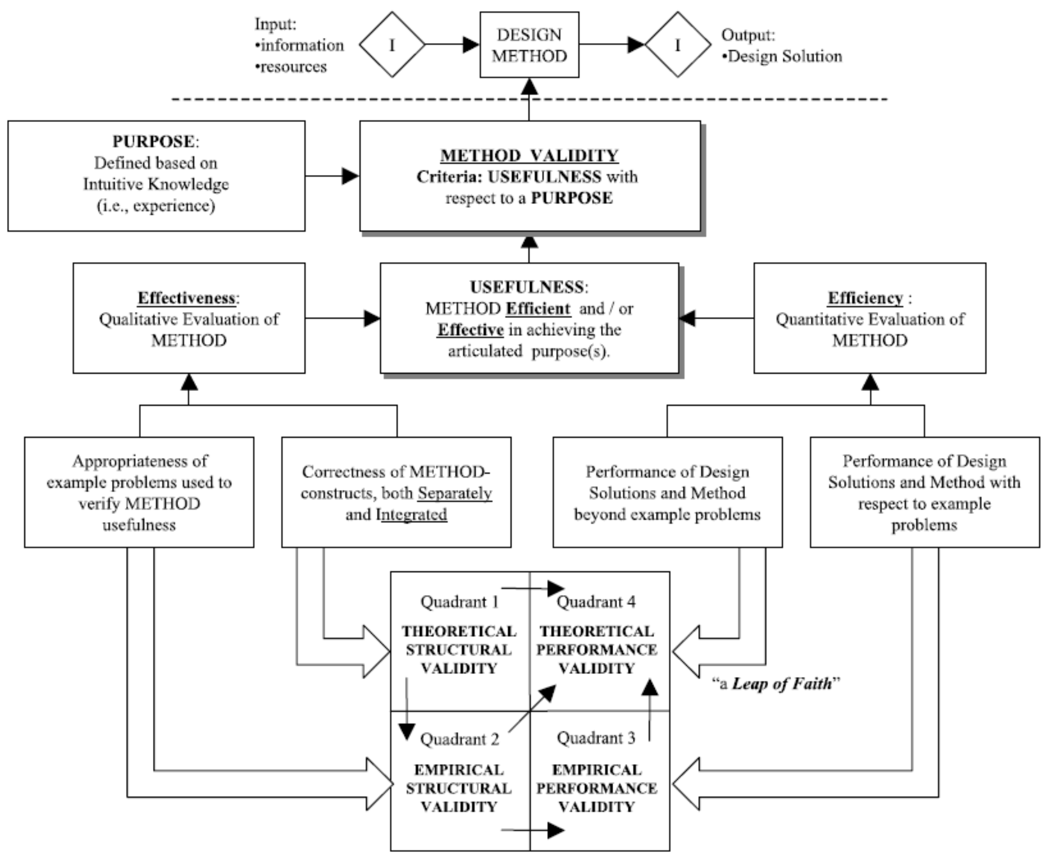


Figure 1.3: The Validation Square (Seepersad and co-authors, 2006b)

1.4.1 Structural Validation – A Qualitative Process

Being effective implies three steps. It implies: (1) accepting the individual constructs constituting the method; (2) accepting the internal consistency of the way the constructs are put together in the method; and (3) accepting the appropriateness of the example problems that will be used to verify the performance of the method.

<u>Quadrant 1: Theoretical Structural Validity (TSV)</u>

Theoretical structural validity involves Steps (1) and (2): accepting the individual constructs constituting the method; and accepting the internal consistency of the way the constructs are put together in the method. This can be achieved by searching and referencing to literature related to the single constructs, which are already validated elsewhere. Furthermore, the correctness of the information flow throughout the entire design method has to be demonstrated. For this step a flow chart may be useful. To ease the comparison of the theoretical structure and the expected outcomes to the intended properties of the design method, a requirements list should be formulated.

In this thesis, the theoretical structural validity is related to Chapter 2, where different tools and constructs used in development of the method are validated through literature, and Chapter 3, where the method for solution space exploration is proposed through the flowchart involving the steps.

<u>Quadrant 2: Empirical Structural Validity (ESV)</u>

Empirical structural validity involves Step (3) accepting the appropriateness of the example problems that will be used to verify the performance of the method. This means, it has to be shown that the examples are good representations of design problems, for which the method is designed and that the associated data can be used to support a conclusion.

In this thesis, the empirical structural validity is illustrated in Chapters 4, 5 and 6, where three example problems for designing a small power plant, a shell and tube heat exchanger and continuous casting of steel are developed using the tools and construct validated in Chapter 2. The appropriateness of the chosen example problem is illustrated in Chapters 4, 5 and 6.

1.4.2 Performance Validation – A Quantitative Process

Efficiency implies three steps. It implies (4) accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s); (5) accepting that the achieved usefulness is linked to applying the method; and (6) accepting that the usefulness of the method is beyond the case studies.

Quadrant 3: Empirical Performance Validity (EPV)

Empirical performance validity is about showing the usefulness of the method for solving the example problems which includes Steps (4) and (5): accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s); accepting that the achieved usefulness is linked to applying the method. The results achieved using the design method has to be analyzed and assessed. The analysis should also include assessment of data with regard to internal consistency, for example multiple starting points and convergence in optimization exercises.

In this thesis, the empirical performance validity is shown in Chapters 4, 5 and 6 by implementing the steps proposed in the method and analyzing the results which are the outcome of using the method.

Quadrant 4: Theoretical Performance Validity (TPV)

Theoretical performance validity involves Step (6) accepting that the usefulness of the method is beyond the case studies; a “leap of faith” from the usefulness of the design method for the chosen example problems to the general validity of the method, which means building confidence in the generality of the method and accepting that the method is useful beyond the example problems. This can be supported by showing that the example problems are representative for a general class of engineering design problems as well as a final critical analysis of the entire validation process.

In this thesis, the theoretical performance validity is shown in Chapter 7, in which the general usefulness of the solution space exploration method presented in Chapter 3 is discussed. In Figure 1.4, the validation strategy of all 4 Quadrants is presented.

Validation Square is adapted in this thesis to validate and verify the solution space exploration method through various design examples discussed in different chapters. To outline what is covered in each chapter, the organization of the thesis is detailed in the next section.

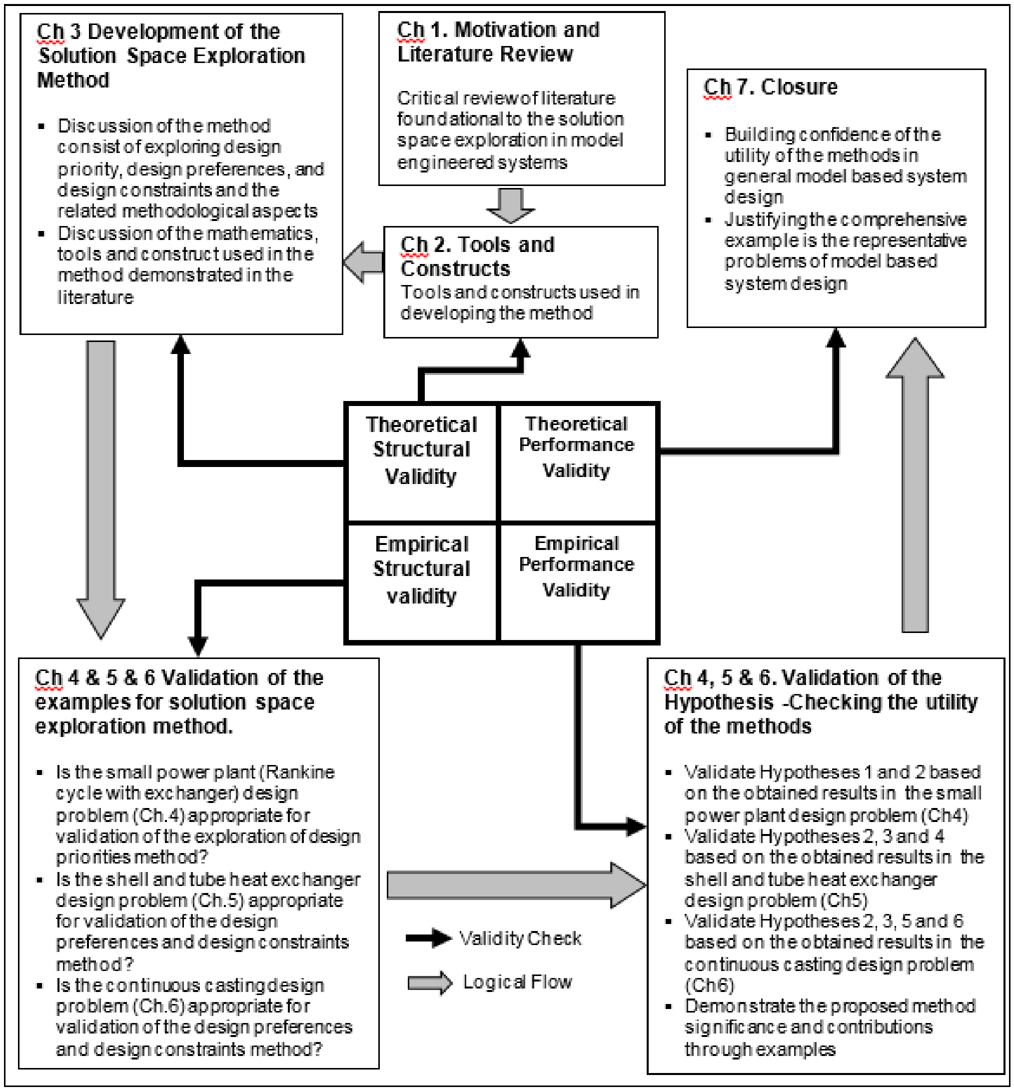


Figure 1.4: Validation strategy for this thesis

1.5 Organization of the Thesis

Chapter 1 is designed as an introduction to solution space exploration in model-based engineered systems. The intent is to discuss the importance of decision making in model-based engineered systems to set the stage for the remainder of this thesis. The background and related literature review is discussed in Section 1.1.2. In the next chapter, several mathematical tools and constructs for developing solution space exploration method are presented as shown in the thesis organization diagram in Figure

1.5. These tools and constructs are utilized due to their relevance to one or more research questions posted in 1.3.1. The compromise DSP is discussed in Section 2.1, robust design in Section 2.2, response surface models in Section 2.3 and DSIDES in Section 2.4.

The tools and constructs introduced in Chapter 2 are then employed to develop the method on solution space exploration proposed in Chapter 3. There are different parts involved in this method: in Section 3.1, exploring design selection and its connection to decision making is discussed, in Section 3.2, exploring design priorities and its connection to decision making is presented, in Section 3.3, exploring design preferences and its connection to decision making is explained, and in Section 3.4, exploring design constraints and its connection to decision making is described.

The method proposed in Chapter 3 is then tested through three different design examples. In Chapter 4, exploring design priorities through goal ordering is tested in designing a small power plant, namely, a Rankine cycle with an exchanger (small power plant). In Chapter 5, exploring design preferences and design constraints through weight sensitivity and constraints sensitivity analysis respectively is tested in designing shell and tube heat exchanger. Exploring design selection is also discussed in material selection of shell and tube heat exchanger in Chapter 5. In Chapter 6, a comprehensive example, namely, continuous casting of steel is modeled and its solution space is explored. Some of the tools and constructs such as RSM and robust design concept are specifically used in this chapter to increase design efficiency and bring robustness to the design.

In these three chapters, first the design example is introduced and the compromise DSP is formulated (Sections 4.1, 5.1 and 6.1), then the results captured from DSIDES, a computer software to solve a compromise DSP, and their implications are discussed.

In Chapter 7, the thesis is summarized and reviewed to determine if the objective is met. Finally, at the end of Chapter 7, possible future work is presented and relevant contributions from this thesis are outlined.

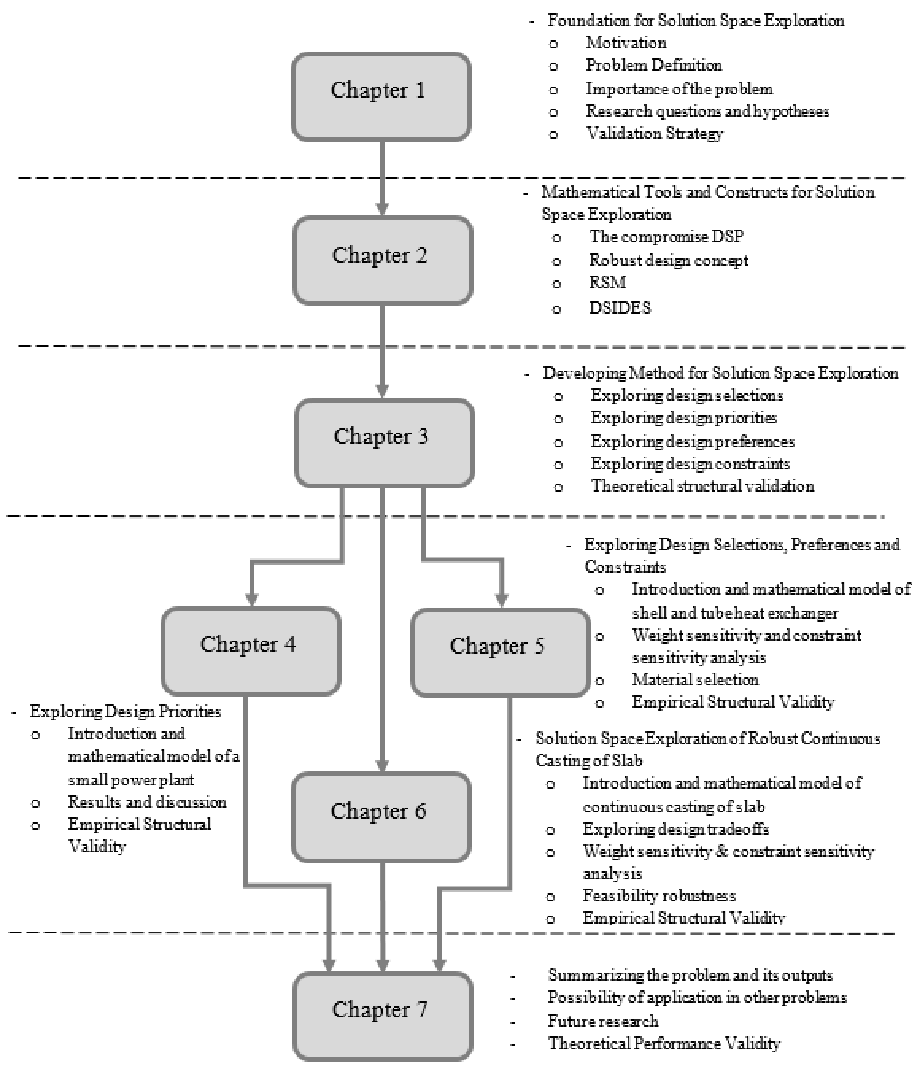


Figure 1.5: Organization of the thesis

CHAPTER 2 SOLUTION SPACE EXPLORATION: MATHEMATICAL TOOLS AND CONSTRUCTS

Having begun laying a foundation for solution space exploration in the previous chapter, several mathematical tools and concepts are presented in this chapter which are useful for developing the solution space exploration method. In this chapter mainly the first research question identified in Chapter 1 on *how can a design decision be modeled?* is addressed. This chapter begins in Section 2.1 with a description of the compromise Decision Support Problem (cDSP) which is a multi-objective decision model suitable for modeling any engineered systems. In Section 2.2, the concept of robust design under uncertainty is discussed to provide foundation for feasibility robustness incorporated into the compromise DSP in the proposed method in Chapter 3. As a means for increasing computational efficiency and increasing design knowledge, Response Surface Method (RSM) is discussed in Section 2.3. In section 2.4, DSIDES (Decision Support in the Design of Engineering Systems) is described as the computer environment for solving the compromise DSP.

2.1 The Compromise Decision Support Problem

The compromise DSP is a multi-objective decision model which is a hybrid formulation (Mistree and co-authors, 1993a). It incorporates concepts from both traditional Mathematical Programming and Goal Programming. The compromise DSP is used to find the values of design variables to satisfy a set of constraints and to achieve a set of conflicting goals. An important aspect of solution space exploration is to analyze the design constraints and tradeoffs between the conflicting goals as well as design preferences associated with those conflicting goals in order to support decision making. The compromise DSP is used to model such decisions since it is capable of handling constraints, goals, and multiple objectives (Mistree and co-authors, 1994). In particular, the compromise DSP offers the following capabilities:

- handle single-objective or multi-objectives
- use either preemptive or Archimedean formulation to formulate objectives
- generate feasible solutions more frequently
- quickly generate results for several different weighting schemes

The compromise DSP has been successfully used in designing aircraft (Marinopoulos and co-authors, 1987), thermal energy systems (Bascaran and co-authors, 1987; Fuchs and co-authors, 1990), mechanisms (Mudali, 1987), damage tolerant structural systems (Shupe and co-authors, 1987), ships (Mistree and co-authors, 1990c), and material composite design (Fuchs and co-authors, 1990). Formulating a compromise DSP is described in the next section, a critical review of DSPs is presented in Section 2.1.2 while its usefulness for exploring the solution space is discussed in Section 2.1.3.

2.1.1 The Compromise DSP: Mathematical and Word Formulations

The compromise Decision Support Problem, or cDSP, is a multi-objective decision model that facilitates the design process by providing a means for modeling the decisions that would be encountered (Mistree and co-authors, 1992). Mathematically, the compromise DSP is a domain-independent, multi-objective decision model which is a hybrid formulation by combing concepts from both standard mathematical programming and goal programming (Mistree and co-authors, 1993a). It works by modeling multiple quantified objectives so that a feasible solution space can be derived and used to aid the designer's decision (Mistree and co-authors, 1993). By doing so the compromise Decision Support Problem is an effective support for human judgment. It is defined and described in terms of complementary word- qualitative and math- qualitative formulation. There are four main key words to the compromise DSP: Given, Find, Satisfy, and Minimize.

The word formulation of the compromise Decision Support Problem is as follows:

Given

An alternative that is to be improved through modification.
Assumptions used to model the domain of interest.
The system parameters.
The goals for the design.

Find

The values of the independent *system variables* (they describe the attributes of an artifact).
The values of the *deviation variables* (they indicate the extent to which the goals are achieved).

Satisfy

The *system constraints* that must be satisfied for the solution to be feasible.
The *system goals* that must achieve a specified target value as much as possible.
The *upper and lower bounds* on the system variables.

Minimize

The *objective function, Z,* which is a measure of the deviation of the system performance from that implied by the set of goals and their associated priority levels or relative weights.

Figure 2.1: Compromise DSP word formulation

In Figure 2.1 a comparison between the standard single objective formulation and the compromise DSP for a two dimensional problem is shown. The feasible design space, or the space representing all feasible solutions, is similar in both traditional single objective formulation and the multi objective formulation used in the compromise DSP. This feasible design space is bounded by the system constraints and parameters of the system. In traditional single objective formulation there is a single objective function, Z, and the objective is to minimize it.

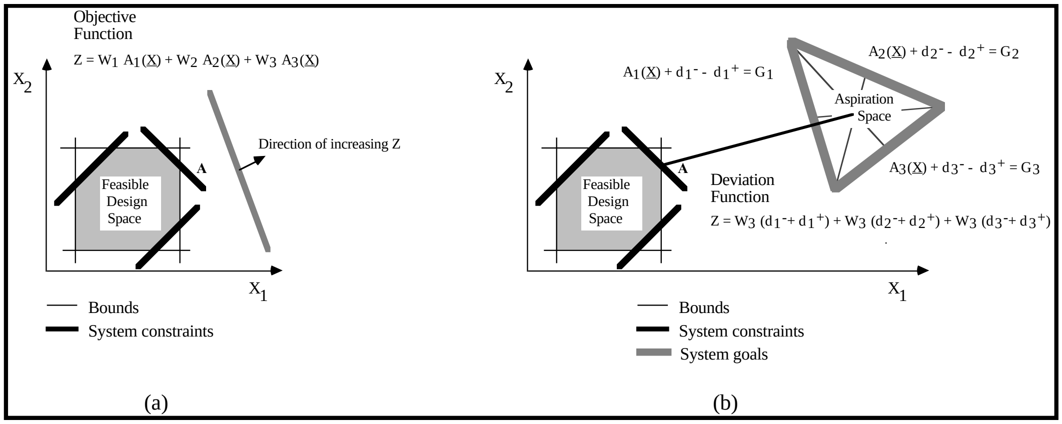


Figure 2.2: A single objective optimization problem and the multi-goal compromise DSP (Mistree and co-authors, 1990c)

In the compromise DSP, however, there is a set of system goals which define an aspiration space (see Figure 2.2b). The aspiration space represents the area of possible solutions, because while the constraints and parameters must be satisfied, the goals are achieved only to the extent possible. The tradeoff between what is desired (aspiration space) and what can be achieved (the design space) is modeled by the solution which is found by minimizing the deviation function. The mathematical formulation of the compromise DSP is summarized in the following figure.

The aspiration of the designer is modeled by a set of system goals. It relates the actual attainment possible, $A_i(\mathbf{X})$, for the i^{th} goal to the targeted value of the goal G_i. There will be two deviation variables for each goal; one determines the extent that the goal under achieved its targeted value, d_i^-, and the other determines the extent that it over achieved it, d_i^+. Consequently, at least one of variables in each goal function will be zero which is ensured by the product constraint, $d_i^- * d_i^+ = 0$.

Given

An alternative to be improved through modification.

Assumptions used to model the domain of interest.

The system parameters:

n	number of system variables
$p+q$	number of system constraints
p	equality constraints
q	Inequality constraints
m	number of system goals
$g_i(\underline{X})$	system constraint function:

$$g_i(\underline{X}) = C_i(\underline{X}) - D_i(\underline{X})$$

$f_k(d_i)$ function of deviation variables to be minimized at priority level k for the preemptive case.

Find

X_i $\quad i = 1, \ldots, n$

d_i^-, d_i^+ $\quad i = 1, \ldots, m$

Satisfy

System constraints (linear, nonlinear)

$g_i(\underline{X}) = 0;$ $\quad i = 1, \ldots, p$

$g_i(\underline{X}) \geq 0;$ $\quad i = p+1, \ldots, p+q$

System goals (linear, nonlinear)

$A_i(\underline{X}) + d_i^- - d_i^+ = G_i;$ $\quad i = 1, \ldots, m$

Bounds

$X_i^{min} \leq X_i \leq X_i^{max};$ $\quad i = 1, \ldots, n$

$d_i^-, d_i^+ \geq 0;$ $\quad i = 1, \ldots, m$

$d_i^- \cdot d_i^+ = 0;$ $\quad i = 1, \ldots, m$

Minimize

Archimedean deviation function (weighted sum)

$\mathbf{Z}(d^-, d^+) = \sum_{i=1}^{m}(W_i d_i^- + W_i d_i^+)$ $\quad i =$ number of goals

Figure 2.3: Mathematical form of a compromise DSP

Additionally, the deviation variables are always positive. The value of the deviation variables is determined by the extent that the achievement function, $A_i(\mathbf{X})$, reaches its targeted value, G_i, and the achievement function is dependent on the system variables,

$\mathbf{X}$ (Mistree and co-authors, 1993a). When maximizing the achievement use the following equation.

$$[A_i(\mathbf{X}) / G_i] + d_i^- - d_i^+ = 1 \qquad \text{Eq. 2.1}$$

And, when minimizing the achievement use the following equation.

$$[G_i / A_i(\mathbf{X})] + d_i^- - d_i^+ = 1 \qquad \text{Eq. 2.2}$$

The objective of the compromise DSP is to minimize a function that is expressed using only the deviation variables (Mistree and co-authors, 1993a). This function is known as the deviation function. The deviation function is a representation of the deviation between the feasible solution space and the aspiration space. As previously described the range of the deviation variables depends on the goals themselves. There are two types of deviation function in the compromise DSP, namely, preemptive and Archimedean formulation. In the preemptive formulation goals must be satisfied in the order specified by the designer and have the advantage of not requiring of assigning weights. In the Archimedean formulation, however, weights for each of the objectives/goals, must be determined using methods such as pair-wise comparison or relative weighting.

The level of importance affiliated with achieving each goal varies for a designer. Hence, the goals are assigned weights, W_i, in order to effect a solution on the basis of a designer's preference (Mistree and co-authors, 1993a). These weights are usually normalized so that the sum is one. First, a preemptive form of the deviation function is formulated, as shown in Figure 2.3, and lexicographically minimized. Where k is the number of priority levels, or weights and the deviation functions, f_i (d_i^- , d_i^+), of lower priority levels are only minimized if those of higher levels will not be negatively affected. After this preemptive formulation, a deeper understanding of the solution space and the regions of interest is obtained and the Archimedean weighted sum can be formulated. The general form of the deviation function, for m system goals, in the Archimedean form is as follows.

$$Z(d^-,d^+) = \Sigma(W_i^- d_i^- + W_i^+ d_i^+) \quad i = 1, 2, \ldots, m \qquad \sum W_i = 1, W_i \geq 0 \qquad \text{Eq. 2.3}$$

Detail explanation of the two types of deviation functions is provided in Chapter 3.

2.1.2 Critical Review of the Decision Support Problem Construct

Within the concept of multiple criteria decision making there are two decision categories, referred to by (Sen and co-authors, 2012) as selection and synthesis, corresponding to selection and compromise in the Decision Support Problem Technique.

Selection is referred to multiple attribute decision-making (MADM) and involves the selection between set of alternatives from a catalogue based on prioritized attributes of the alternatives. Synthesis is referred to multiple objective decision-making (MODM), which is defined as the synthesis of an alternative or alternatives on the basis of prioritized objectives. Objectives in this context are the “goals” in the formulation of compromise Decision Support Problems.

Any complex design can be represented through modelling a network of DSPs (compromise and selection) (Mistree and co-authors, 1993; Mistree and co-authors, 1991b). Being able to work with the complexity of these decision networks is also a foundational construct as are the axioms of the approach as detailed in References. Typically, however, problems can be modeled with no more than three DSPs that are coupled together (e.g., coupled selection/selection/compromise, selection/compromise/compromise, etc) (Mistree and co-authors, 1993; Mistree and co-authors, 1991b).

Reported applications of this approach include the design of ships, damage tolerant structural and mechanical systems, design of aircraft, mechanisms, thermal energy systems, composite materials and the concurrent design of multi-scale, multi-functional materials and products. A detailed set of early references to these applications is presented in (Mistree and co-authors, 1990b). Key applications more recently span specification development (Chen and co-authors, 1999; Lewis and co-authors, 1999), robust design (Allen and co-authors, 2006; Chen and co-authors, 1997a; Chen and co-authors, 1996; Seepersad and co-authors, 2006a), product families (Simpson and co-authors, 1999; Simpson and co-authors, 2001a; Simpson and co-authors, 2001c), the integrated realization of materials and products (Choi and co-authors, 2008a; Choi and co-authors, 2008b; McDowell and co-authors, 2009; Panchal and co-authors, 2007; Seepersad and co-authors, 2008), and a variety of mechanical systems (Chen and co-authors, 1994; Hernamdez and co-authors, 2000; Koch and co-authors, 1998; Sinha and co-authors, 2013).

Once a compromise DSP is formulated, DSIDES, with its operations research tools (traditionally an adaptive sequential linear programming algorithm delivering vertex solutions), is used to deduce “model conclusions” (Mistree and co-authors, 1992). This process may be iterative in nature and demand significant justification especially where conflict exist. It thus becomes imperative to be able to describe and understand the design and aspiration spaces and to be able to explore these spaces.

In reflecting on the compromise DSP, parallels with the "demands" and "wishes" of Pahl and Bietz (Pahl and co-authors, 2007) can be drawn. The demands are met by satisfaction of the DSP constraints and bounds and the wishes are represented by the goals. Collectively, the constraints and bounds define the feasible design space and the goals define the aspiration space. The feasible and aspiration spaces together then form the solution space. Note that a selection DSP can be formulated as a compromise DSP (Bascaran and co-authors, 1989) where the key words "Given", "Find", "Satisfy" and "Minimize" are used.

The advantages of the compromise DSP as a decision construct lie in the support of context and structure for decisions as well as domain independence. DSPs that are solved using DSIDES facilitate the exploration of design and solution space with regard to design requirements and designer priorities/preferences (through use of Archimedean and preemptive formulation) to support decision making. DSPs can be formulated with limited information quickly to be used at any point along a design timeline. Using DSPs, the emphasis is placed on providing viewpoints leading to decisions in which design intent is captured. Post solution sensitivity analysis is also required to bring insight to the designer in face of variations.

2.1.3 Usefulness of Compromise DSPs in Solution Space Exploration

The compromise DSP offers several advantages for exploring the solution space from different perspectives. As mentioned in Section 2.1.2, it can be used to model multiple tradeoffs and decisions, for example (Mistree and co-authors, 1994) which is needed to explore design decisions. Furthermore, a design and how it can changes under different design scenarios can be explored and evaluated by exercising the compromise DSP in variety of ways. Different form of deviation function exist in compromise DSP provides tools to explore the design decision throughout the design time line as design knowledge in increased. Preemptive form is more useful in early stages of design to explore the tradeoffs between the goals at different levels of priorities. Later when design knowledge is increased Archimedean form can be utilized to explore design priorities and study weight sensitivity. On the other hand exploring the constraints are possible throughout the design timeline to gain insight about feasibility robustness and to modify the design when needed. XPLORE which is a DSIDES module discussed in next section, is a quick way of viewing design space and drawing insight about the design tradeoffs. Such exploration using compromise DSP increases design knowledge given that the analysis models are incomplete, inaccurate and with different fidelities. Moreover XPLORE provides a broad view of the whole design space with information about the interesting and satisficing regions to be further explored. In Chapter 4 and 5 an effective use of this module is demonstrated in exploring design priorities and design preferences respectively.

There are two choices of modeling the physical world: either use the exact system equations to predict and explore system behavior, or, use some kind of heuristics to generate approximation of the system behavior. The second approach is used dealing with complex systems when computation is hard or impossible to perform accurate analysis. The solutions found using heuristics are ‘good enough’ or *satisficing* that can be accepted but are not exact or optimal. "In a perfect and stable world, with perfect knowledge, designers could establish optimum designs for all their individual product and process requirements" (Chen and co-authors, 1996). More discussion about robust design concept is provided in Section 2.2. Example problem used in Chapters 4 and 5 are modeled using system equations, however, model used in Chapter 6 is formulated using both response surface modeling, which is approximation of the system behavior, and system equations.

Optimizing and satisficing are different from what they consider to be good for the design in the context of entire design time line. The optimization philosophy is focused on finding the best solution which exists in each stage of design, the satisficing philosophy on the other hand suggests to keep each stage somewhat open to account for the possible concerns that may occur. These concerns comes from the incompleteness and inaccuracy of the models that manifests as uncertainties, particularly in the early stages of design. Figure 2.4[2] is shown to clarify what can happen with an optimum solution in face of uncertainties.

Optimization is based on considering that the models are complete and accurate. With optimum solution of a system, any variation that arise in the design process throughout the design timeline may shift the design so that the optimum solution is not useful for the design as a whole.

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[2] Figures 2.4 and 2.5 were drawn by David Craig in *ME8104: Designing Open Engineering Systems* given at the Georgia Institute of Technology in the 1995 winter quarter.

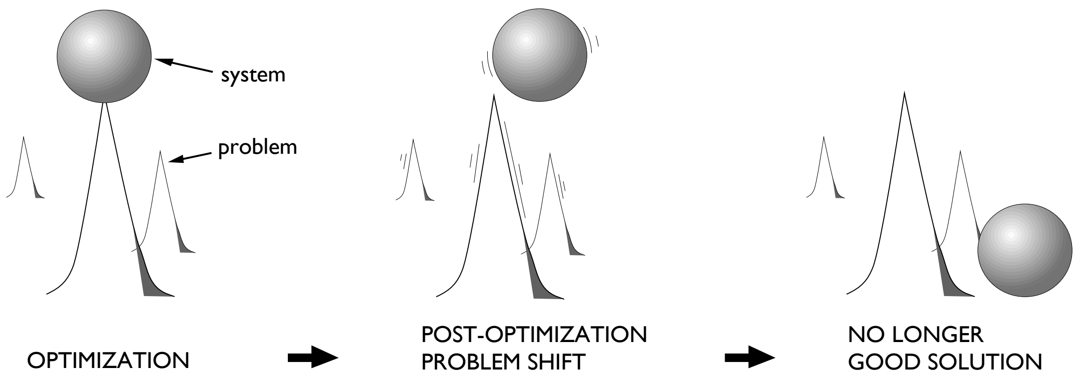


Figure 2.4: What can happen when a rigid optimal solution is prescribed

To overcome this limitation, satisficing solution should be considered which is robust to the variations that might happen in the problem during design timeline. Figure 2.5 is shown to clarify the notion of satisficing solution.

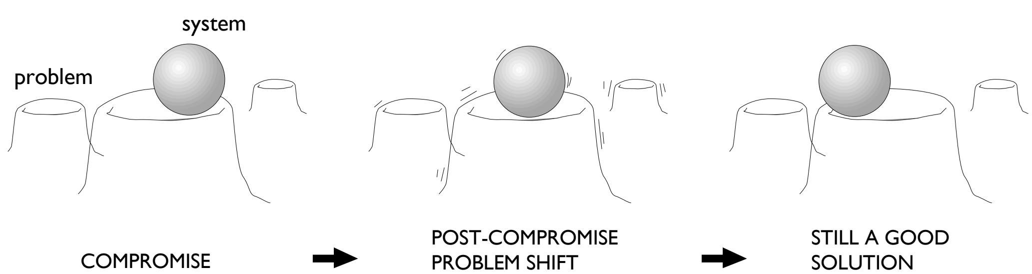


Figure 2.5: A satisficing solution with respect to the evolution of the problem

The usefulness of compromise DSP in solution space exploration is in model based system design when the analysis models are incomplete and inaccurate particularly in the early stages of design that the information is limited. The compromise DSP provides the capability of finding ‘good enough’ solutions that can be improved in the design process when the information is improved through exploration and analysis.

The compromise DSP is particularized for the three example problems used in Chapters 4, 5 and 6, namely, small power plant, shell and tube heat exchanger and continuous casting of steel respectively. To formulate the compromise DSP for continuous casting of steel, feasibility robustness is considered and response surface models are used. The concept on robust design and response surface models are discussed in the next section and Section 2.3 respectively.

2.2 Robust Design under Uncertainty

There are two primary approaches available in managing variations in design. One approach is reducing the uncertainty itself, and the other is designing a system to be insensitive to uncertainty without reducing or eliminating it.

Reducing uncertainty is feasible when a designer has large amounts of data or complete knowledge of a system. Kennedy employ a Gaussian Process model, known as kriging in spatial statistics, for fitting simple model data. They assume the model for detailed simulation data is a combination of the fitted simple model, a linear scale term, and error terms. The linear scale is assumed as an unknown constant and error terms are defined in another Gaussian Process model. By adding some detailed simulation results, unknown scale and error terms are estimated for constructing an approximate model of the detailed simulation (Kennedy and co-authors, 2000).

Qian propose a modified calibrated model by modeling the scale term as an unknown linear approximate regression function (Qian and co-authors, 2006). Brooks propose detailed guidelines for choosing the best model among available mathematical or computer models by measuring levels of detail, complexity, and corresponding model performance (Brooks and co-authors, 1996). Sargent develops a guideline for model validation, which includes data validity, conceptual model validity, computerized model verification, and operational validity (Sargent, 2013). Jin test various metamodeling techniques for different optimization formulations under uncertainty and compare the accuracy of the approximation results (Jin and co-authors, 2003). Simpson also survey sampling and metamodeling techniques and recommend a guideline for the appropriate use of statistical approximation techniques in a given situation (Simpson and co-authors, 2001b).

The second approach for managing variations is designing a system to be insensitive to uncertainty without eliminating or reducing its sources in the system; this is called robust design. In other words, robust design is used to make the system response insensitive to uncontrollable system input variations, thus improving the quality of a designed product. This is also called parameter design. Parameter design alone does not always leads to sufficiently high quality. Further improvement can be achieved by controlling the source of variations. However, the cost associated with controlling the variation sources may be prohibitively high. A robust design approach is introduced to overcome incompleteness and inaccuracy of the models. It also facilitate design at lower cost by sacrificing the achievement of optimal performance.

Typically, in robust design literature, design parameters are divided into three categories: control factors, noise factors, and responses. Control factors, also known as design variables, are parameters that a designer adjusts. Noise factors are parameters that affect the performance of a product or process but are not under a designer’s control. Responses are performance measures for the product or process. The sources of variations reside in system design models, based on which designers make their decision in a scientific manner, with various forms; these are control factors, noise factors, or others.

Taguchi's robust design principles are focused on variations caused by noise factors. The method developed by Chen and co-authors, 1995, to consider the two types of robust design is Robust Concept Exploration Method (RCEM) in which the cDSP is modified to consider robustness. Type I is associated with the variation of uncontrollable parameters (noise factors). Type II is associated with the variation of control factors (design variables).

In model-based system design exploration where the analysis models are incomplete and inaccurate due to assumption, approximations and method limitations, it is crucial to consider variations in order to support decision making. Feasibility robustness brings flexibility to the designer to maintain the systems performance and quality in face of uncertainty which in turn designer confidence can be increased by ensuring that a design meet a range of requirements. This causes reducing the level of sensitivity to design adjustments in the later stages by reducing the risk and variation associated with uncertainty. In this thesis, robustness is considered in the design constraints of the compromise DSP, not all, those that have a higher risk of violations in face of small variations. Detail discussion on how this is conducted is provided in Chapter 3 and Chapter 6 through a design example.

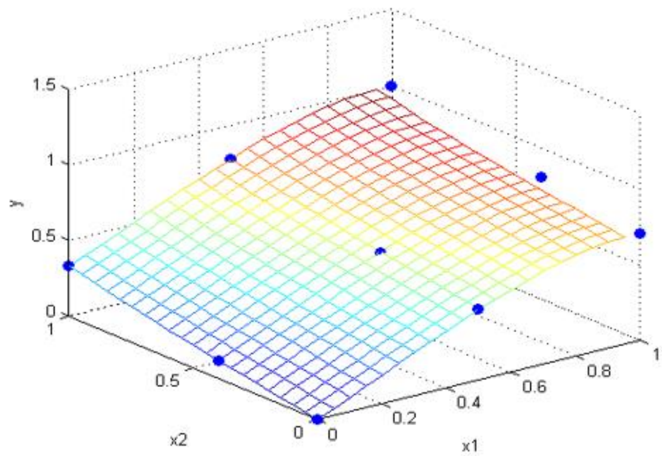
In Section 2.1, the compromise DSP is described, and in this section robust concept is discussed. To formulate goals and constraints of the compromise DSP, one approach is using response surface models to manage computational complexity. In the next section, Response Surface Method is discussed, and the benefits in solution space exploration is highlighted.

2.3 Response Surface Method

A detail design simulation in most cases takes a huge computational time and cost. Response Surface Method (RSM) is a statistical method which supports the Design of Experiments (DOE) and the fitting of a response surface model (Box and co-authors, 1987) to create response surface models through an intensive computer simulation package. The response surface models which relates a response (output) to a number of factors (inputs) are then replaced for complex analysis models in order to improve computational efficiency and increase knowledge during design. This method is particularly used in two situations: 1) when dealing with complex systems that requires complex computational analysis to manage time and cost, and 2) when the information of the system is not sufficient in the early stages of design. The response surface models are created by performing different simulations associated with experiments with different input settings. The RSM can be utilized to monitor the impact of design parameters on systems performance to select a set of design parameters which has the most significant impact (Engelund and co-authors, 1993).

An example of a second-order response surface model and its corresponding equation is shown in Figure 2.6.

RSM can be utilized in formulating the constraints and goals to provide a quick empirical mapping of the relationship between independent design variables (inputs) and their dependent performance (output or response).



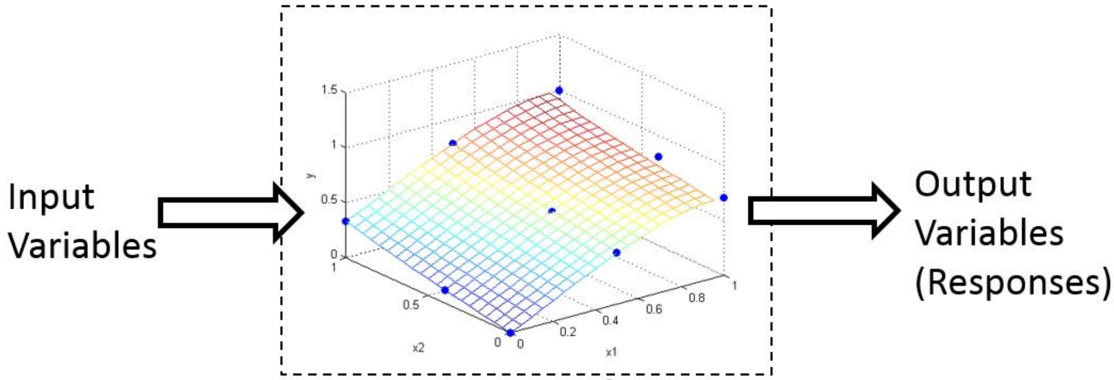
$$y = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{ii} x_i^2 + \sum_{i \leq j} \beta_{ij} x_i x_j$$

Figure 2.6: Response surface model of Rankine cycle efficiency

The main three steps in developing response surface models involve:

- Use design of experiments (DOE) to identify suitable locations in design space for detailed experiments
- Use regression analysis (or other methods) to create a polynomial approximation of the detailed experiments.
- Replace analysis with the surrogate model.

Experimental design technique which is known in physical experiments is adapted to the design of computer experiments to increase the efficiency of the analysis (Fernández, 2002). There are different ways to design experiments such as full factorial, fractional factorial and composite design. The full factorial design is the most basic experimental design (Fernández, 2002), however, the central composite designs are the most widely used method for fitting a second order response surface and monitoring second order effect (Montgomery, 2008).



$$y = \beta_0 + \sum_i \beta_i x_i + \sum_i \beta_{ii} x_i^2 + \sum_{i \le j} \beta_{ij} x_i x_j$$

Figure 2.7: Creating response surface models

Next step is to use regression analysis (or other method) to create a polynomial approximation of the detailed experiments. MATLAB can also be used to develop the equations to be replaced for analysis model. An essential after capturing regression is to first test the significant of the regression to confirm the accuracy of the approximation, and second run additional confirmation tests for the CCD. ANOVA (ANalysis Of VAriance) for the regression analysis can be used to test the significant of the regression.

One of the advantages of using CCD for developing response surface models is that the design factors are normalized; therefore, the coefficients of the quadratic equation directly indicate the significance of the first-order effects (linear terms), interaction effects (interaction terms), and second-order effects (quadratic terms). This provides useful information about the relative contributions of each design factor to the response outputs. The interaction effects between control and noise factors is also an interesting concept in robust design. It can be used to adjust the control factor to manage the impact of noise factor.

In this thesis response surface models are paired with the compromise DSP, used in Chapter 6 to replace the highly nonlinear and complex analysis models of the design problem, continuous casting of steel, in order to increase computational efficiency in conducting solution space exploration. This facilitates a fast analysis module in the compromise DSP solver. Design exploration can be significantly increased by replacing computationally expensive analysis models with associated response surface models.

Moreover, employing response surface models increase the knowledge of significant design drivers by identifying design variables that makes significant contributions to the solution with those that do not. This is beneficial in sensitivity analysis when needed. Also, by knowing the interaction and the effect of design variables on solution, design space can be reduced to further improve effectiveness of the exploration. This reduction is done by eliminating the design variables which do not affect the solution significantly.

When the compromise DSP is formulated, it can be implemented in the cDSP template, DSIDES, to capture and analyze the results.

2.4 The Decision Support in the Design of Engineering Systems (DSIDES)

DSIDES embodies the principles of the decision support problem. The compromise DSP and DSIDES have been used in the conceptual design of ships and airplanes and in the design of aircraft tires, damage-tolerant structural and mechanical system, and composite materials (Mistree and co-authors, 1992). The DSIDES is particularly appropriate for solving multi-criteria problems involving Boolean and continuous variables, that is, the problems that include both selection and compromise.

In Section 2.4.1, implementing a compromise DSP using DSIDES is discussed. The solution search methods used within DSIDES are then explained in Section 2.4.2.

2.4.1 DSIDES: Implementing a Compromise DSP on a Computer

To solve the compromise DSP, a tailored computational environment known as DSIDES has been created and well documented in (Reddy and co-authors, 1992). The implementation of DSIDES requires the user a user specified input file (in the form of a compromise DSP template[3]) consisting of data file and user supplied FORTRAN routines.

The input data is used to define the size of the problem, variable names, goals and constraints, bounds on the variables, and convergence criteria. To create a data file, there are number of mandatory blocks such as SYSVAR which is a description of system variables- name, type, bounds and guess value, and number of optional blocks such as XPLORE which is to explore the design space for best initial points based on pattern search. An example of a data file is provided in Appendix B and D. All mandatory and optional blocks used in creating a data file are shown in Figure 2.8.

The FORTRAN routines in DSIDES are the user specified routines such as USRMON for user specific monitoring of the solution process. A flowchart showing the calls to the user specified subroutines is provided in Appendix A. The routines and brief description are provided in Figure 2.9.

---

[3] A compromise DSP template is a mathematical model of a compromise DSP which is expressed in terms of variables, constraints, goals, etc., and is therefore implementable on a computer.

Mandatory Blocks

PTITLE	1	Problem title
NUMSYS	2	Number of System Variables
SYSVAR	3	Description of System Variables - name, type, bounds and guess value
NUMCAG	4	Number of Constraints and Goals
LINCON	5	Linear Constraints - names and data *(if specified in NUMCAG)*
LINGOL	6	Linear Goals - names and data *(if specified in NUMCAG)*
DEVFUN	7	Deviation Function - number of levels and weights of deviation variabl
STOPCR	8	Stopping Criteria (run and principal print flags, NITER, EPSZ, EPSX)

Optional Blocks

NLINCO	9	Names of Nonlinear Constraints (default names: NLCO##)
NLINGO	10	Names of Nonlinear Goals (default names: NLGO##)
INITFS	11	Automatic Generation of Initial Feasible Solution
ALPOUT	12	Flags for Output Level, Post Processor and Time Statistics
USRMOD	13	Flags for User Modules (USRINP, USROUT, USRMON, USRLIN)
USRDAT	14	User Data Block for Access From USRINP
OPTIMP	15	Optimization Parameters (VIOLIM, REMO, STEP)
ADPCTL	16	Nonlinear Inequality Constraint Adaption Flag (LADAP)
USERAN	17	Information for USRANA (maximum cycles - NANCY, NSYCY)
FIXVAR	18	Fixing of Variables
SUPCON	19	Suppression of Nonlinear Constraints
PVALFX	20	Particular Values for Stationarity of System Variables
PVEPSZ	21	Particular Values for Stationarity of Deviation Function Levels
PVSTEP	22	Particular Values for STEP
PVCVIL	23	Particular Values for VIOLIM
PVREMO	24	Particular Values for REMO
ADREMO	25	Adaptive Reduced Move Parameters
XPLORE	26	Explore the design space for best initial points
ENDPRB	27	End of Problem Definition

Figure 2.8: Mandatory and optional blocks used in DSIDES data file

The user specified routines are used to evaluate the nonlinear constraints and goals, to input data required for the constraint evaluation routines and the design-analysis routines, and to output results in a format desired by the user. In some cases, it is desirable to use a database or design analysis interface associated with the analysis/synthesis cycles (e.g., use of REFPROP to capture thermal properties).

•	`USRINP`	(for user specific input)
•	`USRSET`	(for evaluating nonlinear constraints and nonlinear goals)
•	`USRLIN`	(for updating linear constraint and linear goal coefficients)
•	`USRMON`	(for user specific monitoring of the solution process)
•	`USRANA`	(for relevant analysis cycle calculations)
•	`USROUT`	(for user specific output)

Figure 2.9: User specified routines used in FORTRAN file of DSIDES

The compromise DSP is solved using the Adaptive Linear Programming algorithm incorporated in DSIDES (Mistree and co-authors, 1993b) which provide vertex solutions. The other approach within DSIDES is a zero order search referred to as XPLORE. Based on the algorithm of reference (Aird and co-authors, 1977), it is used to test a range of designs within the stated system variable bounds. The best N designs are kept providing candidate starting points for higher order searches. A second method utilizing a pattern search algorithm is also available within the INITFS (Initial Feasible Solution) module. Used in series, these methods can assist greatly in delivering the Adaptive Linear Programming (ALP) algorithm a starting point from which the likelihood of achieving greater understanding of the solution space is high.

In this thesis different solution search methods are used within DSIDES, namely, pattern search and ALP to explore the design and solution space. In the next section, the two solution search methods are discussed in more detail.

2.4.2 Solution Search Methods

The compromise DSP can be solved using different optimization methods depending on the problem. However solution algorithms fall into two classifications, namely,

- those that solve the exact problem approximately, and
- those that solve an approximation of the problem exactly.

Gradient-based methods, pattern search methods, and penalty function methods fall into the first classification, however, whereas methods involving sequential linearization such as ALP fall into the second classification. In this thesis, methods from both classifications are used to explore the design and solution space.

Pattern Search

Pattern search used in XPLORE feature of DSIDES is one of the classifications of direct search method. Direct search method searches for a set of points around the current point where the value of the objective function is lower than the value at the current point. (Taguchi and co-authors, 1990). Direct search methods are mostly utilized as preliminary solution search. The reason for that is because direct search methods are straightforward and simple, and the requirements are minimal; usually only setting of few parameters are required.

The popular direct search methods are from three categories, pattern search methods, simplex methods (not the simplex method for linear programming), and methods with adaptive sets of search directions (Smith, 1992). In this thesis, pattern search method is implemented as one of the solution search method to discover feasible regions of the design space.

The general pattern search algorithm shown in Figure 2.10 can be summarized as follows:

1) Start at a base point, x_{base}.
2) Perform a cyclic search about x_{base} in each axis, find a direction of improvement and step in that direction assuming monotonic behavior. This represents exploratory move. The new point is now called x_{temp}. If this step is not successful, continue to 3). Otherwise reduce the step size and repeat 2).
3) Perform a pattern move to x_{acc} by setting $x_{acc} = x_{base} + a\,(x_{temp} - x_{base})$.
4) Test y (x_{acc}) vs y (x_{temp}):

   if y (x_{acc}) is better, set $x_{base} = x_{temp}$, $x_{temp} = x_{acc}$ and return to 3), else

   if y (x_{acc}) is worse, set $x_{base} = x_{temp}$ and return to 2).
5) Repeat 2) through 4) until it yields to no improvement with minimum step size.

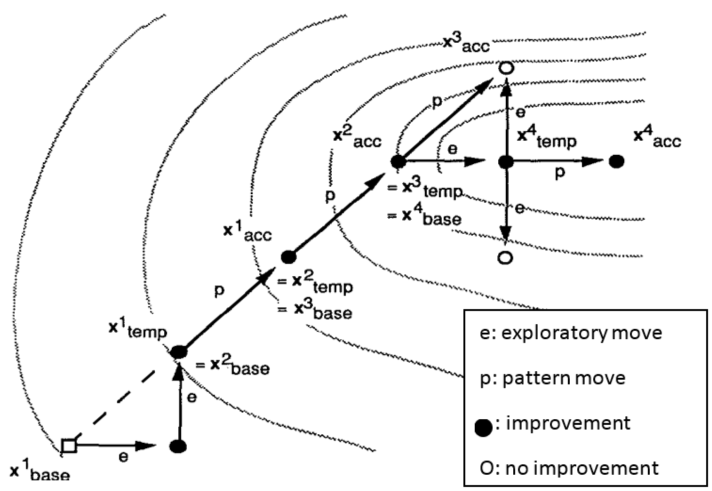


Figure 2.10: Pattern search characteristics in two (Smith, 1992)

Pattern search can be costly when the starting point is far from the optimal point. Yet pattern search is more efficient than other search methods such as Genetic Algorithm and requires less function calls. It is especially efficient when there are not many complicated constraints.

Adaptive Linear Programming

The ALP algorithm implemented in DSIDES to solve compromise DSP can solve the linearized problem exactly. In this part ALP algorithm and how is used in DSIDES is discussed.

The three main characteristics that contributes to the success of the ALP algorithm (Mistree and co-authors, 1992):

- The use of second-order terms in linearization
- The normalization of the constraints and goals and their transformation into generally well-behaved convex functions in the region of interest
- An "intelligent" constraint suppression and accumulation scheme

The ALP algorithm is a modified second-order algorithm, which needs the derivatives of the constraints and goals in addition to the values of these quantities. The derivatives are calculated numerically by the central difference formula.

Illustrated in Figure 2.11 is a flow chart of the implementation of the ALP algorithm on the computer.

The FORTRAN routines in DSIDES are then used to evaluate the nonlinear constraints and goals, to input data required for the constraint evaluation routines and the design-analysis routines, and to output results in a format desired by the user. There are two cycles in the whole algorithm, that is, analysis cycle and the synthesis cycle. Access is provided to a design-analysis program library from the analysis/synthesis cycle and also within the synthesis cycle.

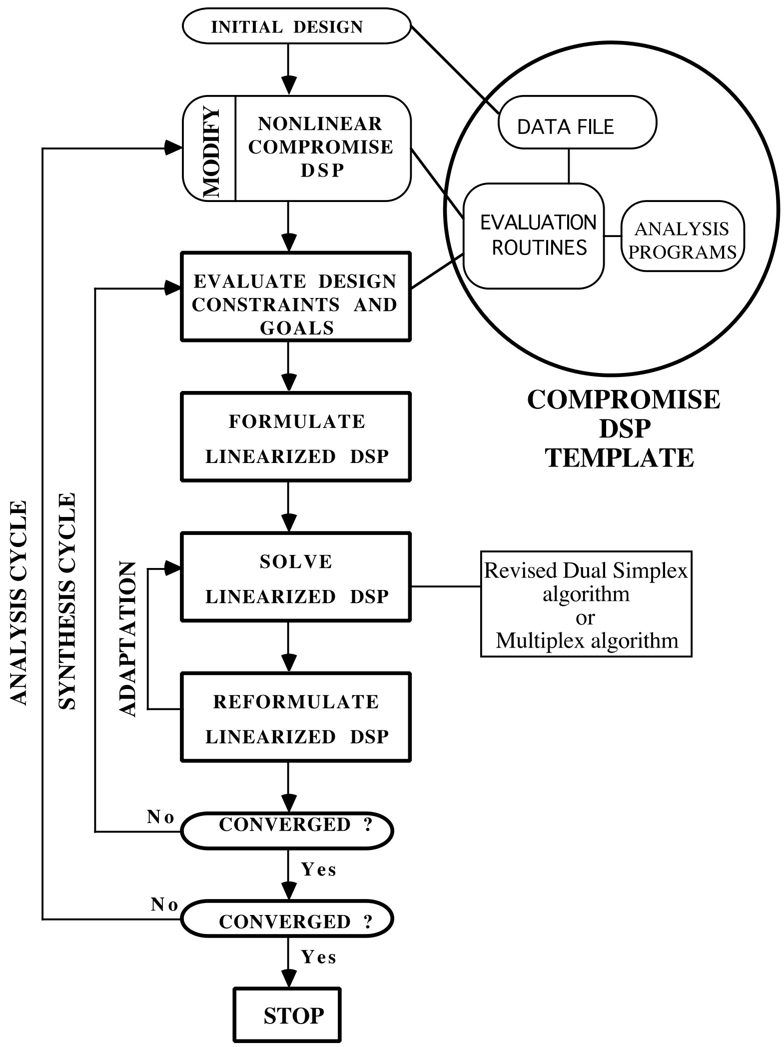


Figure 2.11: Implementation of the ALP algorithm for solving compromise DSPs (Mistree and co-authors, 1993b)

When the nonlinear compromise DSP is formulated and evaluated through the user specified routines, a linear approximation is utilized. The solution of the linear programming problem is calculated using a multiplex algorithm (Simpson and co-authors, 2001b). Once a solution has been obtained, a post-solution analysis can be performed.

Although the ALP algorithm is very efficient in solving compromise DSPs, it has some limitations. For example, the ALP algorithm is only capable of handling Boolean and continuous variables. If there are discrete or integer variables, it is difficult if not impossible to implement the ALP algorithm to solve the design problems. Another limitation is in the case when the system constraints are highly nonlinear and the linearized form of them may cause the feasible design space infeasible. In such cases, ALP algorithm temporarily or permanently suppresses these constraints. It is left to the designer to analyze these permanently suppressed constraints and make an appropriate action. Furthermore, the data file required for the ALP algorithm should contain all the design information, however, sometimes the designer does not have sufficient information about the constraints, especially in original design. In such cases other methods should be implemented first to capture more information about the design. More details of the ALP can be found in (Mistree and co-authors, 1992).

In this section, solution search methods used in this thesis are discussed, and in the next section a method for validating a design method, which is employed in this work, is introduced.

2.5 What Has Been Presented and What is Next

The important tools and concepts for solution space exploration, namely, the compromise DSP (Section 2.1), robust design under variations (Section 2.2), Response Surface Method (Section 2.3) and DSIDES (Section 2.4) are discussed in this chapter.

The compromise DSP is employed to answer to the research question *how can a design decision be modeled?* The preemptive and Archimedean form of the compromise DSP provide a means for answering the research questions related to exploring design priorities and design preferences respectively. Robust design concept and RSM, incorporated in the compromise DSP, are utilized for the design example presented in Chapter 6 to increase design robustness and design efficiency. DSIDES, the computer environment to implement DSPs, is used for all three design examples discussed in this thesis. In the next chapter, Chapter 3, the solution space exploration method is proposed. The goal is to increase design knowledge in order to support designer in the process of decision making. The main research questions addressed in Chapter 3 are:

- *What is the process to explore design tradeoffs in model-based system design?*
- *What is the process to identify design preferences that guarantees a desired solution in which different and conflicting objectives are satisfied?*
- *What kinds of modification are needed if desired solutions that satisfy different and conflicting objective preferences are not found?*
- *What is the process to explore feasibility robustness under the effect of variations?*
- *How can design constraint exploration be beneficial to incorporate feasibility robustness in the model?*
- *How can design selections be modeled?*

CHAPTER 3 SOLUTION SPACE EXPLORATION IN MODEL BASED REALIZATION OF ENGINEERED SYSTEMS

In Chapter 1 of the thesis, the motivation and background for solution space exploration is discussed. Laying down the foundation in Chapter 1, in Chapter 2, several mathematical tools and concepts are introduced which facilitate developing the solution space exploration method. In this chapter, the solution space exploration method is proposed to answer to the research questions identified in Chapter 1:

- ***What is the process to explore design tradeoffs in model-based system design?***
- ***What is the process to identify design preferences that guarantees a desired solution in which different and conflicting objectives are satisfied?***
- ***What kinds of modification are needed if desired solutions that satisfy different and conflicting objective preferences are not found?***
- ***What is the process to explore feasibility robustness under the effect of variations?***
- ***How can design constraint exploration be beneficial to incorporate feasibility robustness in the model?***
- ***How can design selections be modeled?***

With growing interest in the model-based realization of engineered systems there is a need for developing methods to explore the solution space that is defined by models that approximates reality and are typically incomplete, inaccurate with different fidelities.

These characteristics of model-based engineered systems requires good understanding and analysis of the designs/solutions in order to support the designer in the process of decision making. In model based approach, as time passes, the knowledge and confidence of the designer should increase through exploration and analysis that results of completeness and utility of the outcome.

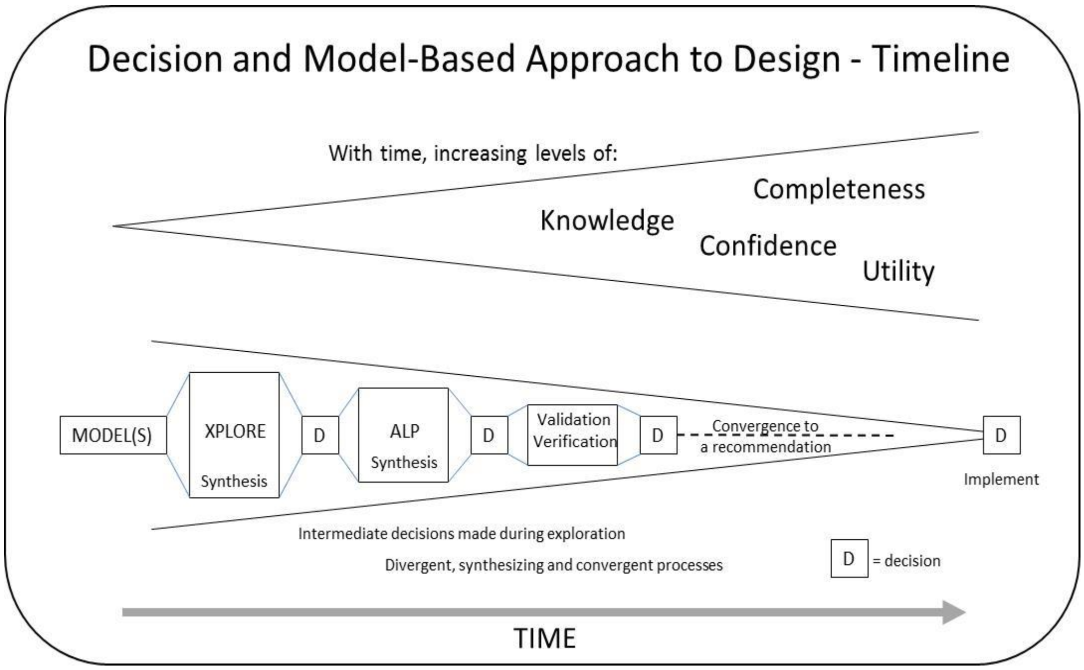


Figure 3.1: Modeling and decision timeline (Smith and co-authors, 2015)

Used is the Decision Support Problem (DSP) construct that is based on the philosophy that design is fundamentally a decision making and model-based process(Marston and co-authors, 2000; Muster and co-authors, 1988). This overall process is diverging, synthesizing and convergent decision making processes. As will become clearer, various tools may be used to support different decisions. Conceptually presented in Figure 3.1, over time, knowledge, confidence and utility increase while converging to a recommended decision. The decisions are made through a series of analysis and synthesis.

Using as a core construct, the compromise DSP, provides the capability to explore a solution space to quantitatively and qualitatively establish trends and a satisficing space. The solutions that form the solution space in the compromise DSP comprise the space defined by the constraints and variable bounds, and the achieved and aspiration space defined by the goals.

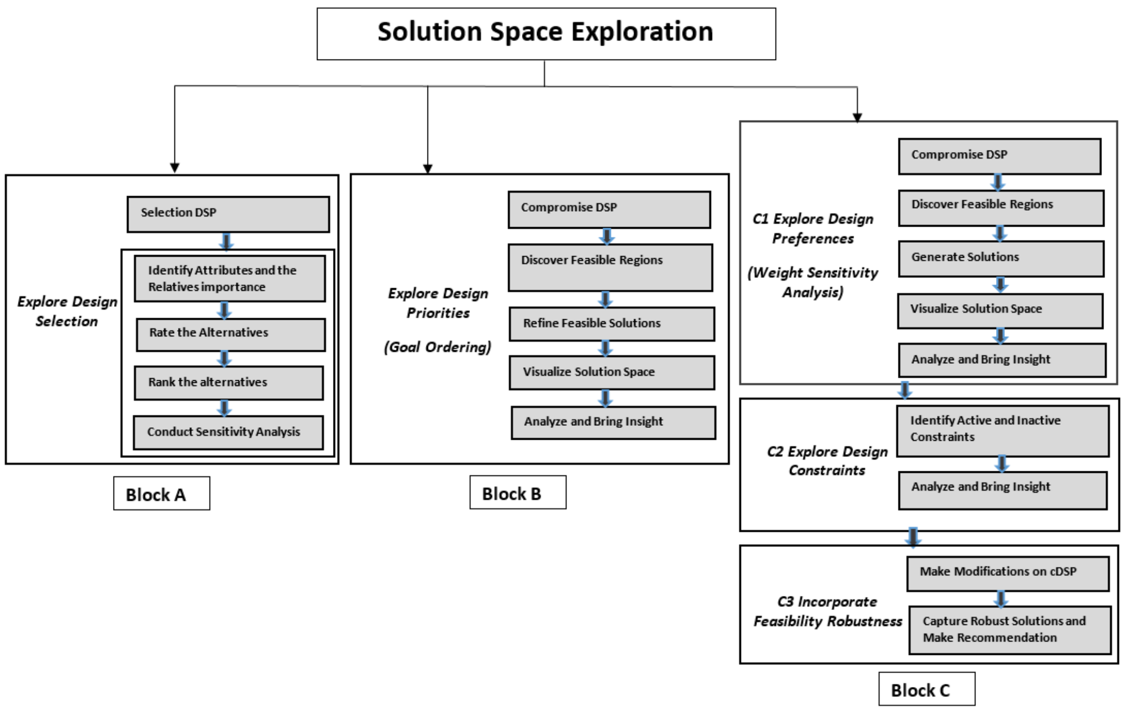


Figure 3.2: Solution space exploration

The method presented in this chapter to explore the solution space consists of various approaches and steps demonstrated in Figure 3.2. Each block is discussed in one section of this chapter.

- **Block A-Figure 3.2: Exploring Design Selection** - Given sets of candidates, identify the principal attributes influencing selection and the relative importance of those attributes, rate the alternatives with respect to their attributes, and rank the alternatives in order of preference based on the computed merit function values.

Finally validate the results, conduct sensitivity analysis, and provide insight. Exploring design selection is discussed in Section 3.1 of this chapter and tested in designing a shell and tube heat exchanger in Chapter 5.

- **Block B-Figure 3.2: Exploring Design Priorities** - Discover regions where feasible designs exist based on satisfying the system constraints and bounds or where feasible designs might exist by minimizing the violation of system constraints. Then from the neighborhood of the better feasible or near feasible regions refine the feasible design space extremities by adjusting the variable bounds and solve the cDSP using a preemptive (lexicographic minimum) representation of the system goals and a higher order search algorithm, for example, ALP – Adaptive Linear Programming. The deviation function (Z) for the preemptive formulation is given in Eq. 3.1 (Mistree and co-authors, 1993a).

  $$Z = [f_1(d_1^-, d_1^+), \dots, f_n(d_n^-, d_n^+)] \qquad \text{Eq. 3.1}$$

  Exploring design priorities is discussed in Section 3.2 of this chapter and tested through a design example, namely, a small power plant, in Chapter 4.

- **Block C1-Figure 3.2: Exploring Design Preferences** - Having refined an understanding of the solution space and the zones of greatest interest, move between the extremes generating deeper understanding by exploring design preferences through weight sensitivity analysis using an Archimedean (weighted sum) formulation of the goals and the same higher order search algorithm, for example, ALP. The deviation function (Z) using an Archimedean formulation is given in Eq. 3.2 (Mistree and co-authors, 1993a).

$$Z(d^-, d^+) = \sum_{i=1}^{m}(W_i d_i^- + W_i d_i^+), i = number\ of\ goals \quad \text{Eq. 3.2}$$

$$\sum_{i=1}^{m} W_i = 1,\ W_i \geq 0\ for\ all\ i \quad \text{Eq. 3.3}$$

where Wi is the weight on deviation variables associated with each goal. The weights should be positive and it is convenient for them to sum to one. Exploring design preferences is discussed in Section 3.3 of this chapter and tested through two design examples, namely, shell and tube heat exchanger and continuous casting of steel in Chapters 5 and 6, respectively.

- **Block C2-Figure 3.2: Explore Design Constraints** - Given desired solutions are found through weight sensitivity analysis, conduct constraint sensitivity analysis to identify active and inactive constraints, explore desired solution's extra capacity in face of variation, and the penalty associated with variations. Exploring design constraints is discussed in Section 3.4 of this chapter and tested through two design examples, namely, shell and tube heat exchanger and continuous casting of steel in Chapters 5 and 6, respectively.
- **Block C3-Figure 3.2: Incorporate Feasibility Robustness** - Given active and inactive constraints are identified through constraint sensitivity analysis, incorporate robustness into those constraints to ensure feasibility robustness in face of variations. This is discussed in Section 3.5 of this chapter and tested through the comprehensive design example, namely, continuous casting of steel in Chapters 6.

In this chapter a method for solution space exploration consists of different parts is proposed. In Section 3.1, exploring design selections is discussed. In Section 3.2 and 3.3, exploring design priorities and design preferences are presented. Exploring design constraints is discussed in Section 3.4. And incorporating feasibility robustness is described in Section 3.5.

3.1 Exploring Design Selections and Decision Making

Design involves a series of decisions which are either selection or compromise (Mistree and co-authors, 1993). Selection between numbers of alternatives occurs in all stages of design. Compromise on the other hand is most used in early stages of design when designer is exploring the tradeoffs between the objectives. In this section, exploring design selections and its connection to decision making is discussed. The flow chart of the sequential steps involved in this part of the method is shown in Figure 3.3.

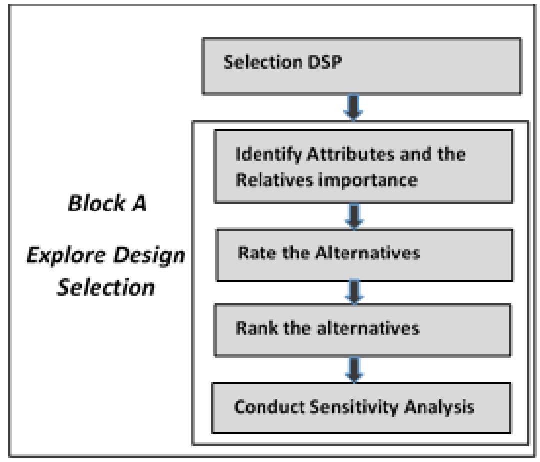


Figure 3.3: Steps for exploring design selections

One effective way of decision making for problems with multiple possible alternatives (selections) is a selection Decision Support Problem, which is the process of making a choice between a number of possibilities, taking into account a number or measures of merit or attributes. The general goal of making a decision based on selection is to reduce a set of potential alternatives to a realistic number of solutions by grading them based upon weighted attributes that allow the qualitative solutions to be quantitatively ranked so that they can be used as input for a computer program. The quality of the output solution is a function of the quality of input data/knowledge and how the tool is used.

Table 3.1: Selection decision support problem description

Given
A set of *candidate alternatives.*
Identify
The principal *attributes* influencing selection. The *relative importance* of attributes.
Rate
The alternatives with respect to their attributes.
Rank
The alternatives in *order of preference* based on the computed merit function values.

Selection DSPs need to first be characterized by a problem statement, which is transformed to the word problem addresses the problem in terms of the key words Given, Identify, Rate, and Rank as shown in Table 3.1. The steps involved in each of the stages of the problem statement are outlined as: *Given* a set of candidate alternatives, *Identify* the principal attributes influencing selection and the relative importance of those attributes, *Rate* the alternatives with respect to their attributes, and *Rank* the alternatives in order of preference based on the computed merit function values. Last step is to validate the results, conduct sensitivity analysis, and provide insight to support decision making. After a problem statement is developed, a scale must be established in order to rank the alternatives based upon each attribute.

The attributes may be quantified using either hard – science-based information or soft – experience-based information. The creation of scales is an extremely important step particularly when dealing with soft information. The best way to deal with the soft attributes common in the selection DSP is to use an interval scale to convert the rankings of alternatives based on these attributes into a numerical scale. Table 3.2 is an example to describe a scale for decision.

Table 3.2: Description of the scale for decision (Smith, 1992)

Rating Interval	Ordinal	Viewpoint
1	Equal preference	The two attributes are equally important
3	Slight preference	Based on experience there is a slight preference for attribute i over attribute j
5	Medium preference	Based on experience attribute i is preferred to attribute j
7	Strong preference	Attribute i is strongly favored over attribute j; its dominance is shown in practice
9	Absolute preference	The preference of one attribute over another is of the highest possible order
2,4,6,8	Intermediate values	When compromise is needed between adjacent ratings

If there are multiple attributes, these must also be compared to each other to determine their relative significance, so they must also be ranked in order to determine which attributes the designer wants to prioritize. There are multiple different ranking methods for both the alternatives and attributes, each method has their own positives and negatives depending on the situation and data. Once these values are obtained via the created scales, the selection DSP formulated may be solved with DSIDES to explore the best alternative mathematically. A design example to explore design selection is discussed in Chapter 5.

In the next section, exploring design priorities through goal ordering is discussed in order to bring insight and support designer in decision making.

3.2 Exploring Design Priorities and Decision Making

Given that design decisions are either selection or compromise (Mistree and co-authors, 1991b), in Section 3.1, design selection is discussed using selection DSP, and in this section exploring design priorities is described using compromise DSP. The first step is to formulate a cDSP for a given problem statement. It is described in Section 2.1. Next is to explore the solution space through different approaches. Exploring the solution space in this study is conducted using different approaches presented in this chapter. A design example of a small power plant related to exploring design priorities is presented in Chapter 4. The steps involved in this part of the method are shown in Figure 3.4.

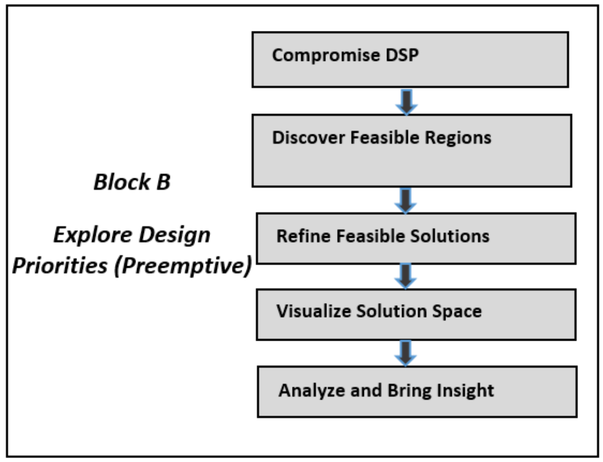


Figure 3.4: Steps of exploring design priorities

The two main steps in exploring design priorities are: 1) discrete search of the space using XPLORE feature of DSIDES to discover feasible regions, and 2) refining the feasible design space extremities by adjusting the variable bounds and solve the cDSP using a preemptive (lexicographic minimum) representation of the system goals and a higher order search algorithm, for example, ALP – Adaptive Linear Programming.

3.2.1 Discovering Feasible Regions: XPLORE

The most rudimentary approach within DSIDES is a pattern search referred to as XPLORE. Based on the algorithm of reference (Aird and co-authors, 1977), it is used to test a range of designs within the stated system variable bounds. In the other word it is used to search a bounded design space in a macro sense to identify regions of potentially good solutions. The best N designs are kept to provide candidate starting points for higher order searches. The quality of each point is monitored based on the constraint violation and the defined deviation function from the compromise DSP. User can assign the number of points to be generated, and based on this number, the fidelity of the surface plots can be controlled. Having more points, a more detailed representation is produced, however, additional computation time is required. Data on a user supplied number of best points is then saved and visualized to provide insight to a designer in decision making.

The main reason to utilize XPLORE is to identify points in the solution space that are close to feasible points based on satisfying the system constraints and bounds or where feasible designs might exist by minimizing the violation of system constraints. This can include the use of pattern search implemented in the DSIDES module XPLORE within the design space defined by the variable bounds. The solution search methods used within DSIDES are discussed in Section 2.4.2 in Chapter 2.

Infeasibility in this approach is measured by the total sum of all constraint violations. The heuristic search through the space is conducted to identify the regions of potentially good solutions, especially when there exist a conflict between the goals. See

Figure 3.5. The figure is from the results of design example discussed in Chapter 4.

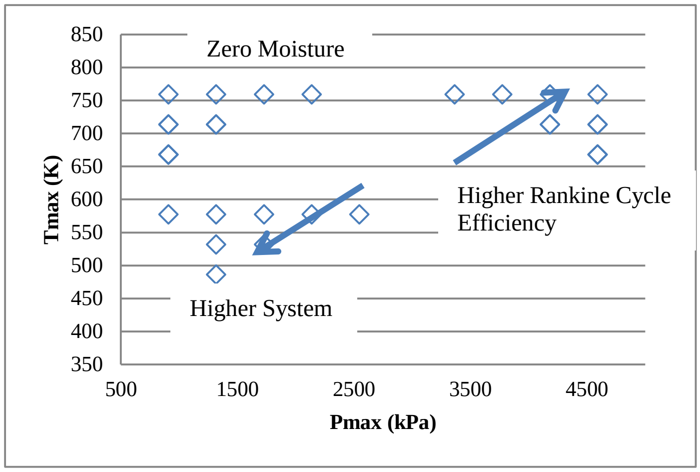


Figure 3.5: XPLORE - A quick view to the design space and design tradeoffs

In this manner, XPLORE is utilized to capture a quick view of the design space during concept exploration which provides additional information during the early stages of design. This approach is useful to find reasonable starting point for nonlinear optimization algorithms in which local minima is identified at best.

Given that a feasible region exists for a given set of requirements, this space may be effectively explored through the modification of the goal priorities and therefore the objective function structure.

3.2.2 Framing Feasible Design: The Preemptive cDSP

To frame feasible design from the neighborhood of the better feasible or near feasible regions found using zero order search, the feasible design space extremities can be refined by adjusting the variable bounds and solve the cDSP using a preemptive (lexicographic minimum) (Ignizio, 1981) representation of the system goals and a higher order search algorithm, for example, ALP – Adaptive Linear Programming. This will grow understanding of what is achievable given a variety of priority levels.

LEXICOGRAPHIC MINIMUM Given an ordered array $f = (f_1, f_2, \dots, f_n)$ of nonnegative elements f_k's, the solution given by $f^{(1)}$ is preferred to $f^{(2)}$ iff

$$f_k^{(1)} < f_k^{(2)}$$

And $f_i^{(1)} < f_i^{(2)}$ for $i = 1, \dots, k-1$; that is all higher-order elements are equal. If no other solution is preferred to f, then f is the lexicographic minimum.

In the compromise DSP formulation the objective is to minimize the difference between the aspiration space which is desired by designer and the achieved space which can be achieved by reducing the deviation function. The difference between the aspiration and the achievable is expressed by deviation function $Z(d^-, d^+)$. See Equation 3.1. The deviation function provides information of the extent up to which a specific goal is achieved.

All goals may not be equally important to a designer and Archimedean and Preemptive formulation facilitate the designer to weight or rank them though deviation function.

In this section Preemptive formulation which is related to design priorities and how it can be utilized by designer in the early stages of design to support decision making is discussed. In the next section Archimedean formulation which is related to design preferences is discussed.

The Preemptive formulation (or lexicographic minimization) is particularly appropriate for industrial problems or in the earlier stages of design where weights are not necessarily required instead the goals are rank ordered based on their importance or priority. Deviation variables associated with the goal in the first priority level are minimized first, then the second level and so on.

The mathematical definition of lexicographic minimum is defined as follows (Ignizio, 1981, 1985):

In lexicographic minimization, the aim is to achieve the goal in the first priority. For example, if there are three goals, the deviation function in the compromise DSP may be formulated as follows:

$$Z(d^-, d^+) = [d_1^-, d_2^-, d_3^+] \qquad \text{Eq. 3.4}$$

In this case, three priority levels are considered. The deviation variable d_1^- is minimized first. Then, d_2^- is minimized, while d_1^- is kept in the achieved value. Finally, d_3^+ is minimized, while d_1^- and d_2^- kept in their achieved values. Since one goal is considered in each priority level, weights are not required.

The limitation of the preemptive formulation on the other is that one goal is assumed infinitely more important than the other(s). However this approach is most suitable in the early stages of design in which no conclusions can be made with respect to which one goal is more important than the other or with respect to quantitative tradeoffs between multiple goals. The other advantage of the preemptive approach is hierarchical decision making in design where decisions in different disciplines of the hierarchy may be focused on goals in different preemptive levels. However, in the later stages of design, designer has more information and design preferences are usually ones of degree, and tradeoffs are necessary.

In this preemptive formulation there are n! ways of ordering n goals having one goal per priority level, and for that reason only a small number of possibilities can be explored, and it indicates that solutions achieved using Archimedean approach are not always achievable with preemptive approach.

3.3 Exploring Design Preferences and Decision Making

Another part of the solution space exploration method is about exploring, visualizing and analyzing design preferences to provide a tool for the designer in decision making related to design preferences (Figure 3.2, Block C). This approach is about moving between the extremes tradeoffs using an Archimedean (weighted sum) formulation of the goals. This can be conducted when the space is framed and the zones of greatest interest is found using Preemptive approach, or it can be done independently. Two design examples, namely, shell and tube heat exchanger and continuous casting of steel is discussed in Chapters 5 and 6, respectively, to test this part of the solution space exploration method. In this section, generating design scenarios by Archimedean formulation is discussed followed by solution space visualization and weight sensitivity analysis.

3.3.1 Moving Between Extremes: The Archimedean cDSP

Archimedean formulation in the compromise DSP is the most general form of the deviation function for multiple goals. In this approach the deviation function is formulated as follows:

$$Z(d^-, d^+) = \sum_{i=1}^{m} (W_i d_i^- + W_i d_i^+), i = number\ of\ goals \qquad \text{Eq. 3.5}$$

$\sum_{i=1}^{m} W_i = 1,\ W_i \geq 0\ for\ all\ i$ Eq. 3.6

where the weights (W_1, W_2, …, W_n) are assigned to the deviation variables associated with each goal and the reflect the importance to a designer of achieving each of the goals. The weights should be positive and sum up to one.

The Archimedean form of the cDSP is time consuming in early stages of design when designer does not have sufficient information to determine *a priori*, the right set of weights to be assigned to the deviation variables associated with each goal.

Therefore, weights are usually chosen either arbitrarily or through unwieldy iterations. In the first step, a designer may find designs by assigning weights arbitrarily and monitoring the extent in which design requirements are satisfied. If not a new set of weights are assigned till the design requirements are met. In order to overcome this difficulty and provide sufficient information to the designer, different scenarios by different weights on each goal can be explored, visualized and analyzed to support designer in the process of decision making.

The solution space can then be explored by assigning different weights on the goals according to a designer preference. This requires generating several scenarios according to designer choice.

As solutions are found from a range of weight vectors associated with the deviation variables, understanding of the solution space on reflection increases and confidence for the decision maker naturally grows. By structuring the experimental variation of the weights, a perception for the sensitivity of the solutions to variation in weights and other driving characteristics can be derived and understood.

By varying the weights associated with the deviation variables and exercising the compromise DSP a designer is able to identify the ranges of design preferences in which desired solution is guaranteed; solutions that are insensitive to the changes of weights assigned to deviation variables associated with the goals. This allows a designer to gain insight into the solution space and arrive at an informed decision which is discussed in the next section.

3.3.2 Visualization and Weight Sensitivity Analysis

In this section, the solution space is visualized and explored by generating different design scenarios and capturing the solutions for each scenario. There are various methods for visualizing data to aid decision making. Ternary plots are incorporated in this method; see Figure 3.8. The steps involved in this part of the method reflected in Figure 3.6 is explained as follows:

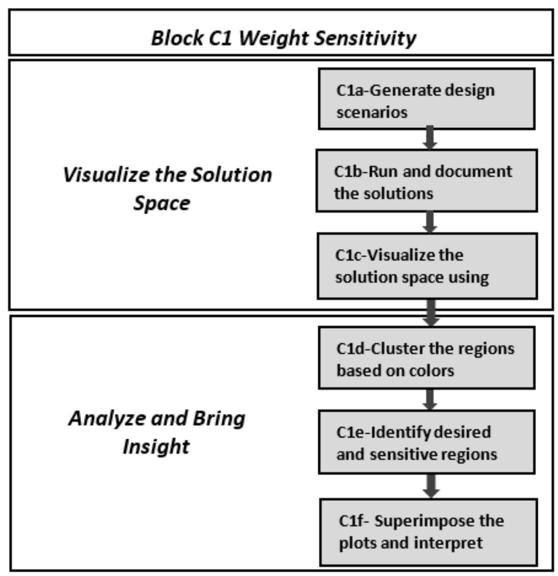


Figure 3.6: Solution space exploration – Weight sensitivity analysis

Step C1a - Generate design scenarios by assigning different weights to the deviation variables associated with the goals. Three goals are mandated in this method to be able to use a ternary plot, and seven to ten scenarios are recommended as a minimum to cover the space. As mentioned in Section 3.3.1, Eq. 3.5, weights should be positive, and for each scenario it is convenient that they sum up to one. An example of seven different scenarios to be run to support weight sensitivity analysis in is shown in Table 3.3.

Table 3.3: Design scenarios for weight sensitivity

Design Scenarios	Weight associated with devotion variable of each goal			Sum of the weights
	Goal 1	Goal 2	Goal 3	
DS 1	1	0	0	1
DS 2	0	1	0	1
DS 3	0	0	1	1
DS 4	0.5	0.5	0	1
DS 5	0	0.5	0.5	1
DS 6	0.5	0	0.5	1
DS 7	0.33	0.33	0.33	~ 1

Step C1b - Run the scenarios and document the final solution, value of the deviation variable for each goal. The values of deviation variables and goals are normalized between 0 and 1.

Step C1c – Visualize the solution space. To visualize the solution space in this method, ternary plots are recommended. Ternary plots can be utilized for three or more goals, however, for two goals contour plots are recommended. The ternary plots are generated for each goal using the MATLAB code illustrated in Figure 3.7. One plot is created for each goal and to do so, one set of scenarios like what is presented in Table 3.3 is needed, and the fourth column shown in the figure is the deviation value of one goal at the time. There are six separate files needed in the MATLAB code of ternary plots, which are *tersurf, terplot, ternaryc, termain, terlabel, tercontour* and *ter_main.* The solution space created in this plot represent the relation of one goal with respect the other two.

```
% Main file for ternary plot
close all;clear all
warning                                            off
MATLAB:griddata:DuplicateDataPoints

%For Energy
%    col1     col2   col3   col4
A = [1        0      0      0.24
     0        1      0      0
     0        0      1      1
     0.5      0.5    0      0
     0.0      0.5    0.5    0.27
     0.5      0.0    0.5    0.25
     0.33     0.33   0.33   0.01]

l=length(A);
v=0.29./sqrt(A(:,4));

figure;

colormap
[hg,htick,hcb]=tersurf(A(:,1),A(:,2),A(:,3
),A(:,4));

% Add the labels

hlabels=terlabel('Objective2','Objective1'
,'Objective3');
```

Figure 3.7: MATLAB codes to generate ternary plots

A ternary plot is a diagram used to plot three (input or state) variables which sum to a constant, and to show a relationship between those variables ("Ternary Plot," 2014). For example, in our context, the possible weighting to three goals, can be visually contour mapped against the achieved goal, deviation function or other parameter of interest. Ternary plots are used in this method for several reasons. The aim is to visualize and explore the solution space based on three goals where summation of their deviation weight sum up to a constant. Moreover the attempt is to show the relations between the goals and find desired and sensitive regions of the solution space to help the designer in decision making. Ternary plots are used in this method to understand the performance reflected in the fourth dimension (color) contours.

Steps C1d and C1e - Cluster the plots based on the desirable region and undesirable region which are presented with different colors. By desirable solutions, the solutions with lower values of deviation variable are considered. In the compromise DSP the objective is to minimize the deviation function in which the goal is improved, therefore blue area which contains the minimum value of the deviation variable is desired. However the designer should decide about what range of solutions are desired, and for each goal, the range of desired solution may be different.

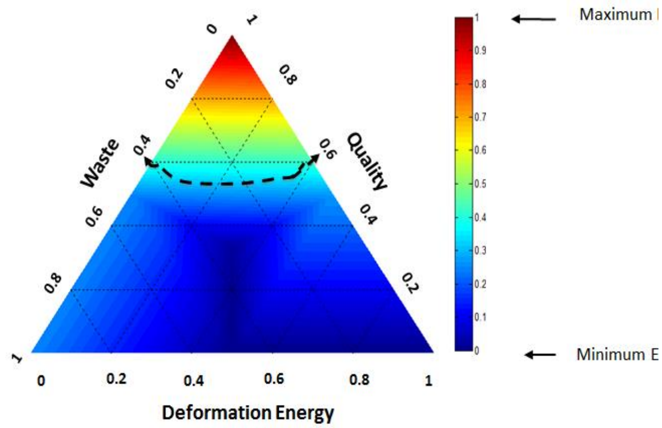


Figure 3.8: Weight sensitivity analysis

For example, in the case of Figure 3.8, the desired solutions can be defined as solutions with the deviations below 0.25. The weight associated with a solution (deviation) inside the solution space can be read as sown in Figure 3.9. For this purpose draw parallel lines are drawn from a point (solution) to each side of the triangle. Figure 3.9 is shown to read Point 1. Point 1 has the values of 60% A, 20% B and 20% C which sum up to 100%.

In the case shown in Figure 3.8, the range of weights are as follows: 0.0 to 1 for G1, 0.4 to 1.0 for G2, and 0.0 to 0.6 for G3. This range of design preferences guarantees a desired solution for G1.

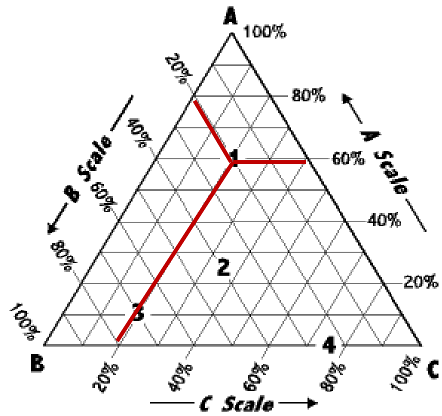


Figure 3.9: How to read ternary plot ("Ternary Plots ", 2000)

Step C1f - Superimpose the plots and interpret. To conduct this step, it is preferred to have all the goals/deviations either minimized or maximized. In the case of this thesis, the objective is to minimize all the deviations associated with the goals, however, the range of desired solution may be different for different goals. In this step, a common region in the solution space that provides desired solutions satisfactory to all the goals is identified and the weight range associated with that region is documented.

It is possible that no overlap of the desired solutions that meet all the goals is found. This means a high conflicts between the goals, thus tradeoffs are necessary. In such cases, the designer should compromise one, two or all the goals to make the overlap possible. This can be done by either changing the target values associated with the goals in the cDSP or simply changing the range of desired solutions when interpreting the plots. By tuning the target values related to the goals the aspiration spaced is modified to satisfy all design objectives. Aspiration space is discussed in Section 2.1.

Exploring design preferences through weight sensitivity analysis is one part of the solution space exploration method proposed in this section which provides insights and support to the designer in process of decision making related to design preferences. In the next section, design constraints are explored through constraint sensitivity analysis.

3.4 Exploring Design Constraints and Decision Making

Desired solutions are identified in the last section through weight sensitivity analysis. In this section, those solutions are monitored in terms of feasibility robustness through constraint sensitivity analysis.

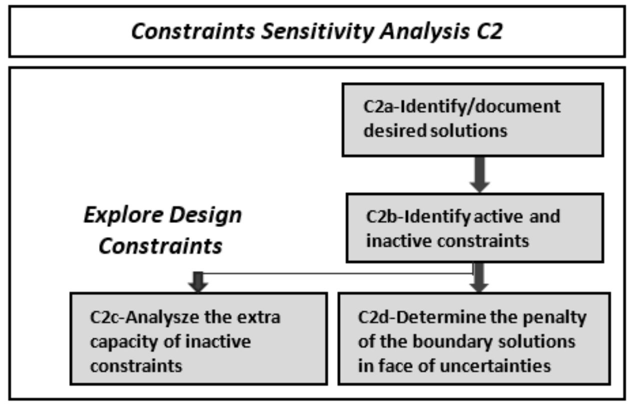


Figure 3.10: Solution space exploration - Constraints sensitivity analysis

In the other word the satisficing solutions found in Section 3.3 are filtered one more times with constrain sensitivity analysis to identify active and inactive constraints for those solutions provide insight to the designer in decision making. To account for variation associated with the constraints in traditional design, past experiment-based experiences were used to define a safety factor instead of dealing with the ideal case. This is done to insure extra capacity of the system in presence of uncertainty. However there is not a straightforward method to properly define the safety factor (Yao and co-authors, 2011). Larger safety factors cause over capacity in the solution which results giving up of the system performance, on the other hand lower safety factor leads to risk on system reliability. To overcome the limitations dealing with the aforementioned traditional methods, constraints sensitivity analysis of the proposed method on solution space exploration is presented.

In this section, exploring design constraint is presented to monitor constraints of the desired solutions found in the last section to determine the extra capacity of those solutions in face of uncertainty. Active and inactive constraints are monitored for each solution. Solutions with one or more active constraints are boundary solutions with the risk of becoming infeasible in face of variations; however the extra capacity of the solutions is not the same for different constraints in different design scenarios. Sequential steps introduced in Figure 3.10 are to be taken to conduct constraints sensitivity analysis.

Figure 3.11 is shown to clarify the meaning of boundary solution, active and inactive constraint. The solution space is typically bounded with several constraints which is formed based on our knowledge and incompleteness of the model. In Figure 3.11a, the red solution is a boundary solution with two active constraints that are colored in orange. Boundary solutions are the solutions with zero tolerance to change, and have one or more active constraints. Such constraints have zero capacity, and that means any small variation can causes the feasible space to shrink. It is possible that the constraints are violated by some worse combinations of the design parameters with uncertainties. This problem becomes critical when at the solution point, part of the constraints which involve variations are active, i.e., close to boundary. The source of such variations is usually from lack of knowledge when modeling specially in early stages of design. As shown in Figure 3.11b, such variation results the boundary solution to end up in the infeasible space, however, a robust solution with extra capacity provides flexibility to the design and brings confidence in decision making.

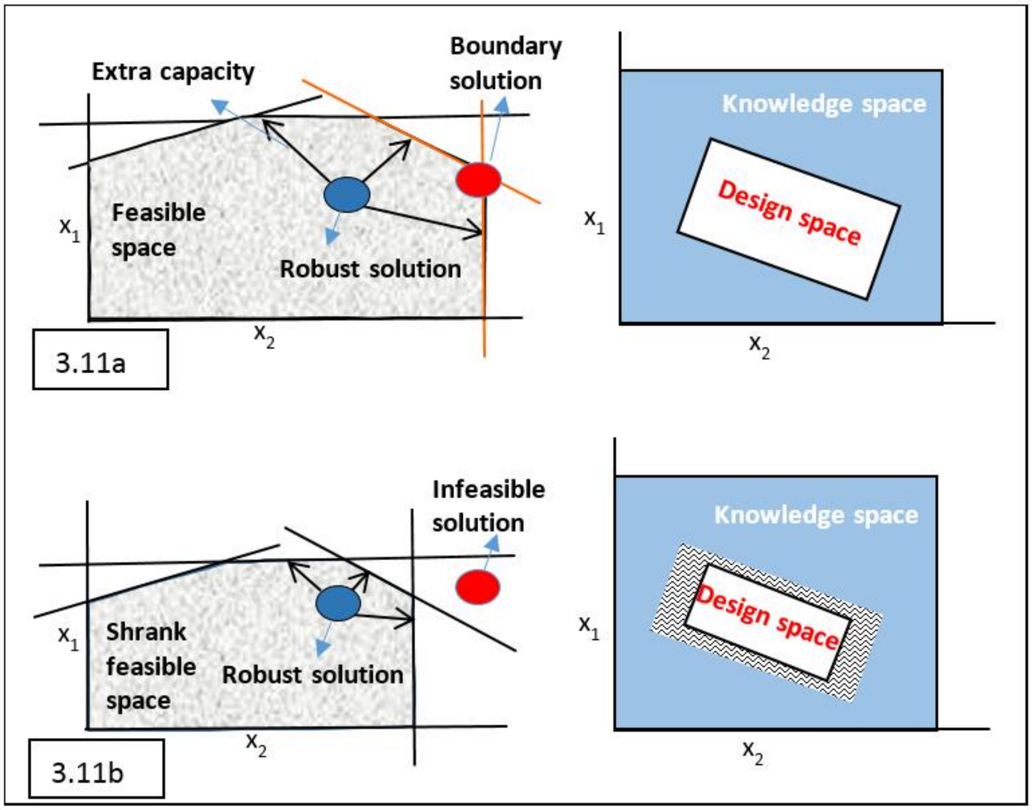


Figure 3.11: Active and inactive constraints

The methodology involved in this part of the method as shown in Figure 3.10 is as follows:

Step C2a - Identify and document the design scenarios associated with desired solutions found through weight sensitivity analysis, and capture value of the constraints (extra capacity) for those design scenarios. These values in operation research are called slack variables. For instance, if the constraint is $x + y \geq z$, then the value calculated for $x + y - z$ for each constraints needs to be documented.

Step C2b - Identify active and inactive constraints of the desired solutions. In Linear Programing, an active constraint is a constraint that is satisfied at equality. For example, if the constraint is $x + y \geq z$, is active when $x + y = z$, and inactive when $x + y > z$.

Some of the constraints may have a value of zero, while the value varies in other constraints. This value is called *capacity* in this work. Constraints with zero capacity are called active, and inactive otherwise.

Steps C2c- Analyze the extra capacity of the inactive constraints for the desired solutions. The extra capacity is what a solution has to be changed without penalty for the system. The extra capacity of different constraint are different and it may change for various desired solutions. The main task in this step is to identify the constraints with limited capacity that are in high risk. This step largely depends on the specific design problem.

Step C2d – Determine the penalty associated with the constraints with zero or limited capacity in face of uncertainty. This is different for different solutions. This step also largely depends on the specific design problem and its constraints. Detail discussion is provided through a comprehensive design example in Chapter 6.

Some of the constraints are hard and some are soft (Gemperline and co-authors, 2003; Wildasin, 1997). Hard constraints are the one that must be satisfied for the system in order to operate. They can be seen as hard requirements. For example safety is a hard constraint but cost is a soft constraint. If the active constraints are hard, the system fails in face of any variation, however if the active constraints are soft, variations in the problem may affect the performance of the system. In early stages of design in which concept exploration is the case, most of the constraints are soft, however, the proposed method is applicable for any stages in design.

Exploring design constraints discussed in this section is tested by two design examples in Chapter 5 and Chapter 6, which provides knowledge and confidence to the designer in decision making, and also leads to the next step in the solution space exploration method to ensure feasibility robustness.

3.5 Incorporating Feasibility Robustness

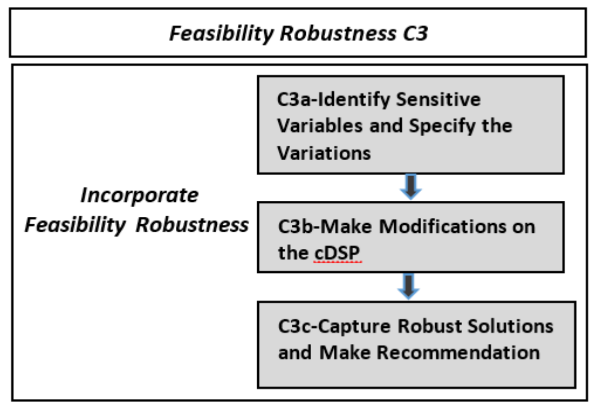


Figure 3.12: Solution space exploration – Incorporating feasibility robustness

In Section 3.3, weight sensitivity analysis is discussed in order to identify desired solutions. It follows by discussing constraint sensitivity analysis for the desired solutions in order to identify constraints with zero or limited capacity (last section). In this section, incorporating feasibility robustness to those constraints is described in order to ensure feasibility robustness of the desired solutions. Feasibility robustness involves determining the relative insensitivity of the solution to incompleteness of the mathematical representation of phenomena and aspirations modeled as constraints in the compromise DSP. The general steps to incorporate feasibility robustness is illustrated in Figure 3.12. The first task is to identify sensitive variables and specify the variations. As shown in Figure 3.13, the variations of the design variables are considered in this part and is applied in the compromise DSP to reduce the risk of infeasibility and provide flexibility to the solution. There are three main steps in this part of the method as follows.

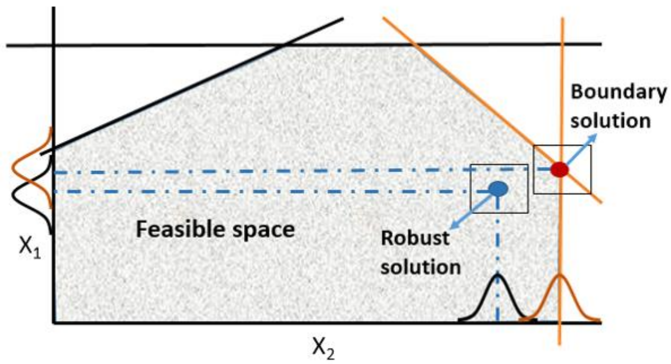


Figure 3.13: Feasibility robustness

Step C3a - Identify sensitive variables and specify the variations. The variation of the sensitive constraints is caused by deviations of input variables involved in those constraints. The deviation of the input variables need to be found through either engineering experience or literature. This deviation should be then given to the compromise DSP.

Step C3b – Make modification on the compromise DSP to incorporate feasibility robustness. To consider the variations of constraints caused by deviations of input variables, uncertainty is added to the boundary solutions. This is done by adding some extra space to the constraints with zero or limited capacity. For instance, consider the case in which the constraint (Y) is a function of a design variable (x) and a design parameter (c), and the source of uncertainty is from the design parameter (c). Then, the constraint,

$E[Y(x, \mu c)] \geq \text{Min}$

should be modified to:

$E[Y(x, \mu c)] + (\delta Y/\delta c) * \Delta c \geq \text{Min}$

where ($\delta Y/\delta c$) is the standard deviation. This case is explained through an example in Chapter 6, where solution space of continuous casting of steel is explored.

Step C3c – Capture robust solutions and make recommendations. After the compromise DSP is modified, the design scenarios associated with desired solutions found in weight sensitivity analysis are run again to capture desired and robust solutions. There are usually more than one solutions, and insight is needed with respect to each solution to make the final recommendation. The insight is based on two main factors: values of the goals (or deviation) and values of the variables. In this step, value of deviation variables should be checked to ensure that they are within the ranged specified in weight sensitivity analysis.

This part of the solution space exploration method is discussed through a design example in Chapter 6.

3.6 Theoretical Structural Validity

In this thesis, a method for solution space exploration is proposed to provide a tool and support a designer in the process of decision making. The solution space exploration method is proposed in this chapter, and to validate the design method, Validation Square is adapted which is discussed in Chapter 1.

In this section, the theoretical structural validity of the proposed method, namely, solution space exploration is checked. Theoretical structural validity, as described in Section 1.4, involves Steps (1) and (2): accepting the individual constructs constituting the method; and accepting the internal consistency of the way the constructs are integrated in the method.

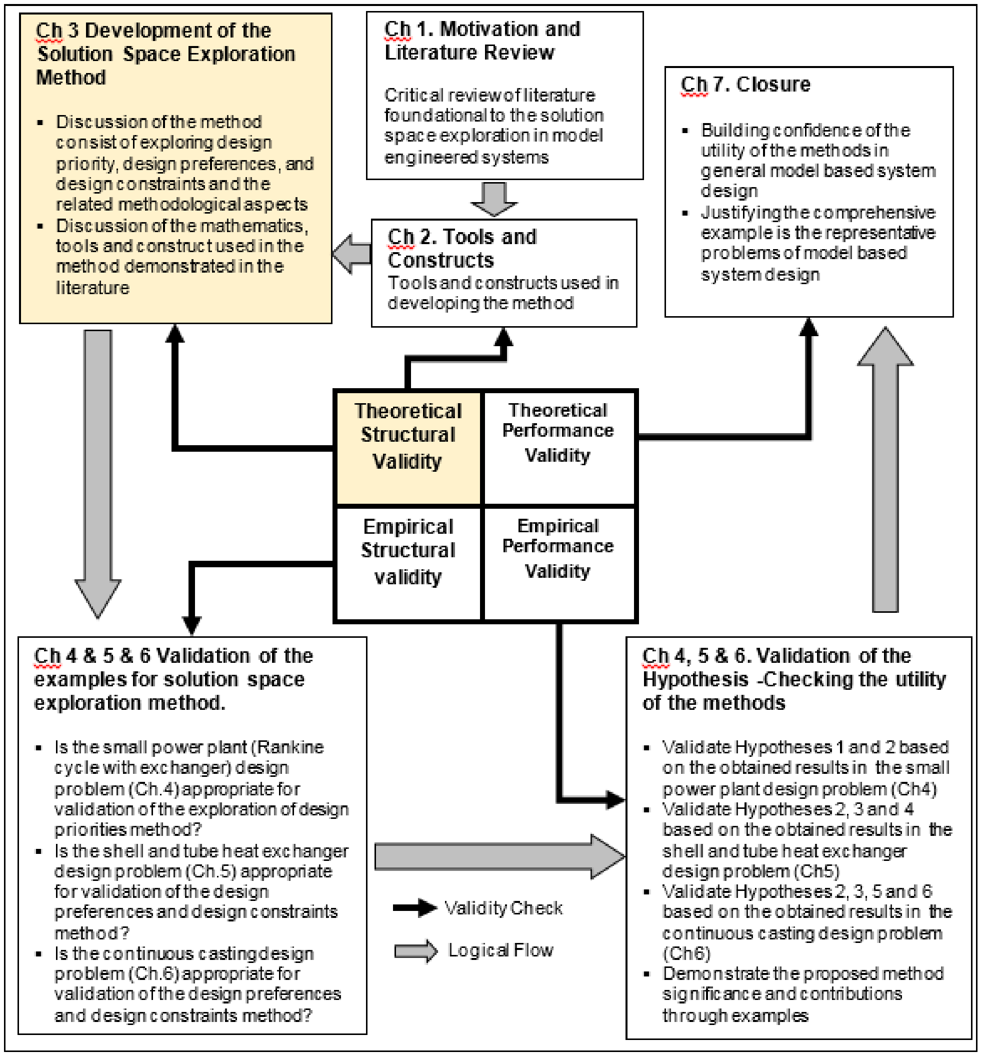


Figure 3.14: Validation square road map

In this thesis, the theoretical structural validity is related to Chapter 2 and Chapter 3. In Chapter 2, different tools and constructs used in development of the method are validated through literature, and in this chapter, the design method on solution space exploration is proposed through the flowchart involving the steps. The procedure of different elements of the method are followed utilizing three different examples. See Figure 3.14.

Validation Step (1) in theoretical structural validity is to accept the individual constructs consisting the method. The main constructs and tools used in the solution space exploration method are presented in Chapter 2 such as the compromise DSP, the RSM and DSIDES.

In Chapter 2, the validation of all the tools and constructs are shown through a literature search of more than fifty papers. Furthermore different parts of the method, namely, exploring design priorities, exploring design preferences and exploring design constraints are validated in Chapters 4 and 5 and published (Sabeghi and co-authors, 2015; Smith and co-authors, 2015). The entire method is validated through a comprehensive design example, namely, continuous casting of steel in Chapter 6. Also exploration of design selections as part of the method is based on selection DSP which is validated in the literature and tested several times before and is also validated in this work in Chapter 5.

Validation Step (2) in theoretical structural validity is to accepting the internal consistency of the way the constructs are integrated in the method. The methodology of the proposed method which is shown in this chapter through the flow charts are tested by developing and applying the method in three different design examples in Chapters 4, 5 and 6. In Chapter 4, exploration of design priorities through goal ordering is tested by developing a small power plant design example, applying the method, analyzing the results and validating them through response surface modeling and statistical tests by

ANOVA. In Chapter 5, exploration of design preferences through weight sensitivity and constraints sensitivity analysis is tested by applying the proposed methodology on a design example of a shell and tube heat exchanger and analyzing the results. The results are then validated through partial hand calculations. In Chapter 6, a design example of a continuous casting of steel is presented as a comprehensive example to test the method. This example is validated through the data and the use in industry.

3.7 What Has Been Presented and What is Next

In this chapter, the solution space exploration method consist of different parts is proposed and discussed in detail.

In order to increase design knowledge and confidence, exploration, visualization and analysis are suggested. There are four parts in the method proposed:

- exploring design priorities through goal ordering,
- exploring design preferences through weight sensitivity,
- exploring feasibility robustness through constraint sensitivity analysis,
- exploring design selections

The method is discussed in detail in this chapter, and is tested after through different design examples in Chapters 4, 5 and 6. In Chapter 4, exploring design priorities is tested and validated by designing a small power plant consists of a Rankine cycle with an exchanger (Smith and co-authors, 2015). In Chapter 5, exploring design preferences is tested and validated by designing a shell and tube heat exchanger (Sabeghi and co-authors, 2015). In Chapter 6, solutions space exploration method is tested by a comprehensive example, the process design for continuous casting of steel.

In the next chapter, the first design example being a small power plant is introduced and modeled as a compromise DSP. Design priorities are explored through goal ordering and visualization. Insight is provided to support designer in the process of decision making.

CHAPTER 4 SOLUTION SPACE EXPLORATION: EXPLORING DESIGN PRIORITIES IN DESIGN OF RANKINE CYCLE

The solution space exploration method for model-based realization of engineered systems is proposed in this thesis in order to bring insight to the solutions and support designers in the process of decision making. See Figure 4.1. The method is discussed in Chapter 3, and based on Quadrants 3 and 4 of the Validation Square (Section 1.4), different aspects of the method is verified through different design examples in Chapters 4, 5 and 6. In this chapter, **Block B: exploring design priorities through goal ordering** is discussed by developing and exploring design of a small power plant.

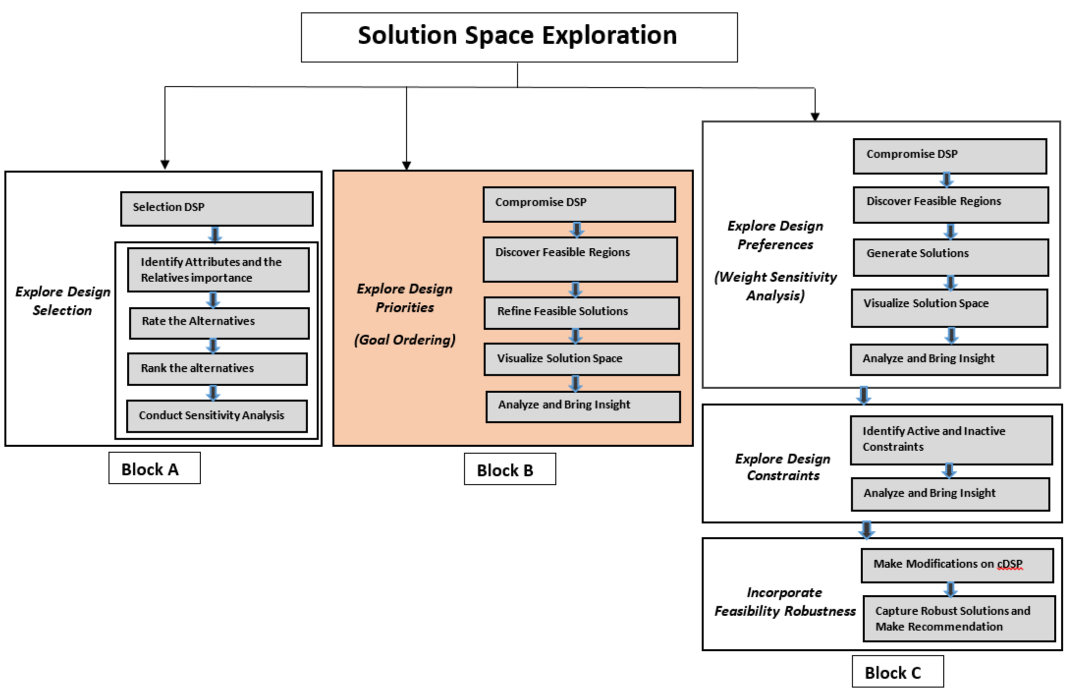


Figure 4.1: Solution space exploration

This chapter consists of two sections. In Section 4.1, the mathematical model of the Rankine cycle with an exchanger is developed, and the goals and problem statement are introduced to address empirical structural validity (Quadrant 3) of the method relater to exploring design priorities. In Section 4.2, exploring design priorities is discussed, and the results are presented to address empirical performance validity (Quadrant 4) of the method relater to exploring design priorities.

4.1 Developing a Mathematical Model for Rankine Cycle

The efficacy of one part of the proposed method in Chapter 3, Sections 3.2 is illustrated using a design example of a small power plant, Rankine Cycle with exchanger. The emphasis is on the method rather than the results *per se.* Table 4.1 is shown for the related nomenclature.

Table 4.1: Power plant nomenclature

NOMENCLATURE

DSP	Decision Support Problem	P_{min}	Minimum pressure in Rankine cycle
cDSP	Compromise Decision Support Problem	Q_{in}	Heat transfer into the system
DSIDES	Decision Support In the Design of Engineered Systems	T_1	Temperature at point 1
		T_2	Temperature at point 2
ALP	Adaptive linear programing	T_4	Temperature at point 4
A	Exchanger surface area	$T_{REFPROP}$	Temperature range of the database
C_{pR}	Specific heat in Rankine cycle	T_{maxE}	Maximum temperature in exchanger
d^- & d^+	Deviation variables	T_{minE}	Min temperature in exchanger
d	Tube diameter in exchanger	U	Overall heat transfer coefficient
ε_E	Heat transfer effectiveness in exchanger	$\dot{W}_t$	Power of turbine
h_1	Enthalpy at point 1	$\dot{W}_p$	Power of pump
h_2	Enthalpy at point 2	x_4	Quality of steam at point 4
h_4	Enthalpy at point 4	η_{tE}	Temperature exchange efficiency
h_5	Enthalpy at point 5	η_{system}	System efficiency
L	Tube length in exchanger	η_{carnot}	Carnot efficiency
M	Moisture leaving the turbine	η_R	Rankine cycle efficiency
M_{max}	Maximum allowable moisture	ΔT_m	Log mean temperature
$\dot{m}_R$	Flow rate in Rankine cycle	ΔT_{ER}	Min. temperature drop in the exchanger
$\dot{m}_{\max R}$	Maximum Rankine cycle flow rate	ΔT_E	Minimum cross flow temperature delta
P_{max}	Maximum pressure in Rankine cycle		

In the following section, the Rankine cycle is introduced and the problem statement is defined. Section 4.1.2 follows with the compromise DSP word and mathematical model related to the design problem.

4.1.1 Rankine Cycle Introduction and Problem Statement

The Rankine Cycle, the most common vapor power plant, is the power cycle that converts one type of energy into another more usable form (Hewitt and co-authors, 2008). Rankine cycles use working fluid, most often water, which vaporize and condense alternately. A schematic representation of the Rankine cycle is shown in Figure 4.2, where the primary components of the system are a power producing turbine, a pump to pressurize the flow to the turbine and two heat exchangers, a condenser, and a heater.

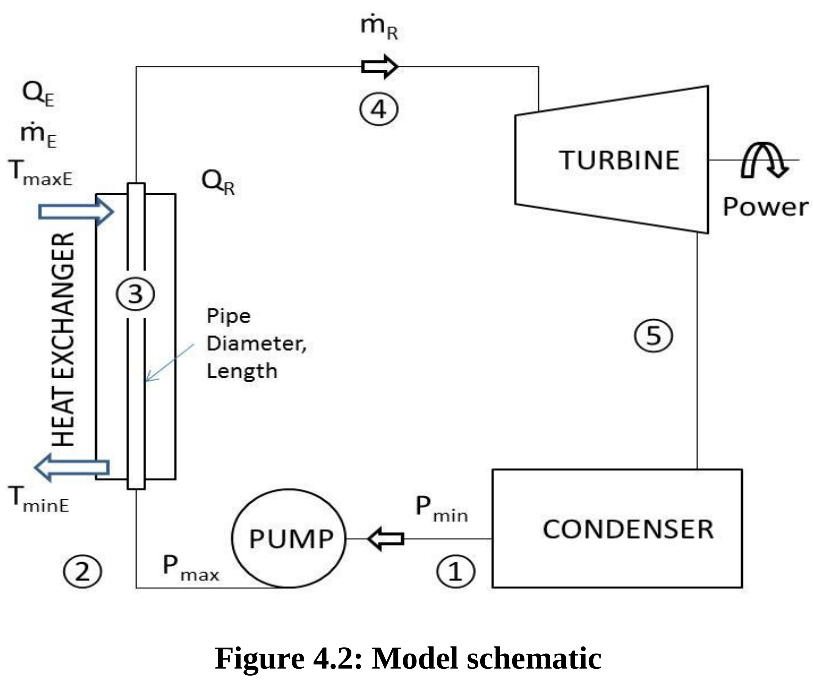


Figure 4.2: Model schematic

The simple Rankine cycle has four processes:

①-② Compression of the working fluid with work input

②-④ Heat addition to the working fluid

④-⑤ Expansion of the working fluid with work output

⑤-① Heat rejection from the working fluid

There are many possible applications for small scale “power” plant systems that make direct mechanical use of the power produced or that run small generators to produce electricity. Examples include provision of power to equipment in farming irrigation systems, driving reverse osmosis systems to produce fresh water for remote communities, and generating electricity for general use in small collectives in both 1st and 3rd world environments.

A common approach given an available heat source is to build such a system around the Rankine cycle, a mathematical representation of a “steam” operated heat engine.

This example is developed to test the method introduced in Chapter 3, Section 3.2 on exploring design priorities and decision making.

This Rankine cycle is defined by the cycle’s maximum and minimum pressures and maximum temperature ($P_{max}, P_{min}, T_{max}$). Energy is transferred to the closed loop Rankine cycle through a heat exchanger. The heat exchanger is assumed to be of a counter flow design where the key characteristic is the maximum temperature of the heating flow (T_{maxE}).

From a decision based design approach, the determination of satisficing values of these variables represents a coupled compromise-compromise DSP dealing with the Rankine cycle ($P_{max}, P_{min}, T_{max}$) and the heat exchanger (T_{maxE}) respectively. The notion of satisficing is discussed in Section 2.1.

The ideal Rankine cycle involves four processes, as shown graphically in the Temperature (T) versus Entropy (S) plot in Figure 4.3. There are two adiabatic isentropic processes: (constant entropy) and two isobaric processes (constant pressure).

Referring to Figure 4.3,

①-② adiabatic pumping of the saturated liquid from P_{min} to P_{max},
②-④ isobaric heat addition in heat exchanger to T_{max},
④-⑤ adiabatic expansion in the turbine from P_{max} to P_{min} producing power with the possibility of wet steam exiting the turbine, and
⑤-① isobaric heat loss in the condenser.

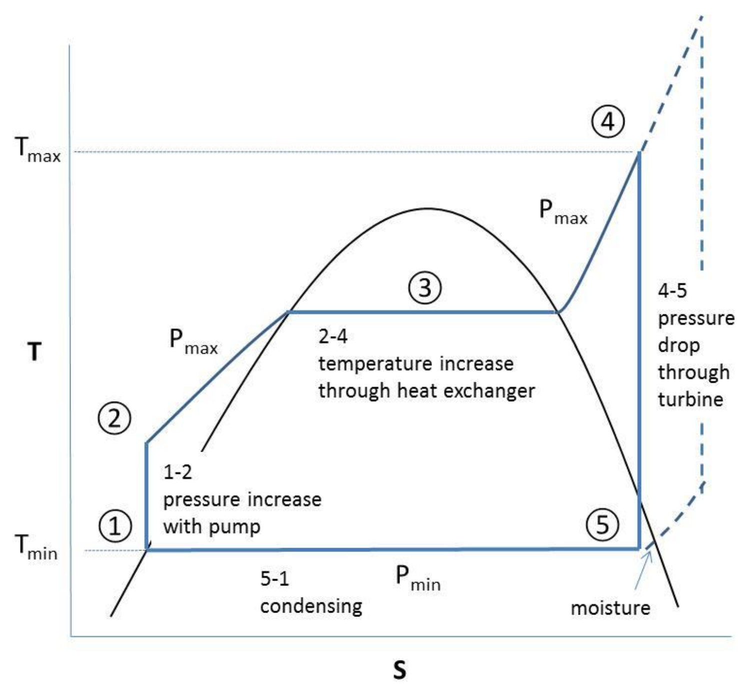


Figure 4.3: Rankine cycle (temperature vs entropy)

The isothermal segments represent movement from saturated liquid to saturated vapor in the case of ③ in the heater and the reverse in the condenser between ⑤-①. For an ideal Rankine cycle, the turbine and pump are assumed to be reversible and adiabatic. The key thermodynamic properties of the working fluid(s) are determined using REFPROP (Lemmon and co-authors, 2013) which is a data based used by National Institute of Standards and Technology. The purpose of creating this example is the compromise-compromise aspects between the Rankine cycle and exchanger. Later in the text, a number of efficiencies are defined to explore the tradeoffs.

Problem Statement

In this example, the attempt is to explore design priorities related to an ideal Rankine cycle working with a heat exchanger to obtain minimum moisture in the turbine, maximum Rankine cycle efficiency, maximum temperature exchanger efficiency, maximum system efficiency, and maximum heat transfer effectiveness in exchanger. The working fluid, water, and the exchanger flow rate and required power output are given. Thermodynamic fluid properties are determined using the data base REFPROP (Lemmon and co-authors, 2013). DSIDES data file with the detailed information of the problem is provided in Appendix B. DSIDES is a computer environment to solve a cDSP, and it is discussed in Section 2.4.

Design Goals

There are a number of design goals that are considered in formulating the Rankine cycle design example. They are discussed below. Equations 4.1 through 4.10 are adapted from literature (Hewitt and co-authors, 2008; Kaminski and co-authors, 2005; Lee,

2010) to develop the analysis model of the power plant.

Moisture in steam leaving the turbine

The first goal of the design in this example is related to goal 1-G1 of the cDSP presented in Section 4.1.2, Figure 4.4: the level of moisture leaving the turbine.

Quality of the steam (x) represents the moisture that is captured at different stages from the REFPROP database by providing two properties at the time. The attempt is to capture designs/solutions with zero percent moisture. The moisture leaving the turbine is controlled by the turbine maximum allowable moisture level which is given as a system requirement. Minimizing the moisture is one of the important goals due to its affect to the life of the turbine by increasing the corrosion of the turbine blades. Furthermore, liquid particles have lesser velocity than that of vapor particles which decreases the total velocity of the steam. This results a part of kinetic energy of steam to be lost.

Rankine cycle efficiency

The second goal of the design in this example is the Rankine cycle efficiency, which is related to goal 2-G2 of cDSP presented in Section 4.1.2, Figure 4.4. The Rankine cycle efficiency is the ratio between net power output and energy created by the exchanger, and it is calculated using the following equation:

$$\eta_R = \frac{\dot{W}_t - \dot{W}_p}{Q_{in}} \qquad \text{Eq. 4.1}$$

where power of the turbine and the pump, and the heat transfer into the cycle are calculated by:

$$\dot{W}_t = \dot{m}_R(h_4 - h_5) \qquad \text{Eq. 4.2}$$

$$\dot{W}_p = \dot{m}_R(h_2 - h_1) \qquad \text{Eq. 4.3}$$

$$Q_{in} = \dot{m}_R\ C_{pR}\ (T_4 - T_2) \qquad \text{Eq. 4.4}$$

Temperature exchanger efficiency

The third goal of the design in this example is the temperature exchanger efficiency, which is related to goal 3–G3 of cDSP presented in Section 4.1.2, Figure 4.4. The temperature exchanger efficiency is the ratio between exchanger outlet net temperature and Rankine inlet net temperature, and it is calculated using the following equation:

$$\eta_{tE} = \frac{T_{maxE} - T_{minE}}{T_{maxE} - T_2} \qquad \text{Eq. 4.5}$$

where T_{minE} is calculated from the given minimum temperature drop in the exchanger, and T_2 is captured from REFPROP by providing maximum pressure, P_{max} and entropy of the system at Point 2.

System efficiency

The forth goal of the design in this example is the system efficiency, which is related to goal 4–G4 of cDSP presented in Section 4.1.2, Figure 4.4. The system efficiency is defined as the product of Rankine cycle efficiency and temperature exchanger efficiency, and is calculated using the following equation:

$$\eta_{system} = \eta_R \eta_{tE} \qquad \text{Eq. 4.6}$$

Heat transfer effectiveness in exchanger

The fifth goal of the design in this example is the heat transfer effectiveness in exchanger which is related to goal 5–G5 of cDSP presented in Section 4.1.2, Figure 4.4. The heat transfer effectiveness in exchanger is calculated using the following equation:

$$\varepsilon_E = 1 - \exp\left(-\frac{UA}{\dot{m}_R\, C_{pR}}\right) \qquad \text{Eq. 4.7}$$

where overall heat transfer coefficient, surface area and log mean temperature are calculated by:

$$U = \frac{Q_{in}}{A\, \Delta T_m} \qquad \text{Eq. 4.8}$$

$$A = \pi L d \qquad \text{Eq. 4.9}$$

$$\Delta T_m = \frac{(T_{minE} - T_2) - (T_{maxE} - T_4)}{ln\left(\frac{(T_{minE} - T_2)}{(T_{maxE} - T_4)}\right)} \qquad \text{Eq. 4.10}$$

These goals along with a set of constraints are utilized to formulate the associated compromise DSP which is discussed in the following section.

4.1.2 Compromise DSP Word and Mathematical Formulation

Three main steps should be taken to formulate a compromise DSP. First, define a problem statement. The problem statement of designing Rankine cycle with an exchanger is given in Section 4.1.1. Second, formulate a related cDSP word problem, which is presented in this section. Third, formulate a mathematical model to support the word model.

The cDSP word formulation is presented in this section followed by the mathematical formulation. The cDSP word formulation of Rankine cycle with an exchanger is as follows:

Given

Water as the fluid in the Rankine cycle
Water as the heat transfer medium in the exchanger
The minimum pressure in the Rankine cycle
Ideal Rankine cycle thermodynamics
Ideal heat transfer in the heat exchanger
Thermodynamic fluid properties (REFPROP)

Find

Maximum pressure in the Rankine cycle
Maximum temperature in the Rankine cycle
Maximum temperature of the heating fluid
The deviation variables

Satisfy

Constraints

C1 Moisture in turbine less than upper limit
C2 Rankine cycle mas flow rate less than upper limit
C3 Temperature at ④ greater than temperature at ③
C4 Quality at ④ is superheated vapor
C5 Max. temperature in the exchanger greater than min. temperature in the exchanger by at least ΔT_E
C6 Min. temperature in the exchanger greater than temperature at ② by at least ΔT_{ER}
C7 Ideal Carnot cycle efficiency greater than system efficiencies (sanity check)
C8, C9, C10, C11 Temperatures within valid ranges for REFPROP fluid database
C12 Product of deviation variables equal
C13 Deviation variables to be positive

Goals

G1 Minimize moisture in steam leaving the turbine
G2 Maximize Rankine cycle efficiency
G3 Maximize temperature exchanger efficiency
G4 Maximize system efficiency
G5 Maximize heat transfer effectiveness in exchanger

Bounds

B1 Minimum value ≤ P_{max} ≤ Maximum value
B2 Minimum value ≤ T_{max} ≤ Maximum value
B3 Minimum value ≤ T_{maxE} ≤ Maximum value

Minimize

The deviation function (Z): Preemptive formulation

Figure 4.4: Power plant cDSP word formulation

In the cDSP formulated, a number of design parameters and thermal properties are given, three system variables in addition to deviation variables are found, thirteen constraints and five goals are defined, three bounds on the system variables are listed, and the objective is to minimize the deviation function. The goals and deviations are normalized. The related mathematical formulation of the power plant is as follows:

Given

Rankine cycle analysis model (Equations)
Parameters ($\Delta T_E, \dot{m}_E, \ldots$)

Thermodynamic fluid properties (REFPROP)

Find

P_{max}
T_{max}
T_{maxE}
d^- and d^+

Satisfy

Constraints

C1 $M \leq M_{max}$
C2 $\dot{m}_R \leq \dot{m}_{\max R}$
C3 $T_3 \leq T_4$
C4 $x_4 \geq 1$
C5 $T_{maxE} - T_{minE} \geq \Delta T_E$
C6 $T_{minE} - T_2 \geq \Delta T_{ER}$
C7 $\eta_{carnot} \geq \eta_{system}$
C8 $T_1 \geq T_{\min REFPROP}$
C9 $T_{\max REFPROP} \geq T_{max}$
C10 $T_{minE} \geq T_{\min E\, REFPROP}$
C11 $T_{maxE\, REFPROP} \geq T_{maxE}$
C12 $d^-_i * d^+_i = 0$
C13 $d^-_i, d^+_i \geq 0$

Goals

G1 $\frac{M_{Target}}{M} - d_1^- + d_1^+ = 1$
G2 $\frac{\eta_R}{\eta_{R_{Target}}} - d_2^- + d_2^+ = 1$
G3 $\frac{\eta_{tE}}{\eta_{tE_{Target}}} + d_3^- - d_3^+ = 1$
G4 $\frac{\eta_{system}}{\eta_{system_{Target}}} + d_4^- - d_4^+ = 1$
G5 $\frac{\varepsilon_E}{\varepsilon_{E_{Target}}} + d_5^- - d_5^+ = 1$

Bounds

B1 $500 \leq P_{max} \leq 5000$ (kPa)
B2 $350 \leq T_{max} \leq 850$ (K)
B3 $350 \leq T_{maxE} \leq 850$ (K)

Minimize

$Z(d^-, d^+) = [f_1(d^-, d^+), \ldots, f_k(d^-, d^+)]$

Figure 4.5: Power plant cDSP mathematical formulation

The six system goals in the example have been placed at six levels of priority in the implemented preemptive model. The implication is that the first level goal function will be satisfied as well as possible, and then, while holding it within a tolerance, the second level goal function will be addressed. When the second goal has been conditionally minimized it will be held within its tolerance and then the third goal will be worked upon, and so on in an attempt to address all the goals across all levels. Achieving satisfaction of the higher priority goals may cause a sacrifice in the achievement of the lower priority goals. By prioritizing the goals differently, comparison may show competing goals driving the solution process in different directions. By grouping more than one goal at the same level, an Archimedean (weighted sum) approach can be accommodated. This approach is discussed with another design example in Chapter 5.

4.2. Exploring Design Priorities by Tradeoffs Analysis through Goal Ordering in Design of Rankine Cycle: Results and Discussion

In Chapter 3, the solution space exploration method in model-based realization of engineered systems is proposed. Part of the method is about exploring design priorities through goal ordering which is discussed in Section 3.2 along with its relation to decision making. In this chapter, a design example of a small power plant is developed to test that part of the method. In the following sections, 4.2.1, 4.2.2 and 4.2.3, results associated with the example are discussed, however, the focus of this thesis is on the method not necessarily the results per se.

4.2.1 Exploring Design Priorities: XPLORE and Tradeoffs

Consider that a plant producing a baseline of 25kW is required and that higher power is sought, but the maximum steam that can be produced is only 0.1 kg/s. What are the characteristic values that define the Rankine cycle and the heat exchanger?

In answering this question, a two-step process using DSIDES is used, first with the XPLORE grid search module and then with the ALP algorithm. The XPLORE and ALP algorithm are discussed under DSIDES in Section 2.4.

Variable bounds have been defined, but do they encompass feasible designs? Using XPLORE, this question is examined. Presented in Figure 4.5 is a plot of T_{max} versus P_{max} showing discrete tested combinations that lead to feasible designs for 25, 50 and 70kW cases. Feasible designs exist where the constraint violation is zero. The extent of the plot reflects the bounds of each system variable. In the two dimensions shown in the following figures, the contradiction in the number of designs and the size of solution space is evident. The area covered by these designs/solutions can be interpreted as being representative of the feasible solution space(s).

Further use of XPLORE is done to examine the regions where goals are fully satisfied. To ensure longevity of the plant, the operational requirement is that moisture in the steam exiting the turbine is minimized. Therefore, the Level 1 priority goal for all results presented is that of minimizing moisture.

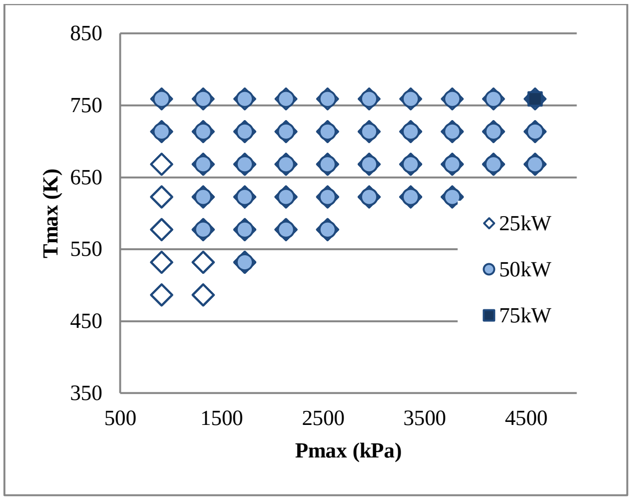


Figure 4.6: Feasible designs using XPLORE (less than 12% moisture)

If this were the only goal specified, Figure 4.6 denotes that multiple designs could achieve less than 5% moisture while producing 25 kW or 50 kW. Shown in Figure 4.7 are those designs which produced zero percent moisture. It follows that other goals need to be subsequently specified to achieve singular (local) convergence.

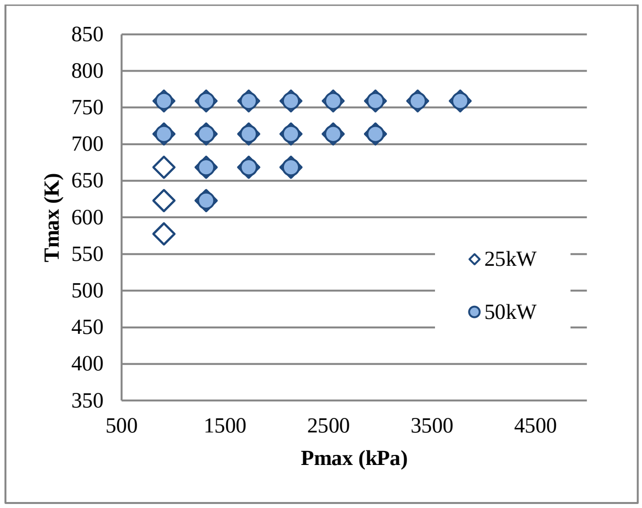


Figure 4.7: Feasible designs with moisture less than 5% using XPLORE

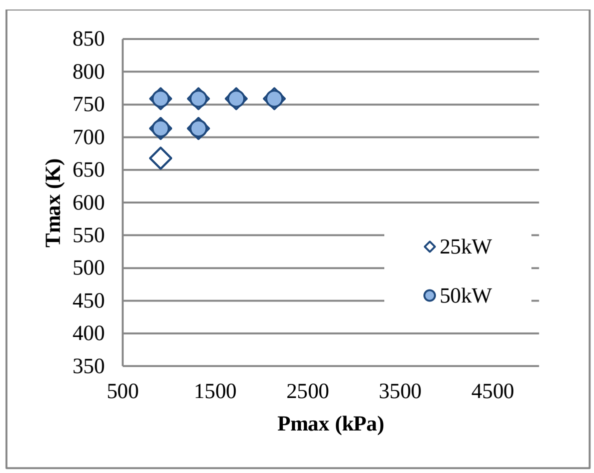


Figure 4.8: Feasible designs with 0.000% moisture using XPLORE

For the 25kW designs, if some moisture is allowed (i.e., up to 12%). higher Rankine cycle efficiencies can be achieved with designs depicted in the region shown in top right of Figure 4.8 (efficiencies better than 27.5%). However, when constraining the designs to have zero moisture caps, the best Rankine cycle efficiency is found at 25% (P_{max} 2136 kPa and T_{max} 759K), significantly to the left of the Figure 4.8 cluster. This reflects the best "Order 1" XPLORE solution. The two orders which represent design priority scenarios are reflected in Table 4.2.

Table 4.2: Design priority scenarios

	Design Priorities
Order 1	1) Minimize moisture 2) Maximize Rankine cycle efficiency 3) Maximize temperature exchanger efficiency 4) Maximize system efficiency 5) Maximize exchanger effectiveness
Order 2	1) Minimize moisture 2) Maximize system efficiency 3) Maximize temperature exchanger efficiency 4) Maximize exchanger effectiveness 5) Maximize Rankine cycle efficiency

Considering the system efficiency goal representation, η_{system}, if set as priority one, values of 16% in the lower left region shown in Figure 4.8 are possible. If, constraining the designs to have zero moisture caps, the best η_{system} value found is 12% (P_{max} 909 kPa and T_{max} 668 K), significantly higher than the Figure 4.8 cluster. This reflects the best "Order 2" XPLORE solution.

To summarize, higher Rankine cycle efficiencies are achieved with high temperatures and high pressures. In contrast, the higher system efficiency results from low temperatures and low pressures. In addition, to achieve zero moisture in the turbine, the requirement is high temperatures with lower pressures. See Figure 4.9. Clearly, the right decision is not straightforward, hence the compromise and tradeoff is necessary. Just as

XPLORE results are discussed, the following Section, 4.2.2, will explore the tradeoffs found in the ALP results.

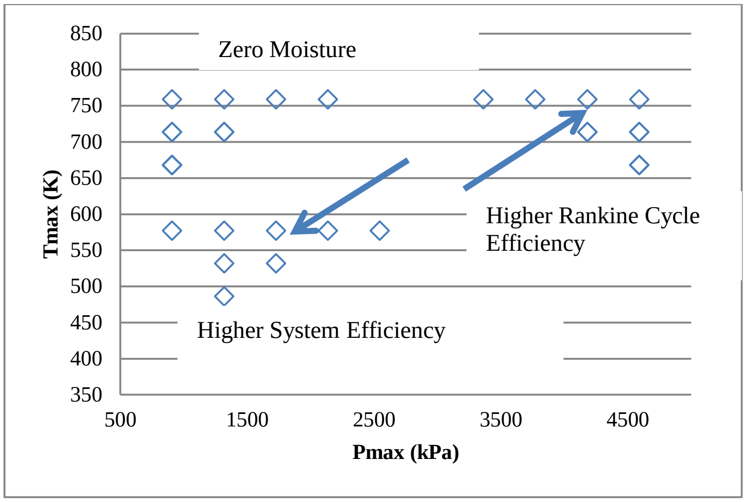


Figure 4.9: Trade-offs for feasible designs for 25kW (less than 12% moisture)

4.2.2 Exploring Design Priorities: ALP and Tradeoffs

While the framing value of using the XPLORE DSIDES module has been demonstrated, what further insights can be developed using the DSIDES ALP algorithm to refine understanding?

The next set of results presented is for the two aforementioned groupings of the goals: Order 1 (Figure 4.10), producing high temperature and pressure results and Order 2 (Figure 4.12), low temperatures and pressures. This is the tradeoff between the two design priority sets which can be seen from system variables perspective in those two figures.

The deviation variable associated with each goal have been named with a leading "d", for example $d\eta_R$ referring to the Rankine Cycle Efficiency goal. The values of the deviations are normalized between 0 and 1. The convergence of the deviation variables associated with each goal is shown for Order 1 and 2 in Figures 4.11 and 4.13. Monitoring exchanger efficiency, η_{tE}, in both figures, shows it increases to 0.7 for Order 1 but decreases to almost zero for Order 2, highlighting the tradeoffs for the two sets of design priorities.

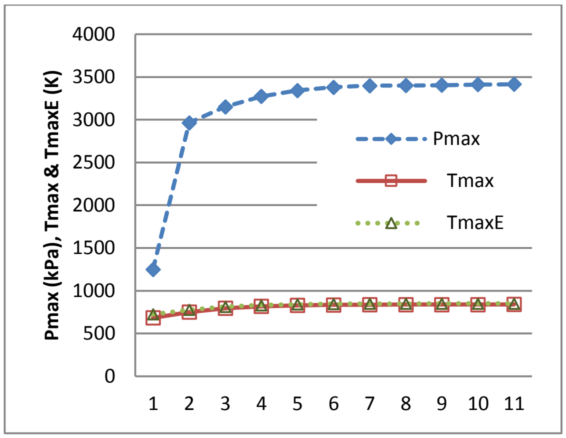


Figure 4.10: Order 1 system variable (25kW) convergence plotted against iteration

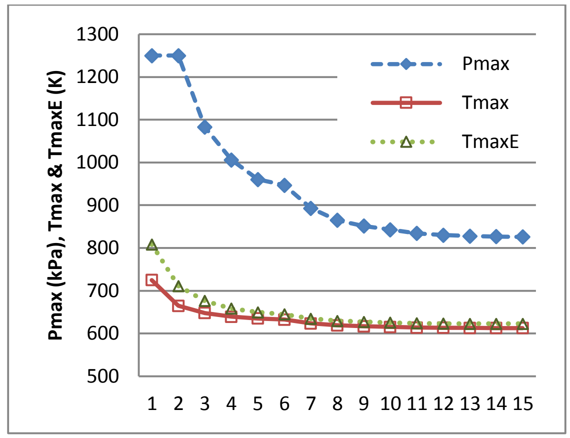


Figure 4.12: Order 2 system variable (25kW) convergence plotted against iteration

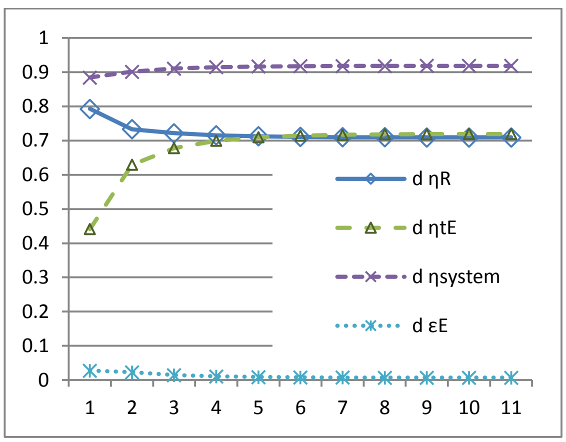


Figure 4.11: Order 1 deviation variable (25kW) convergence plotted against iteration

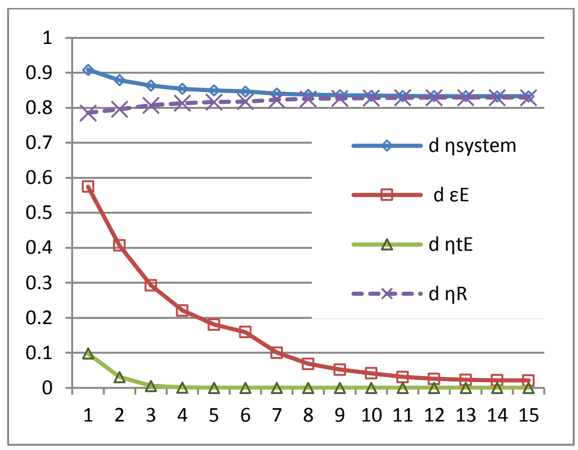


Figure 4.13: Order 2 deviation variable (25kW) convergence plotted against iteration

The behavior of the model can be assessed in a number of ways including convergence of the system and deviation variables. For the benchmark 25kW cases, the convergence history for Order 1 is presented in Figures 4.10 and 4.11 and for Order 2 in Figures 4.12 and 4.13. All curves reach a stable final steady state. In the case of Order 1, zero moisture in the turbine is not achieved until Iteration 9. This aspect - zero percent moisture dominated the solution process to this point. However, $d\eta_R$ is seen to be generally decreasing. The reverse is true for Order 2. In Order 2, zero percent moisture is achieved beginning of Iteration 5 from which point reductions in $d\eta_{system}$, $d\eta_{tE}$ and $d\varepsilon_E$ are evident, again noting the tradeoffs for the two sets of design priorities. Clearly, an indicator of excess capacity in considering the baseline 25kW case is that the flow rate in the turbine is well below the defined bound on this variable of 0.1kgs-1. In framing and exploring a design model, the nature of the specified variable bounds needs to be understood. Of note, some bounds are determined based on true physical constraints and others may be arbitrary.

4.2.3 Exploring Design Priorities: Parametric Study and Tradeoffs

Given an upper limit on the mass flow rate in the Rankine cycle of 0.1kgs-1, a parametric study is done to establish the power output limit for the system. Shown by the results tabulated in Table 4.3 (for both Order 1 and Order 2), are solutions for 25, 50 and 75 kW configurations. While not shown in Table 4.3 to maintain clarity, for each of the six arrangements (combinations of power output and goal priority order), different starting points are attempted. The solutions for each power output are, for all intents and purposes, the same, suggesting, though not guaranteeing, that the global minima for the formulation may have been found.

Table 4.3: Parametric study of power

		ORDER 1 Priority 1,2,3,4,5				ORDER 2 Priority 1,4,3,5,2			
		25 kW	**50 kW**	**75 kW**	NOTES	**25 kW**	**50 kW**	**75 kW**	NOTES
INITIAL SOLUTION	Pmax (kPa)	2000	2000	4250		1250	1250	4250	
	Pmin (kPa)	100	100	100		100	100	100	
	Tmax (K)	767	767	767		683	683	767	
	TmaxE (K)	808	808	808		725	808	808	
	L (m)	154	154	154		113	154	154	
FINAL SOLUTION	**Pmax (kPa)**	3415	3415	3417	*Consistently high (constant)*	826	1287	2889	*Lower but increases with power*
	Tmax (K)	840	840	840	*Consistently high (constant)*	613	743	810	*Lower but increases with power*
	TmaxE (K)	850	850	850	*Consistently high (constant)*	623	753	820	*Lower but increases with power*
	L (m)	50	50	50	*Formulation insensitive to L*	50	50	50	*Formulation insensitive to L*
GOALS (Deviations)	d M	0.000	0.000	0.000	*Zero Moisture achieved in all*	0.000	0.000	0.000	*Zero Moisture achieved in all*
	d ηR	0.709	0.709	0.709		0.830	0.780	0.723	
	d ηtE	0.720	0.430	0.120		0.020	0.010	0.010	
	d ηsystem	0.918	0.833	0.745		0.833	0.783	0.727	
	d εE	0.007	0.001	0.000		0.000	0.000	0.000	
Derived Values	**$\dot{m}$R (kgps)**	0.027	0.050	0.080	*Comparitively "low"*	0.050	0.080	0.090	*Comparitively "high"*
	ηR	0.291	0.291	0.291	*Comparitively "high"*	0.170	0.220	0.280	*Comparitively "low"*
	ηtE	0.281	0.573	0.876	*Comparitively "low"*	0.980	0.990	0.990	*Consistently high (constant)*
	ηsystem	0.081	0.167	0.255	*Comparitively "low"*	0.167	0.216	0.273	*Comparitively "high"*
	εE	0.990	0.990	1.000	*Stable - Ideal transfer assumption*	1.000	1.000	1.000	*Stable - Ideal transfer assumption*
	CARNOT	0.556	0.556	0.556	*Theoretical MAX in Rankine*	0.392	0.498	0.540	*Theoretical MAX in Rankine*

The parametric study of power has provided the flow rate results depicted in Figure 4.14. For Order 1 where Rankine cycle efficiency is favored, the flow rate is lower because of the improved efficiency. Extrapolating to where both flow rate curves would intersect the 0.1 kgs-1 upper bound, it would appear that approximately 90 kW would be available in the modeled ideal system. A companion plot of the Rankine cycle efficiency versus power is given in Figure 4.15 where a consistently high efficiency is achieved for Order 1.

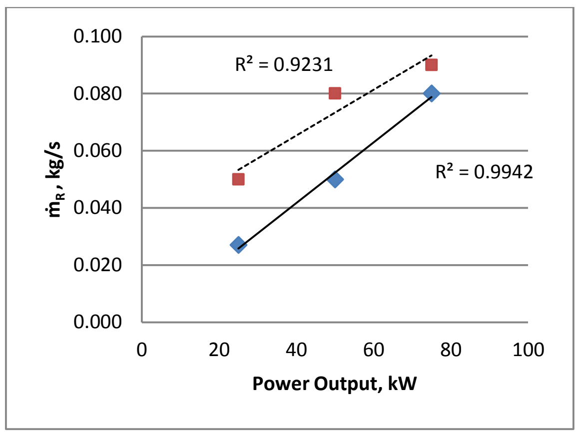


Figure 4.14: Rankine cycle mass flow rate versus power output (Order 1 – solid line; Order 2 – dashed line)

The efficiencies produced under Order 2 are forced to increase to produce the higher power demands. In contrast, the final plot presented, Figure 4.16, is used to highlight how higher values of system efficiencies are achieved by prioritizing the goals as per Order 2. The system efficiency is a product of the efficiencies of two primary system components, the exchanger and the Rankine cycle.

Since the idealized efficiency of the exchanger is higher than that of the Rankine cycle, this term dominates and therefore drives the solution to the lower temperatures and pressures that suit the exchanger. The monotonically increasing curves shown in Figure 4.16 further suggest that higher overall efficiencies will come with higher power output.

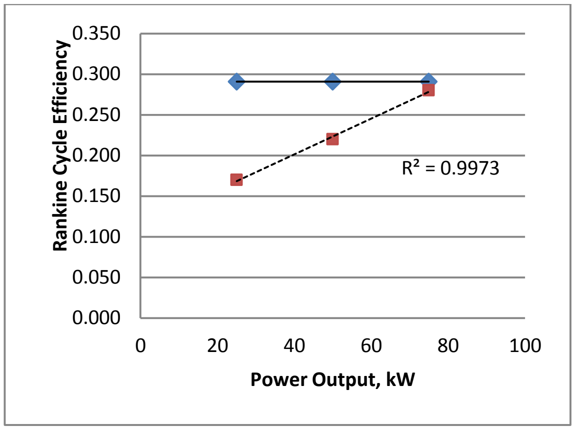


Figure 4.15: Rankine cycle efficiency versus power output (Order 1 – solid line; Order 2 – dashed line)

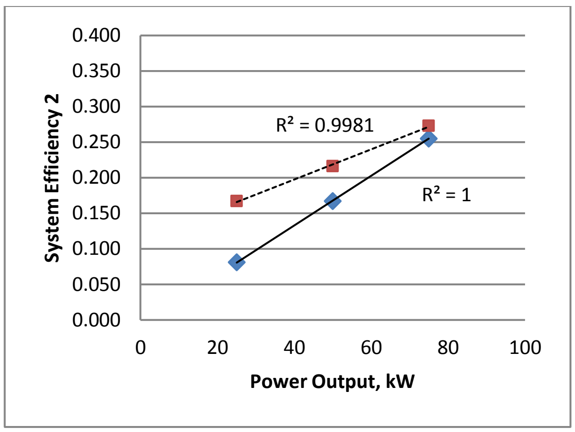


Figure 4.16: System efficiency versus power output (Order 1 – solid line; Order 2 – dashed line)

In Sections 4.1 and 4.2, the Rankine cycle example is introduced and usefulness of results applying the solution space exploration method is discussed, respectively. In the next section, empirical structural and performance validity of the solution space exploration is discussed.

4.3. Empirical Structural and Performance Validity

To test solution space exploration method proposed in Chapter 3, Validation Square is adapted, which involves different steps. The Validation strategy is discussed in Chapter 1. In this chapter, the empirical structural and performance validity of the proposed method is checked. Shown in Figure 4.17, empirical structural validity involves Step (3) accepting the appropriateness of the example problems that is used to verify the performance of the method. In essence, it must be shown that the examples are good representations of design problems, for which the method is designed, and that the associated data can be used to support a conclusion. Empirical performance validity is about showing the usefulness of the method for solving the example problems which includes Steps (4) and (5): accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s); accepting that the achieved usefulness is linked to applying the method. In essence, results achieved using the design method has to be analyzed and assessed.

The solution space exploration method involves different aspects which is verified using different design examples. The design example presented in this chapter, a small power plant, is chosen to test the utility of one part of the proposed method, namely, exploring design priorities through goal ordering.

This is an appropriate example due to its compromise-compromise notion in which design tradeoffs can be discussed from different perspectives. The example consists of five goals related to the Rankine cycle and the exchanger. Two goal-ordering scenarios are designed and explored. In Section 4.2.1, design priorities are explored using the

XPLORE feature of DSIDES in which feasible regions are discovered for different required power output. In Section 4.2.2, ALP is used and the design tradeoffs are shown and discussed through the convergence of the solutions related to different orders. Finally, design tradeoffs between two of the goals are explored through a parametric study on the flow rate and power output. The results and discussion provide insight and support for a designer during their decision-making processes.

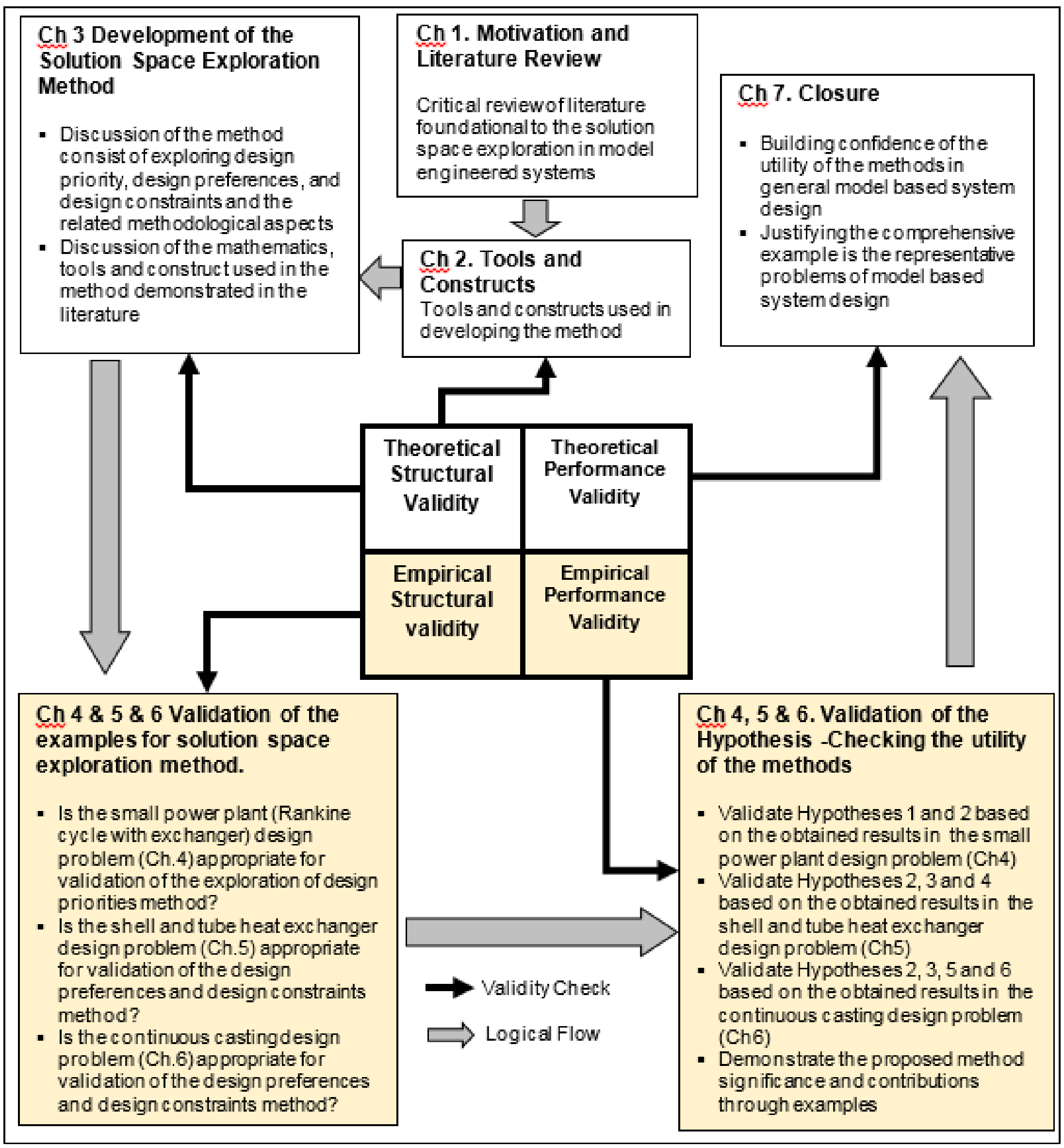


Figure 4.17: Validation square road map

This is an appropriate example due to its compromise-compromise notion in which design tradeoffs can be discussed from different perspectives. The example consists of five goals related to the Rankine cycle and the exchanger. Two goal-ordering scenarios are designed and explored. In Section 4.2.1, design priorities are explored using the XPLORE feature of DSIDES in which feasible regions are discovered for different required power output. In Section 4.2.2, ALP is used and the design tradeoffs are shown and discussed through the convergence of the solutions related to different orders. Finally, design tradeoffs between two of the goals are explored through a parametric study on the flow rate and power output. The results and discussion provide insight and support for a designer during their decision-making processes.

Moreover, the performance validity of the model is checked through exercising the thermal model (i.e., investigation of the model by parametric study such as net power output). For instance, since the power is a function of Rankine flow rate, it is expected that higher flow rates are necessary to produce higher power. This is verified and is discussed in more detail in Section 4.2.3.

The model is also checked by monitoring the behavior of the model having conflicting goals. This model includes five goals, four of which estimate measures of efficiency: the Rankine cycle efficiency, the heat exchanger efficiency, system efficiency, and the heat exchanger effectiveness. Individually, each of these efficiency measures has a justifiable meaning and influence on the system. By exploring different goal priority orders, and by examination of the monotonicity of the goals (Smith and co-authors, 1994), it is discovered that the prioritization of the efficiency goals in a preemptive formulation drives the system in two different directions in the solution space, shown in Figure 4.9.

If prioritization is given to the Rankine cycle efficiency, the solutions are of high temperature and high pressure character; in discussing the results, this order of priority is referred to as “Order 1”. In contrast, low temperature and low pressure solutions are preferred if the heat exchanger efficiency, system efficiency and/or heat transfer effectiveness are prioritized (Order 2). This behavior of the model is appropriate and predictable given the model goal formulations.

Furthermore, the model and results are validated through use of design experimentation and response surface models created by MATLAB. Twenty seven experiments are designed having three independent variables/factors (P_{max}, T_{max}, and T_{maxE}) and three levels with three dependent variables/responses (Rankine efficiency, exchanger efficiency, and system efficiency).

Response surface models of the Rankine cycle efficiency are obtained (see Figures 4.18 and 4.19). The tradeoffs between the two goals, namely, Rankine cycle efficiency and system efficiency, are demonstrated in Figure 4.20. In all these figures, x1, x2 and x3 represent P_{max}, T_{max} and T_{maxE}, respectively.

Using SPSS, the effect for each of the independent variables and the combination of their effect on the dependent variables is measured. The results indicate that P_{max} and T_{max} have significant main effects on dependent variable 1, Rankine cycle efficiency (F_{PMAX}) (1,2) = 3.7 * 10^30, *p (Sig)* < 0.0001; F_{TMAX} (1,2) = 8.1 * 10^29, *p* < 0.0001. The R^2 is the same as computed by MATLAB to be 1. Furthermore,

P_{max} and T_{max} have a significant combined effect on Rankine efficiency, $F_{PMAXE*TMAX}(1,4) = 1.2 * 10^{27}$, $p < 0.0001$. However, as expected, T_{maxE}, the maximum temperature of the hot fluid in the exchanger, has no effect on Rankine efficiency, $F_{TMAXE}(1,2) = .000$, $p > .05$. More detailed discussion of the results which are obtained using response surface models are provided in Appendix C.

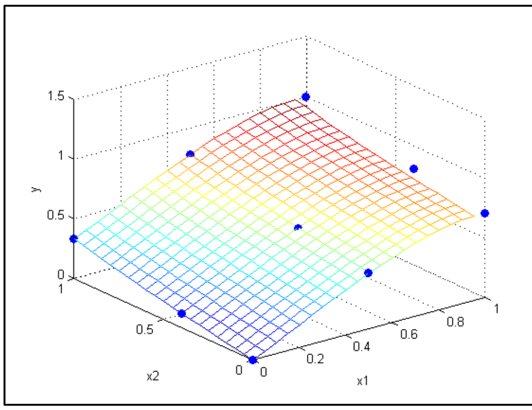


Figure 4.19: Response surface model for Rankine cycle efficiency

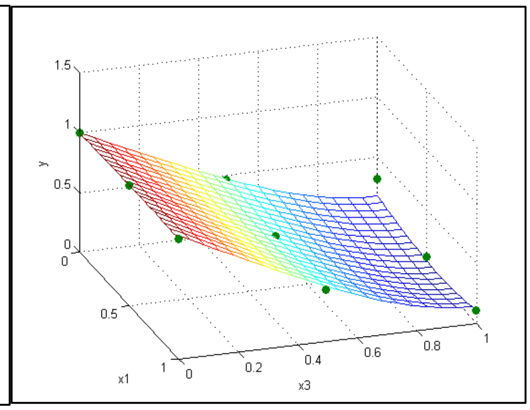


Figure 4.18: Response surface model for system efficiency

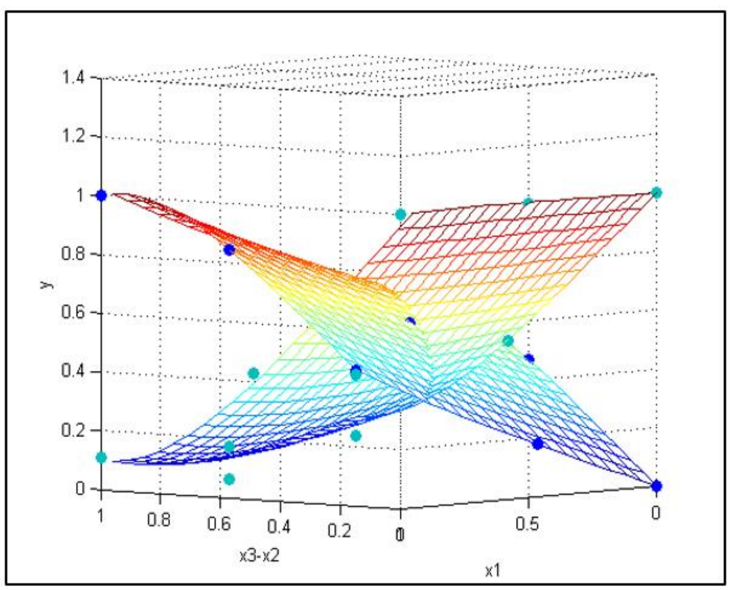


Figure 4.20: Tradeoffs between Rankine cycle and system efficiencies

4.4 What Has Been Presented and What is Next

In this thesis a method for solution space exploration is proposed. The method consists of different dimensions which are discussed in Chapter 3. To verify the method, different design examples are used in this thesis.

In this chapter, design priorities in designing a small power plant are explored through goal ordering. The mathematical model related to Rankine cycle with exchanger is developed and described in Section 4.1. Results and discussion are covered in Section 4.2. The intent is to illustrate the method, and provide insight for a designer in decision making related to design priorities particularly in presents of conflicting goals. In such cases, decision making is not straight forward and designer needs to explore different options, and gain sufficient knowledge and information to make a satisfying decision.

In the next chapter, two other parts of the method, namely, exploring design preferences through weight sensitivity analysis, and exploring design constraints through constraint sensitivity analysis are tested utilizing design of shell and tube heat exchanger.

CHAPTER 5 SOLUTION SPACE EXPLORATION: EXPLORING DESIGN PREFERENCES, DESIGN CONSTRAINTS AND DESIGN SELECTIONS IN DESIGN OF A SHELL AND TUBE HEAT EXCHANGER

In this thesis, a method for solution space exploration in model-based realization of engineered systems is proposed, in order to bring insight to the solutions and support designers in the process of decision making (see Figure 5.1). The method is discussed in Chapter 3, and based on Quadrants 3 and 4 of the Validation Square discussed in Chapter 1, different aspects of the method is verified through different design examples. In Chapter 4, a design example is developed for a small power plant and explored in terms of design priorities. In this chapter, the mathematical model for the shell and tube heat exchanger is developed and explored to show the efficiency of the method in **Block C: exploring design preferences and design constraints** using compromise DSP, and **Block A: exploring design selections** using selection DSP (highlighted in Figure 5.1).

There are three sections in this chapter. The mathematical model for the shell and tube heat exchanger is developed in Section 5.1, and design goals and problem statement are introduced. Next, exploring design preferences through weight sensitivity analysis, and exploring design constraints through constraint sensitivity analysis are discusses in Section 5.2. Finally, in Section 5.3 design selections are investigated for choosing material for the shell and tube heat exchanger.

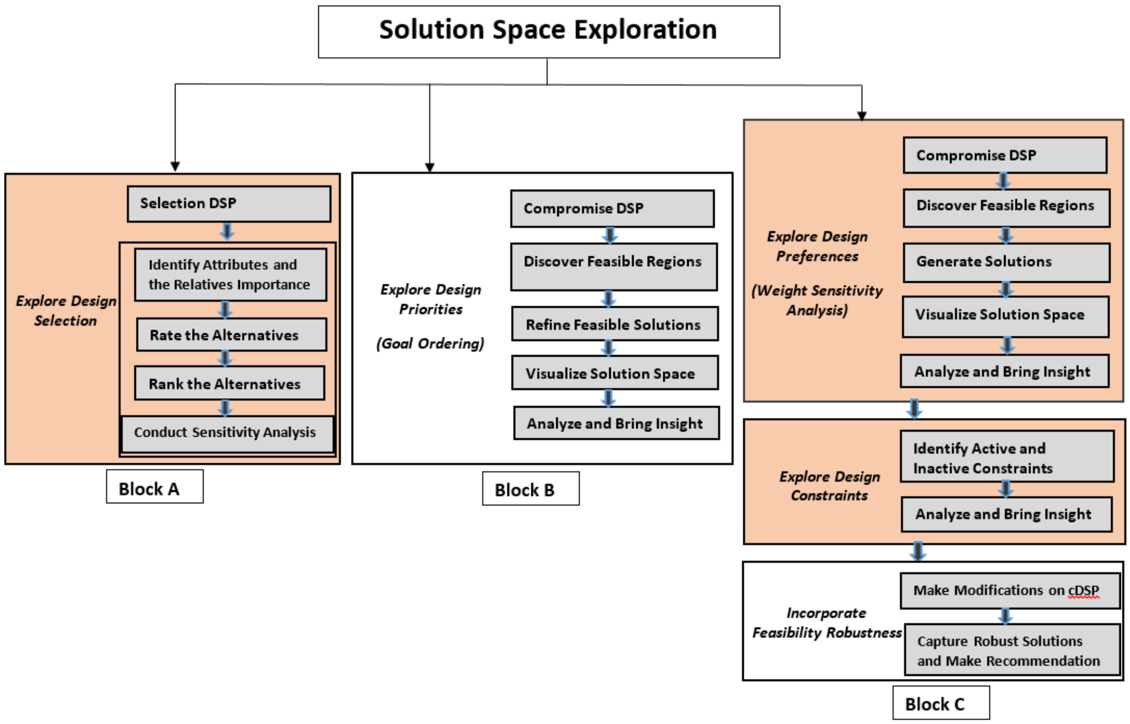


Figure 5.1: Solution space exploration

5.1 Developing a Mathematical Model for Shell and Tube Heat Exchanger

The efficacy of the proposed solution space exploration method in Chapter 3 (Sections 3.1 and 3.3) is illustrated in this chapter using a design example of a shell and tube heat exchanger. The method is generalizable to other decision constructs. The emphasis lies in the method rather than the results *per se*. Table 5.1 identifies related nomenclature.

In this section, the shell and tube heat exchanger is first introduced and the problem statement is defined (Section 5.1.1). Following, the compromise DSP word and mathematical formulation are described (Section 5.1.2). Exploration and analysis of the results are provided in Section 5.2.

Table 5.1: Shell and tube nomenclature

NOMENCLATURE

DSP	Decision Support Problem	$\dot{m}_t$	Tube flow rate
cDSP	Compromise Decision Support Problem	N_{tps}	The number of tube passes
DSIDES	Decision Support In the Design of Engineered Systems	N_t	Number of tubes
		P_t	Tube pitch
RCEM	Robust Concept Exploration Method	$\dot{Q}$	Total heat transfer
A_0	Exterior surface area of one tube	$\dot{Q}_{act}$	Actual heat transfer
$A_{0Target}$	Target value for heat transfer area	$\dot{Q}_{max}$	Maximum heat transfer
A_c	Tube cross section area	r_i	Tube inner radius
C_{pt}	Specific heat	r_0	Tube outer radius
C_t	Tube clearance	T_t	Tube thickness
ε	Effectiveness	T_{t_i}	Tube inner temperature
ε_{Target}	Target for effectiveness	T_{t_o}	Tube outer temperature
f_t	Tube friction factor	T_{s_i}	Inner shell temperature
F	Correction factor	T_{s_o}	Outer shell temperature
G_t	Tube side mass velocity of the fluid	U	Overall heat transfer coefficient
HL	Allowable heat lost	ΔP_t	Tube pressure drop
h_i	Convective HT coefficient (interior fluid)	$\Delta P_{tTarget}$	Target for tube pressure drop
h_0	Convective HT coefficient (exterior fluid)	ΔT_m	Log mean temperature difference
L_t	Tube length	ρ_t	Density of tube fluid
M_k	Tube thermal conductivity	Φ_t	Viscosity ratio (tube)
$\dot{m}_s$	Shell flow rate		

5.1.1 Shell and Tube Heat Exchanger Introduction and Problem Statement

Heat exchangers are thermal systems that are widely used to transfer heat from one fluid to another. There are different types of heat exchangers with different applications, however, they all follow fundamental rules of thermodynamics. The basic functions involved in heat exchangers are: 1) convective heat transfer from fluid to the inner wall 2) conductive heat transfer through the wall 3) convective heat transfer from the outer wall to the fluid. One of the fluids is hot and the other is cold. The hot and cold fluids can move in either the same or opposite directions. The aforementioned flow arrangements are called parallel flow and counter flow, respectively. The parallel flow and counter flow are shown in Figure 5.2.

Figure 5.2: Parallel flow and counter flow ("Heat Exchangers," 2015)

Among various types of heat exchangers, the shell and tube is the most widely used in industry, and typically used in the processing industry (65% of the market (Lee, 2010)). This type of exchanger facilitates the transfer of heat in heating and air conditioning, chemical processes, power generation, oil refrigeration, manufacturing, and medical applications.

The name itself, shell and tube, explains the physical structure consisting of round tubes mounted in a cylindrical shell with the tubes parallel to the shell. The tube design can be either a U pattern or a straight pattern, and they may have single pass or multiple passes. One fluid flows inside the tubes and the other fluid flows outside of the tubes, inside the shell, which in turn exchanges heat through the tube wall between the two fluids. Shell baffles, a component of shell and tube heat exchangers, directs the flow of fluid and increases the rate heat transfer. A single pass shell and tube heat exchanger with parallel flow is shown in Figure 5.3. With this type of exchanger, the fluids have different initial temperatures and can be either liquids or gases. In addition, the hot and cold fluids can be placed in either the tube or shell. The advantage of this kind of heat exchanger is the large ratio of heat transfer area to volume and weight, which facilitates energy saving and effective heat transfer. Heat exchangers operate in either single phase or double/multiple phases. It is called single phase if none of the fluids goes under phase change from gas to liquid or vice versa. However, power plants that use steam-driven turbines uses heat exchangers to boil water into steam.

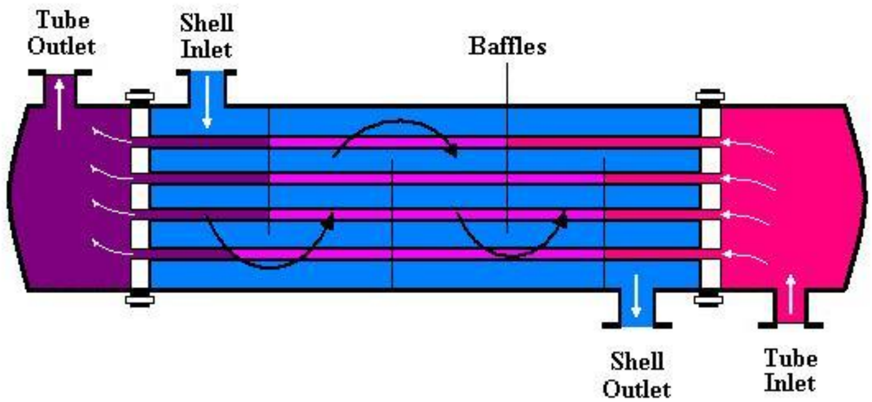


Figure 5.3: Shell and tube heat exchanger ("Heat Exchangers," 2015)

The selection of tube material is a key factor in design of STHX to facilitate conductive heat transfer by increasing the temperature difference between the two fluids. Common tube materials include copper, aluminum, stainless steel, and brass. Their characteristics differ in heat conductivity, density, corrosion resistance, and cost, which are the drivers in the design selection. Design selection exploration discussed in Chapter 3 Section 3.1 is adapted to explore material selection in this example. The results are discussed in Section 5.3.

Shell and tube heat exchanger design involves complex processes including selection between component alternatives such as material, working fluid, a large number of geometric variables, and the compromise between different goals such as heat transfer area, pressure drops in the shell and tube, and heat transfer effectiveness. Designing and decision making in such cases required exploring different options and gaining insight to facilitate an informative decision. Exploring design preferences and design constraints, two parts of the solution space exploration method discussed in Chapter 3, Section 3.3 and 3.4, are illustrated in this chapter in designing of a shell and tube heat exchanger, and the results are presented in Section 5.2.2 and 5.2.3, respectively.

Problem Statement

In this example, solution space of a one-pass shell and tube heat exchanger is explored to obtain minimum heat transfer area, minimum pressure drop, and maximum effectiveness. For this concept, designers use water for fluid, copper for the material, a triangular pitch orientation and keep both inlet pressures and temperatures constant. In addition to those specifics, turbulent flows are considered. Thermodynamic fluid properties are determined using the data base REFPROP (Lemmon and co-authors, 2013). A DSIDES data file with detail information is provided in Appendix D.

Design Goals

There are several design goals that are considered in this problem and discussed below. Equations 5.1 to 5.26 are adapted from literature (Hewitt and co-authors, 2008; Kaminski and co-authors, 2005; Lee, 2010) to develop the analysis model of shell and tube heat exchangers.

<u>Heat transfer area</u>

The first goal of the design in this example is the heat transfer area (Goal 1-G1 of the cDSP presented in Section 5.1.2 Figure 5.6.). The heat transfer area of a shell and tube heat exchanger can be obtained from Equation 5.1:

$$A_0 = \frac{\dot{Q}}{UF\Delta T_m} \qquad \text{Eq. 5.1}$$

where A_0 is the heat transfer surface area based on the outer diameter of the tube, and $\dot{Q}$ is the heat transfer rate of the exchanger. Since one pass exchanger is considered, the correction factor, F, is assumed to be 1. The log mean temperature difference for the counter flow for the inlet and outlet temperatures of the fluid in the tube and shell, ΔT_m, is calculated by:

$$\Delta T_m = \frac{(T_{ti}-T_{so})-(T_{to}-T_{si})}{ln(\frac{(T_{ti}-T_{so})}{(T_{to}-T_{si})})} \qquad \text{Eq. 5.2}$$

The overall heat transfer coefficients, U, depends on both the tube and shell heat transfer coefficients:

$$U = \frac{N_t}{\frac{1}{h_0}+\frac{(r_0)}{M_k}ln\left(\frac{r_0}{r_i}\right)+\frac{r_0}{h_i r_i}} \qquad \text{Eq. 5.3}$$

where N_t is the number of tubes, h_i and h_0 represent the convective heat transfer coefficient on the tube interior fluid, and the convective heat transfer coefficient on the tube exterior fluid, respectively. r_i and r_0 are tube inner and outer radii, and M_k is the tube material thermal conductivity. The equations below are to support computing of h_i:

$$h_i = \frac{k(Nu_i)}{2(r_i)} \qquad \text{Eq. 5.4}$$

$$Nu_i = \frac{\left(\frac{f}{2}\right) Re\ Pr}{1.07+12.7\left(\frac{f}{2}\right)^{0.5}(Pr^{\left(\frac{2}{3}\right)}-1)} \qquad \text{Eq. 5.5}$$

$$Pr = \frac{C_p\ \mu}{k} \qquad \text{Eq. 5.6}$$

$$f = \left(1.58\, ln\, Re - 3.28\right)^{-2} \qquad \text{Eq. 5.7}$$

$$Re = \frac{\rho V(2*r_i)(N_{tps})}{\mu N_t} \qquad \text{Eq. 5.8}$$

The equations below are to support computing of h_o:

$$h_0 = \frac{k(Nu_o)}{D_e} \qquad \text{Eq. 5.9}$$

$$D_e = \frac{4\left(\frac{P_T{}^2(\sqrt{3})}{4} - \frac{\pi d_0{}^2}{8}\right)}{\frac{\pi d_0}{2}} \qquad \text{Eq. 5.10}$$

$$Nu_o = 0.36(Re)^{0.55}(Pr)^{\frac{1}{3}}(\frac{\mu_b}{\mu_w})^{0.14} \qquad \text{Eq. 5.11}$$

$$Re = \frac{D_e G_S}{\mu} \qquad \text{Eq. 5.12}$$

$$G_s = \frac{\dot{m}}{A_s} \qquad \text{Eq. 5.13}$$

$$A_s = \frac{D_S CB}{P_T} \qquad \text{Eq. 5.14}$$

$$D_s = \sqrt{\frac{4N_T A}{(CTP)\pi}} \qquad \text{Eq. 5.15}$$

$$A = (CL)P_T{}^2 \qquad \text{Eq. 5.16}$$

$$Pr = \frac{C_p\, \mu}{k} \qquad \text{Eq. 5.17}$$

where Nu, Pr, Re, and f are dimensionless parameters, the Nussle number, Prandtl number, Reynolds number and friction factor, respectively. The number of tube and shell pass is assumed to be 1, CTP is the tube count constant (0.93) for one tube pass, and CL is the tube layout constant (0.87) for triangular tube orientation. P_T, C, and B are the tube pitch, clearance between adjacent tubes, and length of the flow area, respectively (see Figure 5.4).

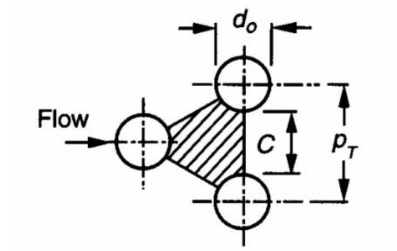


Figure 5.4: Tube triangular orientation

Pressure drop

The second goal of the design in this example is the tube pressure drop, which is related to Goal 2-G2 of cDSP presented in Section 5.1.2 Figure 5.6. In heat exchanger design, pressure drop considerations are of high interest due to the close physical and economical relation to heat transfer. Tube side pressure drop is calculated by:

$$\Delta P_t = \frac{N_t f {G_t}^2 L N_{tps}}{4\rho_t r_i \emptyset_t} \qquad \text{Eq. 5.18}$$

where G_t and $\emptyset_t$ are the mass velocity and viscosity ratio, respectively.

$$G_t = \frac{\dot{m}}{A_{cs}} \qquad \text{Eq. 5.19}$$

$$\emptyset_t = (\frac{\mu}{\mu_{wall}})^{.14} \qquad \text{Eq. 5.20}$$

Unbaffled shell is considered in this problem and shell side pressure drop for such assumption is calculated by:

$$\Delta P_s = \frac{f_s {G_s}^2 L N_{sp}}{2\rho_s D_H \emptyset_s} \qquad \text{Eq. 5.21}$$

where D_H represents the hydraulic diameter of the shell, and f_s is the friction factor.

$$D_H = \frac{4(\left(\frac{\pi D_S{}^2}{4}\right) - (\pi(2r_0)^2 N_t))}{\pi 2 r_0 N_t + \pi D_S} \qquad \text{Eq. 5.22}$$

$$f_s = \exp(0.576 - 0.19\, In\, (Re_s)) \qquad \text{Eq. 5.23}$$

Heat transfer effectiveness

The third goal of the design in this example is the heat transfer effectiveness (Goal 3–G3 of cDSP presented in Section 5.1.2 Figure 5.6). The effectiveness is represented by the ratio between the actual heat transfer rate and the maximum possible heat transfer rate calculated by:

$$\varepsilon = \frac{\dot{Q}_{act}}{\dot{Q}_{max}} \qquad \text{Eq. 5.24}$$

where $\dot{Q}_{max}$ is the maximum possible heat transfer and $\dot{Q}_{act}$ is the actual heat transfer. These measurements are calculated by:

$$\dot{Q}_{act} = \dot{m}_t * C_{pt} * (T_{ti} - T_{to}) \qquad \text{Eq. 5.25}$$

$$\dot{Q}_{max} = C_{min} * (T_{ti} - T_{si}) \qquad \text{Eq. 5.26}$$

where C_{min} is the lowest specific heat of the two fluids.

Given that analysis model is developed, next step is to formulate the related compromise DSP. The next section discusses the formulation of the associated compromise DSP.

5.1.2 Compromise DSP Word and Mathematical Formulation

Three main steps are taken to formulate a compromise DSP. First, defining a problem statement. The problem statement of designing shell and tube heat exchanger is given in Section 5.1.1. Second, formulating a related compromise DSP word problem, which is presented in this section. Third, developing a mathematical model to support the word model. The compromise DSP mathematical formulation is also presented in this section followed by the word formulation.

The compromise DSP word formulation of shell and tube heat exchanger is as follows:

Given

Correction factor
Tube material
Shell and tube side fluid
Shell inlet temperature
Tube inlet temperature
Shell inlet pressure
Tube inlet pressure
Targets for the goals
Maximum pressure drop in shell
Maximum pressure drop in tube
Maximum tube thickness
Minimum tube thickness
Maximum Heat lost percentage
Thermodynamic fluid properties (REFPROP)

Find

Number of tubes
Tube length
Tube outer radius
Tube inner radius
Tube clearance
Tube fluid outlet temperature
Shell fluid outlet temperature
Shell fluid flow rate
Tube fluid flow rate
The deviation variables

Satisfy

<u>Constraints</u>

C1 Tube inlet temperature is greater than outlet temperature
C2 Shell inlet temperature is less than outlet temperature
C3 Tube inlet temperature is greater than shell outlet temperature
C4 Shell fluid inlet temperature is less than tube outlet temperature
C5 Pitch ratio 1
C6 Pitch ratio 2
C7 Maximum allowable P.D. in the tube
C8 Maximum allowable P.D. in the shell
C9 Tube thickness
C10 Tube thickness
C11 Tube outer radius greater then inner radius
C12 Heat balance
C13 Heat lost
C14 Positive clearance
C15 Pitch and clearance relation
C16 Tube turbulent flow
C17 Product of deviation variables equal
C18 Deviation variables to be positive

Goals

G1 Minimize heat transfer area
G2 Minimize tube pressure drop
G3 Maximize heat exchanger effectiveness

Bounds

B1 Minimum value $\leq N_t \leq$ Maximum value
B2 Minimum value $\leq L_t \leq$ Maximum value
B3 Minimum value $\leq r_o \leq$ Maximum value
B4 Minimum value $\leq r_i \leq$ Maximum value
B5 Minimum value $\leq C_t \leq$ Maximum value
B6 Minimum value $\leq T_{to} \leq$ Maximum value
B7 Minimum value $\leq T_{so} \leq$ Maximum value
B8 Minimum value $\leq \dot{m}_s \leq$ Maximum value
B9 Minimum value $\leq \dot{m}_t \leq$ Maximum value

Minimize

The deviation function (Z): Archimedean formulation

Figure 5.5: Shell and tube heat exchanger cDSP word formulation

A number of design parameters, thermal properties, and target values are given in the compromise DSP formulated above. In addition, nine system variables and deviation variables are specified, 18 constraints and three goals are defined, and nine bounds on the system are listed. The objective is to minimize the deviation function which is in Archimedean formulation. The related mathematical formulation of shell and tube heat exchangers is shown in Figure 5.6.

The nomenclature is provided in Section 5.1. Once the analysis model and the compromise DSP is formulated, the next step is to explore the solution space through weight sensitivity analysis and constraints sensitivity analysis to test the efficiency of the method presented in Chapter 3 Section 3.2. The results and discussion is presented in the next section.

Given

Shell and tube heat exchanger analysis model (Equations)
Parameters (HL, Mk....)

Targets (ε_{Target}....)
Thermodynamic fluid properties (REFPROP)

Find

N_t
L_t
r_0
r_i
C_t

T_{to}
T_{so}
$\dot{m}_s$
$\dot{m}_t$
d^- and d^+

Satisfy

Constraints

C1 $T_{ti} \geq T_{to}$
C2 $T_{si} \leq T_{so}$
C3 $T_{ti} * 1.02 \geq T_{so}$
C4 $T_{si} \leq T_{to} * 1.02$
C5 $2.5 < P_t / r_o$
C6 $P_t / r_o < 3$
C7 $\Delta P_t \leq 50kPa$
C8 $\Delta P_s \leq 10kPa$

C9 $0.008 \leq T_t$
C10 $T_t \leq 0.15$
C11 $r_o \geq r_i$
C12 $\dot{Q}_{out} \geq \dot{Q}_{in}$
C13 $\dot{Q}_{in} \geq \dot{Q}_{out} - (HL * \dot{Q}_{out})$
C14 $C_t > 0$
C15 $P_t \geq 0.005 + 2 * r_o$
C16 $Re_t \geq 4000$
C17 $d^-_i * d^+_i = 0$
C18 $d^-_i, d^+_i \geq 0$

Goals

G1 $\frac{A_{0\text{Target}}}{A_0} - d_1^- + d_1^+ = 1$ Related to Eq. 5.1
G2 $\frac{\Delta P_{t\text{Target}}}{\Delta P_t} - d_2^- + d_2^+ = 1$ Related to Eq. 5.16
G3 $\frac{\varepsilon}{\varepsilon_{\text{Target}}} + d_3^- - d_3^+ = 1$ Related to Eq. 5.22

Bounds

B1 $40 \leq N_t \leq 200$
B2 $1.0 \leq L_t \leq 4.0$(m)
B3 $0.05 \leq r_o \leq 0.5$(m)
B4 $0.04 \leq r_i \leq 0.4$(m)

B5 $0.005 \leq C_t \leq 0.2$(m)
B6 $279.0 \leq T_{to} \leq 355.0$(K)
B7 $285.0 \leq T_{so} \leq 369.0$(K)
B8 $10.0 \leq \dot{m}_s \leq 40.0$(kg/s)
B9 $8.0 \leq \dot{m}_t \leq 30.0$(kg/s)

Minimize

$$Z = \sum_{i=1}^{3} (W_i d_i^- + W_i d_i^+);$$

$$\sum W_i = 1, \; W_i \geq 0$$

Figure 5.6: Shell and tube heat exchanger cDSP mathematical formulation

5.2 Exploring Design Preferences and Design Constraints in Design of Shell and Tube Heat Exchanger: Results and Discussion

In Chapter 3, solution space exploration in model based realization of engineered systems is discussed. In Sections 3.3 and 3.4, parts of the method for exploring design preferences and design constraints, and their relation to decision making are proposed, respectively. In this chapter, a design example of a shell and tube heat exchanger is developed to test the proposed method. In the following sections, 5.2.1 and 5.2.2, results associated with the example are discussed. Of note, the focus of this thesis is on the method not the results *per se*.

5.2.1 Exploring Design Preferences - Weight Sensitivity Analysis

The mathematical model of the shell and tube heat exchanger is developed and practiced to test a different part of the proposed method in Chapter 3. In this section, the focus is to explore design preferences by weight sensitivity. The first step consists of discovering feasible regions through XPLORE, as discussed in Section 3.2.1. This is a grid search to refine the system variable bounds by identifying the feasible regions in the design space.

In Figures 8 through 11, feasible designs for two variables at a time are shown. The data provided by the grid search module XPLORE, in DSIDES, helps the designer to frame the design space based on feasible bounds. A wide range on the system variable's bounds is first considered. Using a grid search, the region where feasible designs exist for each variable is found. For instance, the tube side flow rate's starting range is wider within 1.0 kg/s to 50 kg/s, but as shown in Figure 5.7, it's feasible range is found to be around 10 kg/s to 28 kg/s. Therefore in the mathematical model presented in Figure 4, *"Bounds"* are modified based on these results. The same process is done to modify the bounds given to system variables. In Figure 5.8 also the feasible bounds for shell side and tube side outlet temperature are identified.

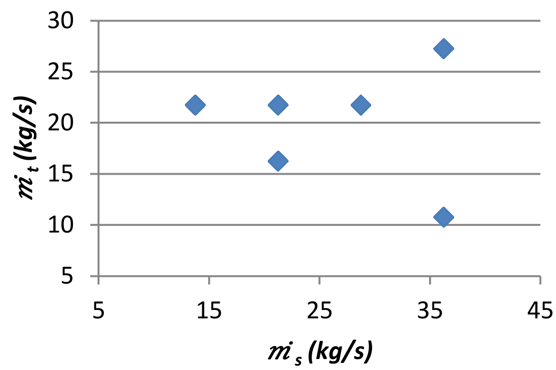


Figure 5.7: Feasible designs for tube and shell mass flow rate

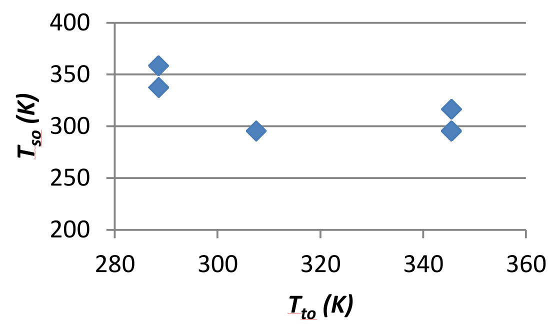


Figure 5.8: Feasible designs for shell and tube outlet temperature

To refine the solutions found in the previous step, Adaptive Linear Programming, a feature in DSIDES, is used with the more promising results. In this step the solutions found through grid search are used as the starting points for ALP. In Figure 5.9, the typical convergence of both the shell mass flow rate (FLOWS) and the tube mass flow rate (FLOWT) are shown. The convergence of the solutions is checked for the rest of variables. Having the variables converged, confidence about the model and its correct behavior is gained.

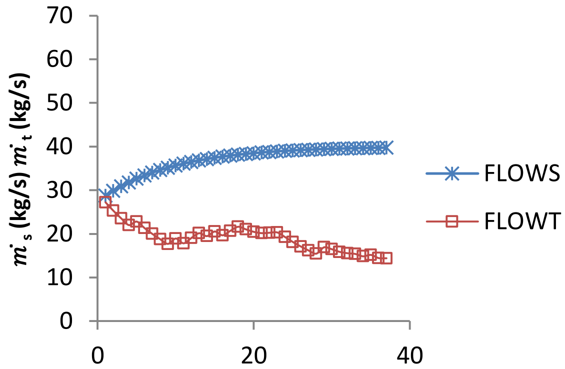


Figure 5.9: System variable convergence plotted against iteration

Employing the Archimedean form of cDSP (Eq. 3.2), using various design scenarios with respect to weights on the deviation variables, is tested and explored. Table 5.2 is presented to show the design scenarios and the deviation values achieved in each case. Only a limited number of design scenarios is needed to visualize the solution space, however, the plot becomes clearer as more design scenarios are used.

Table 5.2: Scenarios of weight sensitivity analysis

Design Scenarios				Deviations			Values		
	H.T. Area (W_1)	Tube P.D. (W_2)	H.T. Effect. (W_3)	H.T. Area	Tube P.D.	H.T. Effect.	H.T. Area	Tube P.D.	H.T. Effect.
DS 1	0	1	0	0.919	0.009	0.151	123.874	3.027	0.849
DS 2	1	0	0	0.039	0.933	0.060	10.407	44.529	0.940
DS 3	0	0	1	0.740	0.920	0.061	38.394	37.283	0.939
DS 4	0.5	0	0.5	0.068	0.926	0.061	9.657	40.609	0.940
DS 5	0	0.5	0.5	0.883	0.081	0.062	77.147	2.177	0.938
DS 6	0.5	0.5	0	0.057	0.026	0.062	10.604	3.079	0.938

Heat transfer area and tube pressure drop are the conflicting goals and this can be observed in the deviation values. For instance, when the weight on tube pressure drop has a value of 1 (highest preference), the deviation of heat transfer area is high (0.92). This identifies that if a low pressure drop design is desired, not much heat transfer can be expected. Contrarily, the lowest deviation value, 0.039, is when the highest weight (a value of 1) is given to heat transfer area. These results increase the confidence about the model's validity. The deviation values should be collected for all goals.

The cDSP is solved using DSIDES, and data obtained is used in MATLAB to generate the ternary plots which is discussed in Chapter 3. Following ternary plots are presented to visualize the solution space of shell and tube heat exchangers based on the weights assigned to the deviation variables, and the tradeoffs between them.

Since the objective is to minimize the deviation, the area with lower values in the plots is desired. However, the designer should decide what range for deviations/solutions are desired for each goal. This depends on the application. Visualization of the solution space helps the designer to rapidly adjust the design preferences based on the designer/customer choice with more confidence having better understanding of the space.

In Figures 5.10 through 5.12, heat transfer area, effectiveness, and tube pressure drop are respectively visualized, and clustered based on satisfactory solutions. The bar next to the plots helps to read the value of deviations inside the plot, and it is discussed in detail in Chapter 3. Figure 5.10 is the solution space associated with heat transfer area. In this figure, the desirable solutions, defined as any solution with the value of deviation lower than 0.25, lay in the area where the weights on heat transfer area falls in the range of 0.4 to 1.0, the weights on effectiveness is in the range of 0.0 to 0.6, and the weights on tube pressure drop is in the range of 0.0 to 0.6.

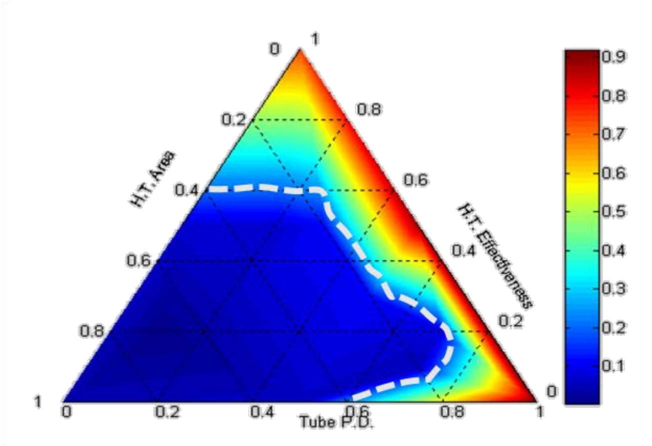


Figure 5.10: Solution space for heat transfer area

Any combination of the aforementioned weights shown in Table 5.3, which represents different design preferences, guarantees a desired solution with respect to the heat transfer area. Note that summation of the weights for each design presence should be 1.

Table 5.3: Weight range of desired solutions for heat transfer area

Goals	Weight Range
Heat Transfer Area	W_1: 0.4 – 1.0
Tube Pressure Drop	W_2: 0.0 – 0.6
H. T. Effectiveness	W_3: 0.0 – 0.6

The solution space of the other two goals (effectiveness and tube pressure drop) are visualized in Figures 5.11 and 5.12. The same argument is applied to the following plots. The weight range of desired solutions associated with effectiveness and tube pressure drop is shown in Tables 5.4 and 5.5 respectively. Choosoing the design preference in the range that is captured garantees a desired solution for one goal at the time.

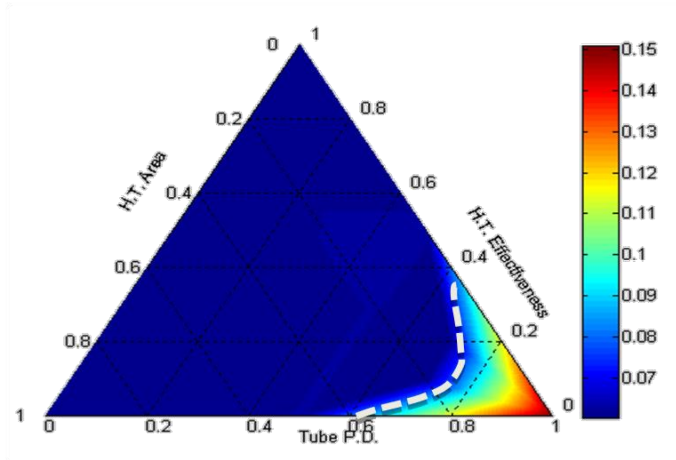


Figure 5.11: Solution space for heat transfer effectiveness

Table 5.4: Weight range of desired solutions for heat transfer effectiveness

Goals	Weight Range
Heat Transfer Area	W_1: 0.0 – 1.0
Tube Pressure Drop	W_2: 0.0 – 0.6
H. T. Effectiveness	W_3: 0.4 – 1.0

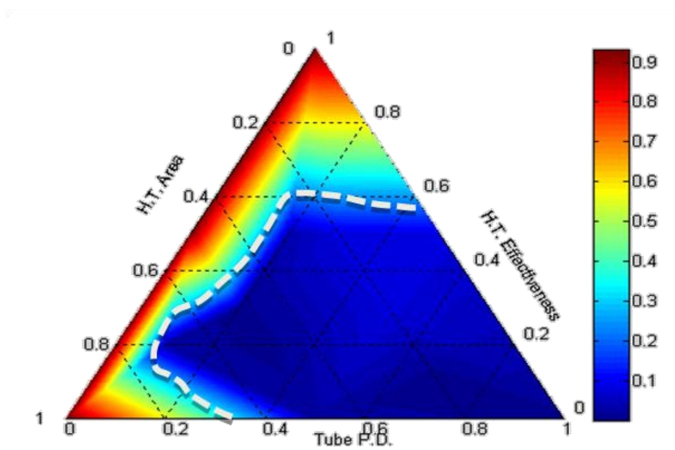


Figure 5.12: Solution space for tube pressure drop

Table 5.5: Weight range of desired solution associated with tube pressure drop

Goals	Weight Range
Heat Transfer Area	W_1: 0.2 – 0.8
Tube Pressure Drop	W_2: 0.3 – 1.0
H. T. Effectiveness	W_3: 0.0 – 0.6

These plots can also be interpreted to find the tradeoffs between different goals. For example, the conflicts between heat transfer area and pressure drop can be seen in Figures 5.10 and 5.12. Desired solutions in those two figures appear on opposite sides of the plot with different weight combinations, however, there is some overlap between the two plots that can satisfy both.

Analyzing each plot individually, the desired solutions and design preferences associated with those solutions are identified for each goal. In the following step three plots are interpreted together to find desired solutions that satisfies all of the goals requirements. By overlapping the plots, the common region can be found; in this case the blue area in the middle of the triangle shown in Figure 5.13.

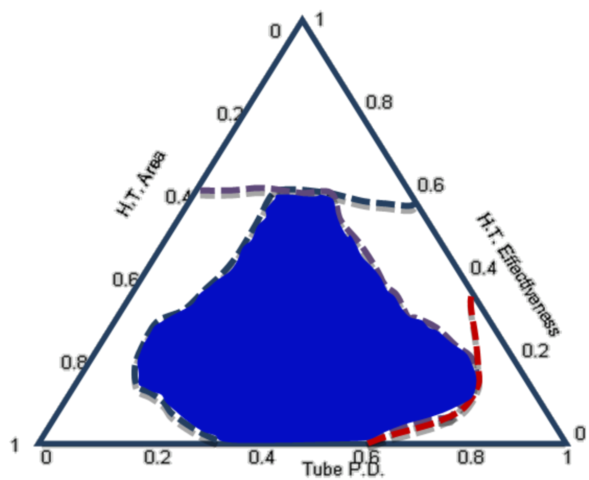


Figure 5.13: Desirable region satisficing all three goals

The blue area, the overlapping region highlights where the solutions are all satisfactory where the designer has the flexibility to change the weight/design preference without any tradeoffs. The weight range that meet all the goals is documented in Table 5.6. This information provides confidence to the designer in decision making.

Table 5.6: Weight range of desired solution satisficing all the goals

Goals	Weight Range
Heat Transfer Area	W_1: 0.2 – 0.8
Tube Pressure Drop	W_2: 0.3 – 0.6
H. T. Effectiveness	W_3: 0.0 – 0.6

If such a region is not found when interpreting all plots together, the goals have a large conflict which indicates that tradeoffs are necessary. In that case, designer should make tradeoffs by modifying the target value of one or more goals which results changing of the deviations. Another approach is to change the range of desired solutions. That means, if the designer have defined the desired solutions are those with values lower than 0.2, it can be changed to a higher value to make the overlap possible. This can be done for one or more goals

Given that desired solutions are identified through weight sensitivity analysis, the next step is to explore the constraints of those solutions and provide deeper insight with respect to feasibility robustness.

5.2.2 Exploring Design Constraints - Constraint Sensitivity Analysis

Desired solutions are identified in the previous section. In this section, those solutions are monitored in terms of constraint sensitivity analysis. This is done by monitoring the active and inactive constraints of those solutions. The notion of active and inactive constraints are discussed in Chapter 3. Active constraints are those with zero tolerance to change. Solutions with active constraints are boundary solutions, such solutions are sensitive with a risk of becoming infeasible in face of variations. Any small variation in design variables related to the active constraints may cause the solution to become infeasible. Moreover, the extra capacity of the inactive constraints is not the same for different design scenarios.

The cDSP mathematical formulation of the shell and tube heat exchanger introduced in Section 5.1.2, has 18 constraints. Constraints 17 and 18 are those on deviation variables. In Table 5.7, the other 16 constraints are listed and monitored for five of the design preferences in which desired solutions are found in Section 5.2.1. In all of them, constraint C9 is active.

Table 5.7: Active and inactive constraints

Constraints		Design Scenarios				
		"Design 1" W_1=0.5, W_2=0.5, W_3=0.0	"Design 2" W_1=0.5, W_2=0.3, W_3=0.2	"Design 3" W_1= 0.2 W_2= 0.5 W_3= 0.3	"Design 4" W_1= 0.5 W_2= 0.2 W_3= 0.3	"Design 5" W_1= 0.2 W_2= 0.3 W_3= 0.5
C1: T_{ti} - T_{to}	(K)	86.31	86.41	86.31	86.41	86.31
C2: T_{so} -T_{si}	(K)	90.64	90.95	90.84	90.95	90.84
C3: $(T_{ti}*1.02)$ - T_{so}	(K)	8.76	8.45	8.56	8.45	8.56
C4: T_{si} -($T_{to}*1.02)$	(K)	0.13	0.03	0.13	0.03	0.13
C5: $(P_t/ro)-2.5$		0.02	0.01	0.04	0.01	0.04
C6: $3-(P_t/r_o)$		0.48	0.49	0.46	0.49	0.46
C7: $50 - \Delta P_t$	(kPa)	46.92	47.98	47.83	47.98	47.83
C8: $10 - \Delta P_s$	(kPa)	9.99	9.99	9.99	9.99	9.99
C9: T_t-0.008	(m)	0.00	0.00	0.00	0.00	0.00
C10: 0.15-T_t	(m)	0.14	0.14	0.14	0.14	0.14
C11: r_o - r_i	(m)	0.01	0.01	0.01	0.01	0.01
C12: $\dot{Q}_{out}$ - $\dot{Q}_{in}$	(W)	420.12	749.59	837.36	749.59	837.36
C13: $\dot{Q}_{in}$- $\dot{Q}_{out}$+$(HL*\dot{Q}_{out})$	(W)	65.54	228.30	29.12	228.30	29.12
C14: C_t	(m)	0.03	0.05	0.05	0.05	0.05
C15: P_t-($0.005+2*r_o)$	(m)	0.03	0.04	0.04	0.04	0.04
C16: Re_t - 4000		462.64	2178.85	2383.59	2178.85	2383.59

Depending if the active constraint is hard or soft, the penalty is different in face of uncertainty. Hard constraints must be satisfied for the system to operate. For example, safety is usually a hard constraint. In the early stages of design in which concepts are being explored, as is the case of these analyses, most of the constraints are soft. Therefore, failure of the system in face of uncertainty is not a concern for the boundary solutions in early stages of design. However, there may be penalty associated with variations.

Constraint 9 concerning tube thickness directly affects the heat transfer, and therefore the performance of the system. The uncertainty associated with tube thickness may be from two common sources: manufacturing and fouling. Larger tube thickness results in lower heat transfer and higher pressure drop. Tube thickness is a function of tube radius which means any variations on that can impact feasibility of the solution and also affect the system performance. Although there is one active constraint with zero capacity for change, inactive constraints have different capacity in various design preferences. For instance, tube radius to pitch ratio, C5, have different values in different designs. For some of the constraints, although inactive, the capacity is limited (see C11) and for some other constraints there is no concern with respect to variations (see C1 or C2). Moreover, "Designs 2 and 4", and "Designs 3 and 5" are the same in terms of constraints capacity, which means the variations of the weights/design scenarios has not affected the solution.

At this stage, other factors of solutions are monitored, i.e., values of system variables and goals. In Table 5.8, system variables related to two of the desired solutions found through weight sensitivity analysis are documented.

Table 5.8: System variables of desired and robust solutions

System Variables	Design Scenarios	
	"Design 4" W_1= 0.5, W_2= 0.2, W_3= 0.3	"Design 5" W_1= 0.2, W_2= 0.3, W_3= 0.5
N_t: Number of tubes	43	40
L_t: Tube length	1.00	1.01
r_0: Tube outer radius	0.09	0.08
r_i: Tube inner radius	0.08	0.08
C_t: Tube clearance	0.05	0.05
T_{to}: Tube outlet temp.	283.59	283.69
T_{so}: Shell outlet temp.	368.95	368.84
$\dot{m}_s$: Shell mass flow rate	23.59	20.48
$\dot{m}_t$: Tube mass flow rate	26.93	23.89

There are slight different between the two designs such as number of tubes, N_t, and mass flow rate in the tube and shell. The values of goals and deviation associated with the desired solutions then may be monitored. Table 5.9 compares the two designs from this perspective. It can be seen that "Design 5" has lower deviation, which is more desired, although both designs satisfy the design requirements. Depending on the sources of variations associated with design of shell and tube heat exchanger, different designs can be selected.

Table 5.9: Deviations and goal values for desired and robust solutions

		Design Scenarios	
		"Design 4" $W_1 = 0.5$, $W_2 = 0.2$, $W_3 = 0.3$	"Design 5" $W_1 = 0.2$, $W_2 = 0.3$, $W_3 = 0.5$
Deviations	H.T. Area (m)	0.054	0.107
	Tube P.D. (kPa)	0.008	0.079
	Effectiveness	0.061	0.062
Goal Values	H.T. Area (m)	9.514	10.083
	Tube P.D. (kPa)	2.016	2.170
	Effectiveness	0.939	0.938

Constraint sensitivity analysis, as part of the solution space exploration method, is conducted in this section which provides deeper understanding of the desired solutions found through weight sensitivity analysis. This information is beneficial for the designer in making informative decision. Furthermore, constraint sensitivity analysis can lead to applying feasibility robustness to the design which is discussed in Chapters 3 and 6.

Another part of the solution space exploration method is about exploring design selections. In the next section, selection DSP of shell and tube heat exchangers is proposed to explore the design selection presented in Chapter 3 Section 3.1.

5.3 Exploring Material Selection in Design of Shell and Tube Heat Exchanger

One aspect of the solution space exploration method presented in Chapter 3 focuses on the design selections (Section 3.1). The selection between multiple alternatives may occur in all stages of the design process. Designing shell and tube heat exchangers involves primarily selecting the material for the tubes. This selection has a large impact on system performance and cost.

In this section, material selection for a shell and tube heat exchanger is considered by first defining selection DSP word and mathematical formulas, followed by a discussion of the results.

5.3.1 Selection DSP Problem Statement, Word and Mathematical Formulation

There are three main steps in formulating a selection DSP: defining the problem statement, word formulation, and mathematical formulation. They are as follows:

Problem Statement - Selection DSP

In this example, design selections for tube material in designing shell and tube heat exchangers are explored in order to obtain maximum heat transfer, minimum cost, and minimum weight. The maximum heat transfer has the highest importance, then cost and weight are in the second and third priorities, respectively. The options for these tubes are copper, stainless steel, aluminum, and brass. The material's heat conductivity, density, and cost per unit in the market are described below.

Selection DSP Word and Mathematical Formulation:

Selection DSP is another form of DSPs. Like cDSP, sDSP has three steps in formulation: first is to define a problem statement which is done above. The next steps are to formulate the sDSP word and mathematical problem.

Selection DSP word formulation for selecting tube material in design of a shell and tube heat exchangers is as follows:

Given

Alternatives: 4

- SS304 (Stainless Steel)
- Copper
- Aluminum
- Brass

Identify

Attributes: 3

- Cost – How much would it cost to construct the heat exchanger out of a certain material; lower value is preferred; Ratio Scale
- Density – Lower density means lower overall weight; lower value is preferred; Ratio Scale
- Heat Conductivity – How well the material will facilitate the heat transfer necessary for the exchanger to function; higher value is preferred; Ratio Scale

Relative importance

Rate

Specify scales, rate the alternatives with respect to each attribute and normalize.

Need information to rate the alternatives with respect to each attribute. Then convert the attribute rating (A_{ij}) to normalized attribute ratings (R_{ij}).

Normalized Rating = (Alternative Value)/(Upper Bound) if higher value is desired, or 1 – ((Alternative Value)/(Upper Bound)) if lower value is desired.

Rank

Evaluate the merit function for each alternative (for each selection).

$$MF_i = \sum_{j=1}^{n} I_j R_{ij} \quad i = 1, \ldots, m$$

I_j = relative importance of j^{th} attribute

R_{ij} = rating of alternative i for the attribute j

MF_i = value of merit function for alternative i

m = number of alternatives

n = number of attributes

Figure 5.14: Shell and tube heat exchanger selection DSP word formulation

There are four options and three attributes shown in Figure 5.14, to explore during this process, and the needed information on heat conductivity, cost, and density of each material are captured from literature and market respectively.

The Selection DSP mathematical formulation for selecting tube material in design of a shell and tube heat exchanger is as follows:

Given

Alternatives: 4

SS304 (Stainless Steel); Pros: Low Density, Low Cost; Cons: Low Heat Conductivity

Copper; Pros: High Heat Conductivity; Cons: High Density, High Cost

Aluminum; Pros: Low Density, Low Cost; Cons: Low Heat Conductivity

Brass; Pros: Low Cost; Cons: High Density, Low Heat Conductivity

Identify

Attributes: 3

Cost - Upper Bound: 3.00, Lower Bound: 0.00; Lower value preferred

Density - Upper Bound: 9000.00, Lower Bound: 0.00; Lower value preferred

Heat Conductivity - Upper Bound: 600.0, Lower Bound: 0.00; Higher value preferred

Relative importance:

Cost: 0.25

Density: 0.15

Heat Conductivity: 0.60

Rate

Cost

SS304 = .66 USD/lb

Aluminum = .81 USD/lb

Brass = 2.11 USD/lb

Copper = 2.83 USD/lb

Density

Aluminum = 2700 kg/m^3

SS304 = 7970 kg/m^3

Brass = 8480 kg/m^3

Copper = 8960 kg/m^3

Heat Conductivity

Copper = 401 W/mK

Aluminum = 167 W/mK

Brass = 109 W/mK

SS304 = 15.5 W/mK

Rank

Evaluate the merit function for each alternative (for each selection).

$$MF_i = \sum_{j=1}^{n} I_j R_{ij} \quad i = 1, \ldots, m$$

I_j = relative importance of j^{th} attribute

R_{ij} = rating of alternative i for the attribute j

MF_i = value of merit function for alternative i

m = number of alternatives

n = number of attributes

Figure 5.15: Shell and tube heat exchanger selection DSP mathematical formulation

The weights and bounds for the sDSP are up to the discretion of the designer. In the case of this work, the weights are chosen to heavily favor heat conductivity (0.6) over cost (0.25) and density (0.15), and the bounds are chosen to make the highest attribute value closest to one.

5.3.2 Exploring Material Selection in Design of Shell and Tube Heat Exchanger: Results and Discussion

Data used in formulating the selection DSP is presented in the tables below. They are related to attribute data and rating.

Attribute Data

In Table 5.10, the user-defined data for each of the attributes used in the sDSP is shown. The preference listed for each attribute shows whether a higher or lower value is desired for each of the attributes being tested, which changes later normalization calculations. The importance of each attribute is shown through that attribute's weight in the calculation; for the sDSP that is conducted, these values must add up to one. As indicated before the highest importance is given to thermal conductivity. This shows the designer preference and can be changed to explore other options.

Table 5.10: Attributes in selection DSP

	Attributes		
	Thermal Cond.(W/mK)	Cost (USD/lb)	Density (kg/m^3)
Preference	High	Low	Low
Importance	0.6000	0.2500	0.1500
Lower Bound	0.00	0.00	0.00
Upper Bound	600.00	3.00	9000.00

In this work, only one option is discussed, however, sensitivity analysis is conducted in the end to ensure robustness of the solution. The upper and lower bounds illustrate the highest and lowest accepted value for each attribute, and are also used in normalization calculations. For most attributes, the lower bound is equal to zero and does not affect these calculations.

Attribute Ratings (Raw)

In Table 5.11, the pertinent data for each of the materials being measured is shown. Each of the material options and their attributes are compared to one another to decide which is best based on the previous user-given conditions. Each of these values is a well-known, readily accessible value associated with each of the given alternatives. Thermal conductivity and density for each material is captures from literatures, and cost is captured from market data base.

Table 5.11: Attributes raw rating

	Attributes		
	Thermal Cond. (W/mK)	Cost (USD/lb)	Density (kg/m^3)
SS304	15.5	0.66	7970
Copper	401.0	2.83	8960
Aluminum	167.0	2.11	2700
Brass	109.0	0.81	8480

Attribute Ratings (Normalized)

In Table 5.12, the data in the previous table is adjusted based on each pertinent bound shown. This adjustment is done by utilizing the following calculations:

Normalized Rating = (Alternative Value) / (Upper Bound)

if a higher value is desired, OR

Normalized Rating = 1 – ((Alternative Value) / (Upper Bound))

if a lower value is desired.

Table 5.12: Attributes normalized rating

	Attributes		
	Thermal Cond. (W/mK)	Cost (USD/lb)	Density (kg/m^3)
SS304	0.026	0.780	0.114
Copper	0.668	0.057	0.004
Aluminum	0.278	0.730	0.700
Brass	0.182	0.297	0.058

Normalizing the ratings makes the merit function calculations significantly simpler and makes it easier to manipulate and understand the data.

Alternative Rankings and Merit Function Values

The merit function values are calculated using the following equation:

$$MF_i = \sum_{j=1}^{3} I_j \, R_{ij} \quad i = 1, \dots, 4 \qquad \text{Eq. 5.27}$$

where I_j is the relative importance of the j^{th} attribute and R_{ij} is the normalized rating of the I^{th} alternative with respect to the j^{th} attribute.

In Table 5.13, the final merit function values for each material, as well as the percent difference from the highest ranked alternative is shown.

Table 5.13: Alternative ratings and merit function values

Alternative	Rank	Merit Function Values	Percentage Difference from #1
Aluminum	1	0.446	0.000
Copper	2	0.429	3.801
SS304	3	0.226	49.359
Brass	4	0.194	56.439

These merit function values represent the rankings of the four alternatives based on how well they adhere to the three attributes, and are calculated before factoring in the percent of variations. These results mean that, for the current environment created by the user's submitted values, Aluminum is the best material to use for the construction of a shell and tube heat exchanger, with the other options following in order. The values generated by the sDSP can be used to aid in decision making during the design process of the heat exchanger, and can be tweaked as new developments appear throughout the process. Note that these values are only correct for the specific instance defined by the attribute weights and bounds that are given at the beginning of this example, and the preliminary values can be changed almost infinitely to generate the exact scenario that designer might like to test for. Additionally, sDSP is capable of testing of as many or as few alternative materials and attributes the designer wishes within a single scenario as long as the necessary values are obtained beforehand. Results such as these are, however, limited to a single scenario. Obtaining information from multiple different instances would require a different sDSP formulation.

Sensitivity Analysis and Merit Function Values

Post-solution sensitivity analysis is conducted to account for variations. The source of variation is either from relative importance (designer preference), or attribute ratings. For this study, 10% uncertainty in relative importance is considered. Uncertainties related to attribute rating depends on the application. The important source of variation in the case of this work is the cost due to rapid changes in the market. Heat conductivity and density can varies by different factors such as impurities and unbalance alloying elements while manufacturing the material, however, is not in a high concern. That is the reason 5% uncertainty in the cost, 0.5% for the thermal conductivity and density is considered respectively. The sensitivity analysis is performed using exact interval arithmetic. As a result of this analysis, the best and the worst possible rank for an alternative is obtained. In Table 5.14, the maximum and minimum merit values considering aforementioned uncertainty is shown.

Table 5.14: Sensitivity analysis and merit function values

Alternative	Variation	Maximum Value	Minimum Value	Rank
Aluminum	± 0.055	0.502	0.392	1 to 2
Copper	± 0.046	0.475	0.384	1 to 2
SS304	± 0.032	0.259	0.194	3 to 4
Brass	± 0.024	0.218	0.171	3 to 4

Based on the results for variations that are considered, ranking of the first and second alternative is subject to change if the minimum value of one with the maximum value of the other are considered. The same argument is true for alternatives 3 and 4. This indicates that the solutions are sensitive to those variations. Sensitivity analysis is extremely helpful when either the design preference or the ratings or both are not known very accurately. In this section, exploring design selection which is one part of the solution space exploration method is performed to verify that part of the method. Verification of the results is done through hand calculation and is provided in Appendix E.

5.4 Empirical Structural and Performance Validity

To test solution space exploration method proposed in Chapter 3, Validation Square is adapted, which involves different steps. The Validation Strategy is discussed in Chapter 1. In this chapter, the empirical structural and performance validity of the proposed method in Chapter 3, namely solution space exploration, is checked. The method is consists of different aspects, and is verified through three different design examples. Three aspects of the method namely, exploring design preferences, exploring design constraints and exploring design selections are tested in this chapter in designing of a shell and tube heat exchanger.

Empirical structural validity as discussed in Chapter 1, involves Step 3: accepting the appropriateness of the example problems that is used to verify the performance of the method, shown in Figure 5.16. There has to be shown that the examples are good representations of design problems, for which the method is designed and that the associated data can be used to support a conclusion. Empirical performance validity is about accepting the usefulness of the method for solving the example problems which includes Steps (4) and (5): accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s); accepting that the achieved usefulness is linked to applying the method. In essence, results achieved using the design method has to be analyzed and assessed.

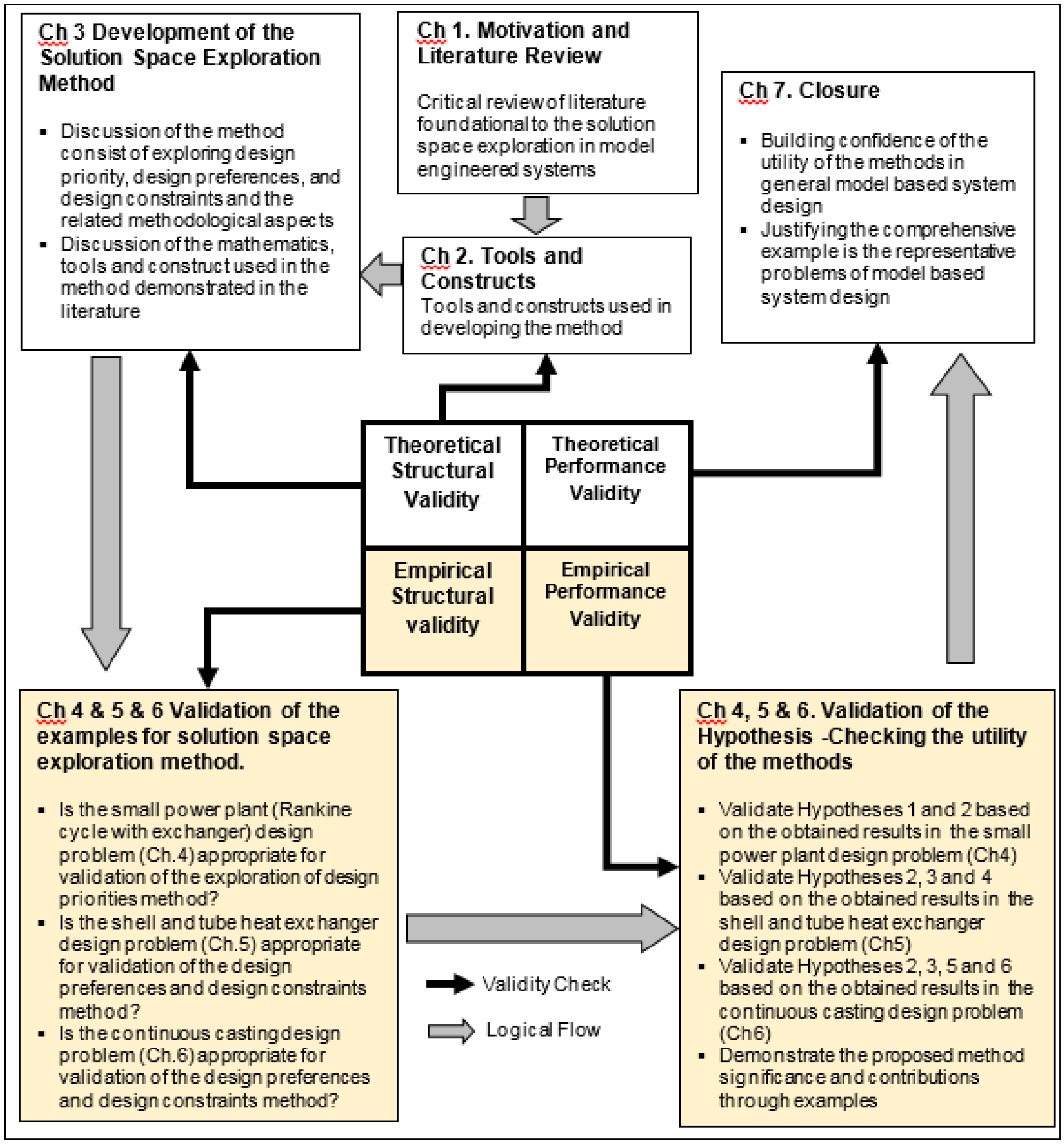


Figure 5.16: Validation square road map

The design example presented in this chapter, shell and tube heat exchanger, is chosen to test the utility of some parts of the proposed method, namely, exploring design preferences through weight sensitivity analysis, exploring design constraints through constraint sensitivity analysis, and exploring design selections.

Shell and tube heat exchanger design is an appropriate example due to its multi-objective notion. It involves complex processes including selection between component alternatives such as material, working fluid, a large number of geometric variables, and the compromise between different goals such as heat transfer area, pressure drops in the shell and tube, and heat transfer effectiveness. Moreover, it involves important constraints such as heat lost and allowable pressure drop. Designing and decision making in such cases required exploring different options and gaining insight to facilitate an informative decision.

Design preferences in designing a shell and tube heat exchanger is explored by conducting weight sensitivity analysis. The importance of the goals such as pressure drop and heat transfer area and the conflict between them make it difficult for the designer to come up with a design preference that meets all the goals. The outcome of this analysis is a range of weights in which desired solutions that satisfy all the goals are guaranteed. Such solutions are then monitored by identifying active and inactive constraints to provide deeper understanding of the solution which can lead to a better decision in designing of such system. Also, design selection is explored in selection of tube material. Post-solution sensitivity analysis is performed to bring insight and support decision making.

Furthermore, the model behavior is monitored through convergence of the results shown in Figure 5.9. Thermal properties captured from the data base REFPROP although validated by National Institute of Standard and Technology, is verified by comparing with literature.

5.5 What Has Been Presented and What is Next

A method for solution space exploration is proposed in Chapter 3 of this thesis. In this chapter, three parts of the proposed method, namely, exploring design preferences through weight sensitivity analysis, exploring design constraints through constraints sensitivity analysis, and exploring design selections are tested through the design of a shell and tube heat exchanger.

The mathematical model related to the shell and tube heat exchanger is developed and discussed in Section 5.1. Results for the weight sensitivity and constraint sensitivity analysis are discussed in Section 4.2. The mathematical model and results associated with exploring design selections are presented in Section 5.3.

In the next chapter, a comprehensive example, namely, process design of continuous casting of steel, is presented to verify the three main parts of the solution space exploration method:

- Exploring design preferences through weight sensitivity analysis
- Exploring design constraints through constraints sensitivity analysis
- Incorporating feasibility robustness

CHAPTER 6 SOLUTION SPACE EXPLORATION OF THE PROCESS DESIGN FOR CONTINUOUS CASTING OF STEEL

The solution space exploration method proposed in this thesis is verified based on the Validation Square discussed in Chapter 1. In the previous two chapters different aspects of the method, namely, exploring design priorities, exploring design preferences, exploring design constraints and exploring design selections, are tested based on Quadrants 3 and 4 (empirical structural and performance validity) of the Validation Square using design of a small power plant and a shell and tube heat exchanger.

In this chapter, a comprehensive example problem, namely, continuous casting of steel, is utilized to illustrate the utility of the solution space exploration method, Block C, shown in Figure 6.1.

The exploration in this chapter involves **weight sensitivity analysis, constraint sensitivity analysis and incorporating feasibility robustness**. These analysis allows a designer to ascertain to what extent the solution is insensitive to uncertainties inherent in the modeling of the decision problem, and answering to the research questions identified in Chapter 1 such as:

- ***What is the process to identify design preferences that guarantees a desired solution in which different and conflicting goals are satisfied?***
- ***What kinds of modification are needed if desired solutions that satisfy different and conflicting design preferences are not found?***
- ***What is the process to explore feasibility robustness under the effect of variations?***

- ***How can design constraint exploration be beneficial to incorporate feasibility robustness in the model?***

The utility of the method is illustrated in providing decision support for the continuous casting operation.

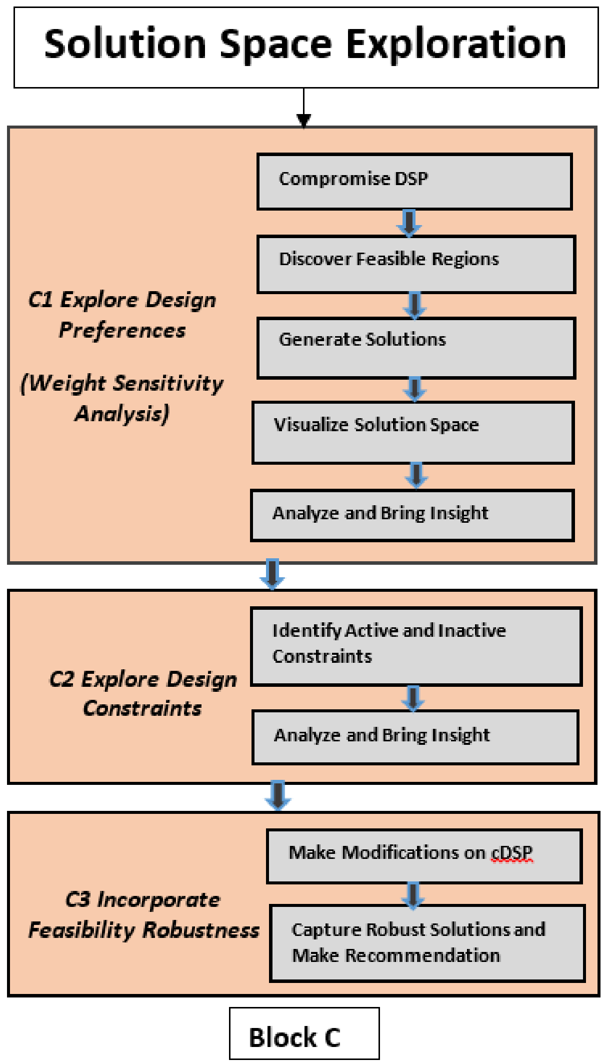


Figure 6.1: Solution space exploration

The analysis models of this example that is developed provided by Tata Consulting Services (Shukla and co-authors, 2014) is utilized in this chapter to test the solution exploration method proposed in Chapter 3. In Section 6.1, continuous casting of steel is described followed by the problem description and mathematical model for this example. Section 6.2 includes the results and discussion in three parts: exploring design preferences, exploring design constraints and incorporating feasibility robustness. Finally, empirical structural validity of the method is discussed in Section 6.3. The emphasis of the work is on the method rather than the results *per se*.

6.1. Developing a Mathematical Model for Continuous Casting of Steel

Continuous casting is the process of solidifying molten metal to produce different products such as billet, bloom, or slab. This process can be formulated mathematically in terms of conflicting goals including productivity, quality and production costs to satisfy sets of constraints such as oscillation mark depth, metallurgical length and center line segregation. The goals are conflicting in the sense that, if the productivity is increased, there is a reduction in other performance measures. These performance specifications are greatly influenced by operating conditions such as casting speed, superheat, mold oscillation frequency, and secondary cooling conditions. The process of identifying the set points for the continuous casting operation is iterative and expensive. The uncertainties inherent in modeling the phenomena computationally behooves exploration of the solution space to determine the quality of the solution and gain insight.

The solution space exploration method shown in Figure 6.1 includes weight sensitivity analysis, constraint sensitivity analysis and incorporating feasibility robustness. This analysis allows a designer to ascertain to what extent the solution is insensitive to uncertainness inherent in the modeling of the decision problem. This is a crucial step towards determining desired and robust solutions for performance measures. The utility of the method is illustrated in providing decision support for the continuous casting operation in presence of variability in the operating parameters and conflicting end requirements, such as productivity and quality parameters.

In this section, the state of the art related to this example problem is first discussed (Section 6.1.1). Next, the problem statement and solution strategy are presented (Section 6.1.2). Finally, the compromise DSP formulated in word and mathematical form for the process design of continuous casting of slab is proposed (Section 6.1.3). Table 6.1 is shown for the related nomenclature.

Table 6.1: Continuous casting of slab nomenclature

NOMENCLATURE			
X_1	Cooling condition in Segment 1, W/m2K	CLS	Center Line Segregation Index
X_2	Cooling condition in Segment 2, W/m2K	htci	Heat Transfer Co-efficient in Each Segment
X_3	Cooling condition in Segment 3, W/m2K	ICI	Internal Crack Index
X_4	Cooling condition in Segment 4, W/m2K	SCI	Surface Crack Index
X_5	Cooling condition in Segment 5, W/m2K	A_{mold}	Mold Acceleration, m/s2
X_6	Cooling condition in Segment 6, W/m2K	EqFrac	Equiaxed Fraction
X_7	Cooling condition in Segment 7, W/m2K	CER	Columnar to Equiaxed Ratio
X_8	Cooling condition in zone 1 of narrow face of slab, W/m2K	$Prod_{Target}$	Target Productivity, tons/day
X_9	Superheat, °C	OMD_{Max}	Maximum Oscillation Mark Depth, mm
X_{10}	Casting Speed, m/min	CLS_{Max}	Maximum Center Line Segregation Index
X_{11}	Slab Thickness, mm	Z	Deviation Function
X_{12}	Slab Width, mm	TL	Liquidus Temperature, °C
X_{13}	Mold Oscillation Frequency, /min	Ceq	Carbon Equivalent
T_N	Negative Strip Time, sec	dT_{mush}	Mushy Zone Temperature Gradient, °C
N_{cast}	Casting Speed, m/min	Y1	Shell Thickness at Mold Exit, m
f	Mold Oscillation Frequency, cycles/min	Y2	Metallurgical Length, m
S	Mold Stroke, mm	Y3	Surface Temperature at Unbending, °C
P(Xi)	Productivity, tons/day	Y4	Shell Thickness at Unbending, m
ρ	Density of Steel, kg/m3	B_{max}	Maximum Bulging Displacement, mm
σ^2	Variance	F	Shape Factor
di+ , di-	Deviation Variables	L	Roll Pitch, mm
X_i	Design Variables	P	Ferrostatic Pressure, MPa
$\sigma^2 X_i$	Variability in Design Variables	T_{surf}	Surface Temperature, °C
ST_{ME}	Shell Thickness at Mold Exit, m	D	Shell Thickness, mm
d	Oscillation Mark Depth, mm	C_L	Final Concentration of Solute
ML	Metallurgical Length, m	C_0	Initial Concentration of Solute
T_{UP}	Temperature at Unbending Point, °C	K_{eff}	Effective Partition Coefficient
T_R	Reheating Temperature, °C	FS	Average Solid Fraction in slab cross-section
K_m	Mass Transfer Co-efficient	R	Linear Rate of Solidification

6.1.1 Continuous Casting of Steel – State of the Art

Continuous casting is dynamically adjusted and involves certain degree of variability in the operating practices. Modeling such a complex operation process involves making assumptions, simplifications and approximations that manifest as uncertainty in the model. With growing interest in the model-based realization of complex systems there is a need for developing methods to explore the solution space that is defined by models that approximate reality and are typically incomplete.

Continuous casting of steel is a unit operation in which liquid steel is continuously solidified into a strand of metal. A schematic diagram of the continuous casting process is shown in Figure 6.2.

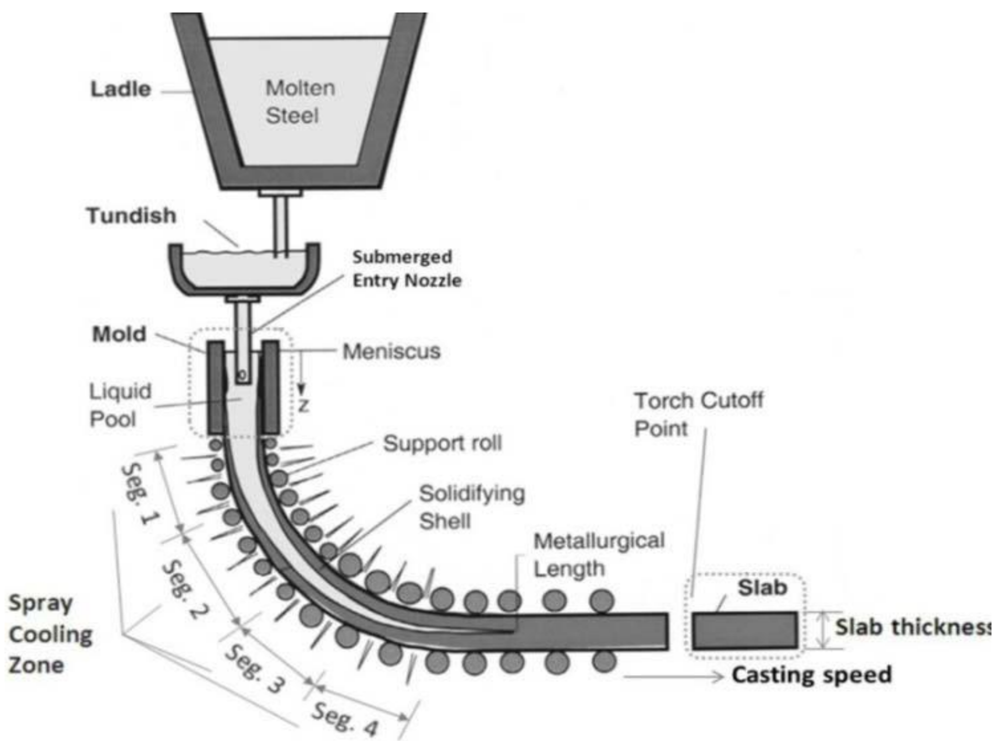


Figure 6.2: Schematic diagram of continuous casting process (Cramb, 2010)

Liquid steel is tapped from ladle into the mold via tundish. The tundish acts as a buffer between ladle and mold that converts a batch process into a continuous process and also facilitates removal of inclusions. The solidification of liquid steel starts to take place in the mold and a thin solidified shell is formed at the mold steel interface. To avoid sticking of steel to mold surface and break out, the mold is continuously oscillated in vertical direction with a specified frequency. The strand is taken out of the mold by means of a dummy bar and is supported by rolls and it is cooled by water with the help of spray nozzles.

There are several segments of rolls, varying in roll pitch and roll diameter. The rolls need to be positioned close enough to avoid bulging or break out of the thin shell. In this work, seven segments of rolls are considered, the location of some of these segments are depicted in Figure 6.2. Additional cooling is required to further solidify the thin shell of steel coming out of the mold and is achieved by means of a system of water sprays situated between the rolls. Once the solidification is completed, the slab is cut using a torch to predefined slab lengths. Details of the process are reported by Cramb in Reference (Cramb, 2010).

Continuous casting involves a number of phenomena such as solidification, fluid flow, segregation, columnar-equiaxed transition, crack formation etc. Considering the importance of continuous casting operation, all these phenomena are widely studied using various modelling and simulation techniques, a glimpse of which are provided next. Huang and co-authors present a mathematical model to predict temperature distribution, heat flux and calculate shell thickness profile of solidifying shell. The model predictions are found to be in close agreement with the experiments and is used to study the importance of superheat during casting operation (Huang and co-authors, 1992). Wang and co-authors present a transient, two dimensional model to predict shrinkage during solidification of a round billet. The model is then used to optimize the design of mold for minimizing shrinkages in cast billets (Tongmin and co-authors, 2010). Park and co-authors report on the behavior of copper molds in thin slab casting and have developed thermal-elastic viscoplastic models to predict the formation of cracks in the mold region. The study suggests higher probability of surface crack formation for the case of funnel-shaped molds (Park and co-authors, 2002).

Iwaski and co-authors present a thermal-mechanical model of the solidifying shell to predict shell thickness profiles and predict the formation of break outs. Insights have been provided to have good lubrication and narrow face tapered mold for reducing the possibility of instances of break outs during continuous casting (Iwasaki and co-authors, 2012). Choudhary and co-authors report on their investigation of segregation pattern and morphology in high carbon steel billets and have correlated the observations with operating parameters of continuous casting operation. The effect of cooling conditions, superheat and casting speed on segregation ratio and transition from U-segregation to V-segregation pattern is discussed (Choudhary and co-authors, 2007).

Knowledge of the location of columnar to equiaxed transition (CET) is critical. Straffelini and co-authors have developed a numerical model to calculate local solidification rate and thermal gradient and thereby relate these parameters to predict CET (Straffelini and co-authors, 2011). Mayer and co-authors have developed a two phase volume averaging model to study the effect of bulging on macrosegregation. The effect of bulging on modification of flow pattern is studied which compares well with the previous studies (Mayer and co-authors, 2010).

Lieftucht and co-authors have developed an online algorithm to detect longitudinal cracks during continuous casting of thin slab (Lieftucht and co-authors, 2008). The model is integrated with a mold monitoring system and is used to control the operating conditions of casting for maintaining the quality requirements. The models discussed above are used to model different phenomena and subsequently used to optimize the casting operation and ensure achievement of slab requirements with respect to productivity and quality parameters.

In order to define slab quality in a way which can be incorporated in the compromise DSP, the focus is on estimating key quantitative parameters such as segregation index, oscillation mark depth and columnar equiaxed ratio. The segregation index is a parameter to quantify severity of segregation in slab. Segregation leads to increase in concentration of elements in the center of slab and is caused by the rejection of solute particles by the liquid steel during solidification as they are less soluble in the solid phase as compared to the liquid phase.

The segregation pattern in a cast slab is shown in Figure 6.3. As discussed earlier, the mold is oscillated to prevent sticking of liquid steel, however vertical oscillation leads to formation of oscillation marks which is detrimental for the quality of slab. Oscillation marks in the cast slab are shown Figure 6.3.

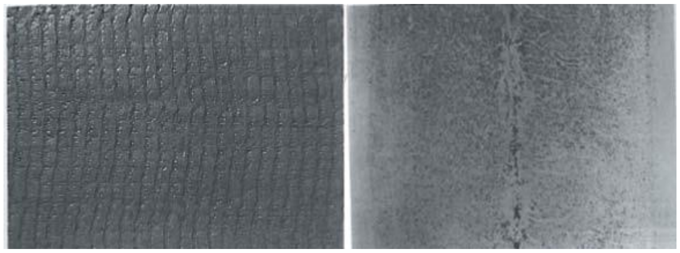


Figure 6.3: Oscillation marks (left) and segregation pattern (right) (Cramb, 2010)

The performance of casting operation is assessed in terms of these quality parameters and productivity, and the need is to operate casting in a way so as to meet the specified requirements. Apart from these performance measures, another important aspect that influences the selection of process design variables are the process constraints. A number of process constraints have to be satisfied while carrying out the refining operation. Explanation of the constraints is provided next.

Shell Thickness

The thickness of solidified steel shell at the mold exit should be more than a critical value, which depends on the grade of steel. This constraint ensures that solidified shell has sufficient strength to withstand the ferrostatic pressure of the molten metal and prevent break out of steel shell.

Metallurgical Length

The point along the length of the slab at which last drop of liquid steel solidifies is termed as metallurgical length. The constraint on metallurgical length is to ensure that the last instance of solidification occurs after the unbending point. This prevents possibility of crack formation in the slab ("Continuous Casting ", 2005).

Reheating

Reheating occurs in different segments due to changes in the values of heat extraction rate. As the slab moves from mold to spray and subsequently to radiation cooling zones, the amount of heat extracted from the slab gradually decreases which in turn leads to reheating of the slab. Restricting the value of reheat within a specified limit is important to prevent formation of cracks in the cast slab (Cheung and co-authors, 2001).

Segregation Index (SI)

Segregation creates problem during subsequent downstream processing so has to be removed during reheating operation. Higher severity of segregation will lead to increase in duration of reheating operation and thereby reducing the overall productivity. This is why a limit is provided on segregation index.

Oscillation Mark Depth (OMD)

The depth of oscillation marks on the surface of slab is OMD and is caused because of vertical oscillation of mold. OMD cannot be completely removed as oscillation of mold is required to prevent sticking of liquid steel, however restricting OMD within a specified limit is critical.

Quality Parameters

Constraints on other quality parameters such as surface and internal crack index, columnar to equiaxed ratio and equiaxed fraction are included to ensure the quality of slab is maintained.

Most of the investigators have limited their investigation to casting speed and secondary cooling zone parameters while optimizing the process with respect to specified performance measures. Several other parameters are critical to the casting operation and should be considered while designing the process, for example mold oscillation frequency. Moreover, the reported methods result in single point “optimum” solutions that do not account for the incompleteness of the computational models.

The continuous casting process is highly unsteady as there is always involvement of noise factors and variability in the operating conditions. Due to the unsteady nature of the process, “optimum” solutions can become unsatisfactory with small changes in the inputs. The previously described models do not take into account the uncertainty involved in a process. Hence, there is a need to design a process considering the involved uncertainty and thereby come up with a robust solution.

6.1.2 Problem Description and Solution Strategy

In this thesis a method on solution space exploration is introduced (Chapter 3) and in this chapter its utility in designing the continuous casting operation for a specific set of slab requirements (in terms of productivity and quality) is illustrated. The solution space exploration of the continuous casting are undertaken to support decision making in design with respect to different design preferences and also predict process design variables (set points), namely, casting speed, superheat, mold oscillation frequency cooling conditions in the secondary cooling zone, to meet the conflicting requirements of maximizing productivity and improving quality (which is measured by parameters such as segregation index and oscillation mark depth), while satisfying the constraints and ensuring feasibility robustness of the solution. The problem statement for solution space exploration of the continuous casting is introduced below.

Problem Statement

In this example, the solution space of continuous casting of steel is explored to obtain maximum productivity, minimum Center Line Segregation (CLS) and to achieve minimum Oscillation Mark Depth (OMD). Some parameters are assumed to be fixed. Density of steel is 7.8 g/cc, mold stroke is 6 mm and caster downtime is 1 hour. Target value of productivity is given to be 7821 tons/day. Maximum value of CLS and OMD is obtained to be 0.03 and 0.30 (mm) respectively.

Design Goals

There are several design goals that are considered in this problem and discussed below.

Productivity

Productivity ($P(X_i)$, tons/day) is one of the most important design goals for any industry. However, usually obtaining higher productivity results lower quality. This conflict can be managed through exploring different design preferences and identifying the desired solutions that satisfy both productivity and quality specifications. The formulation for productivity is given in Eq. 6.1.

$$P(X_i) = X_{10} \times X_{11} \times X_{12} \times \rho \times \left(24 - caster\ downtime\right) \times \frac{60}{10^6} \qquad \text{Eq. 6.1}$$

where X_{10} is the casting speed, X_{11} and X_{12} are the slab thickness and slab width respectively. ρ is density of steel and caster downtime is given to be 1 hour.

Center Line Segregation (CLS)

Center line segregation is one of the important design goals from quality perspective. The detail discription of this goal is provided in Section 6.1.1. The equations involved in developing the model for CLS and descriptions are as follows:

Maximum bulging of the solidified shell between rolls, due to the pressure exerted during withdrawl of solidifying steel shell from rolls is given by Eq. 6.2.

$$B_{max} = (7.15 * 10^{34} * F * L^{6.5} * P^{1.993} * T_{surf}^{8.766})/D \quad \text{Eq. 6.2}$$

The above empirical equation uses the developed Respose Surface Model (RSM) equation for calculation of T_{surf} and D, thereby giving the value of maximum bulging for a given set of input parameters.

Assumption of complete mixing in liquid phase and no diffusion in solid phase has been made for the current study; so, the concentration of different solute elements in liquid metal is calculated using Scheil's equation (Eq. 6.3).

$$C_L = C_0(1 - F_S)\hat{}(K_{eff} - 1) \quad \text{Eq. 6.3}$$

Eq. 6.3 uses the RSM developed for calculation of F_S (average solid fraction in the cross-section) and thereby estimating the concentration of solute.

The effective partition coefficient, K_{eff} is described by Eq. 6.4.

$$K_{eff} = K_e/[K_e + (1 - K_e)\exp(-\frac{R}{K_m})] \quad \text{Eq. 6.4}$$

Finally, Eq. 6.5 is used to calculate the extent of *CLS* in the solidified slab.

$$CLS = (K_1 C_L) + K_{bulge} \sum_{\substack{Critical\\Segments}} (B_{max}^{a} * C_L) + K_{bulge} \sum_{\substack{Critical\\Segments}} [\left(K_{\substack{Segment\\Life}} * B_{max}\right)^{a} * C_L] \quad \text{Eq. 6.5}$$

where K_1, K_{bulge} and a are the model tuning parameters whereas $K_{Segment\ Life}$ is obtained from the developed RSM equation model. The *CLS* is the final output based on which severity of segragation in the slab is decided. Further details about calculation of *CLS*, has been provided in Reference (Singh and co-authors, 2013).

Oscillation Mark Depth (OMD)

The oscillation mark depth is also one of the main design goals in continuous casting of steel. It has a significant effect on surface quality as the mark can act as a nucleation site for surface cracking and transverse cracks. It is calculated using an empirical equation and is given by Eq. 6.6.

$$OMD = 0.065 \times 1.145^{s} \times (200 \times 0.9^{s})^{t_N} \quad \text{Eq. 6.6}$$

$$t_N = \frac{60}{\pi f} \cos^{-1} \frac{1000 v_{cast}}{\pi f s} \quad \text{Eq. 6.7}$$

where t_N, v_{cast}, f and s stands for negative strip time (s), casting speed (m/min), mold oscillation frequency (cycles/min) and mold stroke (mm) respectively.

For other equations involved in modeling the caster refer to (Shukla and co-authors, 2014). The process constraints to be satisfied during the casting operation are explained in Section 6.1.2, the target values of which are listed below:

- segregation index (SI) should be less than 0.03,
- metallurgical length should be less than 28.84 m,

- shell thickness at mold should be greater than 10 mm,
- the temperature at the unbending point should be above the ductility trough,
- oscillation mark depth should be less than 0.30 mm, and
- reheating in the segments should be less than 100 oC.

These constraints are metallurgical constraints and are obtained by experience or taken from literature. A solution is needed that provides balance between the conflicting requirements, satisfies the aforesaid constraints and ensure feasibility robustness in face of variations. To achieve this, a mathematical construct capable of handling multiple objectives and constraints is required. For this purpose, the compromise DSP is used.

Solution and post solution strategy for the continuous casting of steel is shown in Figure 6.4. Detailed mathematical models are developed to model various phenomena as constraints and goals in the compromise DSP. Data generated using these models is then utilized to develop several Response Surface Models (RSM). These RSM's and the set of empirical correlations are then integrated with the compromise DSP to develop an integrated design method, to explore the solution space for continuous casting of steel. Solution space exploration is conducted through weight sensitivity analysis, constraint sensitivity analysis and incorporating feasibility robustness.

The mathematical formulation of the compromise DSP for continuous casting is discussed in Section 6.1.3. The method on solution space exploration is discussed in detail in Chapter 3 and described through continuous casting results in Section 6.2.

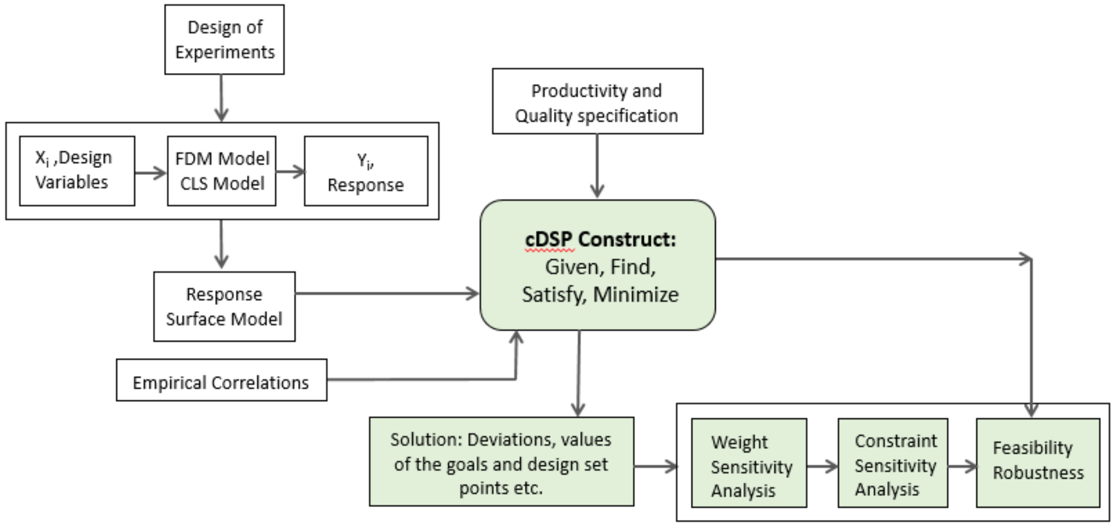


Figure 6.4: Solution and post solution strategy

RSM's are developed to predict various intermediate and final output parameters of continuous casting operation such as surface temperature, shell thickness, metallurgical length etc. Unlike other output parameters, reduced order equations are not developed to predict oscillation mark depth. Rather a well-established empirical equation for oscillation mark depth (d) is utilized, which is shown in Eq. 6.6 and Eq. 6.7 ("Continuous Casting ", 2005).

A transient, 2-D FDM based heat transfer model is developed to get the temperature evolution profile and shell thickness at mold exit. The formulation is based on the fundamental heat transport equation (Cramb, 2010) and modified Scheil's equation (Ghosh, 1990). The assumption is that heat flow by conduction is low compared to the heat flux by bulk movement of slab in the axial direction, which reduces the problem to two dimensions. Also, due to symmetry, only a quarter of the full cross-section of the slab is modeled. Appropriate boundary conditions are used in each zone. During continuous casting, solute segregates at the center-line of the slab, which is detrimental to properties of the final steel product. Segregation during casting depends on a number of factors and is governed several coupled phenomena such as fluid flow, stress evolution, solidification and micro and macro-structure evolution. Details of the CLS model that takes into account the effects of alloy composition, process parameters and the effect of caster health in terms of roll life (roll gap, misalignment etc.) is presented in reference (Singh and co-authors, 2013). In this design example, the comprehensive model that is used for prediction of CLS in the slab is adapted. The RSMs, empirical correlations and quality specifications discussed in this section are utilized to formulate the compromise DSP.

In the next section, the compromise DSP related to continuous casting of slab in word and concise mathematical version is presented which facilitate exploration of the solution space.

6.1.3 Compromise DSP Word and Mathematical Formulation

The details of the continuous casting process, models employed and problem statement are described in Sections 6.1.1 and 6.1.2 respectively. In this section, the word and mathematical formulation of the compromise DSP used for exploration of the solution space of continuous casting operation is described. There are 13 system variables (shown in Table 6.2), 11 constraints, and 3 goals for productivity, center line segregation and oscillation mark depth in this problem. The cDSP word formulation of continuous casting of slab is as follows:

Given

Density of Steel	Target value for productivity
Mold stoke	Center Line Segregation maximum
Caster downtime	Oscillation Mark Depth maximum

Find

The value of design variables	The value deviation variables

Satisfy

Constraints

C1 Shell Thickness	C7 Internal Crack Index
C2 Oscillation Mark Depth (mm)	C8 Surface Crack Index
C3 Metallurgical Length (m)	C9 Equiaxed Fraction
C4 Temperature at unbending (°C)	C10 Columnar to Equiaxed Ratio
C5 Reheating (°C)	C11 Product of deviation variables equal
C6 Centre Line Segregation	

Goals

G1 Maximize productivity
G2 Minimize Center Line Segregation Index
G3 Minimize Oscillation Mark Depth

Bounds

B1- B13 Minimum value $\leq X_i \leq$ Maximum value
B14 Deviation variables to be positive i = 1,…, 13

Minimize

The deviation function (Z): Archimedean formulation

Figure 6.5: Continuous casting of slab cDSP word formulation

Mathematical formulation of the compromise DSP requires specification of goals and constraints involved in the system that is being studied. The explanation and details of involved processing constraints are described in the previous sections. The performance of caster is assessed in terms of productivity and quality parameters such as segregation index, crack index, oscillation mark depth, and columnar equiaxed ratio. The above performance measures can be treated as goals of the compromise DSP. However for current demonstration purpose, only critical performance measures are treated as goals and other performance measures are included as constraints. See Figure 6.6.

Given

$\rho = 7.8$ g/cc,
s = 6 mm
caster downtime = 1 hr
Response surface models

(Prod $_{Target}$) = 7821 tons/day
$CLS_{Max} = 0.03$
$OMD_{Max} = 0.30$ (mm).

Find

X_i, i= 1,…,13

d_i^+ , d_i^- , i= 1,….,3

Satisfy

Constraints

C1 $ST_{ME} - 0.01 \geq 0$
C2 $0.30 - OMD \geq 0$
C3 $28.84 - ML \geq 0$
C4 $(T_{UP} - 800) \times (T_{UP} - 1000) \geq 0$
C5 $100 - T_R \geq 0$
C6 $0.03 - CLS \geq 0$
C7 $(100 - ICI) \geq 0$
C8 $(50 - SCI) \geq 0$
C9 $(Eq_{fraction} - 0.04) \geq 0$
C10 $(25 - CER) \geq 0$
C11 $d^-_i * d^+_i = 0$

Goals

G1 $[P(X_i)/P_{Target}] + d_1^- - d_1^+ = 1$
G2 $[CLS/CLS_{max}] + d_2^- - d_2^+ = 0$
G3 $[OMD/OMD_{max}] + d_3^- - d_3^+ = 0$

Bounds

B1- B13 $0 \leq X_i \leq 1$, i=1,….,13
B14 $d^-_i , d^+_i \geq 0$

Minimize

$$Z = \sum_{i=1}^{m} W_i(d_i^- + d_i^+); \qquad \sum_{i=1}^{5} W_i = 1, W_i \geq 0$$
$$for\ i = 1,..,3$$

Figure 6.6: Continuous casting of slab cDSP mathematical formulation

The process design variables considered in the cDSP are: X_1-X_7 is heat transfer coefficients of seven segments, X_8 is heat transfer coefficient of narrow face of slab, X_9 is superheat, X_{10} is casting speed, X_{11} is thickness of slab, X_{12} is width of slab and X_{13} is mold oscillation frequency. The ranges of process design variables for which the models are developed are shown in Table 6.2.

Table 6.2: Range of design variables

Design Variables	Range
X_1	310-822 W/m^2K
X_2	310-822 W/m^2K
X_3	290-746 W/m^2K
X_4	290-746 W/m^2K
X_5	160-209 W/m^2K
X_6	157-200 W/m^2K
X_7	157-200 W/m^2K
X_8	402-1228 W/m^2K
X_9	10-45 ^oC
X_{10}	0.6-2 m/min
X_{11}	210-230 mm
X_{12}	1100-1500 mm
X_{13}	95-240 /min

In the compromise DSP formulation, the aim is to minimize the difference between the value which is desired and the value which is obtained by reducing the deviation function. The objective of the cDSP is to minimize the deviation function. The deviation function is constructed using Archimedean approach as shown in Figure 6.6, where the system goals and constraints are normalized. The deviation function (Z) provides an indication of the extent to which a specific goal is achieved.

Here, di+, di- are the deviation variables. di+ is a measure of the over achievement and di- is a measure of the under achievement in a specific goal. Smaller value of deviation variables means that the achieved value is closer to the target value of the specified goal. Having done this step, the following steps introduced in the method (Figure 6.1) are discussed in the results section.

6.2 Exploring Solution Space of the Continuous Casting of Slab: Results and Discussion

Results and discussion in this chapter are divided in three parts: weight sensitivity analysis (Section 6.2.1), constraint sensitivity analysis (Section 6.2.2) and feasibility robustness (Section 6.2.3). In each part the key questions addressed in Section 6.1 are addressed.

6.2.1 Exploring Design Preferences through Weight Sensitivity Analysis

Weight sensitivity analysis is conducted to identify the preference (weight) range, assigned to deviation variables associated to different goals, in which desired designs satisfies high priority goals while changing the design preference within that specific weight range does not affect the solution. This information provide support to the designer in the process of decision making by answering to questions such as: What are the preference range in the solution space which desired solutions satisfy the high priority goals?

Employing the Archimedean form of the cDSP, various design scenarios with respect to weights on the deviation variables is tested and explored. Table 6.3 is presented to show the design scenarios and the deviation values achieved in each case. These information is used to visualize the solution space. The conflicts between the goals in some of the design scenarios can be seen in Table 6.3. For example, lowest deviation for productivity to be zero in DS 3 results the highest deviation for OMD which is 0.9. Moreover, the highest weight of CLS, 1, provides largest deviation of OMD and highest weight of OMD provides largest deviation of CLS which is 1. However, both CLS and OMD have their lowest deviation when the weights are equally distributed to be 0.33.

Table 6.3: Design scenarios and deviations

Design Scenarios				Deviations		
Sr. No.	**CLS (W_1)**	**Prod. (W_2)**	**OMD (W_3)**	**CLS**	**Prod.**	**OMD**
DS 1	1	0	0	0.093	0.294	1
DS 2	0.5	0.5	0	0.071	0.082	0.458
DS 3	0	1	0	0.601	0	0.906
DS 4	0.33	0.33	0.33	0.001	0.032	0
DS 5	0.5	0	0.5	0.092	0.291	0.030
DS 6	0	0.5	0.5	0.622	0.055	0.013
DS 7	0	0	1	1	1	0.034

The value of deviation variables, associated with each goal which obtained for different scenarios are used to construct ternary plots (Figures 6.7 to 6.9) and visualize the solution space of caster.

The utility of the plots is to identify the preference range that can be assigned to each goal for achieving a desired solution in which the requirements are met and the conflicts are managed. The goals are formulated in terms of deviation variables (see Figure 6.6, G1 to G3), where deviation variables represent the degree by which achieved value is off the target. The lower the value of deviation variables, the closer the achieved solution is to the target. The solution thus required minimization of deviation variables, i.e., lower values of deviation variables are desired.

The deviation values are read from the bar next to each plot. A designer should decide what range of solutions is desired for each goal. The discussion is focused on discovering the desired region of the solution space where change in design preference does not affect the solutions considerably. Visualization of the solution space helps the designer to rapidly adjust the design based on the designer choice with more confidence having better understanding of the space. The limited number of design scenarios is needed to visualize the solution space, however, more design scenarios results a clearer plot.

In Figures 6.7 to 6.9, the solution space of CLS, OMD and productivity are respectively explored and different regions are clustered based on satisfactory and unsatisfactory. The values inside the space (color contours) are the deviation associated with each goal and the bar next to the triangles indicates those values.

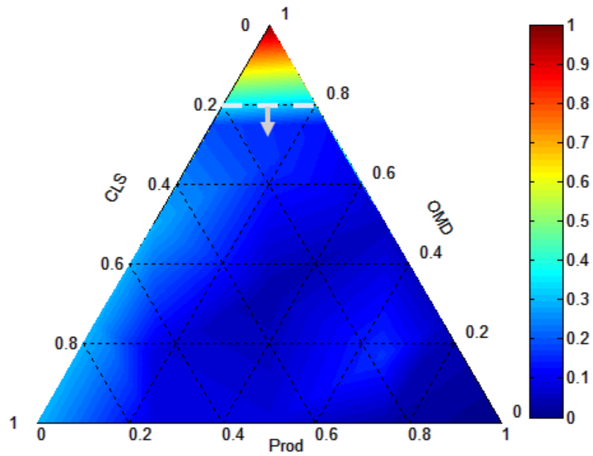


Figure 6.7: Solution space of productivity

Table 6.4: Preference range for productivity

Goals	Weights
CLS	0.2 – 1.0
OMD	0.0 – 0.8
Prod.	0.0 – 1.0

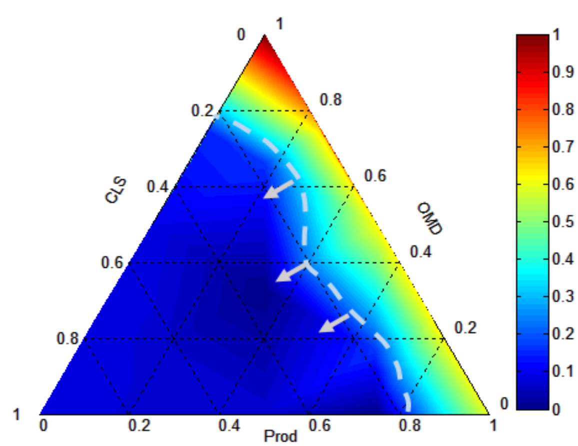


Figure 6.8: Solution space of center line segregation

Table 6.5: Preference range for center line segregation

Goals	Weights
CLS	0.2 – 1.0
OMD	0.0 – 0.8
Prod.	0.0 – 0.8

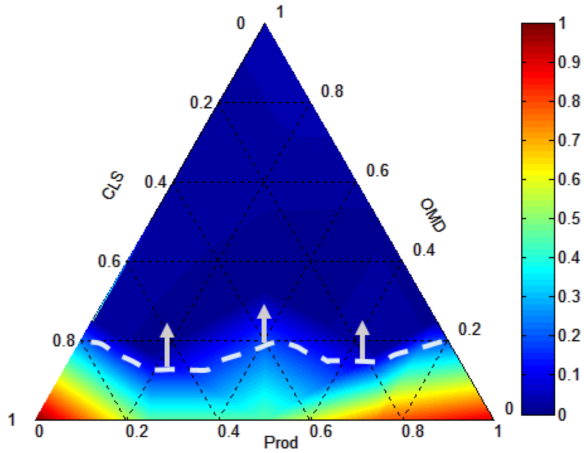


Figure 6.9: Solution space of oscillation mark depth

Table 6.6: Preference range for oscillation mark depth

Goals	Weights
CLS	0.0 – 0.8
OMD	0.2 – 1.0
Prod.	0.0 – 0.8

The acceptable rage of deviations for all the goals is set to be below 0.3. As indicated before, the values of deviations are normalized and the interpretation of this for the actual values is different in each goal. For example, deviation below 0.3 for productivity means around 3165 tons/day and higher in the actual values.

The preference range associated with each goal is documented in tables 6.4 to 6.6. Monitoring one of the plots for example, Figure 6.8 is the solution space associated with CLS. In this figure the desirable solutions which are defined to be any solution with the deviation lower than 0.3, are in the blue region of the plot where the preference on CLS lies in the range of 0.2 to 1, the preference on OMD lies in the range of 0 to 0.8 and the preference on productivity lies between 0 to 0.8. Any combination of aforementioned preferences/weights that sums up to one guarantees a desired solution considering only the first goal – minimum CLS. The same argument is true for the other two goals/plots. However, to make a satisficing decision which satisfies all design goals, the three plots are interpreted together. By overlapping the plots, the common region that satisfies all goals can be identified which is shown in Figure 6.10.

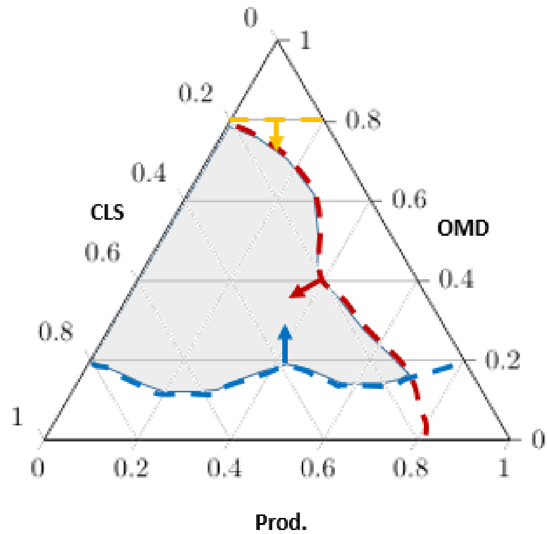


Figure 6.10: Desired region that satisfies all goals

Table 6.7: Preference range to satisfy all goals

Goals	Weights
CLS	0.2 – 0.8
OMD	0.2 – 0.8
Prod.	0.0 – 0.8

The preference range associated with the desired region found in Figure 6.10 is presented in Table 6.7. Any combination of the preferences given in this table guarantees a desired solution in which requirements on all three goals are met. In the case that such region is not found, tradeoffs are necessary. In such cases, targets assigned to goals in the cDSP can be modified to lower values in order to lower the deviations and increase the overlap possible. Weight sensitivity analysis is useful in decision making related to various design preferences, to predict the solution with fewer plant trials, if an industry wants to manufacture slab that meet quality and productivity requirements for a given composition of steel and equipment’s installation.

However, in an industrial set up, it is critical to consider the uncertainties in the process design variables before deciding upon the operating set points. Hence, knowing the preference range that satisfies all the goals, in the next section, the feasibility robustness of those desired solutions is explored through constraint sensitivity analysis.

Identifying the preference range in which all goals are met, more simulations can be done within this range to monitor extra capacity of each constraints in various desired solutions.

6.2.2 Exploring Design Constraints through Constraint Sensitivity Analysis

Desired solutions are identified in the last section through weight sensitivity analysis. In this section, those solutions are monitored and filtered one more time in terms of their flexibility in face of variations through constraint sensitivity analysis to provide confidence to the designer in making robust decision by answering to questions such as: What is the extra capacity in each constraint in face of uncertainty? What is the penalty in presents of variations? This is done by monitoring the active and inactive constraints. Solutions with one or more active constraints are boundary solutions with zero tolerance in face of uncertainty. Such solutions can become infeasible with small variations. The extra capacity depends on the constraint value and is different in each case.

Different design scenarios that are used in weight sensitivity analysis are shown in Table 6.8 along with their constraint values which is associated with their extra capacity. In this table, the constraints are numbered related to the cDSP presented in Figure 6.6. The highlighted scenarios, 4, 5 and 12, are some of the desired solutions that satisfy all the goals, and are identified through weight sensitivity analysis in the last section. Those solutions are not sensitive with respect to different design preferences listed in Table 6.7. Monitoring the constraints of those solutions in a general view, there are both active and inactive constraint in different designs.

Table 6.8: Constraint capacity for different solutions

Design Scenarios				Constraints Values								
	CLS	Prod	OMD	Co. 1	Co. 2	Co. 3	Co. 4	Co. 6	Co. 7	Co. 8	Co. 9	Co. 10
DS 1	1	0	0	0.0	0.0	14.5	21584.4	0.0	99.4	50	0.1	17.5
DS 2	0.5	0.5	0	0.0	0.0	14.1	24180.6	0.0	99.4	50	0.1	17.5
DS 3	0	1	0	0.0	0.0	14.7	24088.2	0.0	100.0	50	0.1	18.3
DS 4	0.33	0.33	0.33	0.0	0.1	13.8	25389.1	0.0	99.3	50	0.1	17.5
DS 5	0.5	0	0.5	0.0	0.1	14.5	21698.2	0.0	99.4	50	0.1	17.5
DS 6	0	0.5	0.5	0.0	0.1	14.8	23288.0	0.0	100.0	50	0.1	18.2
DS 7	0	0	1	0.0	0.1	16.1	24562.5	0.0	100.0	50	0.1	16.4
DS 8	0.75	0.25	0	0.0	0.0	14.1	24180.6	0.0	99.4	50	0.1	17.5
DS 9	0.25	0.75	0	0.0	0.0	13.8	25385.4	0.0	99.3	50	0.1	17.5
DS 10	0	0.75	0.25	0.0	0.1	14.8	23288.0	0.0	100.0	50	0.1	18.2
DS 11	0	0.25	0.75	0.0	0.1	15.0	22209.5	0.0	100.0	50	0.1	18.1
DS 12	0.25	0	0.75	0.0	0.1	14.6	21627.1	0.0	99.5	50	0.1	17.6
DS 13	0.75	0	0.25	0.0	0.1	14.5	21584.4	0.0	99.4	50	0.1	17.5

Constraints 1 and 6 are the active constraints in all the design scenarios with zero capacity to variations. Constraint 1 is on shell thickness which should be greater than or equal to 0.01 m. If the value is less than desired, there is a chance of break out of steel shell as the thickness of shell may not be sufficient to withstand the ferrostatic pressure of the liquid melt.

Constraint 6 is on center line segregation which is segregation of elements like sulfur, manganese and so on towards the center of slab during solidification. In the current work, CLS is calculated for segregation of sulfur and it should be less than or equal to 0.03. Segregation is detrimental for steel and the specifications are provided by the customers depending upon the applications for which slab will be used. One such example is sheet manufacturing. Slabs are used to manufacture sheets, which is then used for making rims of wheel. If segregation level is high, rim of wheels may fail during service (rim of wheel get tear from the center), which makes it critical to control the segregation level. Moreover, segregation creates problem during subsequent downstream processing such as hot rolling so has to be removed during reheating operation. Higher severity of segregation will lead to increase in duration of reheating operation and thereby reducing the overall productivity. In terms of implications, this leads to monetary losses as the productivity gets compromised.

Constraint 2 is active in some of the designs, and has limited extra capacity in other scenarios. Constraint 2 is oscillation mark depth which should be less than or equal to 0.30 mm. OMD is detrimental for the quality of slab and is caused because of oscillation of mold. Oscillation marks are a kind of surface defects and the specifications of which are provided by the customers. If this constraint is violated, this may lead to rejection of slab for further processing and it would have to be scrapped or should be sold to a different customer who uses the slab for a less critical applications. This also leads to monetary losses for the industry.

Constraint 9 is on equiaxed fraction and is considered as an inactive constraint, however it has a limited capacity of 0.1. Equiaxed fraction is about having a same dimension in each direction of the crystal grains which happens during solidification. This is important from the quality perspective.

Since Constraints 1 and 6 are active in all of the desired solutions (DS 4, 5 and 12), these solutions are boundary solutions with zero tolerance. Constraints 2 and 9 should also be considered for their limited capacity. The rest of the constraints are inactive with good amount of extra capacity in face of uncertainty.

It is possible that the constraints are violated by some worst combinations of the design parameters with variations. This problem becomes critical when at the solution point, part of the constraints which involve variations are active or have limited space. In this study, Constraints 1, 2, 6 and 9 can be considered as risky constraints with zero or very small tolerance in terms of feasibility robustness. If the caster is operated at operating set points (predicted based on weight sensitivity analysis, Section 6.2.1), due to the presence of certain degree of variabilities is the process design variables, it may end up violating the processing constraints which will ultimately lead to manufacture of slab with reduced quality and which may fail during service. Adding robustness in such constraints can be done to avoid the aforesaid risk and provide more confidence to the designer in making decision.

Based on the analysis done in this section, cDSP presented in Section 6.1.3 is modified in the next section to consider robustness in the identified processing constraints.

6.2.3 Incorporating Feasibility Robustness

The desired solutions are identified in Section 6.2.1 through weight sensitivity analysis followed by constraint sensitivity analysis to test feasibility robustness of those solutions in presence of uncertainties, in Section 6.2.2. Based on the analysis, modification on the cDSP is suggested in this section in order to incorporate robustness and provide confident to the designer in making a robust decision by answering to questions such as: What needs to be done to ensure feasibility robustness?

From the previous section, Constraints 1, 2, 6 and 9 are considered as risky constraints, and robustness should be incorporated in those constraints. These constraints are functions of the design parameters X_i. For example, Constrain 1, Shell thickness, as one of the active constraints is a function of process design variables X_9, X_{10}, X_{11}, X_{12}. This indicates that variations of one of these parameters may cause infeasibility of the solution. To prevent such sensitivity of the solution, the variability of the input parameters can be considered in formulating the cDSP. Therefore, the constraints 1, 2, 6 and 9 in the cDSP should be modified as shown in Figure 6.11.

Given

ρ = 7.8 g/cc,
s = 6 mm
caster downtime = 1 hr
Response surface models
($Prod_{Target}$) = 7821 tons/day
CLS_{Max} = 0.03
OMD_{Max} = 0.30 (mm).

$\sigma^2_{X_1} = \sigma^2_{X_2} = \sigma^2_{X_3} = \sigma^2_{X_4} = \sigma^2_{X_5} = \sigma^2_{X_6} = \sigma^2_{X_7} = \sigma^2_{X_8} = 25\left(\frac{W}{m^4K^2}\right)$, $\sigma^2_{X_9} = 4\,({}^{\circ}C^2)$, $\sigma^2_{X_{10}} = 0.01\left(\frac{m^2}{min^2}\right)$, $\sigma^2_{X_{12}} = 400(mm^2)$, $\sigma^2_{X_{13}} = 25\,(/min^2)$

Find

X_i, i= 1,…,13

d_i^+, d_i^-, i= 1,….,3

Satisfy

Constraints

C1 $ST_{ME} - 0.01 \geq \Delta(ST_{ME})$
C2 $0.30 - OMD \geq \Delta\,(OMD)$
C3 $28.84 - ML \geq 0$
C4 $(T_{UP} - 800) \times (T_{UP} - 1000) \geq 0$
C5 $100 - T_R \geq 0$
C6 $0.03 - CLS \geq \Delta\,(CLS)$
C7 $(100 - ICI) \geq 0$
C8 $(50 - SCI) \geq 0$
C9 $(Eq_{fraction} - 0.04) \geq \Delta\,(Eq_{fraction})$
C10 $(25 - CER) \geq 0$
C11 $d_i^- * d_i^+ = 0$

Goals

G1 $[P(X_i)/P_{Target}] + d_1^- - d_1^+ = 1$
G2 $[CLS/CLS_{max}] + d_2^- - d_2^+ = 0$
G3 $[OMD/OMD_{max}] + d_3^- - d_3^+ = 0$

Bounds

B1- B13 $0 \leq X_i \leq 1$, i=1,….,13
B14 $d_i^-, d_i^+ \geq 0$

Minimize

$$Z = \sum_{i=1}^{m} W_i(d_i^- + d_i^+)$$

$$\sum_{i=1}^{5} W_i = 1, W_i \geq 0 \; for \; i = 1,\ldots,3$$

Figure 6.11: Modified cDSP to consider feasibility robustness

By adding the extra capacity to Constraints 1, 2, 6 and 9, feasibility robustness is guaranteed in face of variations.

The continuous casting set points and values of the goals after incorporating robustness in the model for desired solutions (design scenarios 4, 5 and 12) are presented in Table 6.9 and 6.10. The values of the constraints obtained for the predicted set points show that all the constraints are getting satisfied even if variations in process design variables are present. This ensures that no metallurgical processing constraints are violated when the casting operation is carried out at the predicted set points, and thus a cast slab of desired quality is manufactured.

Table 6.9: Design set points for desired solutions with consideration of feasibility robustness

Variables	D.S. 4	D.S 5	D.S. 12
X1 (W/m^2K)	311	324	326
X2 (W/m^2K)	420	461	456
X3 (W/m^2K)	321	536	579
X4 (W/m^2K)	301	408	405
X5 (W/m^2K)	160	160	160
X6 (W/m^2K)	157	157	157
X7 (W/m^2K)	156	157	157
X8 (W/m^2K)	403	408	402
X9 (^oC)	35	43	43
X10 (m/min)	1.87	1.75	1.76
X11 (mm)	227	221	221
X12 (mm)	1500	1428	1443
X13 (/min)	186	186	186

Table 6.10: Values of the design goals for desired solutions with consideration of feasibility robustness

	Goal Values		
Goals	**D.S. 4**	**D.S 5**	**D.S. 12**
CLS	0.0051	0.0050	0.0050
OMD (mm)	0.1967	0.2017	0.2013
Prod. (tons/day)	6474	5624	5721

The 3 design scenarios – 4, 5 and 12 - shown in Table 6.9 are desired and robust solutions found through weight sensitivity analysis in Section 6.2.1 and incorporating feasibility robustness in this section. The deviation of these designs are within an acceptable range of below 0.3. The design set points of all the 3 scenarios are also within the range that is specified in Section 6.1.3. The process design variables considered in the study are: X_1-X_7 is heat transfer coefficients of seven segments, X_8 is heat transfer coefficient of narrow face of slab, X_9 is superheat, X_{10} is casting speed, X_{11} is thickness of slab, X_{12} is width of slab and X_{13} is mold oscillation frequency.

In Table 6.10, the values of the goals are shown for the same design scenarios. The CLS and OMD are minimized in which the target is zero. The maximum values that they can get are 0.03 and 0.30 (mm) respectively. The target value of productivity is 7821 tons/day. All these designs are acceptable, however the questions is: Which design is most preferred for someone who is designing the continuous casting operation and why?

Design scenario 4 is preferred for several reasons:

1. A higher productivity which is always desired. The increased productivity is because we are casting at a higher casting speed and casting a slab with a higher cross sectional area as width is more in the case.

2. A lower value of OMD, although very slight difference in scenario 4, of all the cases. The change in segregation level is negligible which means the severity of CLS is not increasing by a considerable amount on increasing the casting speed. Ideally, increase in casting speed should have resulted in higher segregation but the same is not reflected in

solution because the decrease in superheat value compensates for the increased casting speed and help the designer to maintain the segregation level in slab.

3. A comparatively lower value of superheat (around 8 ^{o}C less than other two cases), which reduces the chances of breakouts and spilling of molten steel at mold exit that may happen because of higher degree of superheat.

A process designer, should thus go with DS 4 and operate the casting operation at set points predicted for DS 4 (see Table 6.9) for producing steel slab of a given composition, with maximum productivity and desired quality with respect to oscillation marks and severity of segregation in the slab.

6.3. Empirical Structural and Performance Validity

Solution space exploration method that is proposed in Chapter 3 consists of different aspects. To verify the design method, Validation Square is adapted in this thesis and is introduced in Chapter 1. It involves four quadrants shown in Figure 6.12. In Chapters 4, 5 and 6, the empirical structural and performance validity of the method are addressed using three design examples. In this chapter, empirical structural and performance validity is addressed for Block C of the solution space exploration method through process design of continuous casting of steel.

Empirical structural validity involves Step (3) accepting the appropriateness of the example problems that are used to verify the performance of the method. It has to be shown that the examples are good representations of design problems, for which the method is designed and that the associated data can be used to support a conclusion.

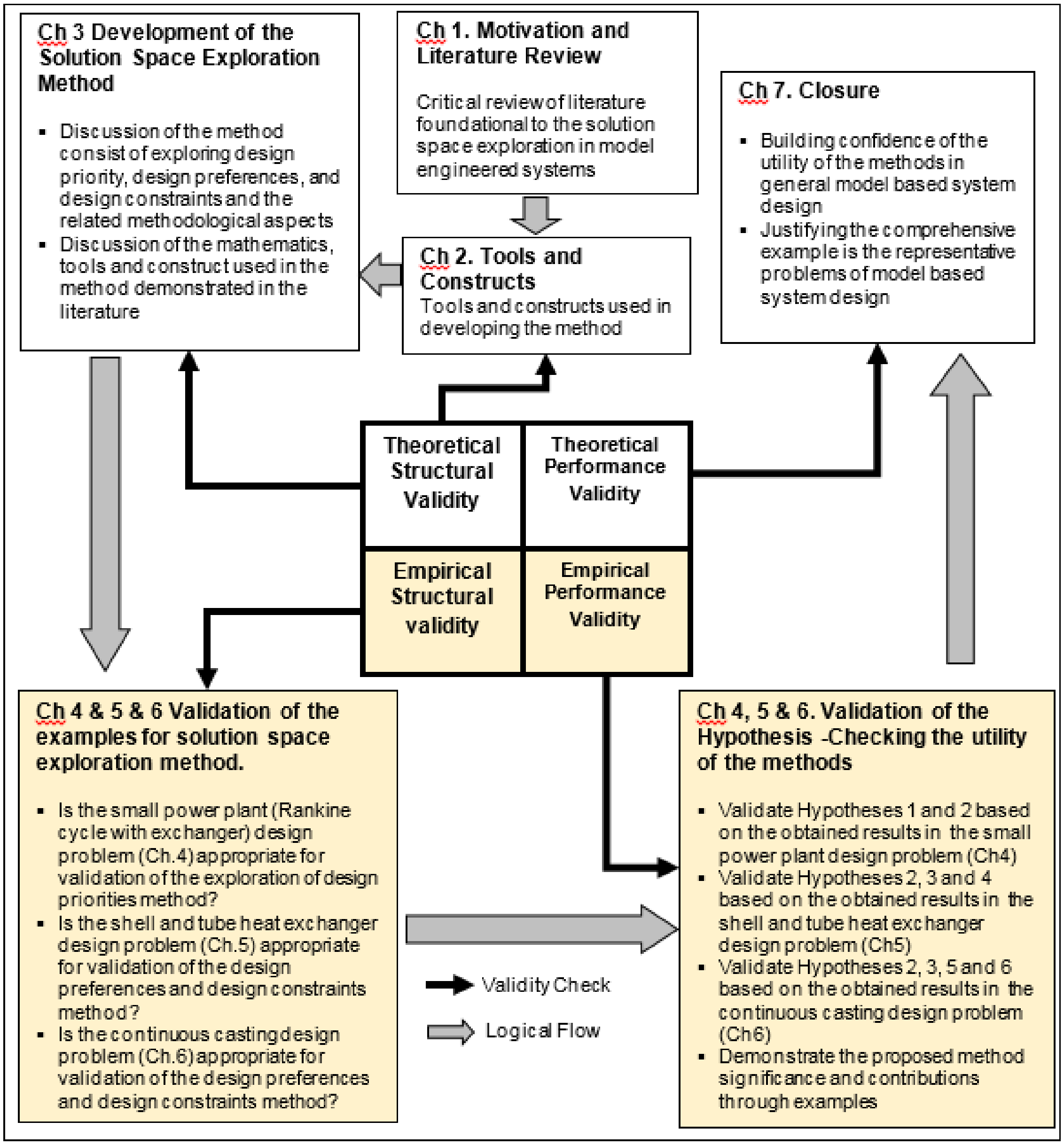


Figure 6.12: Validation square road map

The continuous casting of steel is an appropriate example problem provided by Tata Consulting Services. This design example is a multi-objective problem which is needed to explore design preferences. Three of the design goals used in this chapter are center line segregation, oscillation mark depth and productivity. This example also involves various constraints which are metallurgical constraints and are obtained by experience or taken from literature. An example with various constraints is needed to explore design constraints and incorporating feasibility robustness which make this example a perfect one to verify the method. State of the art and mathematical model of the continuous casting of steel is provided in Section 6.1.

Empirical performance validity is about showing the usefulness of the method for solving the example problems which includes Steps (4) and (5): accepting that the outcome of the method is useful with respect to the initial purpose for some chosen example problem(s); accepting that the achieved usefulness is linked to applying the method. The two steps in this quadrant are related to the results discussed in Section 6.2. Since the example problem is a collaborative work with industry, there is confidence for validity of the data and results. Continuous casting involves a number of phenomena such as solidification, fluid flow, segregation, columnar-equiaxed transition, crack formation etc. Performance of continuous casting process is generally assessed using parameters such as productivity, quality of slab and cost of production. The quality of a slab is determined using several quantifiable parameters such as segregation index, crack index, columnar equiaxed ratio, oscillation mark depth, etc. The aforesaid performance measures need to satisfy stringent norms, which is sometimes difficult as these are conflicting in nature.

The weight and constraint sensitivity analyses are undertaken to predict process design variables (set points), namely, casting speed, superheat, mold oscillation frequency cooling conditions in the secondary cooling zone, to meet the conflicting requirements of maximizing productivity and improving quality (which is measured by parameters such as segregation index and oscillation mark depth), while satisfying the constraints.

In such problems, designer should decide which design preferences provide desirable solution satisficing all goals while ensuring robustness in design. Solution space exploration method that is performed in exploring design of continuous casting (Sabeghi and co-authors, 2016) facilitates decision making related to different design preferences and also ensuring feasibility robustness. The analysis and insight provided in discussing the results bring useful information and therefore confidence to the designer in the process of decision making.

6.4. What Has Been Presented and What is Next

In this chapter, solution space of a process design for continuous casting of steel is explored through weight sensitivity analysis, constraint sensitivity analysis and incorporating feasibility robustness. Mathematical model for continuous casting of steel is discussed in detail in Section 6.1. It includes state of the art, problem description and the related compromise DSP. Results are discussed in three subsections in Section 6.2.

The research questions identified in Chapter 1 are addressed in this chapter through a design example.

- *What is the process to identify design preferences that guarantees a desired solution in which different and conflicting goals are satisfied? (Section 6.2.1)*
- *What kinds of modification are needed if desired solutions that satisfy different and conflicting design preferences are not found?(Section 6.2.1)*
- *What is the process to explore feasibility robustness under the effect of variations?(Section 6.2.2)*
- *How can design constraint exploration be beneficial to incorporate feasibility*

robustness in the model? (Section 6.2.3)

Next chapter is for closure which contains summary of the thesis, relevant contributions and theoretical performance validity of the method. This is about building confidence of the utility of the method and that is generalizable to other applications other than the design examples used in this thesis.

CHAPTER 7 CLOSURE

This is the final chapter of this thesis in which a summary of the work is first presented in Section 7.1 to highlight many of the important points made in the previous chapters. Following this review, theoretical performance validity of the thesis is discussed in which ontology for the solution space exploration method is introduced, and limitations and possible future work are outlined in Section 7.2. Finally, research questions are revisited and answers are briefly mentioned followed by relevant contributions from this thesis in Section 7.3, thus drawing the work to a close.

7.1 A Summary of the Thesis

There is one main goal in this thesis and that is to propose a method to support designer in the process of decision making. In achieving this goal, the method is presented in Chapter 3 which several approaches are discussed. The proposed method is then tested using different design examples.

In Chapter 1, several key words are defined such as “system” and “model-based design” when characteristics of model-based design is presented to establish the motivation for model-based realization of engineered systems (Section 1.1).

In model-based realization of engineered systems, the decision maker must be able to work constructively with decision models that are typically incomplete and inaccurate in order to make defendable decisions under uncertainty. Solution space exploration may be the key to knowledge-based and defendable decisions.

Different dimensions of solution space exploration, e.g., exploring design preference through weight sensitivity analysis, exploring design constraints through constraint sensitivity analysis, and incorporating feasibility robustness are described in Chapter 1, and investigated in the literature. Decision-Based Design and the DSP Technique are introduced in Section 1.2 as the framework for solution space exploration in model-based realization of engineered systems. Research questions and hypothesis are discussed in Section 1.3. Finally, validation and verification strategy in this work is described through the validation square (Section 1.4).

In Chapter 2, different tools/constructs and concepts used in this thesis are described. The compromise Decision Support Problem is the main one. In Sections 2.1, the compromise DSP is introduced along with a critical review of the literature and its usefulness in solution space exploration. Then an overview of the robust design under uncertainty is presented (Section 2.2). One element that facilitates solution space exploration is the response surface models that are discussed in Section 2.3. In Section 2.4, the computer environment to implement DSPs, DSIDES, is described. These tools and constructs are chosen to develop and conduct the method in order to answer to the research questions posed in Chapter 1 and the principal research question, namely *what is needed in model-based system realization to increase design knowledge in order to support decision making given that the models are not complete and accurate?*

Understanding the foundation in Chapter 1, using the tools in Chapter 2, a method on solution space exploration is proposed in Chapter3. The method consists of different parts: exploring design selections (Section 3.1), exploring design priorities through goal ordering (Section 3.2), exploring design preferences through weight sensitivity analysis (Section 3.3), exploring design constraints through constraint sensitivity analysis (Section 3.4), and incorporating feasibility robustness (Section 3.5). Different dimensions of the method are shown in Figure 7.1.

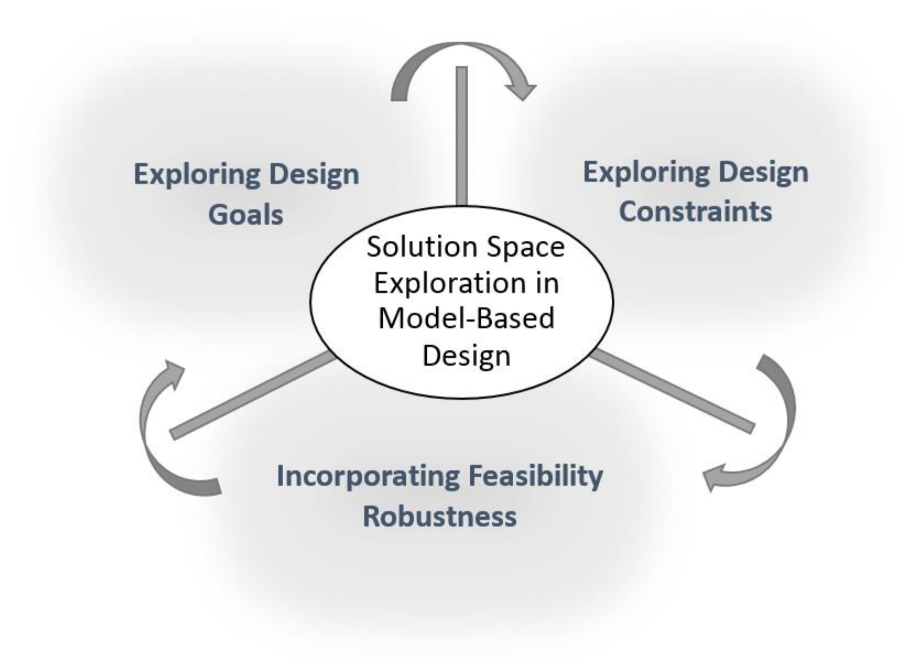


Figure 7.1: Solution space exploration

Exploring design selections, design priorities and design preferences are all under exploring design goals in this method shown in the figure above. The utility of the method is in providing analysis and insight about the design from different perspectives to bring confidence and support to the designer in robust decision making.

In performing weight sensitivity analysis, different design preferences are explored to identify desirable solutions insensitive to change of input weights associated with deviations. In addition, design preferences in which desired solutions satisfy all the goals are identified.

Those solutions are then monitored through constraint sensitivity analysis to identify active and inactive constraints of the boundary solutions, analyze the capacity of each constraint and the penalty associated with variations. This lays the foundation for applying and ensuring feasibility robustness of the desired solutions.

The methodology is proposed in Chapter 3 though flowcharts, and steps are documented in Chapter 3 and Appendix G. This chapter is the foundation to Chapters 4, 5 and 6 in which three design examples, namely, small power plant, shell and tube heat exchanger and continuous casting of steel are developed to test different parts of the method.

<u>A Small Power Plant: (Chapter 4)</u>

In Chapter 4, a design example of a small power plant (Rankine cycle with an exchanger) is developed to test one component of the method which is **exploring design priorities through goal ordering.** In Section 4.1, Rankine cycle with an exchanger is introduced and the mathematical model is developed. Results are presented and discussed from different perspectives such as parametric study in Second 4.2.

To investigate the characteristic values that define the Rankine cycle and the heat exchanger, a two-step process using DSIDES is used, first with the XPLORE grid search module and then with the ALP algorithm.

There are five goals; two priority orders shown in Table 7.1 are defined and explored.

Table 7.1: Design priority scenarios

	Design Priorities
Order 1	1) Minimize moisture 2) Maximize Rankine cycle efficiency 3) Maximize temperature exchanger efficiency 4) Maximize system efficiency 5) Maximize exchanger effectiveness
Order 2	1) Minimize moisture 2) Maximize system efficiency 3) Maximize temperature exchanger efficiency 4) Maximize exchanger effectiveness 5) Maximize Rankine cycle efficiency

To summarize the results, higher Rankine cycle efficiencies are achieved with high temperatures and high pressures. In contrast, the higher system efficiency results from low temperatures and low pressures. In addition, to achieve zero moisture in the turbine, the requirement is high temperatures with lower pressures. Clearly, the right decision is not straightforward, hence the compromise and tradeoff is necessary. The behavior of the model is also assessed by monitoring convergence of the system and deviation variables.

<u>Shell and Tube Heat Exchanger: (Chapter 5)</u>

In Chapter 5, a design example of shell and tube heat exchanger is developed to test three components of the solution space exploration method: **1) exploring design preferences through weight sensitivity, 2) exploring design constraints through constraints sensitivity analysis,** and **3) on exploring design selections.** The organization of this chapter is to first introduce shell and tube heat exchanger and develop the mathematical model (Section 5.1), then present the results associated with exploring design preferences and design constraints (Section 5.2). In the last section exploring design selection is presented and results are discussed (Section 5.3).

There are nine system variables and deviation variables, 18 constraints and three goals are defined. The solution space of three goals namely, heat transfer area, tube pressure drop and effectiveness is visualized, and the preference range where desired solutions are guaranteed is documented. Next, the active and inactive constraints of the desired solutions are monitored. One of the constraints concerning tube thickness is active in all designs which directly affects the heat transfer, and therefore the performance of the system. Tube thickness is a function of tube radius which means any variations on that can impact feasibility of the solution and also affect the system performance. The uncertainty associated with tube thickness may be from two common sources: manufacturing and fouling. Larger tube thickness results in lower heat transfer and higher pressure drop.

Moreover, designing shell and tube heat exchangers involves primarily selecting the material for the tubes. This selection has a large impact on system performance and cost. The selection DSP is formulated for this problem and results are discussed in Section 5.3. The alternatives are copper, aluminum, stainless steel and brass. The attributes are specified to be cost, density and heat conductivity. The results of ranking is based on the designer preference which is reflected as relative importance assigned to the attributes. In the end sensitivity analysis is conducted in which 5% uncertainty in the cost, 0.5% for the thermal conductivity and density are considered. It us shown that ranking is subject to change which means the results are sensitive to the uncertainty, especially variations of the cost.

Continuous Casting of Steel: (Chapter 6)

In Chapter 6, the comprehensive example in design of continuous casting of steel is introduced to test and verify the main three parts of the solution space exploration method discussed in Chapter 3: **1) exploring design preferences, 2) exploring design constraints, and 3) incorporating feasibility robustness**. The state of the art and the mathematical model for continuous casting of steel is introduced in the first section (Section 6.1). In the second section (Section 6.2) results are discussed in three subsections namely, weight sensitivity analysis, constraint sensitivity analysis and feasibility robustness.

In this example, the solution space of continuous casting of steel is explored to obtain maximum productivity, minimum Center Line Segregation (CLS) and to achieve minimum Oscillation Mark Depth (OMD). Some parameters are assumed to be fixed. Density of steel is 7.8 g/cc, mold stroke is 6 mm and caster downtime is 1 hour. Target value of productivity is given to be 7821 tons/day. Maximum value of CLS and OMD is obtained to be 0.03 and 0.30 (mm) respectively.

The important process constraints to be satisfied during the casting operation are explained in Section 6.1.2, and listed below:

- segregation index (SI) should be less than 0.03,
- metallurgical length should be less than 28.84 m,
- shell thickness at mold should be greater than 10 mm,
- the temperature at the unbending point should be above the ductility trough,
- oscillation mark depth should be less than 0.30 mm, and
- reheating in the segments should be less than 100 oC.

Weight sensitivity analysis is conducted and a set of weight range associated with design preferences is identified in which desired solutions satisfies all three goals, provided in Section 6.2.1. Next, those desired solutions are monitored in terms of active and inactive constraints through constraint sensitivity analysis. The constraints with zero or limited capacity are recognized (center line segregation, shell thickness, oscillation mark depth, equiaxed fraction) and the penalty associated with violation of those constraints is discussed in Section 6.2.2. Then, those constraints are subject to modification is the cDSP, and robust and desired solutions are captured. In the end, recommendation and insight is provided, see Section 6.2.3.

The solution space exploration method is proposed in this thesis to facilitate decision making in design by providing an attention directing tool. Although the method is applied in engineered systems in this thesis, it can be applied in other fields where models exists.

This concludes the summary of the thesis. In the next section research questions are recalled from Chapter 1, and the sections where they are addressed, are mentioned.

7.2 Theoretical Performance Validity

Validation Square is adapted in this thesis to verify the proposed method in solution space exploration (Figure 7.2). The discussion is provided in Chapter 1, Section 1.4. The fourth Quadrant is about theoretical performance validity which involves Step (6) accepting that the usefulness of the method is beyond the case studies; a “leap of faith” from the usefulness of the design method for the chosen example problems to the general validity of the method, which means building confidence in the generality of the method and accepting that the method is useful beyond the example problems.

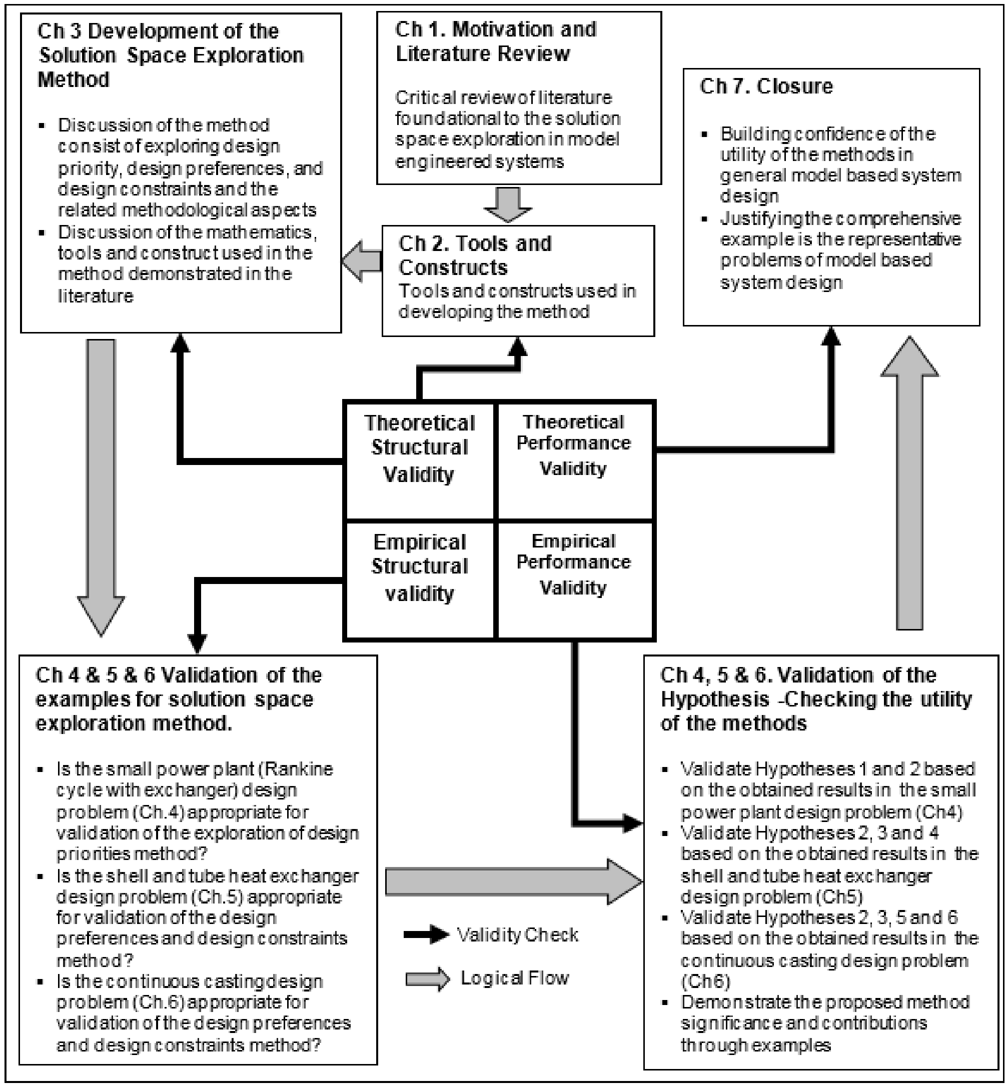


Figure 7.2: Validation strategy

This involves two parts: 1) determining the characteristics of the example problems that make them representative of general classes of problems, and 2) generalization of the solution space exploration method beyond the example problems that are used in this thesis. In Sections 7.2.1, 7.2.2, 7.2.3 and 7.2.4, characteristics of the example problems, ontology for the solution space exploration method, limitations and future work are discussed, respectively.

7.2.1 Characteristics of the Example Problems

Based on the utility of the method (see Section 7.1) and methodology discussed in Chapter 3, the usefulness of the example problems for general classes of problems should be inferred for the Quadrant 4 of the Validation Square.

For empirical structural validation, it is argued in Sections 4.3, 5.4 and 6.3 that the example problems are collectively representative of a general class of problems, defined by the following characteristics.

- Model-based system design in which physical world is modeled using computers.
- The models are not complete and accurate, and the model cannot represent the whole characteristics of the system. Therefore, the optimum solution of the model is not necessarily the optimum solution of the system.
- Multi-objective formulation exists in the example problems.
- Difficulty in decision making related to different design preferences or design alternatives is an issue in robust decision making.
- In order to design the system, conflicts among the system goals need to be considered to capture solutions satisficing all the goals.
- The model involves various important constraints which make feasibility robustness an important design issue.
- Analysis and insight should is needed to make an effective and informative decision.

This is intended to provide a list of signature properties of the design examples for which the effectiveness of the solution space exploration method is demonstrated. It is demonstrated in Chapters 4, 5 and 6, that the solution space exploration method is effective for the design examples with these characteristics. Therefore, there is a reason to believe that the solution space exploration method is effective for general classes of problems with these characteristics. One approach to generalize the method is to create an ontology-based knowledge modeling for solution space exploration method which is discussed in the next section.

7.2.2 Ontology for the Solution Space Exploration Method

The solution space exploration method proposed in this thesis is based on the compromise DSP which is anchored in the notion that design is fundamentally a decision making process. The utility of the method is to facilitate decision making by providing knowledge and insight about the models. The models that are not complete and accurate because they cannot represent the whole characteristics of the system. That is the reason solution space exploration is critical in any model-based system design to identify solutions that are desired and robust.

To generalize the method and make it usable for any other application in model-based design, the ontology-based knowledge model for solution space exploration method is proposed in this section, shown in Figure 7.3. The ontology-based knowledge model that facilitates capturing and formally representing the knowledge of the method to facilitate executability and reusability of the solution space exploration method in a computer.

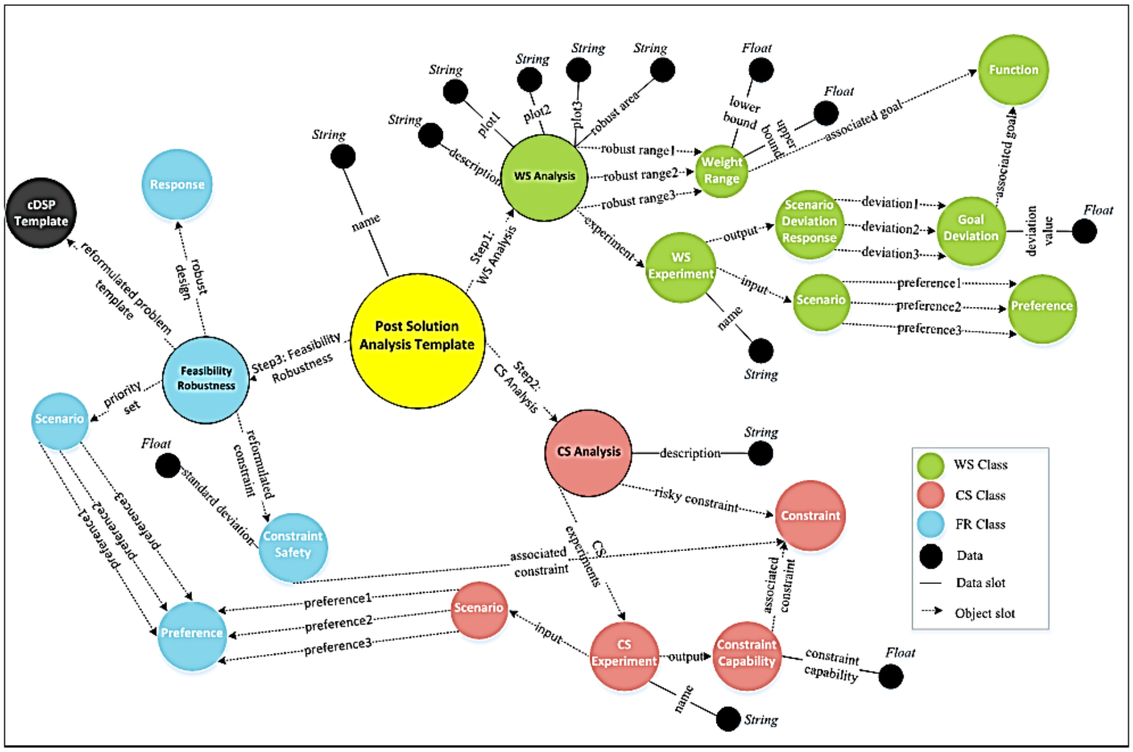


Figure 7.3: Frames based solution space exploration template

In computer science, ontology is defined as “a specification of a conceptualization” (Gruber, 1993). It provides a common vocabulary for the representation of domain-specific knowledge (Noy and co-authors, 2001). With good performance in extensibility and computer-interpretability, ontologies are increasingly being applied in complex applications, e.g., for Knowledge Management, E-Commerce, eLearning, or information integration. For the above mentioned two features (extensibility and computer-interpretability), it makes ontology a suitable representation method for the post solution analysis template.

The two most widely-used ontology modeling paradigms are Web Ontology Language (OWL) and Frames (Wang and co-authors, 2006). One of the primary differences between Frames and OWL is the view of domain: Frames are based on a closed-world assumption in which everything is prohibited until it is permitted, while OWL is based on an open-world assumption in which everything is permitted until it is prohibited (Wang and co-authors, 2006). Since the post solution analysis template is a computational structure within which most of the modules (e.g., WS Analysis, CS Analysis etc.) must strictly comply with certain rules (e.g., in the module “WS Analysis”, three or more goals must be provided), it is more like a closed world than an open world. So in this work Frames are used as the post solution analysis template modeling paradigm. The ontology is developed in Protégé-Frames 3.5 ("Protege-Frames," 2012).

In order to create a relevant ontology for the creation of a post solution analysis template, the definition of the decision template offered by Panchal and co-authors is adapted:

> *A design template is a design decision information structure that comprises of multiple modules with different preset formats and relationships among these modules.*

The “modules” here refer to the classes and the “relationships” refer to the slots in Figure 7.3. A decision template can be executed only after it has been instantiated with specific design information.

In the Frames based solution space exploration template ontology that are shown in Figure 7.3, there are different classes such as WS Analysis which is used to capture the relevant background information about weight sensitivity analysis.

There is a strong connection between the cDSP template developed by Ming (Ming and co-authors, 2015) and the post solution analysis template proposed in this section. Some of the classes used in the post solution analysis template such as *Function, Preferences, Constraint* and *Response,* represent the connection between the two templates. Definitions for the sixteen classes of the post solution analysis template (PSATemplate) are given in Table 7.2.

Table 7.2: Classes

Class Name	**Definition**
PSATemplate	A class that integrates all the template modules and represents the information structure of a post solution process
WS Analysis	A class that represents the information related to exploring design preferences
WS Experiment	A class that represents a sets of scenarios and associated deviations to be used for weight sensitivity analysis
Weight Range	A class that represents a weight range where desired solution for each goal is guaranteed
Scenario Deviation Response	A class that represents the results for deviation values for different scenarios
Goal Deviation	A class that captures deviation value associated with each scenario for each goal
Preference	A class that captures designers' preferences regarding the satisfaction of the system goals. (This is one of the cDSPTemplate classes)
Function	A class that represents system behaviors and performances. (This is one of the cDSPTemplate classes)
CS Analysis	A class that represents the information related to exploring design constraints
Constraint	A class that represents a function with a min/max value that cannot be violated. (This is one of the cDSPTemplate classes)
Constraint Capability	A class that captures the value associated with each constraint capacity
CS Experiment	A class that represents a sets of scenarios and associated deviations to be used for constraint sensitivity analysis
Scenario	A class that represents design preferences
Feasibility Robustness	A class that represents the information related to feasibility robustness
Constraint Safety	A class that capture reformulated constraints
Response	A class that captures the result returned from a problem solver (e.g., DSIDES). (This is one of the cDSPTemplate classes)

Each class involves several slots. The slots for Frame based ontologies are generally divided into two types – data slots and object slots. Data slots are used to link instances to literals (e.g., link a *description* with a data type of 'String' to a *WS Analysis* instance) while object slots are used to link instances to instances (e.g., link a *WS Analysis* instance to a *PSATemplate* instance).

The data slots and the object slots for the post solution analysis template ontology are illustrated in Tables 7.3 and 7.4 respectively.

Table 7.3: Data slots

Slot Name	Definition
name	String. Specifies the name of an instance
description	String. Specifies the descriptive information of a post solution analysis task
plot	String. Specifies the visualized solution space of each goals (three goals) of *WS Analysis*
robust area	String. Specifies the superimposed plot (desired area of the solutions that meet all the goals) of *WS Analysis*
lower bound	Float. Specifies the lower bound of a *Weight Range*
upper bound	Float. Specifies the upper bound of a *Weight Range*
deviation value	Float. Specifies the value of a *Goal Deviation*
constraint capability	Float. Specifies the value of a *Constraint Capacity*
standard deviation	Float. Specifies the value for standard deviation of each constraint of a *Constraint Safety*

Table 7.4: Objective slots

Class Name	Definition
Step1: WS Analysis	Specifies the weight sensitivity analysis: first step in *PSATemplate*
Step2: CS Analysis	Specifies the constraint sensitivity analysis: second step in *PSATemplate*
Step3: Feasibility Robustness	Specifies the weight sensitivity analysis: first step in *PSATemplate*
robust range	Specifies the weight range that guarantees a desired solution for each goal in *WS Analysis*
associated goal	Specifies the goal *Function* that a *Goal Deviation* is associated with
experiment	Specifies the scenarios to be monitored in *Analysis*
risky constraint	Specifies the associated *Constraint* in *CS Analysis*
associated constraint	Specifies the associated constraint that relates *Constraint Safety* to the *Constraint* of the *cDSPTemplate*
reformulated constraint	Specifies the reformulated constraints to ensure *Feasibility Robustness*
reformulated problem template	Specifies the reformulated *cDSPTemplate* after incorporating *Feasibility Robustness*
robust design	Specifies the robust solutions after incorporating *Feasibility Robustness*
priority set	Specifies the scenarios associated with desired solutions found through *WS Analysis*
output	Specifies the input *Experiment* of an *Analysis*
input	Specifies the output *Experiment* of an *Analysis*
deviation	Specifies the value of deviation associated with each goal of a *Scenario Deviation Response*
preference	Specifies the value of weight given to each goal in each *Scenario*

As shown in Figure 7.4, plot 1, plot 2, plot 3, robust area and description are the five data slots, and ws experiment, robust range 1, robust range 2 and robust range 3 are the four object slots under *WS Analysis* Class. The robust area shown in Figure 7.4 is the common area in the solution space that satisfies all the goals. The robust ranges are the weights associated with each goals where a desired solution is guaranteed.

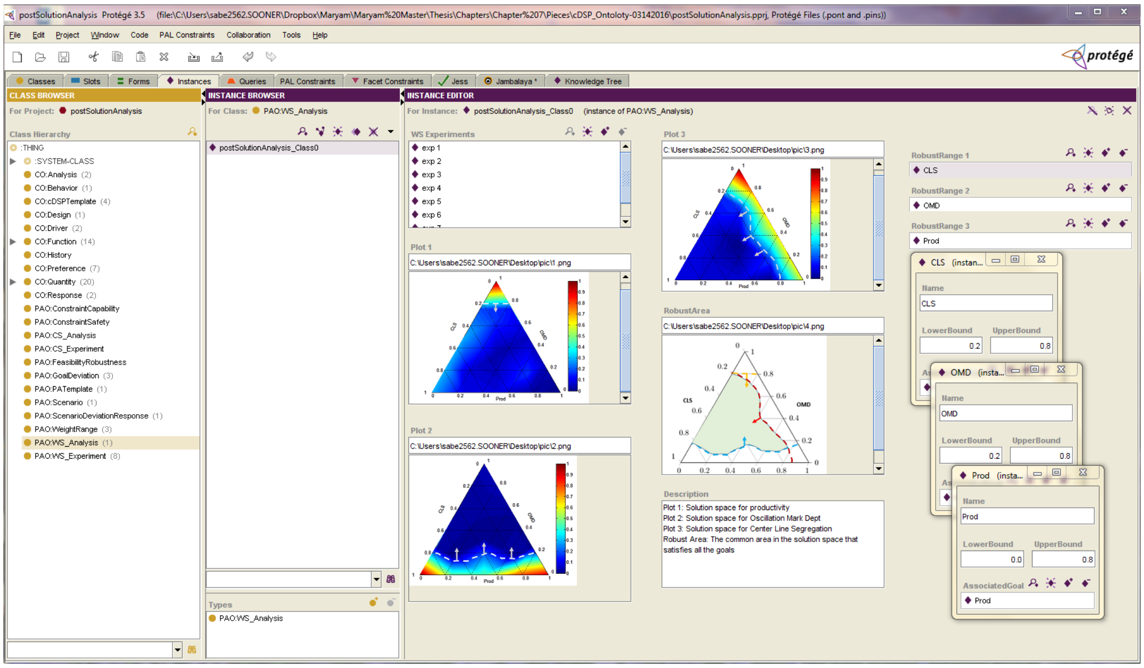


Figure 7.4: Post solution analysis template instance

The general structure of the Frames based post solution analysis template ontology can be seen in Figure 7.3, it presents an insight of how the decision related information is represented. In the ontology, Class *PSATemplate* interrelates with the module Classes *WS Analysis*, *CS Analysis* and *Feasibility Robustness* by corresponding Slots Step1: WS Analysis, Step2: CS Analysis and Step3: Feasibility Robustness. Data properties of each 'module' class are captured by specific data slots. As the superclass of Class *WS Analysis*, Classes *Weight Range*, *WS Experiment*, *Scenario*, *Scenario Deviation response* and *Goal Deviation* captures all the common data properties by the data slots, and so does Classes *CS Experiment* and *Constraint Capability* which are the superclass of Class *CS Analysis*.

The post solution analysis template presented in this section facilitates reusability of the solution space exploration method for any model-based application that has the general characteristics introduced in Section 7.2.1. The template provides an efficient and reliable way to reuse the design decision related knowledge, while the limitation is that it is mainly developed for problems for which single decision making is required in a sequential manner, and single template is needed.

7.2.3 Limitations of the Solution Space Exploration Method

There are two limitations related to the solution space exploration method proposed in this thesis discussed below.

The first limitation is that in order to apply this method a multi-objective problem with the minimum of three high priority goals is needed. This limitation is related to weight sensitivity analysis and visualization associated with that. There are various methods for visualizing data to aid decision making. Ternary plots having three dimensions are incorporated in this method to explore design preferences through weight sensitivity analysis. Ternary plots can be utilized for three or more goals, however, for two goals contour plots are recommended. The two design examples used in this thesis have three goals, however it is possible to have more than three. For example, for four goals 12 ternary plots are needed. The challenge is then in interpretation of the plots to identify a common region where are goals are satisfied. Therefore, to use this method, it is recommended that three high priority goals are selected even if more than three exists.

The second limitation is that in this method, only feasibility robustness is considered. Feasibility robustness which is considered in this method is related to effect of variations in feasibility of the solution. However, effect of variations in the values of the goal may be considered in the same stage where feasibility robustness is incorporated. In the last part of the method, the constraints with zero or limited capacity are subject to robustness and therefore the cDSP is subject to modification. At that stage, robustness related to the value of the goal can also be incorporated to insure robustness of the solution.

Moreover, this method may be adapted for solution space exploration of the problems that have the general characteristics introduced in Section 7.3.1. Also, since the utility of the method is on decision making, interpretation of the results required knowledge of the specific application that the method is used for, especially when conducting constraint sensitivity analysis. In this thesis three design examples are utilized and insight is provided from the technical perspective for each.

These limitations may be considered in expanding the solution space exploration method and therefore the post solution analysis template in the future work.

7.2.4 Recommendations for Future Work

In this thesis, the focus is to develop a method that facilitate decision making in model-based design. In the solution space exploration method that is proposed in Chapter 3, different aspects in sensitivity analysis are considered to identify solutions relatively insensitive to variations. The variations that are mostly caused from lack of knowledge, simplifications and approximations made in developing the models.

The solution space exploration method consists of weight sensitivity analysis, constraint sensitivity analysis and incorporating feasibility robustness. As mentioned in Section 7.3.1, in this method robustness is not considered for the value of the goal. This can be added in the solution space exploration method using Robust Concept Exploration Method introduced by Chen and co-authors. RCEM brings robustness in the solution from variations in controllable (control factor) and uncontrollable (noise factor) parameters. It can be implemented in the last stage of the solution space exploration method when feasibility robustness is considered. This brings more confidence to the designer in decision making.

Another way of expanding the method is by considering analysis of the simplifications and approximations made in developing the models. This is related to lack of knowledge in modeling especially in the early stages of design, or in designing complex systems in which simplifications and approximations are necessary. The solution space exploration method can be expanded to investigate how accuracy or different fidelities of the model can impact the solution.

Moreover, the proposed method can be applied in designing complex systems where different stakeholders have different conflicting preferences, and managing such dilemmas requires a strategy that results meeting all decision participants. For instance, this method can be instantiated for exploring the solution space for critical unit operations associated with steel product manufacturing (ladle, tundish, rolling and annealing) where coupled DSPs and decision network exists. Although the focus and examples of this thesis are in the field of engineering, the proposed method is domain independent and extensible that can be used in any field used such as economy, psychology, etc. where mathematical models are made and decision making is a challenge.

Finally, the post solution analysis template which is connected to the cDSP template as part of the PDSIDES (Knowledge-Based Platform for Decision Support in the Design of Engineered Systems), can be expanded based on the discussion of the future work, and be utilized in exploring any solution space in model-based design. The platform is being designed to facilitate designers to execute, reuse, tailor existing templates and develop new templates. Also, the capability of retrieval search can be considered in expanding the solution space template to facilitate knowledge capturing for a designer.

But this is all work for another time and another day. In the next section, answer to the research questions and relevant contributions of the thesis are cited.

7.3 Answers to the Research Questions and Relevant Contributions

In Chapter 1, the principal research question and several relevant questions are posted that are answered in this thesis. The research questions and the related sections where those are addressed are outlined in Section 7.3.1. Answering to the research questions leads to the relevant contributions from this thesis which is discussed in Section 7.3.2.

7.3.1 Answers to the Research Questions

Recall that the principal research question for the thesis is:

> *What is needed in model-based system realization to increase design knowledge in order to support decision making given that the models are not complete and accurate?*

To answer this question, a series of more direct/focused questions are posed in Section 1.3 which are then investigated throughout this thesis. Much of this information is repeated from the previous sections; therefore the review is quite brief. Please refer back to the cited sections for specific details.

1. ***How can a design decision be modeled?*** The compromise DSP is used in this thesis to formulate different design examples in order to explore the solution space and provide design knowledge that can facilitate decision making (Sections 2.1, 4.1, 5.1 and 6.1).
2. ***What is the process to explore design tradeoffs in model-based system design?*** Using the compromise DSP, two different approaches can be taken to explore design tradeoffs: goal ordering and weighted sum. Both approaches are explored in this thesis through different design examples (Sections 2.1, 3.2, 3.3, 4.2, 5.2 and 6.2).
3. ***What is the process to identify design preferences that guarantees a desired solution in which different and conflicting goals are satisfied?*** Design preferences can be explored through solution space visualization and weight sensitivity analysis (Sections 3.3, 5.2.1 and 6.2.1).
4. ***What kinds of modification are needed if desired solutions that satisfy different and conflicting goals are not found?*** In such case where goals are in high conflicts, target value associated with each goal given in the cDSP can be modified or simply designer should change his/her acceptable range of solutions to expand the acceptable region in the solution space (Sections 3.3.2, 5.2.1 and 6.2.1).

5. ***What is the process to explore feasibility robustness under the effect of variations?*** Feasibility robustness can be explored through constraint sensitivity analysis by identifying active and inactive constraints, and their capacity in face of variations (Sections 3.4, 5.2.2 and 6.2.2).
6. ***How can design constraint exploration be beneficial to incorporate feasibility robustness in the model?*** Conducting constraints sensitivity analysis of the desired solutions provide insight to the designer to incorporate feasibility robustness in the design constraints with zero or limited capacity (Sections 3.5, 5.2.2 and 6.2.3).
7. ***How can design selections be modeled?*** According to DSP, one of the main components of decision making is selection. The selection DSP is adapted in this work to formulate and explore selections in design (Sections 3.1 and 5.3).

As each of these questions is answered, a better understanding of the principal research question is achieved along with a better understanding of the philosophy behind and motivation for solution space exploration in model-based realization of engineered systems (refer to Section 1.1). Answering to the research question successfully leads to relevant contributions from this thesis which is outlined in the next section.

7.3.2 Relevant Contributions

In this thesis, the intent is to lay a foundation for solution space exploration in model-based system design and classify several aspects of it, namely, exploring design goals (design selections, design priorities and design preferences), exploring design constraints and incorporating feasibility robustness. This has been done by investigating a series of research questions throughout the thesis. Light has been shed on three aspects of solution space exploration, namely, the weight sensitivity analysis, constraint sensitivity analysis and ensuring feasibility robustness. The importance of these aspects and the need to conduct sensitivity analysis are discussed in Section 1.1.2. The solution space exploration method is developed and proposed in Chapter 3 to increase design knowledge in order to support designer as a decision maker by providing valuable information related to design. The characteristics of the proposed method which is implemented and demonstrated in this thesis is as following.

Weight Sensitivity Analysis: In the weight sensitivity analysis of the solution space exploration method proposed in Chapter 3, the need for identifying desired solutions that satisfies different goals is considered, the need for compromise and satisficing is recognized, a tool for managing preferences of different groups of decision makers is provided, and a mechanism to visualize and negotiate sound solutions is proposed.

Constraint Sensitivity Analysis: In the constraint sensitivity analysis of the solution space exploration method proposed in Chapter 3, the need for identifying active and inactive constraints is considered, the need for identifying and analyzing extra available capacity of each constraint for different solutions is recognized, and the importance of analyzing the penalty in face of variations is considered.

Feasibility Robustness: In the last part of the solution space exploration method, the need for ensuring feasibility robustness to the constraints with zero or limited capacity is addressed by providing some extra capacity which brings flexibility to the design in face of uncertainty.

The highlight of the solution space exploration method proposed in this thesis is the connection between the three main dimensions: weight sensitivity analysis, constraints sensitivity analysis and feasibility robustness. In conducting the method, first desired solutions are found through weight sensitivity analysis then design constraints of those solutions are explored and analyzed to incorporate and ensure feasibility robustness in face of variations. In the end, the robust solutions (in terms of feasibility) are monitored again to ensure that they are still in the desired range specified in the weight sensitivity analysis, and recommendation is made.

PSATemplate: The post solution analysis template is created and proposed in this chapter to generalize the method. It facilitate reusability and executability of the method in a computer. It also facilitates capturing the background knowledge of each main step involved in the solution space exploration method.

But none of the knowledge captured through solution space exploration can guarantees the best decision in the practical world, however, development of design methods and procedures, in general, provides attention directing tools to improve human judgment to make educated and knowledge-based decision.

Are not there lessons to be learned from this thesis which go far beyond just solution space exploration? This is food-for-thought though, because I have finally reached...

THE END.

References

Advanced Environmental Systems. (2010). Retrieved on November 2015 from http://courses.washington.edu/arch533/

Aird, T. J., & Rice, J. R. (1977). Systematic Search in High Dimensional Sets. SIAM Journal on Numerical Analysis, 14(2), 296-312.

Allen, J., Krishnamachari, R., Masetta, J., Pearce, D., Rigby, D., & Mistree, F. (1992). Fuzzy compromise: An effective way to solve hierarchical design problems. Structural Optimization, 4(2), 115-120.

Allen, J., Simovich, G., & Mistree, F. (1989). Selection under uncertain conditions: A marine application. Paper presented at the Fourth International Symposium on Practical Design of Ships and Mobile Units.

Allen, J. K., Seepersad, C. C., Mistree, F., Savannah, G. T., & Savannah, G. (2006). A Survey of Robust Design with Applications to Multidisciplinary and Multiscale Systems. J Mech Des, 128(4), 832-843.

Archer, G., Saltelli, A., & Sobol, I. (1997). Sensitivity measures, ANOVA-like techniques and the use of bootstrap. Journal of Statistical Computation and Simulation, 58(2), 99-120.

Bascaran, E. (1990). A Conceptual Model for the Design of Thermal Systems: concurrent decisions in designing for concept. Department of Mechanical Engineering, University of Houston, Houston, Texas.

Bascaran, E., Bannerot, R. B., & Mistree, F. (1989). Hierarchical Selection Decision Support Problems in Conceptual Design. Engineering Optimization, 14(3), 207-238.

Bascaran, E., Mistree, F., & Bannerot, R. B. (1987). Compromise: An effective approach for solving multiobjective thermal design problems. Engineering Optimization+ A35, 12(3), 175-189.

Bhattacharya, N. (1990). A comprehensive computer-based decision support system for the preliminary design of aircraft tires.

Blanchard, C., & Stiglitz, M. R. (1992). IEEE Standard Dictionary of Electrical and Electronic Terms. NY, USA: Wiley-Interscience.

Bloebaum, C. L., & McGowan, A.-M. R. (2010). Design of complex engineered systems. Journal of Mechanical Design, 132(12), 120301.

Box, G. E., & Draper, N. R. (1987). Empirical model-building and response surfaces (Vol. 424): Wiley New York.

Brooks, R. J., & Tobias, A. M. (1996). Choosing the best model: Level of detail, complexity, and model performance. Mathematical and computer modelling, 24(4), 1-14.

Chang, C.-T., & Lin, T.-C. (2009). Interval goal programming for S-shaped penalty function. European Journal of Operational Research, 199(1), 9-20.

Chen, W., Allen, J. K., & Mistree, F. (1997a). A Robust Concept Exploration Method for Enhancing Productivity in Concurrent Systems Design. Concurrent Engineering, 5(3), 203-217.

Chen, W., Allen, J. K., & Mistree, F. (1997b). A robust concept exploration method for enhancing productivity in concurrent systems design. Concurrent Engineering-Research and Applications, 5(3), 203-217. Retrieved from <Go to ISI>://WOS:A1997YD70000002

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

Chen, W., Meher-Homji, C. B., & Mistree, F. (1994). Compromise: an Effective Approach for Condition-Based Maintenance Management of Gas Turbines. Engineering Optimization, 22(3), 185-201.

Chen, W., Simpson, T. W., Allen, J. K., & Mistree, F. (1999). Satisfying Ranged Sets of Design Requirements using Design Capability Indices as Metrics. Engineering Optimization, 31(5), 615-619.

Chen, Y., Yu, J., Shahbaz, K., & Xevi, E. (2009). A GIS-based sensitivity analysis of multi-criteria weights. Paper presented at the Proceedings of the 18th World IMACS/MODSIM Congress, Cairns, Australia.

Cheung, N., & Garcia, A. (2001). The use of a heuristic search technique for the optimization of quality of steel billets produced by continuous casting. Engineering Applications of Artificial Intelligence, 14(2), 229-238.

Choi, H.-J., Mcdowell, D. L., Allen, J. K., & Mistree, F. (2008a). An Inductive Design Exploration Method for Hierarchical Systems Design Under Uncertainty. Engineering Optimization, 40(4), 287-307.

Choi, H., McDowell, D. L., Allen, J. K., Rosen, D., & Mistree, F. (2008b). An Inductive Design Exploration Method for Robust Multiscale Materials Design. Journal of Mechanical Design, 130(3), 031402.

Choudhary, S., & Ganguly, S. (2007). Morphology and segregation in continuously cast high carbon steel billets. ISIJ international, 47(12), 1759-1766.

Continuous Casting (2005). Retrieved on January 2016 from http://www.ewp.rpi.edu/hartford/users/papers/engr/ernesto/lankep/THESIS/Supplemental/CC_UserGuide.pdf

Cramb, A. W. (2010). The Making, Shaping and Treating of Steel-Casting Volume, 11th ed., AIST, Warrendale, PA.

Crosetto, M., Tarantola, S., & Saltelli, A. (2000). Sensitivity and uncertainty analysis in spatial modelling based on GIS. Agriculture, ecosystems & environment, 81(1), 71-79.

Danbury, C. (1997). The Encyclopedia Americana: Grolier Inc.

De Neufville, R. (1990). Applied systems analysis: engineering planning and technology management.

Eggert, R. (1991). Quantifying design feasibility using probabilistic feasibility analysis. Paper presented at the 1991 ASME Advances in Design Automation.

Engelund, W. C., Stanley, D. O., Lepsch, R. A., McMillin, M. M., & Unal, R. (1993). Aerodynamic configuration design using response surface methodology analysis. NASA STI/Recon Technical Report A, 94, 10718.

Feick, R., & Hall, B. (2004). A method for examining the spatial dimension of multi-criteria weight sensitivity. International Journal of Geographical Information Science, 18(8), 815-840.

Fernández, M. G. (2002). On decision support for distributed collaborative design and manufacture.

Finger, S. (1990). Design fusion: a product life-cycle view for engineering designs.

Fuchs, W., Karandikar, H., Mistree, F., & Eschenauer, H. (1990). Compromise: an effective approach for designing composite conical shell structures. Journal of Mechanical Design, 112(3), 362-368.

Gaithen, N. (1980). Production and Operations Management: A Problem-Solving and Decision-Making Approach. The Dryden Press, New York.

Gass, S. I. (1986). A process for determining priorities and weights for large-scale linear goal programmes. Journal of the Operational Research Society, 779-785.

Gemperline, P. J., & Cash, E. (2003). Advantages of soft versus hard constraints in self-modeling curve resolution problems. Alternating least squares with penalty functions. Analytical Chemistry, 75(16), 4236-4243.

Ghosh, A. (1990). Principles of secondary processing and casting of liquid steel: Raju Primlani.

Gruber, T. R. (1993). A translation approach to portable ontology specifications. Knowledge acquisition, 5(2), 199-220.

Gunawan, S., & Azarm, S. (2004). On a combined multi-objective and feasibility robustness method for design optimization. Paper presented at the 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference.

Hazelrigg, G. A. (1998). A framework for decision-based engineering design. Journal of Mechanical Design, 120(4), 653-658.

Heat Exchangers. (2015). Retrieved on December 2015 from http://web.mit.edu/16.unified/www/FALL/thermodynamics/notes/node131.html

Hernamdez, G., & Mistree, F. (2000). Integrating Product Design and Manufacturing: a Game Theoretic Approach. Engineering Optimization+ A35, 32(6), 749-775.

Hewitt, G. F., & Barbosa, J. (2008). Heat exchanger design handbook (Vol. 98): Begell House.

Huang, X., Thomas, B., & Najjar, F. (1992). Modeling superheat removal during continuous casting of steel slabs. Metallurgical Transactions B, 23(3), 339-356.

Ignizio, J. P. (1981). The determination of a subset of efficient solutions via goal programming. Computers & Operations Research, 8(1), 9-16.

Ignizio, J. P. (1985). An algorithm for solving the linear goal programming problem by solving its dual. Journal of the Operational Research Society, 507-515.

Iwasaki, J., & Thomas, B. G. (2012). Thermal-Mechanical Model Calibration with Breakout Shell Measurements in Continuous Steel Slab Casting. Supplemental Proceedings: Materials Properties, Characterization, and Modeling, Volume 2, 355-362.

Jin, R., Du, X., & Chen, W. (2003). The use of metamodeling techniques for optimization under uncertainty. Structural and Multidisciplinary Optimization, 25(2), 99-116.

Jones, D., & Tamiz, M. (1995). Expanding the flexibility of goal programming via preference modelling techniques. Omega, 23(1), 41-48.

Kahraman, C., & Büyüközkan, G. (2008). A Combined Fuzzy AHP and Fuzzy Goal Programming Approach for Effective Six-Sigma Project Selection. Multiple-Valued Logic and Soft Computing, 14(6), 599-615.

Kamal, S. (1990). The Development of Heuristic Decision Support Problems for Adaptive Design. Department of Mechanical Engineering, University of Houston, Houston, Texas.

Kaminski, D. A., & Jensen, M. K. (2005). Introduction to thermal and fluids engineering.

Karandikar, H. (1989). Hierarchical decision making for the integration of information from design and manufacturing processes in concurrent engineering.

Kennedy, M. C., & O'Hagan, A. (2000). Predicting the output from a complex computer code when fast approximations are available. Biometrika, 87(1), 1-13.

Kettani, O., Aouni, B. d., & Martel, J.-M. (2004). The double role of the weight factor in the goal programming model. Computers & Operations Research, 31(11), 1833-1845.

Koch, P., Barlow, A., Allen, J., & Mistree, F. (1998). Facilitating Concept Exploration for Configuring Turbine Propulsion Systems. Journal of Mechanical Design, 120(4), 702-706.

Kuppuraju, N., Ittimakin, P., & Mistree, F. (1985). Design through selection: a method that works. Design Studies, 6(2), 91-106.

Lee, H. S. (2010). Thermal design: heat sinks, thermoelectrics, heat pipes, compact heat exchangers, and solar cells: John Wiley & Sons.

Lemmon, E. W., & Huber, M. L. (2013). Implementation of Pure Fluid and Natural Gas Standards: Reference Fluid Thermodynamic and Transport Properties Database (REFPROP): National Institute of Standards and Technology, NIST. Retrieved from http://www.nist.gov/mml/acmd/fluids_modeling/refprop.cfm

Lewis, K., Smith, W. F., & Mistree, F. (1999). Ranged Set of Top-Level Specifications for Complex Engineering Systems, Chapter 10. In U. Roy, J. M. Usher, & H. R. Parsaei (Eds.), Simultaneous Engineering: Methodologies and Applications (pp. 279-303). New York: Gordon and Breach Science Publishers.

Li, M., Azarm, S., & Boyars, A. (2006). A new deterministic approach using sensitivity region measures for multi-objective robust and feasibility robust design optimization. Journal of Mechanical Design, 128(4), 874-883.

Li, X., Beullens, P., Jones, D., & Tamiz, M. (2009). An integrated queuing and multi-objective bed allocation model with application to a hospital in China. Journal of the Operational Research Society, 60(3), 330-338.

Lieftucht, D., Arzberger, M., Reifferscheid, M., & Schlüter, J. (2008). Online prediction of longitudinal facial cracks in thin slab casting using principal component analysis. Journal of Iron and Steel Research, International, 15(Supplement 1), 255-259.

Marinopoulos, S., Jackson, D., Shupe, J., & Mistree, F. (1987). Compromise: An Effective Approach for Conceptual Aircraft Design. AIAA Paper No. AIAA-87-2965.

Marston, M., Allen, J. K., & Mistree, F. (2000). The Decision Support Problem Technique: Integrating Descriptive and Normative Approaches. Engineering Valuation & Cost Analysis, Special Issue on Decision-Based Design: Status and Promise, 3, 107-129.

Martel, J.-M., & Aouni, B. (1990). Incorporating the decision-maker's preferences in the goal-programming model. Journal of the Operational Research Society, 1121-1132.

Mayer, F., Wu, M., & Ludwig, A. (2010). On the formation of centreline segregation in continuous slab casting of steel due to bulging and/or feeding. steel research international, 81(8), 660-667.

McDowell, D. L., Panchal, J., Choi, H.-J., Seepersad, C., Allen, J., & Mistree, F. (2009). Integrated Design of Multiscale, Multifunctional Materials and Products: Butterworth-Heinemann.

Ming, Z., Yan, Y., Wang, G., Panchal, J., Goh, C. H., Allen, J. K., & Mistree, F. (2015). Ontology-Based Executable Design Decision Template Representation and Reuse. Paper presented at the ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference.

Mistree, F., Hughes, O. F., & Bras, B. (1992). Compromise Decision Support Problem and the Adaptive Linear Programming Algorithm. In M. P. Kamat (Ed.), Structural Optimisation: Status and Promise (Vol. 150, pp. 251 - 290). Washington, DC: AIAA.

Mistree, F., Hughes, O. F., & Bras, B. (1993a). The Compromise decision support problem and the adaptive linear programming algorithm. Progress in Astronautics and Aeronautics, 150, 251-251.

Mistree, F., Karandikar, S., Bras, B., & Bollam, T. (1991a). Formulation, storage and solution of decision support problems in a concurrent engineering environment. Paper presented at the Proceedings Third National Symposium on Concurrent Engineering, Washington, DC.

Mistree, F., Lewis, K., & Stonis, L. (1994a). Selection in the conceptual design of aircraft. AIAA Journal, 1153-1166.

Mistree, F., Marinopoulos, S., Jackson, D., & Shupe, J. (1988). The design of aircraft using the decision support problem technique.

Mistree, F., & Muster, D. (1990a). Conceptual models for decision-based concurrent engineering design for the life cycle. Paper presented at the Proceedings of the Second National Symposium on Concurrent Engineering.

Mistree, F., Muster, D., Shupe, J. A., & Allen, J. K. (1989). A decision-based perspective for the design of methods for systems design. Paper presented at the In NASA. Langley Research Center, Recent Advances in Multidisciplinary Analysis and Optimization, Part 3 p 1111-1135 (SEE N89-25201 19-05).

Mistree, F., Muster, D., Srinivasan, S., & Mudali, S. (1990b). Design of Linkages: A Conceptual Exercise in Designing for Concept. Mechanism and Machine Theory, 25(3), 273-286.

Mistree, F., Muster, D., Srinivasan, S., & Mudali, S. (1990a). Design of Linkages: A Conceptual Exercise in Designing for Concept. Mechanism and Machine Theory, 25(3), 273-286.

Mistree, F., Patel, B., & Vadde, S. (1994). On modeling multiple objectives and multi-level decisions in concurrent design. Advances in Design Automation, 69(2), 151-161.

Mistree, F., Smith, W. F., Bras, B., Allen, J. K., & Muster, D. (1990c). Decision-Based Design: A Contemporary Paradigm for Ship Design. Transactions SNAME, 98, 565-597.

Mistree, F., Smith, W. F., Bras, B., Allen, J. K., & Muster, D. (1990b). Decision-Based Design: A Contemporary Paradigm for Ship Design. Transactions SNAME, 98, 565-597.

Mistree, F., Smith, W. F., & Bras, B. A. (1993). A Decision-Based Approach to Concurrent Engineering, Chapter 8. In H. R. Paresai & W. Sullivan (Eds.), Handbook of Concurrent Engineering (pp. 127-158). New York: Chapman-Hall.

Mistree, F., Smith, W. F., & Bras, B. A. (1993b). A Decision-Based Approach to Concurrent Engineering, Chapter 8. In H. R. Paresai & W. Sullivan (Eds.), Handbook of Concurrent Engineering (pp. 127-158). New York: Chapman-Hall.

Mistree, F., Smith, W. F., Kamal, S. Z., & Bras, B. A. (1991b). Designing Decisions: Axioms, Models and Marine Applications (Invited Lecture). Paper presented at the Fourth International Marine Systems Design Conference (IMSDC91), Kobe, Japan.

Model-Based Design. (2015a). Retrieved on November 2015 from http://en.wikipedia.org/wiki/Model-based_design

Model-Based Design. (2015b). Retrieved on November 2015 from http://www.mathworks.com/solutions/model-based-design/

Montgomery, D. C. (2008). Design and analysis of experiments: John Wiley & Sons.

Mudali, S. (1987). The dimensional synthesis of mechanical linkages using compromise decision support problems.

Muster, D., & Mistree, F. (1988). The Decision Support Problem Technique in Engineering Design. The International Journal of Applied Engineering Education, 4(1), 23-33.

Muster, D., Mistree, F., & Allen, J. (1989). Partitioning and Planning for Unified Life-Cycle Engineering Design: A Conceptual Exposition. USAF Contract FY, 1457-1488.

Neely, W. P., Sellers, J., & North, R. M. (1980). Goal programming priority sensitivity analysis: an application in natural resource decision making processes. Interfaces, 10(5), 83-89.

Noy, N. F., & McGuinness, D. L. (2001). Ontology development 101: A guide to creating your first ontology: Stanford knowledge systems laboratory technical report KSL-01-05 and Stanford medical informatics technical report SMI-2001-0880, Stanford, CA.

Pahl, G., & Beitz, W. (2013). Engineering design: a systematic approach: Springer Science & Business Media.

Pahl, G., Beitz, W., Feldhusen, J., & Grote, K. H. (2007). Engineering design, A Systematic Approach (K. Wallace & L. Blessing Eds. Third English ed.): Springer.

Panchal, J. H., Choi, H.-J., Allen, J. K., McDowell, D. L., & Mistree, F. (2007). A Systems-Based Approach for Integrated Design of Materials, Products and Design Process Chains. Journal of Computer-Aided Materials Design, 14(1), 265-293.

Park, J. K., Samarasekera, I. V., Thomas, B. G., & Yoon, U. S. (2002). Thermal and mechanical behavior of copper molds during thin-slab casting (II): Mold crack formation. Metallurgical and Materials Transactions B, 33(3), 437-449.

Parkinson, A., Sorensen, C., & Pourhassan, N. (1993). A general approach for robust optimal design. Journal of Mechanical Design, 115(1), 74-80.

Paterno, F. (2012). Model-based design and evaluation of interactive applications: Springer Science & Business Media.

Protege-Frames. (2012). Retrieved on March 2016 from http://protegewiki.stanford.edu/wiki/Protege-Frames

Qian, Z., Seepersad, C. C., Joseph, V. R., Allen, J. K., & Wu, C. J. (2006). Building surrogate models based on detailed and approximate simulations. Journal of Mechanical Design, 128(4), 668-677.

Reddy, R., Smith, W. F., Mistree, F., Bras, B. A., Chen, W., Malhotra, A., Badhrinath, K., Lautenschlager, U., Pakala, R., Vadde, S., & Patel, P. (1992). DSIDES User Manual (SDL/REP.7.1/92). Retrieved from

Sabeghi, M., Smith, W. F., Allen, J. K., & Mistree, F. (2015). Solution Space Exploration in Model-Based Realization of Engineered Systems. ASME/IDETC Conference. Boston, Massachusetts. Paper Number 46457.

Sabeghi M., Shukla R., Allen J. K., Mistree F. (2016). Solution Space Exploration of the Process Design for Continuous Casting of Steel. ASME/IDETC Conference. Charlotte, NC. Paper Number 59399.

Sage, A. P. (1977). Methodology for large-scale systems: McGraw-Hill College.

Sargent, R. G. (2013). Verification and validation of simulation models. Journal of simulation, 7(1), 12-24.

Seepersad, C. C., Allen, J. K., McDowell, D. L., & Mistree, F. (2006a). Robust Design of Cellular Materials with Topological and Dimensional Imperfections. Journal of Mechanical Design, 128(6), 1285-1297.

Seepersad, C. C., Allen, J. K., McDowell, D. L., & Mistree, F. (2008). Multifunctional Topology Design of Cellular Material Structures. Journal of Mechanical Design, 130(3), 031404.

Seepersad, C. C., Pedersen, K., Emblemsvåg, J., Bailey, R., Allen, J. K., & Mistree, F. (2006b). The validation square: how does one verify and validate a design method? Decision Making in Engineering Design, KE Lewis, W. Chen, and LC Schmidt, eds., ASME Press, New York.

Sen, P., & Yang, J.-B. (2012). Multiple criteria decision support in engineering design: Springer Science & Business Media.

Shukla, R., Goyal, S., Singh, A. K., Panchal, J. H., Allen, J. K., & Mistree, F. (2014). An approach to robust process design for continuous casting of slab. ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Paper Number 34208.

Shupe, J., Muster, D., Allen, J., & Mistree, F. (1988). Decision-based design: Some concepts and research issues. Expert Systems, Strategies and Solutions in Manufacturing Design and Planning, 3-37.

Shupe, J. A., & Mistree, F. (1987). Compromise: an effective approach for the design of damage tolerant structural systems. Computers & structures, 27(3), 407-415.

Simon, H. A. (1981). The Sciences of Artificial Intelligence: Cambridge, MA: MIT Press.

Simon, H. A. (1996). The sciences of the artificial (Vol. 136): MIT press.

Simpson, T. W., Chen, W., Allen, J. K., & Mistree, F. (1999). Use of the Robust Concept Exploration Method to Facilitate the Design of a Family of Products. Simultaneous engineering: Methodologies and applications, 6, 247-278.

Simpson, T. W., Maier, J. R., & Mistree, F. (2001a). Product Platform Design: Method and Application. Research in Engineering Design, 13(1), 2-22.

Simpson, T. W., Poplinski, J., Koch, P. N., & Allen, J. K. (2001b). Metamodels for computer-based engineering design: survey and recommendations. Engineering with computers, 17(2), 129-150.

Simpson, T. W., Seepersad, C. C., & Mistree, F. (2001c). Balancing Commonality and Performance within the Concurrent Design of Multiple Products in a Product Family. Concurrent Engineering, 9(3), 177-190.

Singh, A., Goyal, S., Kumar, P., Reddy, N., Padmanabhan, K., Palai, P., Javed, Y., Tripathy, P., Mahashabde, V., & Venugopalan, T. (2013). Prediction and control of center-line segregation in continuously cast slabs. Paper presented at the Proceedings of the ISISTM Conference, Jamshedpur, India.

Sinha, A., Bera, N., Allen, J. K., Panchal, J. H., & Mistree, F. (2013). Uncertainty Management in the Design of Multiscale Systems. Journal of Mechanical Design, 135(1), 011008.

Smith, W. F. (1985). The development of AUSEVAL an automated ship evaluation system.

Smith, W. F. (1992). The Modeling and Exploration of Ship Systems in the Early Stages of Decision-Based Design. (Dissertation), University of Houston.

Smith, W. F., Milisavljevic, J., Sabeghi, M., Allen, J. K., & Mistree, F. (2015). The Realization of Engineered Systems with Considerations of Complexity. ASME/IDETC Conference. Boston, Masachusetts. Paper Number 46211.

Smith, W. F., & Mistree, F. (1994). Monotonicity and Goal Interaction Diagrams for the Compromise Decision Support Problem. In B. J. Gilmore, D. Hoeltzel, D. Dutta, & H. Eschenauer (Eds.), ASME DE, New York (Vol. 69, pp. 159-168): ASME.

Straffelini, G., Lutterotti, L., Tonolli, M., & Lestani, M. (2011). Modeling solidification microstructures of steel round billets obtained by continuous casting. ISIJ international, 51(9), 1448-1453.

Suh, N. P. (1990). The principles of design (Vol. 990): Oxford University Press New York.

Sundaresan, S., Ishii, K., & Houser, D. R. (1995). A robust optimization procedure with variations on design variables and constraints. Engineering Optimization+ A35, 24(2), 101-117.

Taguchi, G., Chowdhury, S., & Wu, Y. (1993). Robust technology development. Taguchi's Quality Engineering Handbook, 352-376.

Taguchi, G., & Clausing, D. (1990). Robust quality. Harvard Business Review, 68(1), 65-75.

Ternary Plot. (2014). Retrieved on December 2014 from http://www.babylon.com/definition/Ternary%20plot/

Ternary Plots (2000). Retrieved on December 2014 from http://csmres.jmu.edu/geollab/fichter/SedRx/readternary.html

Tongmin, W., Shaowu, C., Jun, L., Jingjing, X., Zongning, C., Jing, Z., Zhiqiang, C., & Tingju, L. (2010). Mould taper optimization for continuous casting steels by numerical simulation. Research & Development, 61-66.

Triantaphyllou, E., & Sánchez, A. (1997). A Sensitivity Analysis Approach for Some Deterministic Multi-Criteria Decision-Making Methods*. Decision Sciences, 28(1), 151-194.

Tribus, M. (2013). Rational Descriptions, Decisions and Designs: Pergamon Unified Engineering Series: Elsevier.

Vadde, S., Allen, J., & Mistree, F. (1994). The Bayesian compromise decision support problem for multilevel design involving uncertainty. Journal of Mechanical Design, 116(2), 388-395.

Wang, H. H., Noy, N., Rector, A., Musen, M., Redmond, T., Rubin, D., Tu, S., Tudorache, T., Drummond, N., & Horridge, M. (2006). Frames and OWL side by side. Paper presented at the Presentation Abstracts.

Wey, W.-M., & Wu, K.-Y. (2007). Using ANP priorities with goal programming in resource allocation in transportation. Mathematical and computer modelling, 46(7), 985-1000.

Whitney, D. E., Nevins, J. L., DeFazio, T. L., Gustavson, R. E., Metzinger, R. W., Rourke, J. M., & Seltzer, D. S. (1988). The strategic approach to product design. Design and Analysis of Integrated Manufacturing Systems, 200-223.

Wildasin, D. E. (1997). Externalities and bailouts: hard and soft budget constraints in intergovernmental fiscal relations (Vol. 1843): World Bank Publications.

Xie, S., Peacock, D., Milthorpe, J., & Smith, W. F. (2002). Modeling and exploring hierarchical systems engineering models with a preliminary ship design focus. Paper presented at the 9th AIAA/ISSMO Symposium and Exhibit on Multidisciplinary Analysis and Optimization, Atlanta, GA.

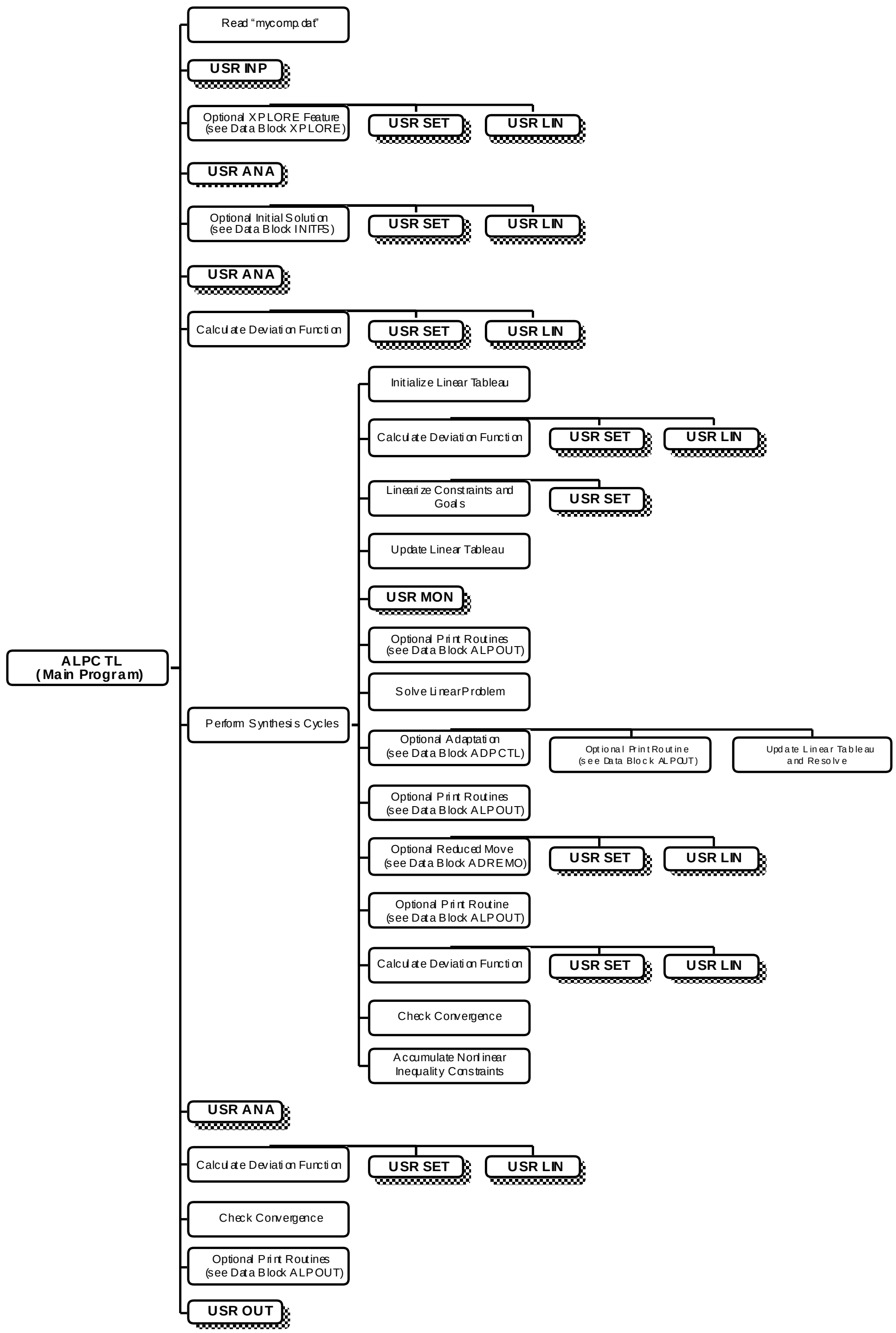
Yao, W., Chen, X. Q., Luo, W. C., van Tooren, M., & Guo, J. (2011). Review of uncertainty-based multidisciplinary design optimization methods for aerospace vehicles. Progress in Aerospace Sciences, 47(6), 450-479. doi:DOI 10.1016/j.paerosci.2011.05.001

Yu, J.-C., & Ishii, K. (1998). Design for robustness based on manufacturing variation patterns. Journal of Mechanical Design, 120(2), 196-202.

Zhou, Q. (1988). The compromise decision support problem: a fuzzy formulation. M.S. Thesis, Department of Mechanical Engineering, University of Houston, Houston, Texas.

Appendix A: ALP Flowchart

The flowchart showing the calls to the user specified subroutines referred from Section 2.4.1. For detail discussion please refer to DSIDES manual.



Appendix B: DSIDES Data File for Rankine Cycle Model

Below is the DSIDES data file for Rankine cycle with an exchanger referend from Section 4.1.1.

```
PTITLE  : Problem Title
Rankine Cycle with fluid Heat Exchanger
Warren Smith with Jelena Milisavljevic & Maryam Sabeghi Dec 2013

NUMSYS  : Number of system variables
   6    0    6    : Real, Integer, Boolean

SYSVAR   : System variable information
PMAX       1    500.0     5000.0     4400.0
PMIN       2    50.0      200.0      100.0
TMAX       3    350.0     850.0      650.0 : absolute max893.150
TMAXE      4    350.0     850.0      700.0
ELEN       5    1.0       60.0       25.0
EDIA       6    0.010     0.100      0.020
SRF1       7    0.0       1.0        1.0       : water
SRF2       8    0.0       1.0        0.0       : CO2
SRF3       9    0.0       1.0        0.0       : R134A
SEF1      10    0.0       1.0        1.0       : water
SEF2      11    0.0       1.0        0.0       : CO2
SEF3      12    0.0       1.0        0.0       : R134A

NUMCAG  : Number of constraints and goals
    3    12    2    0    6   :
nlinco,nnlinq,nnlequ,nlingo,nnlgoa

LINCON  : Linear Constraints
TDELMX  2     : Temperature delta for maximums in exchanger
(4, 1.0) (3, -1.0)
GE 10.0
SRANK   3     : Selection of fluid for Rankine Cycle
(7, 1.0) (8, 1.0) (9,1.0)
EQ 1.0
SEXCH   3     : Selection of fluid for heat exchanger
(10, 1.0) (11, 1.0) (12,1.0)
EQ 1.0

NLINCO  : Names of nonlinear constraints
CMOIST   1   : Moisture in turbine less than upper limit
CFLOWR   2   : Rankine cycle flow rate less than upper limit
CT4T3R   3   : TEMP4 greater than or equal to TEMP3
CQUAL4   4   : Quality at Point 4 is superheated vapour
CTMPSE   5   : TMAXE greater than TMINE by at least TDELE
CTMNT2   6   : TMINE greater than TEMP2 by at least TDELC
CEFCS1   7   : CARNOT efficiency greater than SYSEF1
```

```
CEFCS2   8   : CARNOT efficiency greater than SYSEF2
CTMINR   9   : TEMP1 - DBTMNR
CTMAXR   10  : DBTMXR - TMAX
CTMINE   11  : TMINE - DBTMNE
CTMAXE   12  : DBTMXE - TMAXE
CSREQU   13  : Sum(SRFx*(1.0-SRFx))=0
CSEEQU   14  : Sum(SEFx*(1.0-SEFx))=0

NLINGO  : Names of the nonlinerar goals
GMOIST   1  : Moisture in turbine
GRCEFF   2  : Rankine Cycle Efficiency
GEXEFF   3  : Temperature Exchanger Efficiency
GSYSE1   4  : System Efficiency 1  SYSEF1 = (PTURB-PPUMP)/QOUTE
GSYSE2   5  : System Efficiency 2  SYSEF2 = RCEFF*TEFFEX
GHTEFF   6  : Heat Transfer Efficiency

DEVFUN  : Deviation function
   6     : levels
   1  2  : level 1, 2 terms
  (+1,1.0) (-1,1.0)
   2  2  : level 2, 2 terms
  (+2,1.0) (-2,1.0)
   3  2  : level 3, 2 terms
  (+3,1.0) (-3,1.0)
   4  2  : level 4, 2 terms
  (+4,1.0) (-4,1.0)
   5  2  : level 5, 2 terms
  (+5,1.0) (-5,1.0)
   6  2  : level 6, 2 terms
  (+6,1.0) (-6,1.0)

STOPCR  : Stopping criteria
1  0  40  0.001  0.001

OPTIMP  : Optimization parameters
    -0.01   0.5  0.005

ADPCTL  : Adaption Flag
1

ALPOUT   : Input/output Control
     1   1   1   1   1   1   1   1  1  1

USRMOD  : Input/Output flags
    1   1   0   0

USRDAT  :
10
0.1         Maximum rankine cycle flow rate (kg/s)(FRMXR)
0.12        Turbine maximum allowable moisture
level(TMXL)fraction
0.01        Target for turbine moisture level(TTML)fraction
```

```
5.0         Minimum temperature drop in exchanger(TDELE)(TMAXE-
TMINE)K
5.0         Minimum cross flow temperature delta(TDELC)(TMINE-
TEMP2)K
298.15      Ambient temperature (K) (25 C)   PARAMETER(TAMB)
100.0       Exchanger pressure (kPa)         PARAMETER(PEXCH)
0.3         Exchanger flow rate (kg/s)       PARAMETER(FLOWE)
75.0        Required power output (kW)       PARAMETER(REQPOW)
0           Print Flag, IPRT (1 to print)

FIXVAR :
8
2   6   7   8   9   10  11  12

XPLORE
1000 200 1 1234
9
2   5   6   7   8   9   10  11  12

INITFS  : Generate Initial Feasible Solution
400 2.0 0.5 0.0001 0.1 0.0001

ENDPRB  : Stop reading the data file at this point
```

Appendix C: Response Surface Models

Below is a discussion and the data related to response surface models for the Rankine cycle with an exchanger. This is done for verification of the key outcome of the results presented in Section 4.2. It is referred from Section 4.3 (empirical performance validity).

Design of Experiments (DoE) are used to find the effect of each independent variable (P_{max}, T_{max}, and T_{maxE}) on the dependent variables (η_{system}, η_{tE}, and η_R) and to develop response surface models. Twenty-seven experiments are designed using three independent variables/factors and three levels for each shown in table C.1.

Table C.1: Independent variables and levels

Independent variables	Level 1 - low	Level 2 – medium	Level 3 - high
PMAX (kPa)	1250	2750	4250
TMAX (k)	560	642	767
TMAXE (k)	642	725	810

The 27 experiments are solved by DSIDES using three “do” loops written in the FORTRAN. Values of independent and dependent variables shown in Table C.2 are scaled from 0 to 1.

Table C.2: 27 Experiments and responses

	P_{max} (x_1)	T_{max} (x_2)	T_{maxE} (x_3)	η_R	η_{tE}	η_{system}
1	Low	Low	Low	0.188	0.325	0.061
2	Low	Low	Medium	0.188	0.243	0.046
3	Low	Low	High	0.188	0.190	0.036
4	Low	Medium	Low	0.200	0.305	0.061
5	Low	Medium	Medium	0.200	0.228	0.046
6	Low	Medium	High	0.200	0.179	0.0419
7	Low	High	Low	0.221	0.276	0.061
8	Low	High	Medium	0.221	0.206	0.046
9	Low	High	High	0.221	0.161	0.036

10	Medium	Low	Low	0.235	0.260	0.061
11	Medium	Low	Medium	0.235	0.194	0.045
12	Medium	Low	High	0.235	0.152	0.033
13	Medium	Medium	Low	0.245	0.249	0.061
14	Medium	Medium	Medium	0.245	0.185	0.045
15	Medium	Medium	High	0.245	0.145	0.036
16	Medium	High	Low	0.266	0.229	0.061
17	Medium	High	Medium	0.266	0.171	0.045
18	Medium	High	High	0.266	0.134	0.036
19	High	Low	Low	0.259	0.235	0.061
20	High	Low	Medium	0.259	0.175	0.045
21	High	Low	High	0.259	0.138	0.036
22	High	Medium	Low	0.269	0.227	0.061
23	High	Medium	Medium	0.269	0.169	0.045
24	High	Medium	High	0.269	0.133	0.036
25	High	High	Low	0.288	0.211	0.061
26	High	High	Medium	0.288	0.157	0.045
27	High	High	High	0.288	0.124	0.036

Using the results above, response surface models are created using MATLAB. A third order equation as follows is used to develop the models:

$$Y = b(1) + b(2)\, X_1 + b(3)\, X_1^2 + b(4)\, X_1^3 + b(5)\, X_2 + b(6)\, X_2^2 + b(7)\, X_2^3 + b(8)\, X_3 + b(9)\, X_3^2 + b(10)\, X_3^3 + b(11)\, X_1 X_2 X_3 + b(12)\, X_1^2 X_2 X_3 + b(13)\, X_1 X_2^2 X_3 + b(14)\, X_1 X_2 X_3^2 + b(15)\, X_1^2 X_2^2 X_3^2$$

Results and Discussion:

b values (coefficients) for each response are as follow:

Table C.3: Coefficients for each response

b values for each set of dependent variable			
	η_R	η_{tE}	η_{system}
1	0.0050	0.9496	0.9991
2	0.9958	-0.5489	-0.1041
3	0	0	0
4	-0.2991	0.2024	0.0826
5	0.2688	-0.2026	0.1549
6	0	0	0
7	0.0476	0.0198	-0.1413
8	0.0120	-0.7616	-1.1921
9	0	0	0
10	-0.0079	0.1823	0.3205
11	-0.1216	0.5425	-0.5700
12	0.0254	-0.1427	0.1230
13	0.0383	-0.1588	0.4223
14	0.0850	0.9496	0.2179
15	-0.0495	-0.5489	-0.2064

Response 1: η_R

$R^2 = 0.9935$

$Y = 5.0e\text{-}3 + x_1 - 2.3e\text{-}1\ x_1^3 + 2.7e\text{-}1\ x_2 + 4.8e\text{-}2\ x_2^3 + 1.2e\text{-}2\ x_3 - 7.9e\text{-}3\ x_3^3 - 1.2e\text{-}1\ x_1\ x_2\ x_3 + 2.5e\text{-}2\ x_1^2\ x_2\ x_3 + 3.8e\text{-}2\ x_1\ x_2^2\ x_3 + 8.5e\text{-}2\ x_1\ x_2\ x_3^2 - 5.0e\text{-}2\ x_1^2\ x_2^2\ x_3^2$

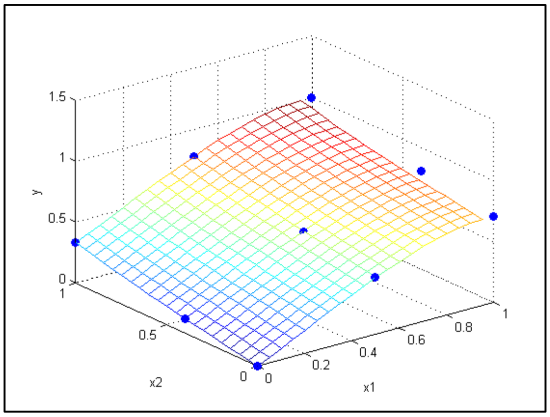


Figure C.1: Response surface model of η_R

Response 2: η_{tE}

$R^2 = 0.9937$

$Y = 9.5e\text{-}1 - 5.5e\text{-}1\ x_1 + 2.0e\text{-}1\ x_1^3 - 2.0e\text{-}1\ x_2 + 2.0e\text{-}2\ x_2^3 - 7.6e\text{-}1\ x_3 + 1.8e\text{-}1\ x_3^3 + 5.4e\text{-}1\ x_1\ x_2\ x_3 - 1.4e\text{-}1\ x_1^2\ x_2\ x_3 - 1.6e\text{-}1\ x_1\ x_2^2\ x_3 - 9.3e\text{-}2\ x_1\ x_2\ x_3^2 + 1.1e\text{-}2\ x_1^2\ x_2^2\ x_3^2$

Response 3: η_{system}

$R^2 = 0.9897$

$Y = 1 - 1.0e\text{-}1\ x_1 + 8.3e\text{-}2\ x_1^3 + 1.5e\text{-}1\ x_2 - 1.4e\text{-}1\ x_2^3 - 1.2\ x_3 + 3.2e\text{-}1\ x_3^3 - 5.7e\text{-}1\ x_1\ x_2\ x_3 + 1.2e\text{-}1\ x_1^2\ x_2\ x_3 + 4.2e\text{-}1\ x_1\ x_2^2\ x_3 + 2.2e\text{-}1\ x_1\ x_2\ x_3^2 - 2.1e\text{-}1\ x_1^2\ x_2^2\ x_3^2$

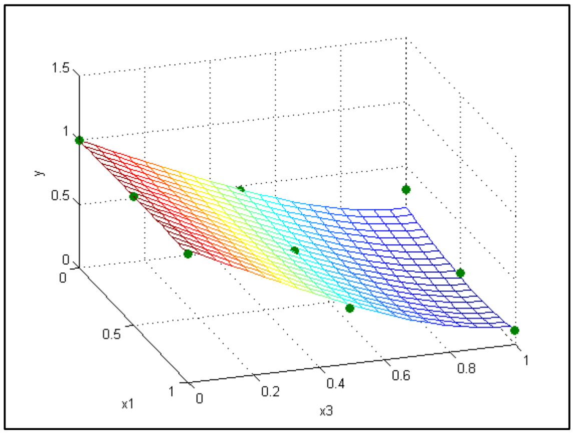


Figure C.2: Response surface model of η_{system}

Effect Test:

Dependent variable 1: Rankine cycle efficiency

Using SPSS, the effect for each of the independent variables and combination of their effects on the dependent variables is measured. The results indicated that P_{max} and T_{max} have a significant main effect on dependent variable 1, Rankine cycle efficiency, F_{PMAX} (1,2) = 3.7 * 10^30, *p (Sig)* < 0.0001; F_{TMAX} (1,2) = 8.1 * 10^29, *p* < 0.0001. The R^2 is the same as computed by MATLAB to be 1. Furthermore, P_{max} and T_{max} have a significant combined effect on Rankine efficiency, $F_{PMAXE*TMAX}$ (1,4) = 1.2 * 10^27, *p* < 0.0001. However, as expected, T_{maxE} (the maximum temperature of the hot fluid in the exchanger) has no effect on Rankine efficiency, F_{TMAXE} (1,2) = .000, *p* > .05.

Table C.4: Tests of between-subjects effects/effect of η_R

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	2.665[a]	25	0.107	3.893E29	0.000
Intercept	7.453	1	7.453	2.721E31	0.000
$\boldsymbol{P_{max}}$	2.035	2	1.017	3.715E30	0.000
$\boldsymbol{T_{maxE}}$	0.000	2	0.000	0.000	1.000
$\boldsymbol{T_{max}}$	0.445	2	0.223	8.129E29	0.000

$\boldsymbol{P_{max}}$ * $\boldsymbol{T_{maxE}}$	0.000	4	0.000	0.000	1.000
$\boldsymbol{P_{max}}$ * $\boldsymbol{T_{max}}$	0.001	4	0.000	1.210E27	0.000
$\boldsymbol{T_{maxE}}$ * $\boldsymbol{T_{max}}$	0.000	4	0.000	0.000	1.000
$\boldsymbol{P_{max}}$ * $\boldsymbol{T_{maxE}}$ * $\boldsymbol{T_{max}}$	0.000	7	0.000	0.000	1.000
Error	2.74E-31	1	2.74E-31		
Total	10.313	27			
Corrected Total	2.665	26			
a. R Squared = 1.000 (Adjusted R Squared = 1.000)					

The relationship between independent and dependent variables is measured by a Pearson correlation in SPSS. The results of the Pearson correlation for dependent variable 1 indicated a strong, positive and significant relationship between P_{max} and dependent variable 1: r = 0.897, p < 0.0001. T_{max} also had a positive and significant relationship with the dependent variable 1, however this relationship is not as strong as P_{max}: r = 0.408, p <0.05.

<u>Dependent variable 2: Temperature exchanger efficiency</u>

There is no significant main effects on dependent variable 2 (p>0.05). This could be due to an error in mathematical formulation.

Table C.5: Tests of between-subjects effects/effect of $\boldsymbol{\eta_{tE}}$

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.768[a]	25	0.071	0.964	0.682
Intercept	3.850	1	3.850	52.464	0.087
P_{max}	0.472	2	0.236	3.214	0.367
T_{maxE}	1.164	2	0.582	7.932	0.244
T_{max}	0.092	2	0.046	0.628	0.666
P_{max}* T_{maxE}	0.028	4	0.007	0.096	0.968
P_{max}* T_{max}	0.018	4	0.004	0.061	0.984
T_{maxE}* T_{max}	0.009	4	0.002	0.029	0.996
P_{max}* T_{maxE}* T_{max}	0.009	7	0.001	0.018	1.000
Error	0.073	1	0.073		

Total	5.706	27				
Corrected Total	1.842	26				
a. R Squared = .960 (Adjusted R Squared = -.036)						

The Pearson correlation results for dependent variable 2 indicated that there is a strong, negative, and significant relationship between T_{maxE} and dependent variable 2 (r = - .762, p<0.0001). This relationship for PMAX is also negative and significant, however, not as strong as T_{maxE}: r = - .470, p<0.05). No significant relationship is found for T_{max}.

<u>Dependent variable 3: System efficiency</u>

Although the F ratio for T_{maxE} on dependent variable 4 is large (F (1,2) = 11.57), it is not significant (p<0.05).

Table C.6: Tests of between-subjects effects/effect of η_{system}

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	3.494[a]	25	0.140	0.974	0.679	0.961
Intercept	7.409	1	7.409	51.635	0.088	0.981
P_{max}	0.044	2	0.022	0.155	0.874	0.236
T_{maxE}	3.321	2	1.661	11.572	0.204	0.959
T_{max}	0.033	2	0.017	0.115	0.902	0.187
P_{max}* T_{maxE}	0.004	4	0.001	0.006	1.000	0.024
P_{max}* T_{max}	0.053	4	0.013	0.092	0.970	0.268
T_{maxE}* T_{max}	0.001	4	0.000	0.003	1.000	0.010
P_{max}* T_{maxE}* T_{max}	0.005	7	0.001	0.005	1.000	0.033
Error	0.143	1	0.143			
Total	10.930	27				
Corrected Total	3.637	26				
a. R Squared = .961 (Adjusted R Squared = -.026)						

Similarly, in the Pearson correlation analysis for dependent variable 4, a strong, negative, and significant relationship between T_{maxE} and system efficiency is shown: *r* = - .949, *p*<0.0001. The relationship for both T_{max} and P_{max} is not significant.

In previous analyses, it is determined that that two of the goals, Rankine cycle efficiency and exchanger efficiency conflict. Thus, there is a negative correlation between the two. This is verified in this project using a surrogate model, and the conflict is shown in Figure C.3.

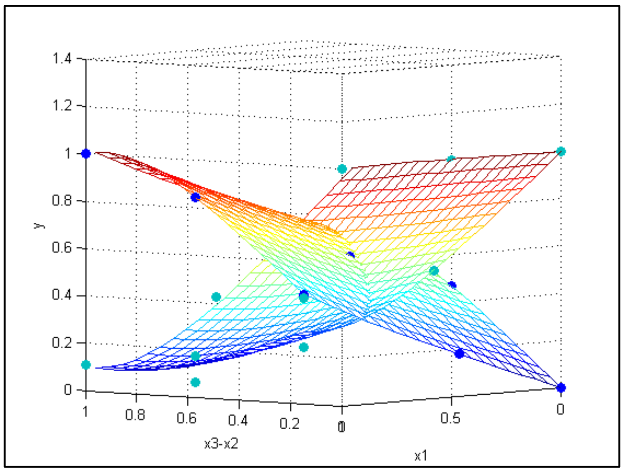


Figure C.3: Conflicting goals of the system η_{system} and η_R

Appendix D: DSIDES Data File for Shell and Tube Heat Exchanger

Below is the DSIDES data file for shell and tube heat exchanger model referred from Section 5.1.1.

```
PTITLE  : Problem Title
Shell and Tube Heat Exchanger (STHX)
Maryam Sabeghi May 2014

NUMSYS  : Number of system variables
  9    0    15    : Real, Integer, Boolean

SYSVAR   : System variable information
TUBLEN       1    1.0     4.0       3.25     :m
TUBro        2    0.005   0.2       0.15125  :m
TUBri        3    0.004   0.15      0.077    :m
TUBCLR       4    0.005   0.2       0.15125  :m
Tto          5    279.0   355.0     317.0    :K
Tso          6    285.0   369.0     327.0    :K
FLOWS        7    10.0    40.0      28.75    :kg/s
FLOWT        8    8.0     30.0      27.25    :kg/s
NTUB         9    40.0    150.0     50.0     :integer
STM1         10   0       1         1        :Copper
STM2         11   0       1         0        :Brass
STM3         12   0       1         0        :Stainless
Steel
STM4         13   0       1         0        :Aluminum
Bronze
SIPCH1       14   0       1         0        :square Pitch
SIPCH2       15   0       1         1        :triangular
Pitch
SNTPS1       16   0       1         1        :Number of
tube pass
SNTPS2       17   0       1         0        :Number of
tube pass
SNTPS3       18   0       1         0        :Number of
tube pass
STF1         19   0       1         1   :Selection of tube
fluid 1
STF2         20   0       1         0        :Selection of
tube fluid 2
STF3         21   0       1         0        :Selection of
tube fluid 3
SSF1         22   0       1         1        :Selection of
Shell fluid 1
```

```
SSF2          23   0       1         0        :Selection of
shell fluid 2
SSF3          24   0       1         0        :Selection of
shell fluid 3

NUMCAG  : Number of constraints and goals
    0    18    5    0    5   :
nlinco,nnlinq,nnlequ,nlingo,nnlgoa

NLINCO  : Names of nonlinear constraints
CTti     1   : Tube inner temperature is greater than
outer temperature
CTsi     2   : Shell inner temperature is less than outer
temperature
CTts1    3   : Tube inner temperature*1.02 is greater than
shell outer temperature
CTts2      4   : Shell inner temperature is less than tube
outer temperature*1.02
CPTR1    5   : Pitch ratio (2.5 < TUBPCH/TUBro)
CPTR2    6   : Pitch ratio (TUBPCH/TUBro < 3)

CMXTPD   7   : Maximum allowable pressure drop in the tube
CMXSPD   8   : Maximum allowable pressure drop in the
shell
CTTHK1   9   : Tube thickness greater than 0.008m
CTTHK2   10  : Tube thickness less than 0.15m
CTUBR    11  : Tube outer raduis greater then inner raduis
CQBL1    12  : Heat balance (QINSHL<=QOUTUB)
CQBL2    13  : Heat balance (QINSHL>= QOUTUB-
(HLSMX*QOUTUB))
CPTCHC   14  : Pitch and clearance relation (TUBCLR>0)
CPTro    15  : Pich and TUBro relation (TUBPCH>=
0.005+2*TUBro)
CTUBRE   16  : Tube Re
CSHLRH   17  : Shell Re HIGH
CNTSD    18  : Number of tubes and shell diameter relation
CSTM     19  : (STM1*STM2*STM3*STM4)=0
CSIPCH   20  : (SIPCH1*SIPCH2)=0
CSNTPS   21  : (SNTPS1*SNTPS2*SNTPS3)=0
CSTF     22  : (STF1*STF2*STF3)=0
CSSF     23  : (SSF1*SSF2*SSF3)=0

NLINGO  : Names of the nonlinerar goals
GHEATA   1  : Heat transfer area
GTSIZE   2  : Total size of the heat exchanger

GTUBPD   3  : Pressure drop in tube
```

```
GSHLPD   4  : Pressure drop in shell
GHXEFC   5  : Effectiveness of the heat exchanger

DEVFUN  : Deviation function (Archimedean)
1      : Levels
1  10   : Level1, 10 terms
(+1,0.6) (-1,0.6) (+2,0.0) (-2,0.0) (+3,0.4)
(-3,0.4) (+4,0.0) (-4,0.0) (+5,0.0) (-5,0.0)

STOPCR  : Stopping criteria
1   0   50  0.04  0.04

OPTIMP  : Optimization parameters
 -0.01   0.5  0.005

ALPOUT   : Input/output Control
 1   1   1   1   1   1   1   1  1  1

USRMOD  : Input/Output flags
 1   1   0   0

USRDAT  :
18
1.0        Correction factor                    :CORFAC
9.81       Gravity acceleration                 :GRAVIT
278.0      Shell inlet temperature  (k)         :Tsi
370.0      Tube inlet temperature   (k)         :Tti
101.3      Shell inlet pressure (kPa)           :SHLPi
101.3      Tube inlet pressure (kPa)            :TUBPi
10.0       Maximum pressure drop in shell(kPa)  :SMXPD
50.0       Maximum pressure drop in tube (kPa)  :TMXPD
0.15       Maximum tube thickness (m)            :TMXTH
0.008      Minimum tube thickness   (m)          :TMITH
0.1        Maximum Heat lost presentage         :HLSMX
20000.0    Required Heat Duty                  :TOTLQ
9.0        Target value for heat transfer area :TTUBAo
0.1        Target value for Size                :TSIZE
2.0        Target value for tube pressure drop :TTPD
0.0        Target value for shell pressure drop:TSPD
1          RETTUR Flag, (1 if turbulent)        :IFTTU
0          Print Flag, IPRT (1 to print)

FIXVAR :
15
10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

ENDPRB  : Stop reading the data file at this point
```

```
XPLORE
50000 200 1 1234
15
10 11 12 13 14 15 16 17 18 19 20 21 22 23 24

ADPCTL  : Adaption Flag
0

INITFS  : Generate Initial Feasible Solution
400 2.0 0.5 0.0001 0.1 0.0001
```

Appendix E: Selection DSP Results Verification

This appendix is about the selection DSP results verification through hand calculation referred from Section 5.3.2.

Preliminary Ordinal selection DSP

Given:

- Alternatives: 4
  1. SS304 (Stainless Steel); Pros: Low Density, Low Cost; Cons: Low Heat Conductivity
     - Cost = .66 USD/lb
     - Heat Conductivity = 15.5 W/mK
     - Density = 7970 kg/m^3
  2. Copper; Pros: High Heat Conductivity; Cons: High Density, High Cost
     - Cost = 2.83 USD/lb
     - Heat Conductivity = 401 W/mK
     - Density = 8960 kg/m^3
  3. Aluminum; Pros: Low Density, Low Cost; Cons: Low Heat Conductivity
     - Cost = .81 USD/lb
     - Heat Conductivity = 167 W/mK
     - Density = 2700 kg/m^3
  4. Brass; Pros: Low Cost; Cons: High Density, Low Heat Conductivity
     - Cost = 2.11 USD/lb
     - Heat Conductivity = 109 W/mK
     - Density = 8480 kg/m^3

Identify

- Attributes: 3
  1. Cost – How much would it cost to construct the heat exchanger out of a certain material; lower value is preferred; Ratio Scale

2. Heat Conductivity – How well the material will facilitate the heat transfer necessary for the exchanger to function; higher value is preferred; Ratio Scale
3. Density – Lower density means lower overall weight; lower value is preferred; Ratio Scale

Comparison of Attributes (Weights)

Heat Conductivity: .6000; Upper Bound: 600.0, Lower Bound: 0.00; Higher value preferred
Cost: .2500; Upper Bound: 3.00, Lower Bound: 0.00; Lower value preferred
Density: .1500; Upper Bound: 9000.00, Lower Bound: 0.00; Lower value preferred
Assigned based on user-defined weights for the relative importance of each attribute based on its impact on what is wanted out of the heat exchanger.

Rate

Alternative Initial Ratings

- **Heat Conductivity**
  1. Copper = 401 W/mK
  2. Aluminum = 167 W/mK
  3. Brass = 109 W/mK
  4. SS304 = 15.5 W/mK
- **Cost**
  1. SS304 = .66 USD/lb
  2. Aluminum = .81 USD/lb
  3. Brass = 2.11 USD/lb
  4. Copper = 2.83 USD/lb
- **Density**
  1. Aluminum = 2700 kg/m^3
  2. SS304 = 7970 kg/m^3
  3. Brass = 8480 kg/m^3
  4. Copper = 8960 kg/m^3

Normalized Alternative Ratings

Normalized Rating = (Alternative Value)/(Upper Bound) if higher value is desired, or 1 – ((Alternative Value)/(Upper Bound)) if lower value is desired.

- **<u>Heat Conductivity</u>**
  1. Copper = (401 W/mK)/(600 W/mK) = .668
  2. Aluminum = (167 W/mK)/(600 W/mK) = .278
  3. Brass = (109 W/mK)/(600 W/mK) = .182
  4. SS304 = (15.5 W/mK)/(600 W/mK) = .026
- **<u>Cost</u>**
  1. SS304 = 1 – (.66 USD/lb)/(3.00 USD/lb) = .78
  2. Aluminum = 1 – (.81 USD/lb)/(3.00 USD/lb) = .73
  3. Brass = 1 – (2.11 USD/lb)/(3.00 USD/lb) = .30
  4. Copper = 1 – (2.83 USD/lb)/(3.00 USD/lb) = .06
- **<u>Density</u>**
  1. Aluminum = 1 – (2700 kg/m^3)/(9000.00 kg/m^3) = .700
  2. SS304 = 1 – (7970 kg/m^3)/(9000.00 kg/m^3) = .114
  3. Brass = 1 – (8480 kg/m^3)/(9000.00 kg/m^3) = .058
  4. Copper = 1 – (8960 kg/m^3)/(9000.00 kg/m^3) = .004

<u>Rank</u>

<u>Merit Functions</u>

- SS304: $\sum_{j=1}^{3=n} I_j R_{ij} = (.60)(.026) + (.25)(.78) + (.15)(.114) = .228$
- Copper: $\sum_{j=1}^{3=n} I_j R_{ij} = (.60)(.668) + (.25)(.06) + (.15)(.004) = .416$
- Aluminum: $\sum_{j=1}^{3=n} I_j R_{ij} = (.60)(.278) + (.25)(.73) + (.15)(.7) = .454$
- Brass: $\sum_{j=1}^{3=n} I_j R_{ij} = (.60)(.182) + (.25)(.30) + (.15)(..058) = .192$

<u>Final Rankings</u>

1. Aluminum – .454
2. Copper – .416
3. SS304 – .228
4. Brass – .192

Appendix F: Response Surface Models Information

This appendix provides more information about the response surface models used for developing the cDSP related to solution space exploration of the process design of continuous casting of steel in Chapter 6.

Similarly to the methodology adopted for *CLS* calculation, empirical relations and the developed simplified models are used for calculation of other output parameters as well. The explanations provided in this section will help the reader to have a better understanding of the methodology adopted for development of Response Surface Model.

As explained above, there are more than 200 RSM's that have been developed, providing validation for each one of them is beyond the scope of this paper and will be presented in a separate paper. But, to give an idea about the accuracy of the developed RSM's, co-efficient of determination (R^2) values for some cases have been provided in Table F.1.

Table F.1: Coefficient of determination values

.	Output Parameters	R^2 Value
1	Shell Thickness at Mold Exit	0.98
2	Metallurgical Length	0.99
3	Surface Temperature at Unbending	0.99
4	Shell Thickness at Unbending	0.96
5	Columnar Zone Fraction	0.97
6	Equiaxed Zone Fraction	0.97
7	Mixed Zone Fraction	0.96

The reported values of R^2 for the developed RSM's are in the range 0.95-1, which means the output predicted by Response Surface Model (RSM) is in good agreement with the values obtained from the detailed mathematical simulations. Information provided in this section is useful to understand the accuracy level of the developed RSM, as compared to the detailed comprehensive models using which these RSM's have been developed.

Appendix G: Solution Space Exploration Manual

This appendix is the solution space exploration manual referred from Chapter 7. This manual mostly repeat the steps discussed in Chapter 3 where the solution space exploration method is proposed. However, some more detain about the codes are provided in the manual in compare to Chapter 3.

There are several steps to conduct solution space exploration method, and they are documented in Chapter 3. Here the steps are repeated for weight sensitivity analysis, constraint sensitivity analysis and feasibility robustness with more detailed information.

<u>Steps in Weight Sensitivity Analysis:</u>

1. Generate design scenarios by assigning different weights to the goals. Three goals are mandated in this method to be able to use a ternary plot, and seven to ten scenarios are recommended as a minimum to cover the space. As mentioned in Section 3.3.1, Eq. 3.5, weights should be positive, and for each scenario it is convenient that they sum up to one. An example of seven different scenarios to be run to support weight sensitivity analysis in is shown in Table G.1.

Table G.1: Design scenarios for weight sensitivity

Design Scenarios	**Weight associated with devotion variable of each goal**			**Sum of the weights**
	Goal 1	**Goal 2**	**Goal 3**	
DS 1	1	0	0	1
DS 2	0	1	0	1
DS 3	0	0	1	1
DS 4	0.5	0.5	0	1
DS 5	0	0.5	0.5	1
DS 6	0.5	0	0.5	1
DS 7	0.33	0.33	0.33	~ 1

2. Run each scenario in DSIDES and document the final solution, value of the deviation variable for each goal. It is recommended that the values of deviation variables and goals be normalized between 0 and 1.

Note: To run each scenario, the block DEVFUN (deviation function, Archimedean) in the data file of DSIDES should be modified.

```
DEVFUN  : Deviation function (Archimedean)
1       : Levels
1  10   : Level1, 10 terms
(+1,0.5) (-1,0.5)   (+2,0.0) (-2,0.0)   (+3,0.5)  (-3,0.5)
```

In the code above, one level and 3 goals are specified. The DS 6 shown in Table G.1 is illustrated in the code. For more detain explanation refer to DSIDES manual Chapter 9, page 9.11. Also see the data file related to the shell and tube heat exchanger in Appendix D.

3. Visualize the solution space. To visualize the solution space in this method, ternary plots are recommended. Ternary plots can be utilized for three or more goals, however, for two goals contour plots are recommended. The ternary plots are generated for each goal using the MATLAB code illustrated in Figure G.1. One plot is created for each goal and to do so, one set of scenarios like what is presented in Table G.1 is needed, and the

```
% Main file for ternary plot
close all;clear all
warning                                          off
MATLAB:griddata:DuplicateDataPoints

%For Energy
%   col1    col2  col3  col4
A = [1      0     0     0.24
     0      1     0     0
     0      0     1     1
     0.5    0.5   0     0
     0.0    0.5   0.5   0.27
     0.5    0.0   0.5   0.25
     0.33   0.33  0.33  0.01]

l=length(A);
v=0.29./sqrt(A(:,4));

figure;

colormap
[hg,htick,hcb]=tersurf(A(:,1),A(:,2),A(:,3
),A(:,4));

% Add the labels

hlabels=terlabel('Objective2','Objective1'
,'Objective3');
```

Figure G.1: MATLAB codes to generate ternary plots

fourth column shown in the figure is the deviation value of one goal at the time. There are six separate files needed in the MATLAB code of ternary plots, which are *tersurf, terplot, ternaryc, termain, terlabel, tercontour* and *ter_main.* The solution space created in this plot represent the relation of one goal with respect the other two.

4. Cluster the plots based on the desirable region and undesirable region which are presented with different colors, and document the weight range associated with each goal for each plot. By desirable solutions, the solutions with lower values of deviation variable are considered. In the compromise DSP the objective is to minimize the deviation function in which the goal is improved, therefore blue area which contains the minimum value of the deviation variable is desired. However the designer should decide about what range of solutions are desired, and for each goal, the range of desired solution may be different. For example, in the case of Figure G.2, the desired solutions can be defined as solutions with the deviations below 0.25. The weight associated with a solution (deviation) inside the solution space can be read as sown in Figure G.3. For this purpose draw parallel lines are drawn from a point (solution) to each side of the triangle. Figure G.3 is shown to read Point 1. Point 1 has the values of 60% A, 20% B and 20% C which sum up to 100%.

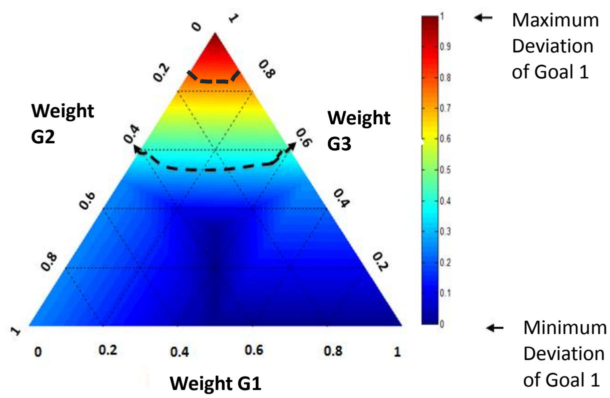


Figure G.2: Weight sensitivity analysis

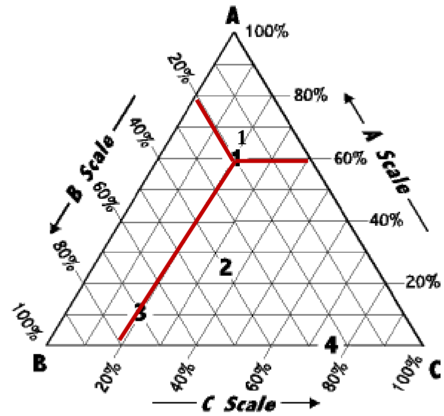


Figure G.3: How to read ternary plot ("Ternary Plots ", 2000)

In the case shown in Figure G.2, the range of weights are as follows: 0.0 to 1 for G1, 0.4 to 1.0 for G2, and 0.0 to 0.6 for G3. This range of design preferences guarantees a desired solution for G1.

5. Superimpose the plots and interpret. To conduct this step, it is preferred to have all the goals/deviations either minimized or maximized. In the case of this thesis, the objective is to minimize all the deviations associated with the goals, however, the range of desired solution may be different for different goals. In this step, a common region in the solution space that provides desired solutions satisfactory to all the goals is identified and the weight range associated with that region is documented.

It is possible that no overlap of the desired solutions that meet all the goals is found. This means a high conflicts between the goals, thus tradeoffs are necessary. In such cases, the designer should compromise one, two or all the goals to make the overlap possible. This can be done by either changing the target values associated with the goals in the cDSP or simply changing the range of desired solutions when interpreting the plots. By tuning the target values related to the goals the aspiration spaced is modified to satisfy all design objectives. Aspiration space is discussed in Section 2.1.

Steps in Constraint Sensitivity Analysis:

1. Select/create several design scenarios that are within the weight range found in Step 5 of weight sensitivity analysis. Those are the solutions that satisfies all the goals.

2. Run each scenario and document the value of their constraints. These values in operation research are called slack variables. For instance, if the constraint is $x + y \geq z$, then the value calculated for $x + y - z$ for each constraints needs to be documented. This value can be calculated either within DSIDES, or using an excel sheet. Constraints are evaluated in Block 3 of DSIDES FORTRAN file. The code line to print the constraint value for this case is:

CONSTR(1) = $x + y - z$

WRITE(NOUT,1000) 'C1: $x + y - z$:' ,CONSTR(1)

The problem with capturing the value through DSIDES is that it prints this value for each iteration and in the case of too many constraints and iterations, the output file will be huge. Since the value is only needed for the final solution, this calculation can be done in a excel sheet as well.

3. Identify active and inactive constraints. In Linear Programing, an active constraint is a constraint that is satisfied at equality. For example, if the constraint is $x + y \geq z$, is active when $x + y = z$, and inactive when $x + y > z$.

Some of the constraints may have a value of zero, while the value varies in other constraints. This value is called *capacity* in this work. Constraints with zero capacity are called active, and inactive otherwise.

4. Analyze extra capacity of the inactive constraints. The extra capacity of different constraint are different and it may change for various desired solutions. The main task

in this step is to identify the constraints with limited capacity that are in high risk.

5. Determine the penalty associated with the constraints with zero or limited capacity in face of uncertainty.

Steps in Incorporating Feasibility Robustness:

1. Identify sensitive variables and specify the variations. The variation of the sensitive constraints is caused by variations of input variables involved in those constraints. The variation of the input variables need to be found through either engineering experience or literature.
2. Make modification on the compromise DSP to incorporate feasibility robustness. The modification is in two parts of the cDSP: GIVEN and SATISFY, system constraints. The variations found in Step 1 should be given to the cDSP, and to consider variation of the constraints, uncertainty is added to the desired boundary solutions. This is done by adding some extra space to the constraints with zero or limited capacity. For instance, consider the case in which the constraint (Y) is a function of a design variable (x) and a design parameter (c), and the source of uncertainty is from the design parameter (c). Then, the constraint,

$$E[Y(x, \mu c)] \geq \text{Min}$$

should be modified to:

$$E[Y(x, \mu c)] + (\delta Y/\delta c) * \Delta c \geq \text{Min}$$

where $E[Y(x, \mu c)]$ is the expected value of the constraint and $(\delta Y/\delta c)$ is the standard deviation. The standard deviation of each constraint is calculated using the variance of the input variables (Step 1). This modification should be done in Block 3 of DSIDES FORTRAN file where the constraints are evaluated.

The constraint

CONSTR(1) $= x + y - z$

should be modified to:

CONSTR(1) $= x + y - z$ + abs (stdev $(x + y - z)$)

3. Capture robust solutions and make recommendations. After the compromise DSP is modified, the design scenarios associated with desired solutions found in weight sensitivity analysis are run again to capture desired and robust solutions. There are usually more than one solutions, and insight is needed with respect to each solution to make the final recommendation. The insight is based on two main factors: values of the goals (or deviation) and values of the variables. In this step, value of deviation variables should be checked to ensure that they are within the ranged specified in weight sensitivity analysis.

All the steps involved in solution space exploration is discussed through a design example, continuous casting of steel, in Chapter 6.