

**Enhancement of Set-Based Design Practices Via Introduction of
Uncertainty Through the Use of Interval Type-2 Modeling and
General Type-2 Fuzzy Logic Agent Based Methods**

by

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Dedication

To my family and friends, for their support, encouragement, and guidance.

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List of Symbols & Abbreviated Terms

SBD	Set-based design
T1	Type-1
FLS	Fuzzy logic system
T2	Type-2
TQM	Total quality management
TOC	Theory of constraints
CE	Concurrent engineering
DFMA	Design for manufacturing assembly
QFD	Quality functional deployment
SBCE	Set-based concurrent engineering
IT2M	Interval type-2 modeling
GT2	General type-2
MF	Membership function
$\mu(x)$	Membership grade, also called the preference level, of a membership function
$\mu'(x)$	Membership grade at x after an IT2M FL randomization
x	An individual, numerical, value from within the entire set-range. x is either a discrete or continuous real-numbered value.
$[x_{min}, x_{max}]$	The minimum and maximum values that define a set-range
IT2	Interval type-2
$J(x, \mu(x))$	Defuzzified joint output preference value

JOP	Joint output preference. Is equal to $J(x, \mu(x))$ and typically refers to JOP curve, which consist of all $J(x, \mu(x))$ for the set-range
P	Linguistic preference, Preferred
M	Linguistic preference, Marginal
U	Linguistic preference, Unpreferred
$x-ll$	Left-lower defining point for trapezoidal (and triangular) MFs
$x-lu$	Left-upper defining point for trapezoidal (and triangular) MFs
$x-ru$	Right-upper defining point for trapezoidal (and triangular) MFs
$x-rl$	Right-lower defining point for trapezoidal (and triangular) MFs
Yrand	The interval type-2 modeling FLS method of randomizing the preference level of MF values
xRU	The interval type-2 modeling FLS method of randomizing the location of the $x-ru$ MF defining point
xRL	The interval type-2 modeling FLS method of randomizing the location of the $x-rl$ MF defining point
Slopes	The interval type-2 modeling FLS method of simultaneously randomizing the location of the $x-ru$ and $x-rl$ MF defining points by the same amount and in the same direction to maintain the MF slope during randomization.
σ	A percent standard deviation value used to describe the uncertainty in the IT2M Yrand FLS
ε	A numerical value used to describe the location of the uncertainty bounds for the xRU, xRL, and Slopes IT2M FLSs
$upper_{bound}$	Represents the value (x -coordinate) of the upper bound for randomization of a MF defining curve point
$lower_{bound}$	Represents the value (x -coordinate) of the lower bound for randomization of a MF defining curve point
x_{new}	Represents the value (x -coordinate) for a MF defining curve point after IT2M randomization

y	Is equal to the preference level, membership grade, of a primary (T1) MF
α - plane, \widetilde{A}_α	A horizontal slice (x - y plane) of a general type-2 MF consisting of all secondary grades with the value α (z -value)
FOU	Footprint of uncertainty
\times	Represents the fuzzy logic operation of t -norm, minimum t -norm was used in this research
\tilde{A}	Representation of a type-2 fuzzy set
EKM	Enhanced Karnik Mendel, a set of algorithms to reduce the computational time for the type-2 FLS type-reduction phase
B	Ship design variable, beam
C_b	Ship design variable, block coefficient
D	Ship design variable, depth
KG_c	Ship design variable, cargo vertical center of gravity
KG_m	Ship design variable, machinery vertical center of gravity
KG_s	Ship design variable, structural vertical center of gravity
L_c	Ship design variable, length of cargo box
L_m	Ship design variable, length of machinery room
LWL	Ship design variable, length of waterline
T	Ship design variable, draft
$Threq_d$	Ship design variable, thrust required
V_k	Ship design variable, speed in knots
W_m	Ship design variable, weight of machinery

Abstract

The goal of this research was to discern the effects of introducing uncertainty representation into a set-based design process with applications in ship design. The hypothesis was that the introduction of design uncertainty would enhance the facilitation of set-based design practices.

A presentation of three fuzzy logic agent based methods for the facilitation of set-based ship design practices is offered. The first method utilized a type-1 fuzzy logic system to facilitate set-based design practices and possessed no uncertainty modeling. The next two methods included the representation of design uncertainty in the set-based design space. Of these two methods, one utilized a novel approach that harnessed techniques of randomization to model an interval type-2 fuzzy logic system, the other method made use of general type-2 fuzzy logic methods that were well-known, but still relatively under-utilized in academics and industry when compared to type-1 fuzzy logic systems.

Comparisons of the newly developed fuzzy logic systems with each other, and the type-1 agent based fuzzy logic system provided the basis for conclusions as to the effects of introducing uncertainty modeling into a set-based design process. The results of this experimental research have shown that the inclusion of uncertainty modeling in the set-based design process for the negotiation of design variables enhances the overall set-based design progression, especially when working with highly constrained designs.

In the case of a highly constrained design, the type-1 fuzzy logic system was unable to promote set-convergence within the allotted experimental time without repeated design failures, while the use of uncertainty modeling allowed the interval type-2 modeling and general type-2 fuzzy logic systems to achieve feasible set-based design convergence. When performing a simplistic, loosely constrained design, all three fuzzy logic systems were capable of facilitating the principle practices of set-based design within the feasible solution space; specifically, the set-based practices of delaying design decisions and gradual reduction of the feasible solution space.

This research has led to the enhancement of the set-based design process by providing capabilities to now represent uncertainty in the set-based design space through the use of either the newly developed interval type-2 or general type-2 fuzzy logic systems.

CHAPTER 1

INTRODUCTION

1.1 Research Overview

The United States Navy has, in recent years, recognized a need to begin implementation of set-based design (SBD) practices throughout the ship design process [Sullivan, 2008] [Kassel, Cooper, and Mackenna, 2010] [Eccles, 2010] [Doerry, 2009]. As recently as 2010, the Navy's goals for inclusion of SBD methods for early-stage ship design were outlined in a paper by Kassel, Cooper, and Mackenna, entitled, "Rebuilding the NAVSEA Early Stage Ship Design Environment" [2010]. Liker et. al. have also discussed the need for the development of design tools to "facilitate a proper exchange of information" [1996]. Liker's paper discusses a clear need for a SBD tool to aid in the facilitation of the SBD methodology. In 2003, at the University of Michigan, David J. Singer performed studies utilizing a hybrid agent type-1 fuzzy logic system (T1 FLS) to demonstrate that a design tool was capable of helping to facilitate SBD practices. By helping to facilitate SBD, the design tool also resulted in more robust design solutions when compared to a typical point-based design approach [Singer 2003]. This dissertation presents research on the efforts to further improve the hybrid agent T1 FLS by adding uncertainty modeling capabilities to the SBD environment. The author has utilized set-based preliminary ship design experiments to investigate the effects of introducing

uncertainty modeling into the SBD environment through the use of a novel interval type-2 modeling (IT2M) and general type-2 (GT2) FLSs.

One may ask why uncertainty is needed in the SBD process. The simple answer is that all communications are uncertain to some degree [Wallsten and Budescu, 1995]. Yet, a typical design process treats decisions and data as crisp or well-known, and forces designers to make discrete decisions - in essence discarding the uncertainty associated with information and communications. The SBD method possesses numerous core principles that guide its implementation. One of the core principles is to achieve a reduction of uncertainty before making initial design decisions. Introducing uncertainty modeling into the SBD environment using type-2 fuzzy logic (T2 FL), as opposed to type-1 fuzzy logic (T1 FL) methods, should represent an increase in the information available to designers when trying to make important preliminary design decisions. How this additional information affects the overall SBD process is the driving question behind the investigation and experimental studies detailed in this thesis. The hypothesis is that an enhancement of the overall SBD procedure may be achieved through the introduction of uncertainty representation in the SBD space.

Set-based preliminary container ship designs were performed using a T1, a newly developed IT2M and general type-2 GT2 FLS SBD tool environments. The newly developed IT2M and GT2 FLS SBD environments were compared to the results of the T1 FLS SBD experimental results, which served as a baseline for the experiments. The comparisons allowed for an investigation into the effects of introducing uncertainty modeling into the SBD space.

Two different containership designs were developed utilizing each of the three FLS design tools to perform preliminary set-based ship designs. One ship design was loosely constrained (Ship E) and the other highly constrained (Ship D). The purpose of the two different designs was to test the situational robustness of the SBD FLSs; would the design environments be capable of facilitating a SBD for both a simply constrained and highly constrained design.

The experimental results showed that the introduction of design uncertainty allowed for enhancement of SBD processes through the increased delaying of design decisions and the increase in available design information. The delaying of design decisions resulted from the uncertainty modeling causing a delay in the set-reduction process until uncertainty was adequately reduced. The IT2M and GT2 FLS SBD environments increased the available design information by providing a representation of design uncertainty. The uncertainty modeling proved to be particularly beneficial during the highly constrained ship designs. During these designs, the uncertainty representation helped to prevent the elimination of design values needed for a feasible design. Without the representation of design uncertainty, the T1 FLS SBD environment was unable to achieve a feasible design solution within the allotted experimental time. As for the loosely constrained design, the uncertainty modeling of the IT2M and GT2 FLSs proved to be no more effective at facilitating the SBD process than did the T1 FLS SBD environment.

1.2 Dissertation Contributions

The research outlined in this dissertation provides meaningful contributions to the field of engineering and design systems by demonstrating the advantages to introducing the representation of design uncertainty into a SBD process. The research advances the facilitation of SBD practices by providing new systems for representation of uncertainty inherent in communication and design. The methods also showed improved facilitation of principle SBD practices through the use of novel IT2M and GT2 FLS SBD environments. The specific contributions of this research include:

- 1) The ability to now represent uncertainty in communications and design data.
 - Through the use of the IT2M and GT2 FLS SBD environments.
- 2) Enhancement of the facilitation of SBD processes.
 - Through delaying of design decisions as a result of the representation of design uncertainty.
 - Through the increase in available design information by graphical representation of design uncertainty in the IT2M and GT2 FLS SBD environments.
 - Through representation of robustness of the design solutions via the IT2M Joint Output Preference Histograms; see Chapter 5, Section 5.3.2.
- 3) Development of the new interval type-2 modeling (IT2M) FLS methods.
 - Yrand, xRU, xRL, and Slopes randomization methods.
- 4) Development of the IT2M Joint Output Preference (JOP) histogram for identification of design value robustness in the presence of design uncertainty.
- 5) Development of a simplified GT2 membership function representation that required function definition in only two-dimensions, as opposed to the typical three-dimensions.

These contributions help to advance the research into the fields of SBD facilitation and application, fuzzy logic systems, and uncertainty representation for information communications in the design environment.

1.3 Dissertation Overview

This dissertation uses the remainder of Chapter 1 to outline the differences between the long-practiced point-based design approach and the more recently developed set-based design approach. In this discussion the drawbacks of the point-based design approach and the benefits of the SBD method are outlined. A discussion of previous SBD research is also provided before transitioning into a description of uncertainty in design and communication and how it relates to SBD; Chapter 2.

Communication is a core principle of SBD, but communications are inherently uncertain. Therefore Chapter 2 discusses the different types of uncertainty associated with design and communication of data. Uncertainty of linguistic and numeric data can be represented using FLSs, as such, Chapter 2 also serves to provide the reader with an introduction into fuzzy set theory, as well as T1, interval type-2 (IT2), and GT2 FLSs. The chapter describes the FLS components and how fuzzy logic can be utilized for uncertainty representation. Several detailed examples are also provided to aid in the explanation of fuzzy set theory and FLS operations.

In Chapter 3 the motivation for the development of the IT2M FLS is outlined in detail, describing the advantages and disadvantages of a true T2 FLS. The theory behind the IT2M FLS methodology and the IT2M FLS components are described. The thesis then transitions into detailing the next progression of FLSs and uncertainty representation, via

the GT2 FLS, describing the development of a unique, simplified GT2 MF representation and the two-step centroid type-reduction and defuzzification process.

Chapter 5 provides results from the preliminary development of the IT2M and GT2 FLS SBD environments. These systems were compared to historical data obtained from T1 FLS SBD facilitation research conducted by Singer [2003]. The chapter outlines the development of the unique IT2M FLS randomization methods and the resulting capabilities of the methods for uncertainty representation.

Chapters 6 and 7 introduce the SBD environment as a FLS design tool and discuss the system structure involving the use of Chief engineering agent and design agents to perform the preliminary set-based ship designs. The experimental design for the preliminary set-based ship designs is outlined in detail.

The results of the set-based preliminary ship design experiments are outlined in detail in Chapter 8. Chapter 9 discusses the conclusions formulated from the SBD experimental evidence, limitations of the conducted research, the author's research contributions, and recommendations for future research.

1.4 Introduction to Point-Based Design Concepts

Current ship design practices are fraught with delays, set-backs, and communication flaws. Many of these problems stem from long-standing traditional design practices, such as, use of the commonly applied point-based design method. A point-based design process typically follows the standard design spiral; Figure 1.1. Following the point-based design spiral, designers begin by estimating initial discrete design parameters based

on a preliminary study of similar ships, cars, planes, etc. These initial design parameters are used as the basis for design solutions. Trade-off studies are performed and a single design solution is eventually chosen. The solution is then analyzed in increasing detail and altered as necessary in an attempt to reach a final feasible solution [Liker, Sobek, Ward, and Cristiano, 1996] [Sobek, 1990] [Singer, Doerry, and Buckley, 2009]. Figure 1.1 demonstrates an example of a point-based design spiral for a surface cargo ship as detailed by J.H. Evans [1959].

With a point-based design, as the fidelity of the analyses increases, design flaws begin to surface which require quick solutions to bring the design back into the feasible solution space. It is often the case that the design cannot be altered enough to achieve a feasible solution, at which point a new design alternative is chosen and the design spiral is repeated; “The key point is that a *single* solution is synthesized first, then analyzed and changed accordingly” [Liker, Sobek, Ward, and Cristiano, 1996]. The highly iterative nature of the point-based design process can be quite costly and time consuming [Mistree, et. al., 1990]. Keane and Tibbitts [1996] highlight that the cost of design changes increases while design flexibility decreases as a design progresses throughout the various stages of development; Figure 1.2.

The need for re-design during point-based approaches can be attributed to several sources. For example, engineers are forced to choose discrete values for initial design parameters before they can begin the design, despite often being uncertain as to the best values to choose. Point-based methods also lend themselves to the “over-the-wall” approach of engineering where one departmental design group completes their design work and then passes the project to the next group [Boothroyd, 1994]. The transfer of

design information from the design group to the manufacturing group is a common example of “over-the-wall” point-based communications.

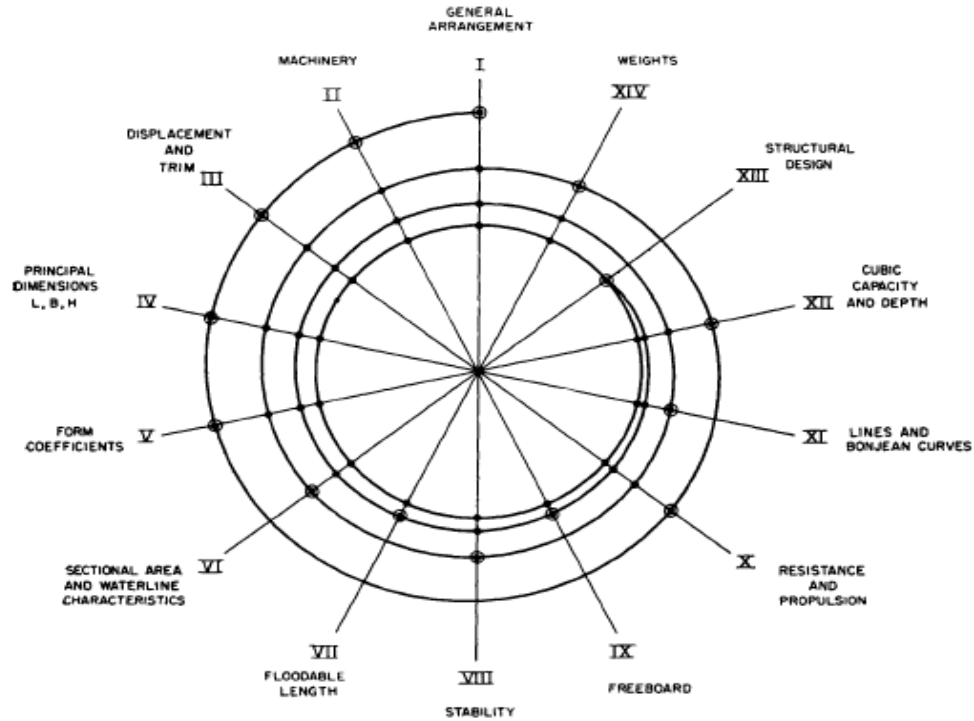


Figure 1.1 Point-based Design Spiral [Evans, 1959]

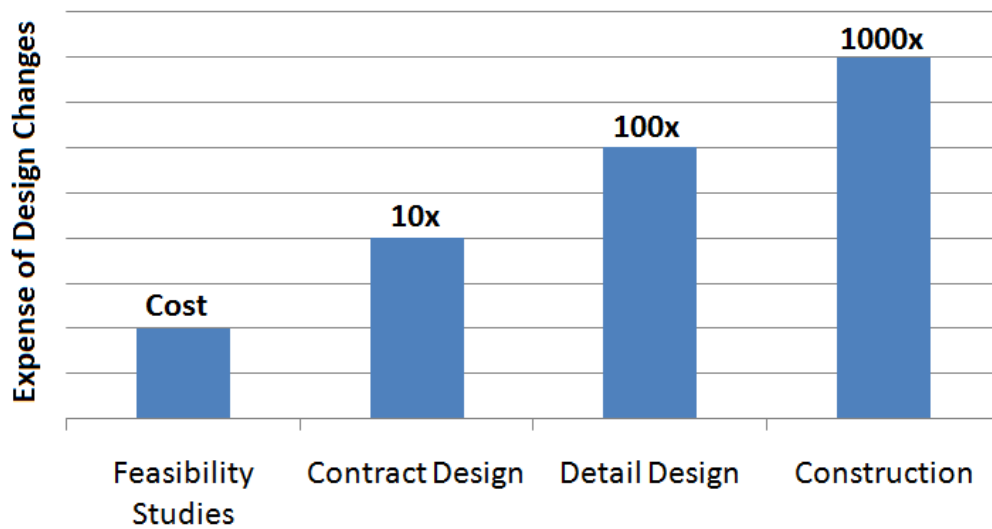


Figure 1.2 Expense of Design Changes During Different Ship Design Phases, Adapted from Keane & Tibbits [1996]

The “over-the-wall” approach represents a lack of inter-department communication among the various design groups, and as a result, forms an entirely down-stream flow of information [Wheelwright and Clark, 1992]. In down-stream information flow, as an upstream design group works to develop a solution that best suits their needs, they often ignore the needs of the remaining downstream design groups. As the design is then passed off to the next group in line, it is frequently necessary to perform some degree of re-design to accommodate the needs of the current design group; thus, creating extra design work and increasing costs. This type of downstream information flow also encourages a sequential development of the design. Sobek, Ward, and Liker refer to this sequential design development as “serial engineering” [1999].

During sequential design development, the downstream design groups will often delay their design work because they worry that they will have to restructure their design once they receive design information from the upstream groups [Ward, et. al, 1995]. As a result of this sequential design progression, the point-based design method tends to be a lengthy design process since design tasks cannot progress concurrently. A further drawback of the point-based design approach is that the iterative process does not guarantee that the method will ever result on a feasible solution [Bernstein, 1997].

Because of the drawbacks to point-based design methods, a great deal of research has been done into alternative design methods resulting in a vast array of newer design methodologies and concepts such as: Lean Product Design, Total Quality Management (TQM), Theory of Constraints (TOC), Concurrent Engineering (CE), Set-Base Design (SBD), Design for Manufacturing Assembly (DFMA), Quality Function Deployment (QFD), Method of Controlled Convergence, Design for Six Sigma, cross-functional

and/or co-located design teams, and various combinations of these concepts [Liker and Lamb, 2002] [Pheng and Teo, 2004] [Berry and Smith, 2005] [Mistree et. al., 1990] [Bernstein, 1998] [Cohen, 1995] [Pugh, 1991].

1.5 Introduction to Set-Based Design Concepts

The Toyota Motor Corp. is often credited with the development of SBD and the application of concurrent engineering (CE), having operated using set-based methods long before the term was even in existence. Jeffrey K. Liker, Durward K. Sobek, and Allen Ward, have authored/co-authored several books and research papers documenting the principles that guide Toyota and the SBD process for engineering, some of which are listed in the references section; [Hopp and Spearman, 2008] [Ward et al. 1995], [Liker 2004], [Sobek et. al. 1999], [Sobek 1996].

Generally, SBD methods use a concurrent approach to engineering. In fact, some researchers prefer the term set-based concurrent engineering (SBCE), since they feel it more accurately emphasizes the concurrent focus of SBD [Sobek, Allen, and Liker, 1999]. Concurrent engineering emphasizes the simultaneous development of both the product and the production process with the goal to shorten lead times, increase quality, and decrease design costs [Sohlenius, 1992]. However, CE does not require the communication of information in terms of sets of data as is done when using SBD methods; work may be done concurrently, but with point-based communications.

During the initial phase of a SBD, individual, functional design groups establish allowable ranges (sets) for design variables. Thus creating a large open design space from which each functional design group may create their own unique sets of design

solutions independently [Sobek, Allen, and Liker 1999]. The set of values for each design variable is then gradually narrowed down as the design trade-offs are more completely understood [Liker, Ettl, and Campbell, 1995]. Since there are a great number of designs being generated at this preliminary stage, only an initial analysis of each design is performed to check for satisfaction of design constraints and goals.

After defining preliminary solutions, the different functional engineering groups then meet to investigate the regions within the design space containing overlapping design solutions. The overlapping regions represent design solutions that are feasible for all functional groups. At this stage of the design process the different functional groups engage in communication about the trade-offs and benefits of the overlapping feasible designs. The groups then separate to rework designs, or generate new designs that fall within the initial region of commonality. This entire process is repeated, steadily reducing the design space and performing higher fidelity analyses, until an understanding of all the design trade-offs is reached [Sobek, Allen, Liker, 1999]. Figure 1.3 diagrammatically emphasizes how the SBD process works: (1) A large open design space is specified, whereby (2) parallel development of individual sets of initial design solutions occurs and regions of overlapping common solutions are identified, (3-4) gradually narrowing the solutions space by eliminating infeasible and less desirable solutions (5) until ultimately reaching a final design.

While narrowing the design space, an emphasis is placed on set-based communication between the different design groups; for instance, the design and manufacturing groups. This emphasis on communication allows for the simultaneous upstream and downstream flow of information. As an example, the design groups better understand the breadth of

the design space they are working within, as well as the capabilities of the manufacturing groups and vice versa [Bernstein, 1998].

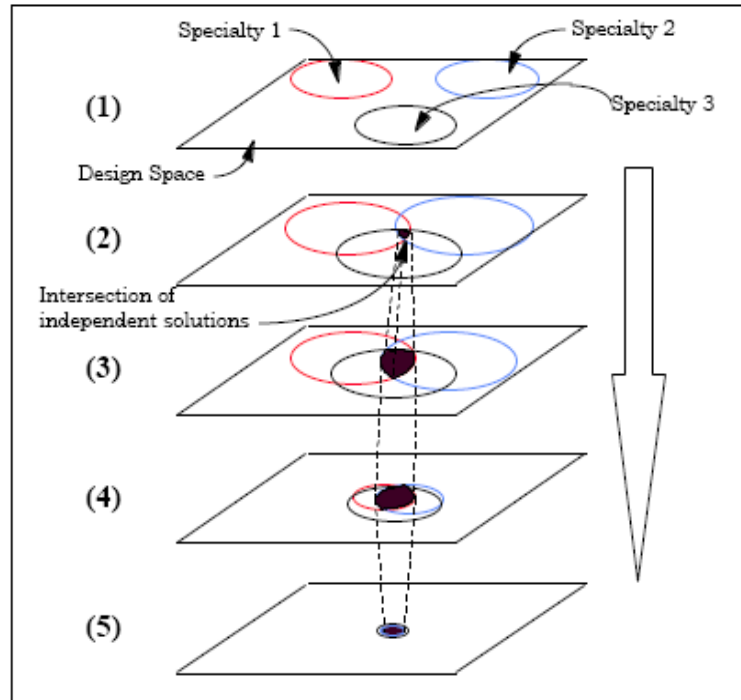


Figure 1.3 Convergence of Set-based Solution Space [Bernstein, 1998]

The example of communications between design and manufacturing groups demonstrates how set-based communication allows for both intra-group and inter-group communications among multiple design groups. It is important to emphasize that during inter-group communications, the groups are communicating about sets of values and sets of solutions. When one group develops sets of solutions, but proceeds to communicate only their single best solution to the other design groups, there is a clear breakdown in the principle practice of set-based communication [Sobek, 1996].

Communication between the design groups is also crucial for the CE aspect of SBD. For instance, during a SBD it is common to provide a preliminary set of designs to the

manufacturing group so that the design of jigs, stamps, assembly processes, etc. can proceed in parallel with the continued narrowing of the design space by the engineering groups. Compared to point-based design, the set-based method of communication helps to facilitate concurrent design in which different design groups are able to work on the design in parallel because of the upstream and downstream information flow.

When utilizing SBCE, to avoid costly re-design of manufacturing equipment and processes as the engineering groups reach a final design, the manufacturing group designs for a large set of possible solutions. The set of possible solutions is based on information that is provided early-on from the upstream design groups. As long as the final design is a subset of the initial design space, the equipment and processes designed by the manufacturing group will still be capable of producing the desired parts [Ward et. al., 1995]. To demonstrate this concept further, reference Figure 1.4 showing a large solution set, *A*, with a smaller solution sub-set, *B*, located within the initial set *A*.

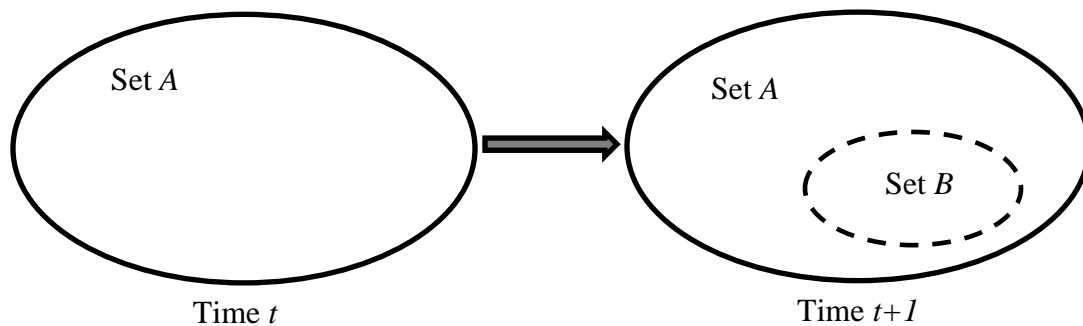


Figure 1.4 Solution Subset B, of Initial Solution Set A

If at time *t* the manufacturing group is provided the solution set *A*, and the group then designs the manufacturing process to produce any part falling within set *A*, then the engineers can select any design within set *A*, say sub-set *B* at time *t+1*, and the

manufacturing group will have no difficulty producing the required parts for this solution since the process was designed to work for any solution within set A [Sobek, 1996]. By designing for set A, the manufacturing group can save time and money by avoiding the need for costly re-design. This example demonstrates the promotion of concurrent and parallel engineering practices through SBD communications.

1.5.1 Set-Based Design Principles

There are several key advantages to the use of SBD for engineering and design. These advantages separate SBD from other design methods and are part of the core principles which must be followed when striving to implement SBD. Ward et. al [1995], list five advantages for set-based design which are quoted in italics below and discussed individually.

- 1) *Set-based concurrent engineering enables reliable, efficient communication.*

Efficient communication is a result of decisions being made in parallel and being based on sets of solutions. As such, any subsequent decisions are still valid if based on a sub-set of the initial set [Sobek, 1996]. This set-based communication helps by allowing work to proceed concurrently since designers are less worried about having to re-work a design at a later date.

- 2) *Set-based concurrent engineering allows for greater parallelism in the process, with more effective, early use of sub-teams.*

The design (upstream) and manufacturing (downstream) groups can benefit by concurrently sharing information throughout the entire design process [Bernstein, 1998]. An example of the benefits of upstream flow of information

includes that of the development of a new manufacturing capability which may allow the engineers to consider designs that were previously infeasible

- 3) *Set-based concurrent engineering bases the most critical, early decisions on data.*

This principle is crucial since early-stage design decisions are typically the most uncertain and yet have the most influence on the overall design and cost [Bernstein, 1998]. As a design process develops, design flexibility decreases while the cost of making design changes increases [Keane and Tibbitts, 1996]; Figure 1.2. Therefore, delaying design decisions, a core SBD practice, allows critical decisions to be made only after the communication of results from design analyses and trade-off studies have occurred and uncertainty has been reduced. Without the added information gained by delaying design decisions, “Decision alternatives may appear equally attractive (or equally unattractive) if people lack the information needed to distinguish them.” [Bashers, 2001]. By purposefully delaying design decisions, the SBD process fosters an attitude of making the right decisions the first time.

- 4) *Set-based design promotes institutional learning.*

As the different functional groups communicate trade-offs between the various overlapping solutions sets, each individual design group gains insight into the technical aspects of the other groups. Institutional learning also relates to the SBD practice developed from Toyota Motor Corp. of keeping detailed documentation of design decisions throughout the entire design process

[Sobek, 1999]. This process of documentation allows the engineers to have a reference database of prior technical decisions that are known to have previously succeeded or failed. The design documentation is used when attempting to modify a current design or create a new product.

5) *Set-based concurrent engineering allows for a search of optimal designs.*

It has been shown that by searching a SBD space it is possible to achieve a more globally optimal design solution when compared to point-based design solutions for the same design project [Singer, Doerry, and Buckley, 2010] [Singer, 2003].

Based on the described advantages of the SBD method, there have been many attempts to apply SBD practices throughout a variety of design industries such as the U.S. automotive, aerospace, cellular phone, and ship building industries. Attempts at implementing SBD practices have produced mixed results. The difficulties in establishing SBD include:

- the intense communication that must be utilized during design,
- feelings of distrust among employees and a sense that the cost of delaying decisions and developing sets of solutions will not truly save money in the long run [Sobek, 1999],
- lack of a strict outline for corporate-wide implementation of set-based design,
- poor management of SBD projects,
- and communicating in terms of sets of data, instead of discrete data values.

It has been stated that, “Since there is no proven formal methodology, learning the (set-based design) process will be slow and error-prone.” [Ward et. al., 1995]. Liker et. al.

have suggested that there is a need, “to develop tools which facilitate a proper exchange of information ... information that reflects the inherent ambiguity and imprecision of design decisions” [1996]. Finally, “it is of utmost importance that in early stages of product design, we maintain design freedom by searching for satisfying solutions ... Maintaining design freedom during the early stages of design facilitates fine-tuning and minimizes the changes that may occur in the later stages of design” [Wang and Terpenney, 2003]. Set-based design provides a way to represent the ambiguities associated with early stage ship design and information communications.

1.6 Set-Based Design: Historical Research & Current Research Scope

A limited amount of research has been conducted on methods by which to facilitate the practice of SBD methods. Current research on methods for the practical application of SBD practices rely on techniques such as type-1 fuzzy logic (T1 FL), discrete event simulations, Responsible Agents for Product/Process Integrated Development (RAPPID), and parametric methods [Singer, 2003] [Wong et. al., 2007] [Nahm and Ishikawa, 2006]. Research into the use of optimization methods, analysis tools, analytical hierarchy processing (AHP), expert systems, group support systems, and multi-criteria decision making for facilitation of SBD has also been performed. However, these particular methods tend to focus on only one specific aspect of SBD; aspects such as, finding the optimal solution, performing trade-off analyses, team communications, or decision making. These methods fail to recognize that SBD requires the simultaneous implementation of many aspects, and to only facilitate one aspect, is to not truly facilitate SBD. Each of the aforementioned methods possesses both positive and negative aspects.

The focus in this research was on the use of fuzzy logic systems (FLSs) to facilitate SBD, as FLSs have shown positive results for the application of and facilitation of SBD processes [Singer, 2003].

To facilitate the use of SBD concepts such as increased communication, communication via sets of solutions, and recording design decisions during the design process, a SBD tool was developed at the University of Michigan by David J. Singer. In Singer's Ph.D. dissertation entitled, "A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation" [Singer, 2003], he detailed how a fuzzy logic (FL) software client was used to elicit increased communication amongst student design team members and how the design tool helped to promote SBD principles.

The hybrid agent FL design tool developed by Singer utilized a type-1 fuzzy logic system (T1 FLS). In this set-based T1 FLS, design variables were negotiated by the FLS using input preference data provided by design agents. The design agents were human subjects assigned to represent different functional design roles, with each design agent possessing unique design goals. A human design agent would analyze a set of values for a design variable and, based on the agent's unique functional design goal, describe preference for different design values using linguistic terms of Preferred (*P*), Marginal (*M*), and Unpreferred (*U*). In Singer's research, the design agents represented their linguistic preferences using T1 MFs. A general example of the agent preference input phase for the SBD environment is shown in the left-hand side of Figure 1.5. The FLS could operate using any number of design agents $1 \dots n$. When applied to perform a preliminary containership design only five design agents were utilized, Cargo, Resistance, Stability,

Hull, and Propulsion. The goals of each agent for a ship design are discussed in Chapter 6, Section 1.

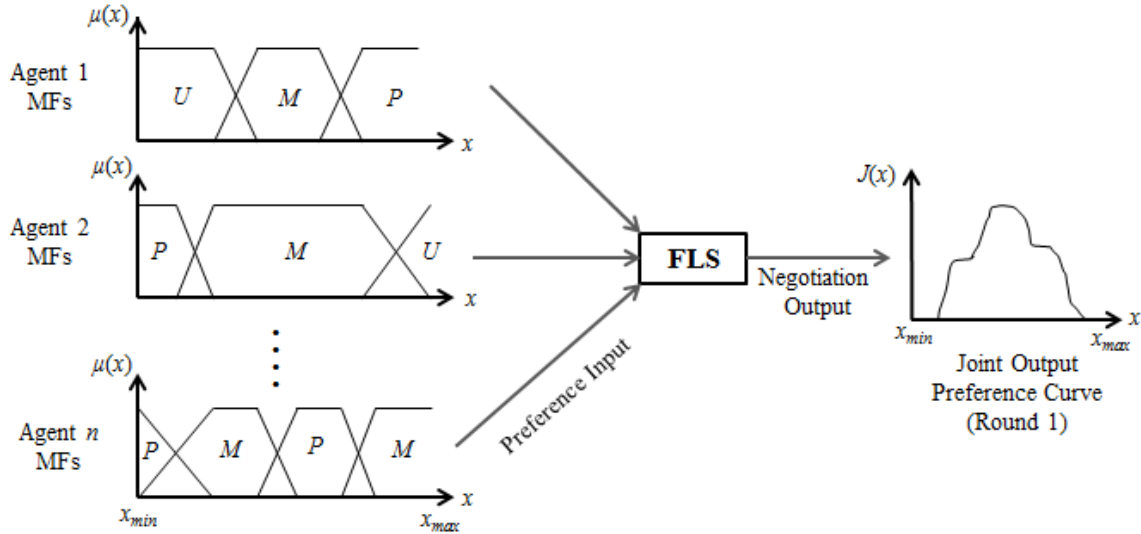


Figure 1.5 T1 FLS Negotiation Example, Agent Preference Inputs and Joint Output Preference Curve for Negotiation Round 1

The design agents' preference information was then input into the T1 FLS where the data was processed and reduced to a single, joint output preference (JOP) curve. The JOP curve, example Figure 1.5, represents the combined preference of all design agents, for each design value in the set of values $[x_{min}, x_{max}]$. Higher JOP values indicated a greater preference for the design value by all design agents. The JOP curve data designated which design values were worth investigating further, and was used by a Chief engineering agent to narrow the set-range for further negotiations; Figure 1.6. Subsequent negotiations typically resulted in changes to the JOP values as design agents learned more about the design and the set-ranges for the design variables was reduced.

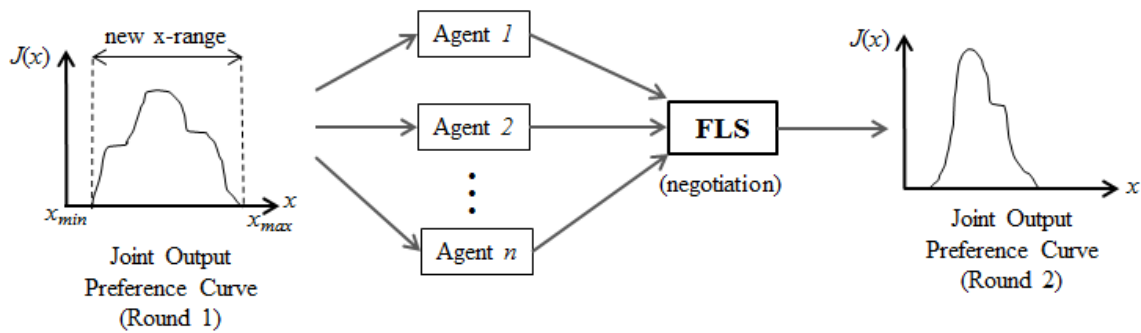


Figure 1.6 T1 FLS Negotiation Example, Round 2 Negotiation of the New x -Range with Subsequent Change in JOP Curve

Singer has shown in his dissertation that it is indeed possible to help facilitate SBD practices through the use of a computational design tool. However, Singer utilized a T1 FLS that cannot truly represent design uncertainty because, once defined, a T1 FLS is comprised of fully known mathematical equations [Mendel and John, 2002]. The studies undertaken recently were done to discover if additional improvements to the FLS and the facilitation of SBD practices could be accomplished by introducing a true representation of design uncertainty via T2 FL methods. In these studies, newly developed interval type-2 modeling (IT2M) and general type-2 (GT2) FLSs were used to create SBD environments which were applied for preliminary ship design. The newly developed FLSs attempt to provide true uncertainty modeling and an increase in the level of information available to human design agents for SBD communications. By improving the ability to model design uncertainty, the new design environments should help to further promote the SBD principles of communication and delaying early design decisions until one can make well-informed decisions.

The advantages for SBD cannot be ignored, but the difficulties and risks of attempting to implement a corporate-wide change in design methodology required to implement SBD

are monumental. Ward et. al. state, “Since there is no proven formal methodology (for SBD), learning the process will be slow and error-prone ... a U.S. company would have to develop a more formal approach” [Ward, et. al., 1995]. If the author can show improvement in the application of set-based practices through use of a FLS SBD tool with uncertainty modeling capabilities, then the FLS could be used by a company as a tool to formally integrate SBD concepts, thus reducing the total risk of incurring losses during the transition to, and implementation of, SBD. Liker et. al. expressed a need for SBD tool research and the need to, “develop tools which facilitate a proper exchange of information ... information that reflects the inherent ambiguity and imprecision of design decisions” [Liker, et. al., 1996]. The research conducted by the author aimed to directly fulfill the clear need for a design tool to implement the exchange of uncertain information and to facilitate the SBD process.

Of the two new approaches studied for the facilitation of SBD, the first method consists of an IT2M FLS that utilized T1 FL methods in conjunction with a randomization technique to model the hypothesized benefits of a true interval type-2 (IT2) FLS. For the IT2M FLS approach, the author developed four different methods of randomization; the key process behind the modeling methods. The IT2M approach and the four randomization methods will be discussed in detail later in Chapter 3. The second SBD FLS method was developed using a general type-2 (GT2) FLS to provide an additional level of uncertainty modeling that cannot be achieved by a T1 FLS or an IT2 FLS; the reasons for this are discussed in the coming chapter. The additional design information provided by the newly developed SBD FLSs stem from the abilities of the new FLSs to describe and model design uncertainty using IT2M and GT2 FLS methods.

As mentioned in Section 1.2.1, one of the main principles of SBD is to purposefully delay making early-stage design decisions until all design trade-offs are more fully understood [Bernstein, 1998]. An increased understanding of design decisions can be developed through further analysis of design solutions, as well as the accumulation of design data and information. The gathering of detailed design information represents a reduction in the uncertainty about the choices for design variables. Reduction of uncertainty through the analysis of solution sets allows for more informed and potentially less risky decisions. Since early design decisions have the greatest effect on the cost of a project, delaying decisions, although counter-intuitive to most design methods, reduces uncertainty and leads to more robust designs [Bernstein, 1998]. As such, any increase in the ability to communicate information, especially uncertainty, is highly desirable.

This research aims to determine if improvements to the facilitation of the SBD process can be achieved in the areas of communication of design information, modeling of design uncertainty, and other core SBD principles.

CHAPTER 2

UNCERTAINTY & FUZZY LOGIC SYSTEMS

This chapter serves to introduce the reader to the concepts of uncertainty in communications and design, as well as the concepts of fuzzy set theory and fuzzy logic, and how they are applied to model uncertainty. The intention is to provide a brief introduction of these concepts so the reader may be familiar with terminology and the general theories applied throughout the described research. For a more in-depth discussion on these topics the reader is directed toward [Mendel, 2001] [Cox, 1999] [Castillo, et. al., 2007] [Mendel, 2007] [Mendel and John, 2002] [Mendel, John, and Liu, 2006] [Mendel, 1995].

2.1 Uncertainty in Communication & Design

Communication is a core concept of the SBD philosophy. Yet, communications are fraught with uncertainties and vagueness. Wallsten and Budescu state, in reference to information, that, “Except in very special cases, all representations are vague to some degree in the minds of the originators and in the minds of the receivers” [1995]. This statement implies that all information possess a degree of uncertainty, whether the information itself is a non-crisp, uncertain value, or a crisp, totally known value.

In human communications, “words mean different things to different people, and are therefore uncertain.” [Mendel, 2007]. There exist two types of uncertainty about a word,

the intrapersonal uncertainty, which is “the uncertainty that a person has about the word”; and interpersonal uncertainty, which is, “the uncertainty that a group of people have about the word” [Wu and Mendel, 2010] [Mendel, 2007]. Even when information is itself inherently certain, the information can be perceived as uncertain by the person receiving or conveying the information. The perception and conveyance of information is greatly affected by the method of communication used.

Humans have the ability to communicate in terms of both numerical and linguistic forms. Each form of communication is, “sensitive to the degrees of vagueness inherent in the events being described, the sources of uncertainty, and the nature of the communication task” [Wallsten and Budescu, 1995]. Research has shown that given a choice, humans prefer to communicate information to others linguistically, since they feel this mode of communication is more capable of conveying inherent uncertainty. Yet, when receiving information from others, humans generally prefer numerical communications, since they view this information to be less uncertain [Wallsten and Budescu, 1995].

To communicate in such a way, it is necessary to have a translator to map the linguistic terms from the person conveying information, into numerical terms for the person receiving the information. It has been suggested that fuzzy logic systems (FLSs) can be used as the method to both represent linguistic terms (called Computing With Words) and convey numerical uncertainty [Lawry, 2001] [Lawry, Shanahan and Ralescu, 2003] [Mendel, 1999] [Wang, 2001] [Zadeh, 1999] [Wallsten and Budescu, 1995] [Wu and Mendel, 2009]. Figure 2.1 & Figure 2.2 illustrate a simple example demonstrating the purpose of information translation for conveying and receiving both linguistic and numeric information and communications.

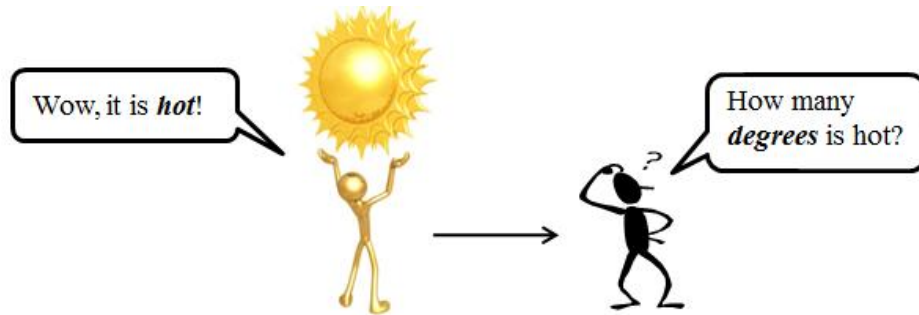


Figure 2.1 A Typical Communications Example

In Figure 2.1, the character is trying to linguistically emphasize that it is very hot. However, this linguistic description is perceived with uncertainty by the character on the right, leaving the character wanting to know a numeric value which could describe precisely how hot it is. Figure 2.2 illustrates how an FLS helps to achieve the preferred communications scheme by translating the linguistically conveyed temperature to a numerically received value. The nature of the communication methods utilized by the characters in Figure 2.2 facilitates the translation of information in a manner that is perceived as having the least amount of uncertainty by both the conveyor and receiver of the information.

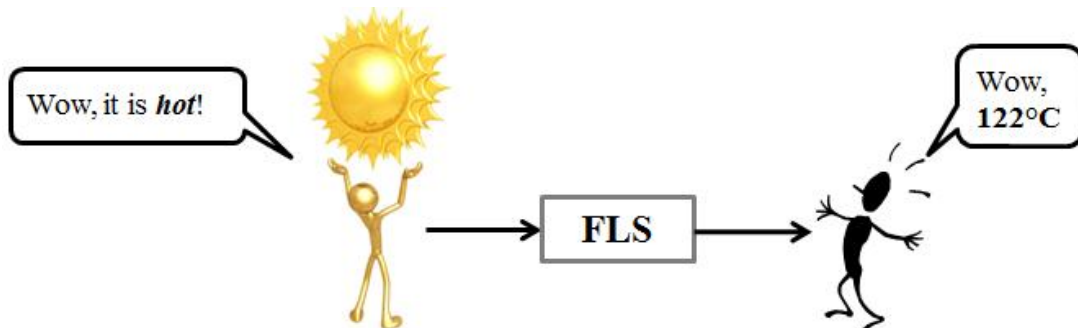


Figure 2.2 Preferred Communications Achieved By Data Transformation Via FLS

The process of designing complex systems involves vast amounts of communication between different functional design groups. The communication process begins when design groups are first provided a set of design constraints. The design constraints are supplied with the intention of guiding the development of the design. It is at this pre-design stage that uncertainty is first introduced into the design via the design constraints. Design constraints can be provided both numerically and linguistically. In a design ship for example, there may be a constraint that states, “The engine room may not be near the sleeping berths.” or more specifically that, “The engine room may not be within 30 m of the sleeping berths.” The linguistic constraint obviously possesses a degree of uncertainty. The uncertainty of the linguistic constraint lies in the definition of the words, “not near”. As for the numerical constraint, traditional cognition frames the idea of a numerical constraint as a crisp and rigid design constraint; set-based design, however, challenges this way of thinking.

When defining a numerical constraint there is often some associated uncertainty that is typically represented by a provided tolerance. Continuing with the engine room example, “ 30 ± 1 m”, may be a provided constraint. With this discrete constraint, the goal is to get as close to 30 m as possible. During a point-based design it may be necessary to deviate from the 30 m ideal value to satisfy some other design constraint and maintain a feasible solution. In this case, the value is chosen out of necessity; it was not specifically designed for.

In set-based design, the uncertainties of numerical constraints are represented by utilizing sets of design values, instead of a single value with an allowable tolerance; in example [27,33] m. As described, the point-based design approach would try to get the sleeping

berths exactly 30 m away from the engine room. In contrast, the set-based approach would enumerate design solutions based on values within the set-range of [27,33] m and then determine the design trade-offs for each enumeration. The larger range of [27,33] m would be chosen since at the beginning of the design the allowable range of design values is unknown; SBD is utilized to narrow in on the allowable set-values. With the set-based approach, design solutions naturally evolve and a value other than 30 m would be chosen only if trade-off analyses showed the design solution to be superior.

Unlike the SBD approach, the point-based design approach does not explore the solution space unless forced to because of a need to make up for design inadequacies. Thus, using point-based design a superior design may be missed simply because the design parameters chosen at the beginning of the design spiral were based on achieving the tightest tolerances possible. The SBD approach purposefully develops sets of solutions to determine the optimal solution. Significant cost savings can be achieved using SBD as designers have the opportunity to consider tradeoffs in the preliminary design stage before making decisions that influence the remainder of the design process [Ward, et. al., 1995].

2.2 Fuzzy Logic for Uncertainty Representation

As demonstrated by the example in the previous section, a FLS can be used to translate between different data types and represent design uncertainty. In the paper, “Impacts of Fuzzy Logic Modeling for Constraints Optimization”, Gray, Daniels, and Signer describe how fuzzy logic can be used to represent the uncertainty inherent in design constraints for the allocation and arrangement of ship spaces [2010]. In a FLS, data translation, as well

as uncertainty representation, is accomplished using fuzzy logic and fuzzy set theory. Fuzzy methods are capable of handling uncertainty due to imprecise and vague language or values [Wallsten and Budescu, 1995] [Zhou and Zenebe, 2008] [Wang and Terpenney, 2003] [Mendel, 2001]. Mathematical functions, called membership functions (MFs), are used in an FLS to represent uncertain data. The MFs can be defined over a set of values and may have different spread or shape, all of which vary based on the context and method of communication the functions represent [Wallsten and Budescu, 1995].

Fuzzy logic systems not only represent uncertainty, but also, “exploit uncertainty in an attempt to make system complexity manageable.” [Zhou and Zenebe, 2008], and, “provide smarter and smoother performance than do traditional systems.” [Chen, 2001]. For these reasons, fuzzy logic was chosen for use by the author to develop a design tool capable of representing the inherent uncertainty in forms of both linguistic and numerical communication, each of which are essential components of SBD philosophy.

2.3 Fuzzy Set Theory

Fuzzy set theory operates by utilizing sets of values which allow for fuzzy decisions, as opposed to crisp theory which works with discrete numerical values and forces crisp decisions. To illustrate the difference between fuzzy and crisp theories, consider the example of trying to classify people as either *not tall* or *tall*. In this example, people represent a universe of discourse P , which is a set of all possible people/values, x [Mendel, 1995]. The sets *not tall* (NT) and *tall* (T), represent subsets of the universe of discourse P . Choosing the NT classification set, crisp theory is explained in further detail.

A crisp set of values is described by listing all values $x \in NT$. The listing of values can be described mathematically by utilizing a relationship such as that expressed by the general terms of Eqn. (2.1) or by a special zero-one membership function (MF), $\mu_{NT}(x)$; Eqn. (2.2). With crisp theory, the degree of membership in a set is described by a membership grade, $\mu(x)$, equal to either one or zero. This means that all values from the universe of discourse are either 100% in the set or 100% out of the set. This mathematical relationship is demonstrated Eqn. (2.2).

$$NT = \{x|x \text{ meets some condition}\} \quad (2.1)$$

$$NT \Rightarrow \begin{cases} \mu_{NT}(x) = 1, \text{ if } x \in NT \\ \mu_{NT}(x) = 0, \text{ if } x \notin NT \end{cases} \quad (2.2)$$

The commonly used condition for a set definition like that of (2.1) involves the use of a decision point, also called a cut-off point. In crisp theory, a decision point is a crisp numeric value. Typically, values from the universe of discourse will be sorted into a set based on whether or not the values are less-than, equal-to, or greater-than the value of the decision point. The use of a decision point forces the choice of a single discrete value for set-classification purposes.

Continuing with the height classification example, to sort people into sets of NT and T , a crisp decision point must be chosen when utilizing crisp theory mathematics. Below the decision point people are considered to have 100% membership in the *not tall* set, with $\mu_{NT}(x) = 1$ and $\mu_T(x) = 0$ for $x < x_{decision}$, and above this point they are considered to have 100% membership in the *tall* set, with $\mu_{NT}(x) = 0$ and $\mu_T(x) = 1$ for $x > x_{decision}$. Using crisp theory, a person/value can have membership in only one set. The relationship

for the decision criteria for height classification is represented by the crisp zero-one MFs of Figure 2.3. Notice that in Figure 2.3 the crisp decision point was set at a height value of $x_{decision} = 70$ inches.

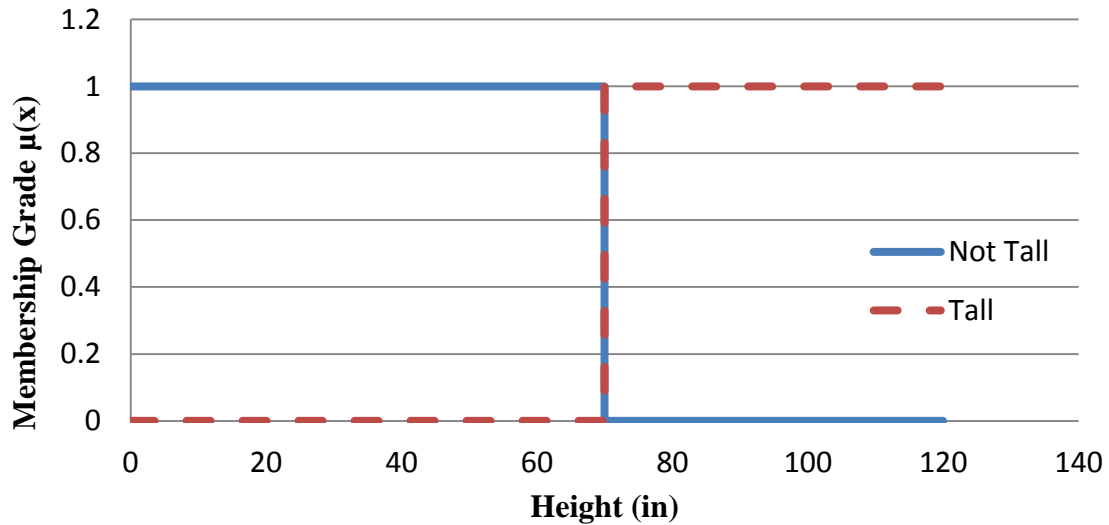


Figure 2.3 Crisp Membership Functions for Sets *Not Tall* and *Tall*

In reality, the classification of people to height categories is not as simple as implied by the use of the crisp MFs. There are vagaries inherent in linguistic descriptions. For one, words themselves may mean different things to different people [Mendel, 2007]. The description of someone's height is affected by the relative height of the individual making the classification. As height is a relative description, a person who is 6'10" might consider someone 6' to be *not tall*, but a person who is 5'4" might consider the same 6' person to be *tall*. Because of the inherent uncertainty associated with linguistic and numeric values, the true nature of the transition from the sets *not tall* to *tall* is much better represented using fuzzy set theory.

Using fuzzy set theory, we can describe a gradual transition from 100% membership in the *not tall* set, to 100% membership in the *tall* set, while in between there exists varying degrees of membership in both sets simultaneously. Figure 2.4, shows how fuzzy MFs are used to represent the gradual change in degree of membership in *not tall* and *tall* fuzzy sets.

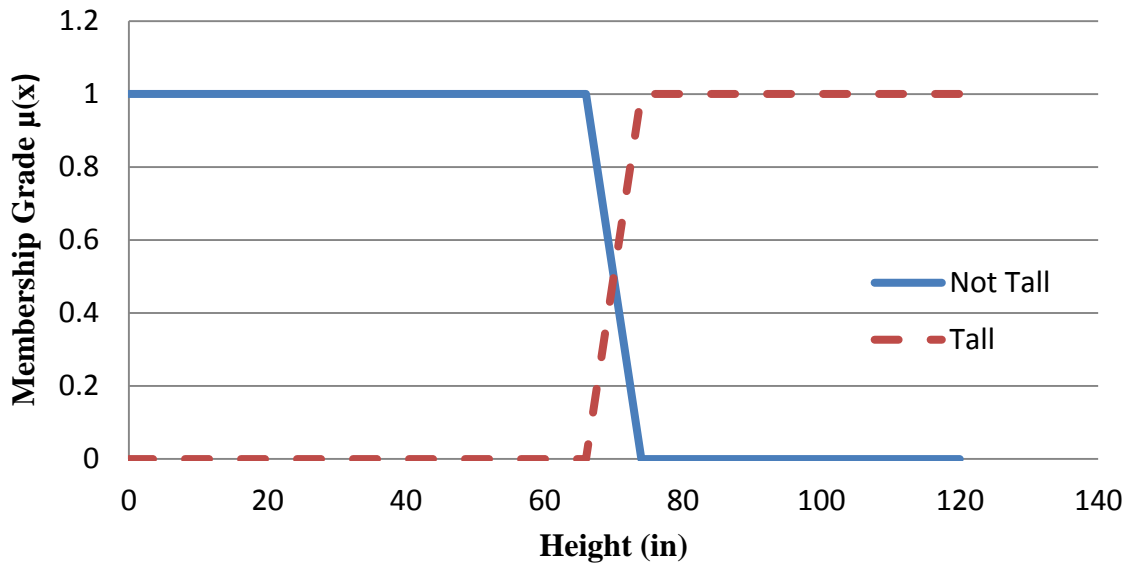


Figure 2.4 Fuzzy Membership Functions for Sets *Not Tall* and *Tall*

Continuing with the use of the *not tall* set, the fuzzy MF for the *NT* set, in the universe of discourse P , can be described using a MF comprised of sets of ordered pairs; equations (2.3), (2.4), (2.5). The order pairs consist of the height value x and the membership grade, $\mu_{NT}(x)$.

$$NT = \{(x, \mu_{NT}(x)) \mid x \in NT\} \quad (2.3)$$

$$NT = \sum_P \mu_{NT}(x)/x \quad (2.4)$$

$$NT = \int_P \mu_{NT}(x)/x \quad (2.5)$$

Unlike the zero-one membership grade of a crisp MF, a fuzzy MF grade may be any of the values in the set [0,1]. Equation (2.3) provides a general description of a fuzzy set, (2.4) is commonly used to describe a fuzzy set that contains only discrete values, and (2.5) describes a fuzzy set with continuous, real-numbered values. In equation (2.4), the summation sign does not actually denote arithmetic addition, but instead represents the set theoretic operation of union, which is the collection of all values $x \in P$ along with the associated MF $\mu_{NT}(x)$. Similarly, the integral sign in equation (2.5) does not represent true arithmetic integration. It, too, is used to represent the collection of all values of $x \in P$ along with the associated MF $\mu_{NT}(x)$.

In both equations (2.4) & (2.5) the slash is used as a reminder that each of the values $x \in P$ is associated with a fuzzy membership grade $\mu_{NT}(x)$. The above terminology and description of fuzzy sets was adapted from an explanation of fuzzy sets provided by Mendel [1995] in, “Fuzzy Logic Systems for Engineering: A Tutorial”, and was used by Mendel to describe automobiles. For additional information on fuzzy set theory see [Mendel, 2001], [Kluwer Academic Publishers, 2001], and [Nguyen and Walker, 2006].

2.4 Fuzzy Logic Systems

Currently there exist three main types of FLSs, the Type-1 (T1), Interval Type-2 (IT2), and General Type-2 (GT2) FLSs. The IT2 and GT2 FLSs are both specific system types

within the broad category of Type-2 FLSs. The differences between the Type-1 and Type-2 FLSs are detailed in the Section 2.4.1 and Section 2.4.2.

2.4.1 Type-1 Fuzzy Logic System

Type-1 FL has been used to represent uncertainty in design variables for numerous applications such as HVAC systems, systems controls, ship arrangements, and medical analyses [Ning and Zaheeruddin 2009] [Liu and Li, 2005] [Gray, Daniels, and Singer, 2010] [Garibaldi, 1997]. A T1 FLS has four main components; a fuzzifier, fuzzy rule bank, fuzzy inference engine, and defuzzifier [Mendel, 2001]; Figure 2.5. As shown in Figure 2.5, the T1 FLS takes in crisp valued inputs x and uses the fuzzifier to create the fuzzy input sets, which then pass through the fuzzy inference process activating rules in the fuzzy rule bank. The fuzzy rules are then used to guide the defuzzification to a translated crisp output value y .

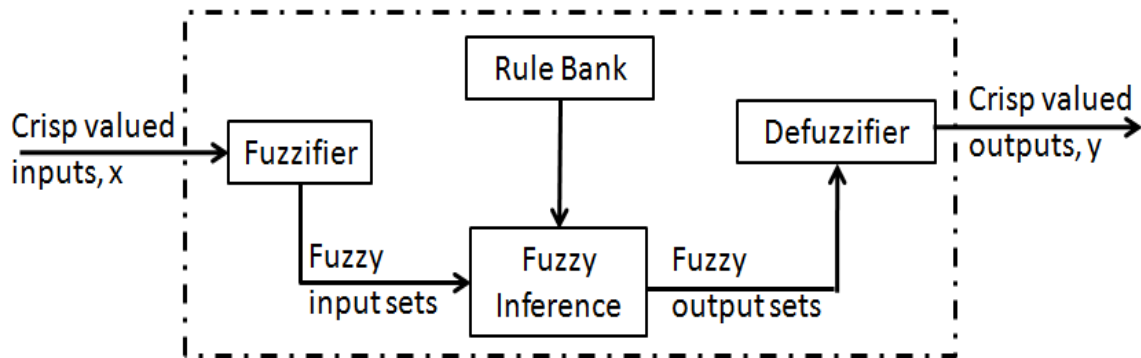


Figure 2.5 Type-1 FLS Components and Processes, Adapted from [Mendel, 2001]

A T1 FLS attempts to represent uncertainty using T1 MFs and fuzzy set theory. In FLSs the typical membership function types include Gaussian (Figure 2.6), Sigmoidal, Trapezoidal (Figure 2.7), and Triangular, as well as many other curve shapes. In the

author's SBD environment, the x -axis represented the individual set values from minimum to maximum, referred to as the "set-range"; $[x_{min}, x_{max}]$. The membership grade of each MF, $\mu_i(x)$, was used to represent the preference value, which was displayed on the y -axis. Note that in Figure 2.7, as well as the author's FL SBD environment, the trapezoidal MF points have a maximum preference value of one and a minimum of zero. The $[0,1]$ scale is typically used in FLSs, especially engineering applications [Cox,1999], as it maintains a logical correlation to percentages 0-100%, allows for the sum of membership grades to be held equal to one, and facilitates comparatively simplistic mathematical computations.

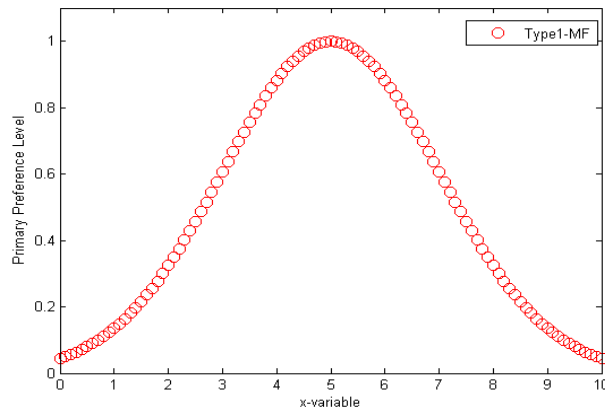


Figure 2.6 Type-1 Gaussian MF

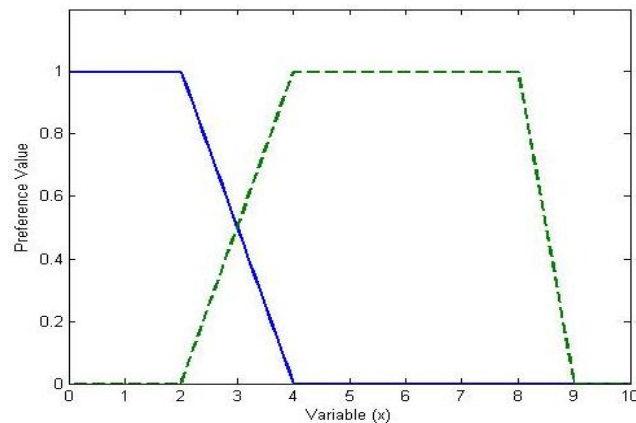


Figure 2.7 T1 Trapezoidal MFs

Type-1 Fuzzy Logic Example

The following example was reproduced with permission from Dr. David J. Singer's Ph.D. dissertation entitled, "A Hybrid Agent Approach for Set-Based Conceptual Ship Design Through the Use of a Fuzzy Logic Agent to Facilitate Communications and Negotiation", [Singer, 2003]. The purpose of the T1 FLS example is to demonstrate the concepts of FL, fuzzy set theory, and the basic operations of a T1 FLS. The theories described in this example are expanded upon when discussing the IT2M and GT2 FL SBD tools later on.

In the example, the goal was to determine a person's level of risk for a heart condition, the FLS output value, given their height and weight, the FLS input values. To begin, the weight variable was classified into three linguistic fuzzy sets Thin, Average, and Heavy; $Weight = \{Thin, Average, Heavy\}$. The height variable was then classified into three linguistic fuzzy sets Short, Average, and Tall; $Height = \{Short, Average, Tall\}$. The FLS output, heart condition risk level was classified into four categories, represented by the linguistic fuzzy set Risk Level = {Low, Average, Moderate, High}.

Given a human subject with inputs values of weight equal to 130 pounds (lbs) and height equal to 5' 3", Figure 2.8 shows the mapping of the subject's specific height and weight to the fuzzy values of each input set. In the first FLS step, the subject's input values were fuzzified into the individual fuzzy sets of weight and height. The weight value of 130 lbs mapped to the fuzzy sets Thin & Average, with membership grades of $\mu_{W-Thin}(x) = 0.5$ and $\mu_{W-Average}(x) = 0.5$, respectively. The height of 5' 3" mapped to fuzzy sets Short and Average, with membership grades $\mu_{H-Short}(x) = 0.8$ and $\mu_{H-Average}(x) = 0.2$.

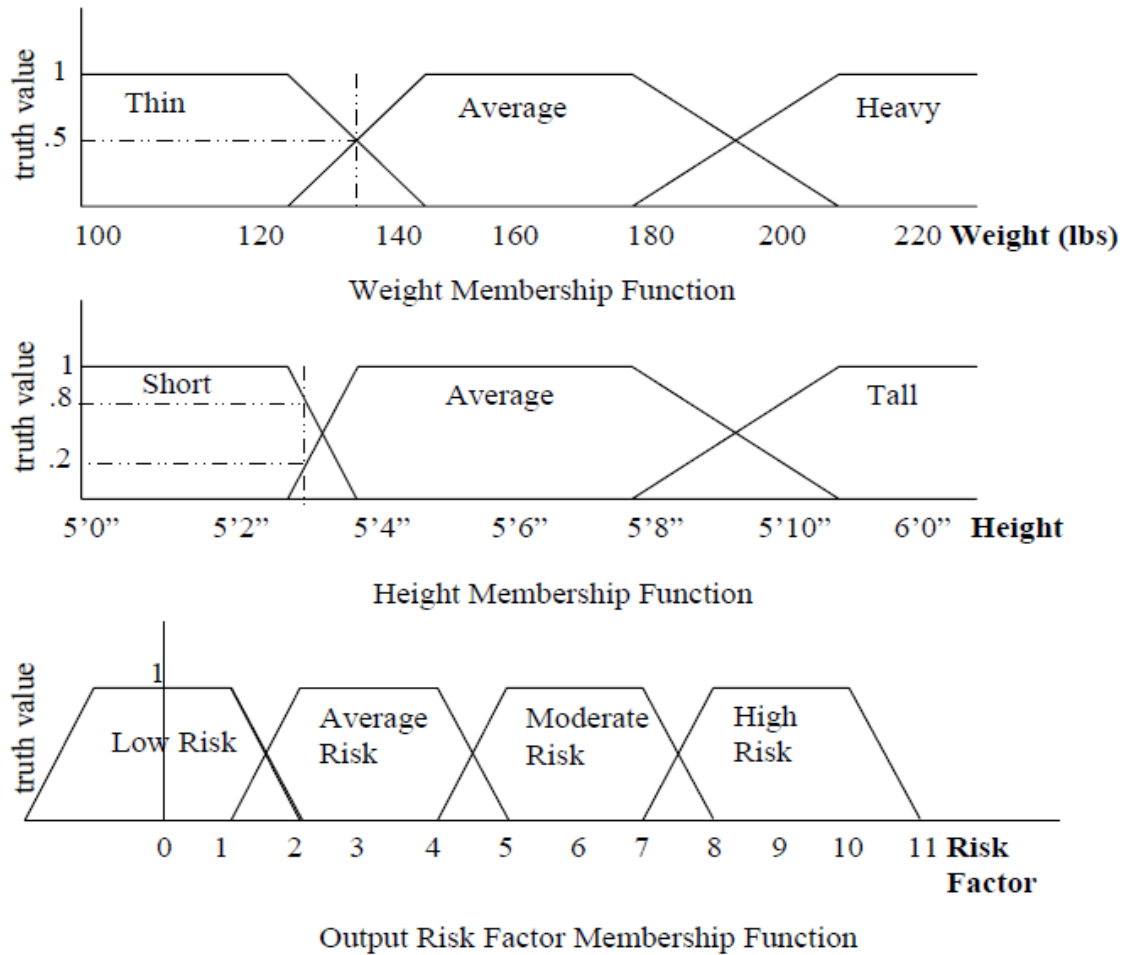


Figure 2.8 Input Fuzzy Sets of Weight & Height for a Heart Condition Risk Level T1 FLS Example

Notice how for both fuzzy variables the sum of membership values was always equal to one. Next the membership grades of the fuzzy values were passed through the fuzzy rule bank, activating fuzzy rules which link input values to output sets. A fuzzy rule bank typically consists of rules with a general IF (antecedent) ... THEN (consequent) expression, written as:

$$\text{IF } X_1 \text{ is } A_1 \text{ AND } \dots \text{ AND } X_m \text{ is } A_m, \text{ Then } Y \text{ is } C. \quad (2.6)$$

In equation (2.6) X_m and Y were fuzzy variables, A_m and C were fuzzy input and output sets, respectively, and there were 1 ... m total input values. The rules of a FLS have considerable impact on the output of the FLS since the rules provide the link between the inputs and output of the FLS. Figure 2.9 shows how the linguistic input fuzzy sets mapped to the various linguistic fuzzy rules and matching linguistic fuzzy output sets for heart condition Risk Level.

	Thin	Average	Heavy
Short	Low Risk	Moderate Risk	High Risk
Average	Low Risk	Average Risk	High Risk
Tall	Low Risk	Low Risk	Moderate Risk

Figure 2.9 Fuzzy Rule Bank for Heart Condition Risk Level T1 FLS Example

Based on the subject's input fuzzy set values for weight and height variables, four fuzzy rules were activated. The four activated rules as indicated by the shaded areas in Figure 2.9 are written as:

- IF Weight is Thin AND Height is Short, THEN Risk Level is Low
- IF Weight is Thin AND Height is Average, THEN Risk Level is Low
- IF Weight is Average AND Height is Short, THEN Risk Level is Moderate
- IF Weight is Average AND Height is Average, THEN Risk Level is Average

After a fuzzy rule was activated, fuzzy inference was used to determine the activation level of the consequent output fuzzy set. The most common inference method is minimum-correlation inference [Cox, 1999]. This inference method is associated with the use of the linguistic modifier AND in fuzzy rules. For the two inputs of this FLS, the minimum-correlation inference equation was:

$$\min\{\mu_W(x_i), \mu_H(x_i)\} \quad (2.7)$$

The minimum-correlation inference process is pictorially demonstrated in Figure 2.10. Looking at the first rule combination, Thin AND Short, the membership grades were $\mu_{W-Thin}(x) = 0.5$ and $\mu_{H-Short}(x) = 0.8$, respectively, and the consequent (activated) output fuzzy set was *Low Risk*. Minimum-correlation resulted in the *Low Risk* fuzzy set being clipped-off at the 0.5 activation level as this was the minimum of the activating membership grades. The clipped MF area is represented by the shaded area labeled **A** in Figure 2.10.

The final step of the FLS process was defuzzification of the fuzzy value back to a crisp output value. Of the many available defuzzification methods, centroid defuzzification is the simplest method. Cox [1999] provides information on how different defuzzification methods affect the FLS output. The centroid defuzzification method works by essentially finding the x -location of the center-of-mass of the clipped output fuzzy sets. Centroid defuzzification can be expressed using:

$$J(x, \mu(x)) = \text{defuzzified crisp value} = \frac{\sum_r \bar{a}_r x_r}{\sum_r \bar{a}_r} \quad (2.8)$$

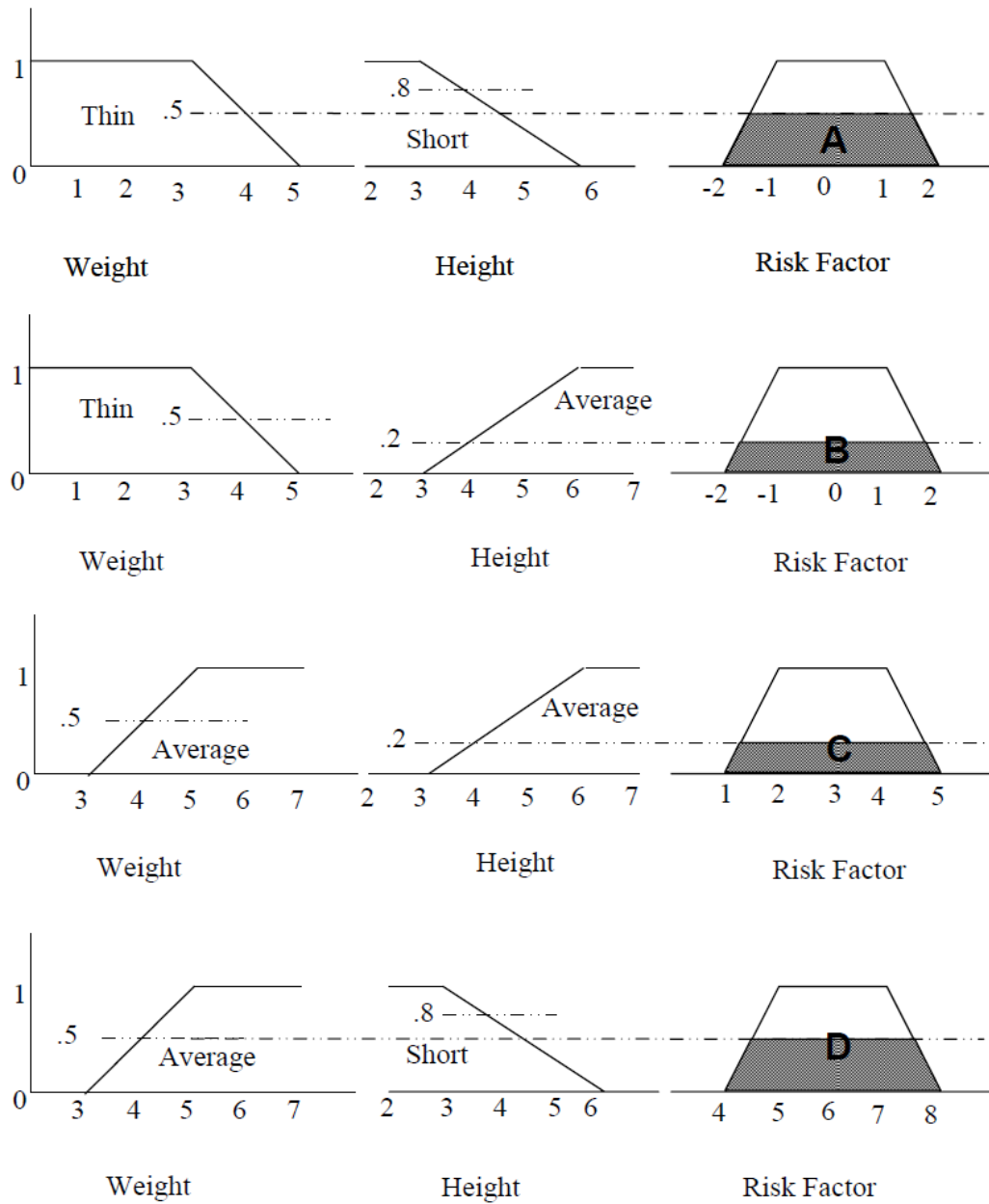


Figure 2.10 Fuzzy Logic Inference Process for Heart Risk Level Example

In equation (2.8), \bar{a}_r represents the area of a clipped output preference fuzzy set, x_r is the centroid of the corresponding output preference fuzzy set, and the subscript r represents the 1 ... r activated rules at the input value x .

Figure 2.11 shows the calculated areas for each of the activated and clipped output fuzzy sets. These values are used in the centroid defuzzification function (2.8) to calculate the crisp output value of heart condition risk level.

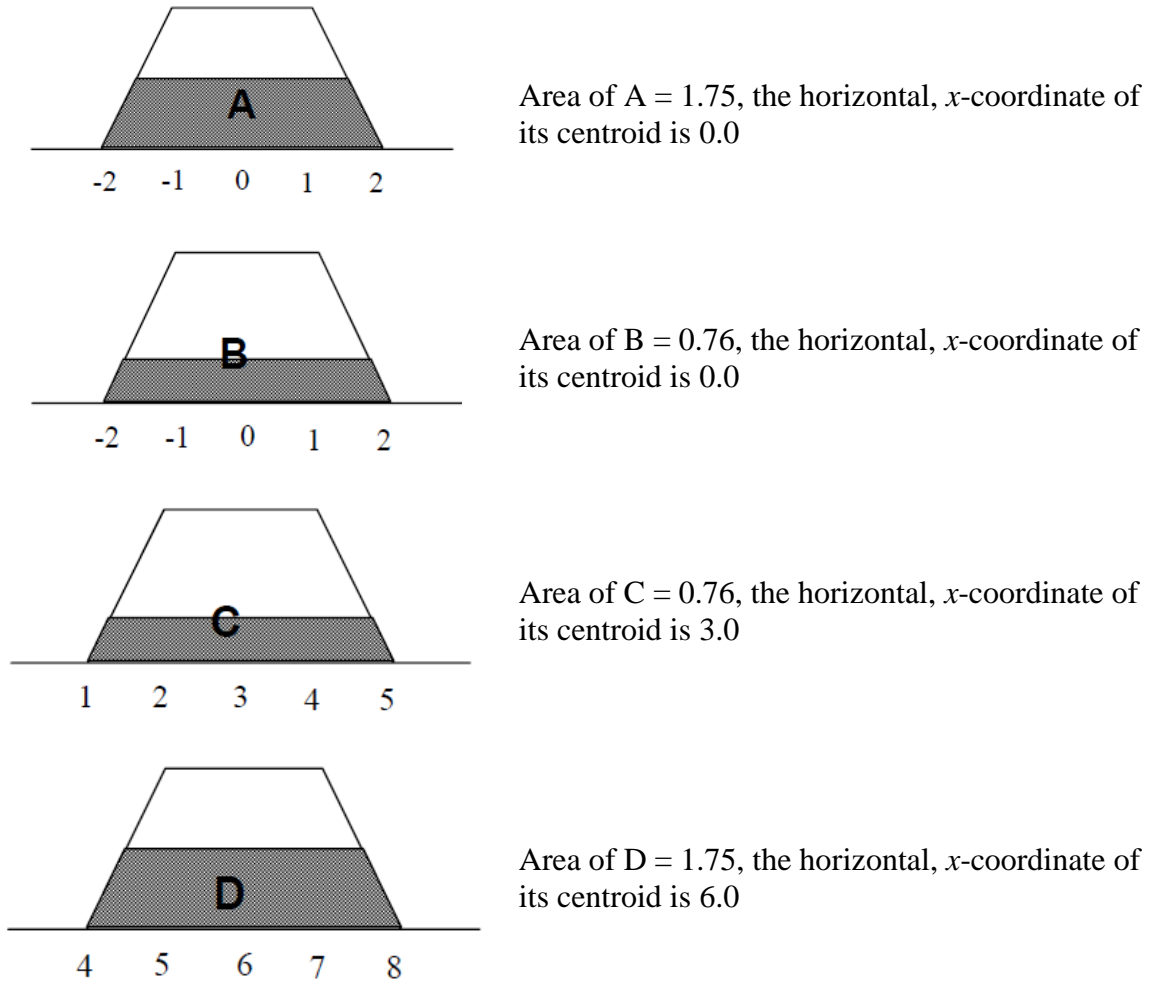


Figure 2.11 Clipped Areas and Centroid Values of Activated Output Fuzzy Sets

After centroid defuzzification, the crisp output for the example subject was a heart condition risk level of $J(x, \mu(x)) = 2.55$ on a scale of $[0,9]$ with zero being the lowest possible risk and nine being the highest possible risk. Linguistically this would translate to an *Average Risk Level*.

A similar methodology was utilized for the FLSs of this research. Chapter 5 provides extensive detail on the T1 FLS SBD method as well as a thoroughly explained example applied to a ship design variable. For now, to briefly frame the context of the coming discussions, the reader should be aware that the T1 FLS utilized fuzzy input sets and then output a set of values in the form of the Joint Output Preference (JOP) curve.

For the author's research, the FLSs were applied to the SBD of a containership. Preference for set-values of ship design variables were described by human design agents using linguistic MFs of Unpreferred (U), Marginal (M), and Preferred (P). The FLS output a joint output preference (JOP) curve that represented the overall preference for the individual set-values from within a large range of values for a design variable. The JOP curve information provided an understanding of which design values were most preferred by all design agents for the ship design. A generic example of the T1 FLS SBD fuzzy input sets and JOP curve output is shown in Figure 2.12.

The Cargo and Stability design agents are negotiating the KGc design variable, with a set-range of [0,15] m. The Cargo agent has chosen the U and M MFs to describe preference for the set values, while the Stability agent has chosen P and M preference MFs. A star symbol was used in Figure 2.12 to indicate the beginning of the M MF for the Cargo design agent and a triangular symbol was used to indicate where the Cargo agent's U MF ended. The FLS swept across the set of input values from x_{min} to x_{max} creating the JOP curve. The JOP curve in Figure 2.12 had JOP values of zero up to the KGc value indicated by the star symbol because up to this point the Cargo agent was 100% Unpreferred and the Stability agent 100% Marginal for the set-values. As the

Cargo agent's preference transitioned from U to M the JOP curve transitions from zero to the value of three, at which point the Cargo and Stability agents are both of Marginal preference at a level of 100%. This process is explained in greater detail in Chapter 5.

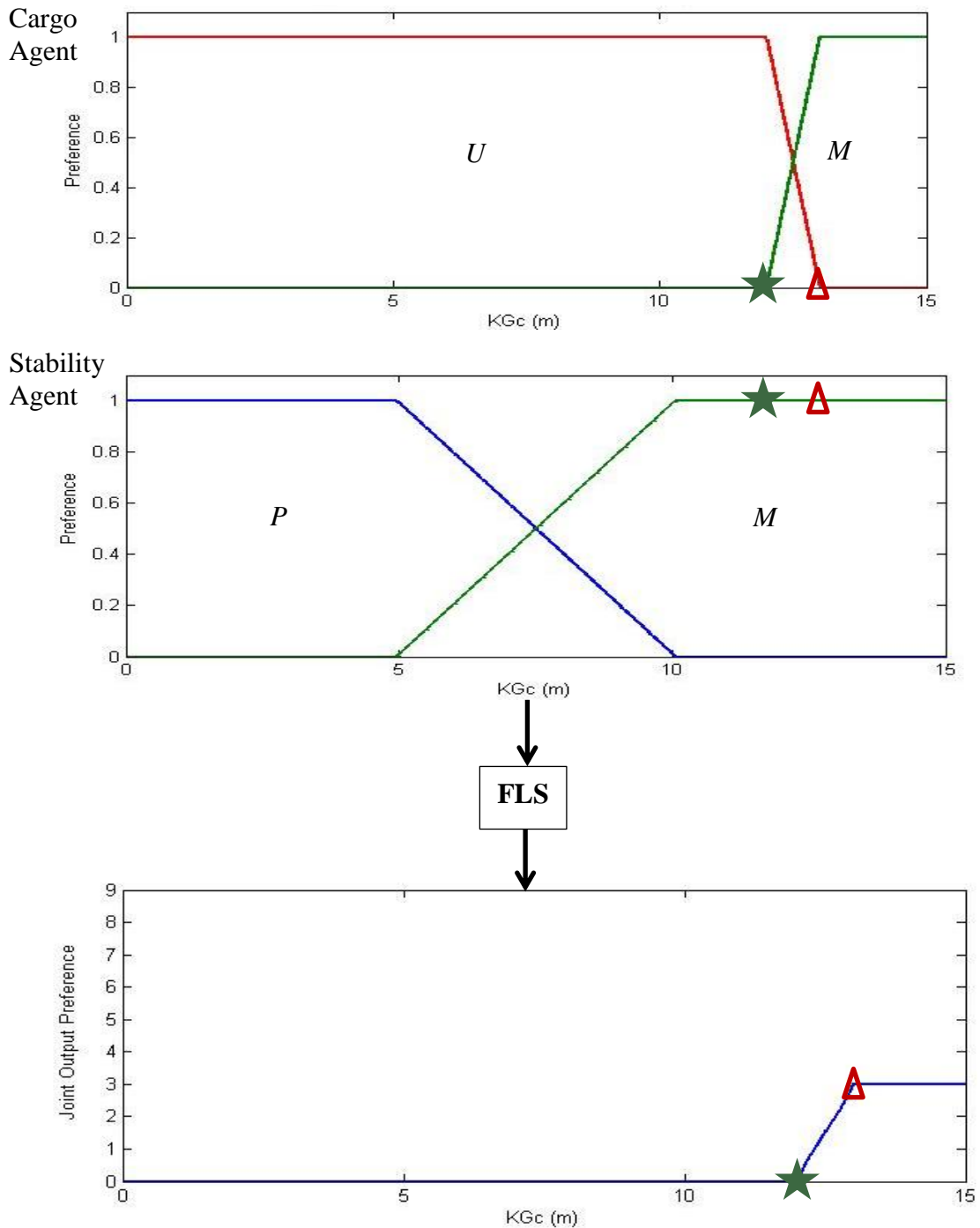


Figure 2.12 Generic Example of T1 FLS SBD Fuzzy Input Sets and JOP Curve

The heart risk level example and the generic SBD FLS example (Figure 2.12) briefly demonstrated one of the most common FLSs, the T1 FLS, which is the simplest FLS, both theoretically and computationally. The simplicity of a T1 FLS also limits its capabilities. In a T1 FLS, T1 FL MFs are inherently certain in the sense that a known function is being used to describe an uncertain value [Mendel, 2001]. In their paper, “Type-2 Fuzzy Sets Made Simple”, Mendel & John [2002] describe four sources of uncertainty that are present in the declaration of T1 fuzzy sets and state that, “Type-1 fuzzy sets are not able to directly model (these) uncertainties because their MFs are totally crisp”. To handle these additional uncertainties T2 FL was developed.

2.4.2 Type-2 Fuzzy Logic Systems: Interval Type-2 & General Type-2

Type-2 FL is capable of modeling an extra degree of uncertainty. The uncertainty modeling allows for representation of the inherent uncertainty associated with the creation of MFs for a T1 fuzzy set. It is hypothesized within this thesis that the extra degree of uncertainty modeling provided by a T2 FLS will allow for better communication of design information, and thus further enhance the promotion of set-based communication of information during a SBD process.

There are two sub-categories of T2 FL referred to as interval type-2 (IT2) FL and general type-2 (GT2) FL. In an IT2 FLS, uncertainty is represented in the 2D plane using a MF defined by upper and lower bounds. These bounds can be thought of as the bounds of uncertainty for the primary MF (a T1 MF). Between the upper and lower bounds of an IT2 MF there exists an infinite number of embedded T1 MFs. In Figure 2.13 one can see a primary T1 MF, which is one of the infinite number of embedded T1 MFs, as well as

the upper and lower bounds of uncertainty of the T1 MF. The secondary MFs are slices of the IT2 MF, and are comprised of an infinite number of preference values falling between the upper and lower bounds. In an IT2 MF, the preference values of the secondary MFs, called secondary grades, are all of equal value, meaning that each primary preference value is equally likely to occur; with a GT2 MF this is not the case [Mendel, 2001].

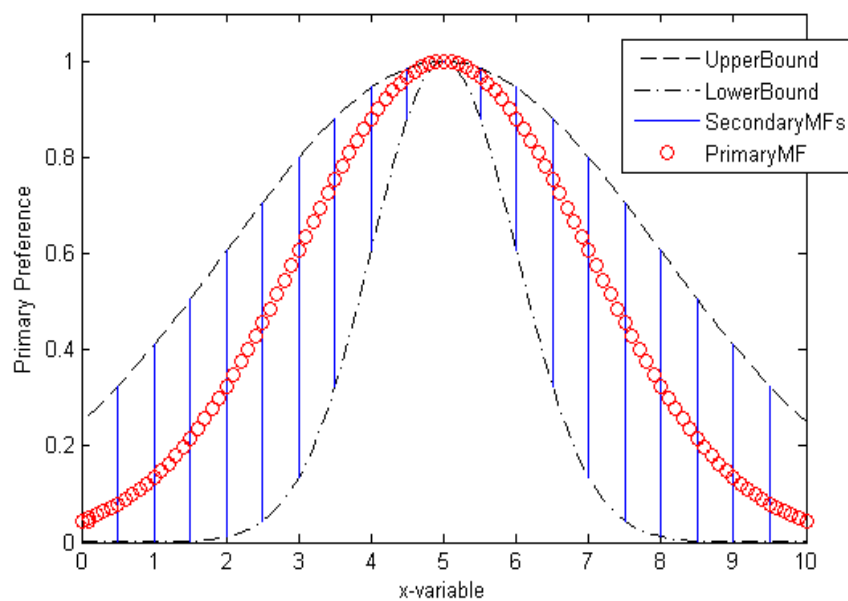


Figure 2.13 Interval T2 Gaussian MF

A GT2 MF uses a third dimension to further represent uncertainty information. As seen in Figure 2.14, the secondary MFs of a GT2 MF are used to represent the varying secondary preference levels for a particular set of primary preference values between the upper and lower bounds of uncertainty [Mendel, 2002]. In a GT2 MF, the secondary MFs are used to add a weighting value to each of the primary preference values between the upper and lower bounds of the function, thereby describing the likelihood of occurrence for each primary preference value.

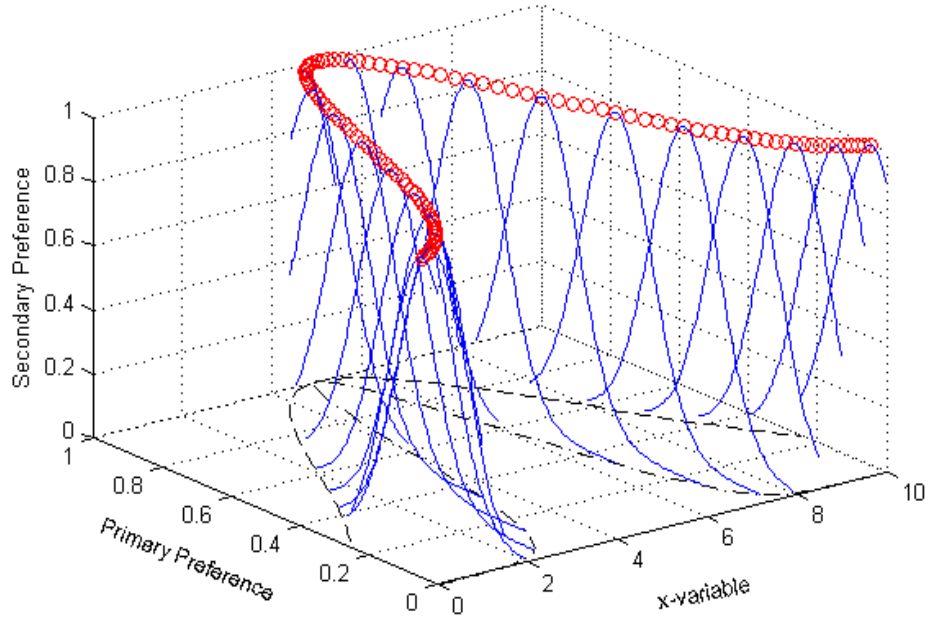


Figure 2.14 General T2 Gaussian MF

In Figure 2.6, Figure 2.13, and Figure 2.14, the progression of uncertainty modeling capabilities from a T1 MF, to an IT2 MF, and finally to a GT2 MF was shown. In Figure 2.6, the T1 MF is a crisp-valued function, where at each value of x there is exactly one membership value $u(x)$; $u(x)$ is also referred to as the preference level. In a T2 MF, the entire set of possible preference values falling between the upper and lower MFs is referred to as the footprint of uncertainty (FOU) for a T2 MF [Mendel, 2001]. If all of the secondary preference levels for the GT2 MF in Figure 2.14 were equal, then the GT2 MF could be represented by an IT2 MF as shown in Figure 2.13.

Type-2 FLSs are much more complex computationally and theoretically than are T1 FLSs because of the additional degree of uncertainty modeling. To deal with the added degree of uncertainty, a T2 FLS includes an additional system component, the type-reducer. The type-reducer is used to reduce the T2 MF inputs to sets of T1 MFs. Figure

2.15 shows a system diagram for a T2 FLS; notice the addition of the type-reducer in the output processing block.

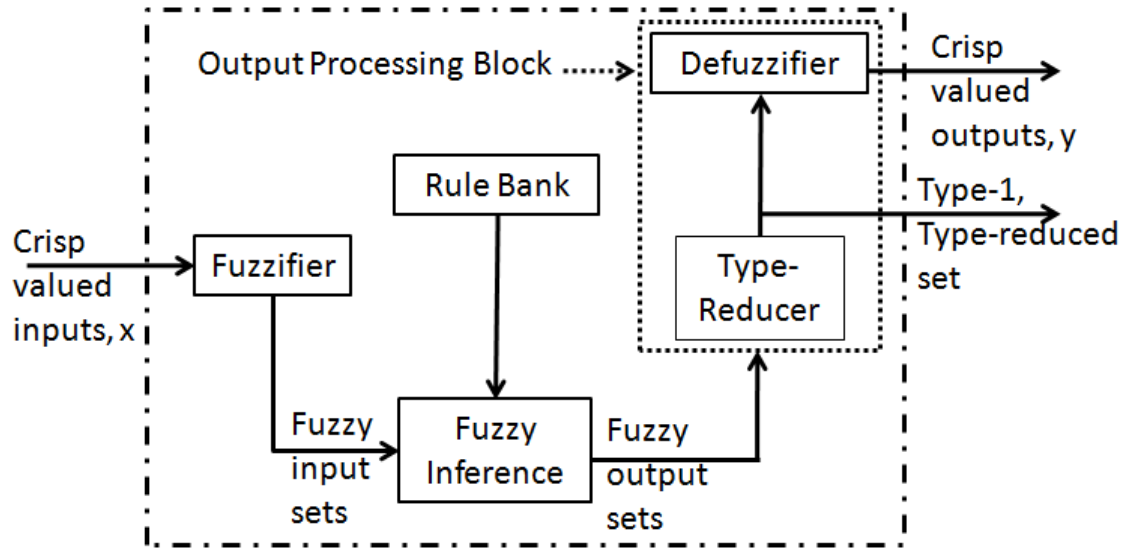


Figure 2.15 Type-2 FLS Components

Each of the different FLSs possesses desirable qualities. The T1 FLS is relatively simplistic in comparison to the T2 FLSs. Yet, the T2 FLSs can model various degrees of uncertainty. The secondary preference level of a GT2 MF is certainly desirable for applications such as the modeling of uncertainty associated with linguistic and numeric values. The combinations of the positive and negative features of the different FLSs led the author to develop a new hybrid FLS method for the modeling of design uncertainty in a SBD process. The following Chapter gives a detailed explanation for the motivation behind the development of the novel FLS, as well as comprehensive description of the system theory.

CHAPTER 3

INTERVAL TYPE-2 MODELING FLS

3.1 Motivation & Inception

Through extensively reviewing the T1 FLS SBD experiments conducted by Singer [2003], it was noticed that Singer did not directly test the robustness of the SBD tool to determine how the tool might react to designs of varying difficulty. A hypothesis was developed that theorized the T1 SBD tool may not be as effective for a difficult, highly constrained, design as it was for the more simplistic, loosely constrained designs in Singer's research. An FLS utilizing IT2 or GT2 FL theory could prove to be more robust and less susceptible to the constraints defining the design problem. The set-based design experimental results later confirmed this hypothesis; see Chapter 8.

In Singer's research [2003], he discussed the use of FL to represent uncertainty and vagueness of linguistic terms. Although T1 FL can be used to represent the fuzzy membership between two sets, T1 FL cannot truly represent uncertainty because T1 MFs are known, well-defined functions consisting of crisp values [Mendel and John, 2002] [Mendel, 2007]. In addition to being unable to truly represent uncertainty, T1 FLSs are themselves uncertain. Sources of uncertainties of T1 FLSs are described by Mendel & John [2002] as including:

- Uncertainty of the words used to describe antecedents and consequents of fuzzy rules.

- Uncertainty associated with the value of consequents, which may best be described by a histogram of values instead of a single crisp (certain) value.
- Uncertainty of the data due to noisy input/output signals or measuring equipment.

The use of T2 FL allows for a more complete representation of the uncertainties associated with design as compared to a T1 FLS. By developing new SBD methods and support tools that utilize T2 FL theory, it is possible to achieve a level of uncertainty representation that could not be accomplished by Singer's T1 FLS SBD tool.

There are numerous methods by which to represent T2 fuzzy sets and perform the type-reduction phase for a T2 FLS. Such methods include approaches like the Karnik-Mendel (KM) algorithms, enhanced KM algorithms, z-slice, α -plane method, wavy slice, point-valued, horizontal slice, and centroid type-reduction [Wu and Mendel, 2009] [Wagner and Hagrass, 2008] [Mendel, Liu, and Zhai, 2009] [Mendel and Liu, 2008] [Liu, 2007] [Nie and Wan Tan, 2008] [Wu and Wan Tan, 2005]. Despite the improvements to speed achieved by using one of the above mentioned type-reducers, T2 FLSs still possess a great deal of mathematical, theoretical, and computational complexity. When discussing the complexities of T2 FL, Mendel and John [2002] make the following observations stating that, Type-2 fuzzy sets are difficult to understand and use because:

- 1) The three-dimensional nature of type-2 fuzzy sets makes them very difficult to draw and visualize.
- 2) There is no simple collection of well-defined terms that let us effectively communicate about type-2 fuzzy sets, and to then be mathematically precise about them (terms do exist but have not been precisely defined).

- 3) Derivations for (set theory) formulas for the union, intersection, and complement of type-2 fuzzy sets all rely on using Zadeh's Extension Principle [Zadeh, 1975].
- 4) Using type-2 fuzzy sets is computationally more complicated than using type-1 fuzzy sets.

These complexities of the T2 FLSs led to the hypothesis that the use of a GT2 FLS for the SBD environment may be prohibitively burdensome for the intended users, especially since the users would be required to specify preference data in three dimensions. Eventually the author developed a simplified process for the definition of GT2 FLS membership functions for facilitation of SBD (Chapter 4, Section 4.1.1), thereby eliminating the hypothesized burdens.

Although GT2 FLSs possess drawbacks due to the required computational time and theoretical complexity, the potential benefits of the T2 systems for uncertainty modeling remain highly desirable. Recognizing a need for a simplistic method for uncertainty representation, the author developed four novel FLSs, each of which utilize T1 FL methods to represent the advantages in uncertainty modeling of an IT2 FLS. The new systems are referred to as interval type-2 modeling (IT2M) FLSs.

To create the IT2M FLS, it was first necessary to determine where the resulting advantages of a true IT2 FLS stem from. After careful analysis of T1 and IT2 FLS components it was realized that the significant difference between T1 and IT2 FLSs is in the definition of the MFs for each of the systems. The FL MFs affect the activated FL rules and thus directly affect the FLS output. The use of IT2 MFs has two principle effects on a FLS:

- 1) The preference value of an active MF is represented by a set of possible values as opposed to a one single value and,
- 2) Opportunities for changes in rule activation due to MF curve uncertainty are now possible.

The first key effect of IT2 MFs can be seen by comparing the graphs of Figure 3.1 and Figure 3.2. Figure 3.1 shows that for any FL rule involving the MFs evaluated at x_1 , there is only one possible set of preference values for the two MFs; $\mu_1(x_1) \approx 0.3$ (●) and $\mu_2(x_1) \approx 0.7$ (◆). In Figure 3.2, the T1 MFs have been blurred to IT2 MFs to represent the uncertainty of the functions. A rule evaluation at x_1 now results in a range of possible output preference values with, $\mu_1(x_1) \approx [0.3,0.8]$ and $\mu_2(x_1) \approx [0.2,0.7]$.

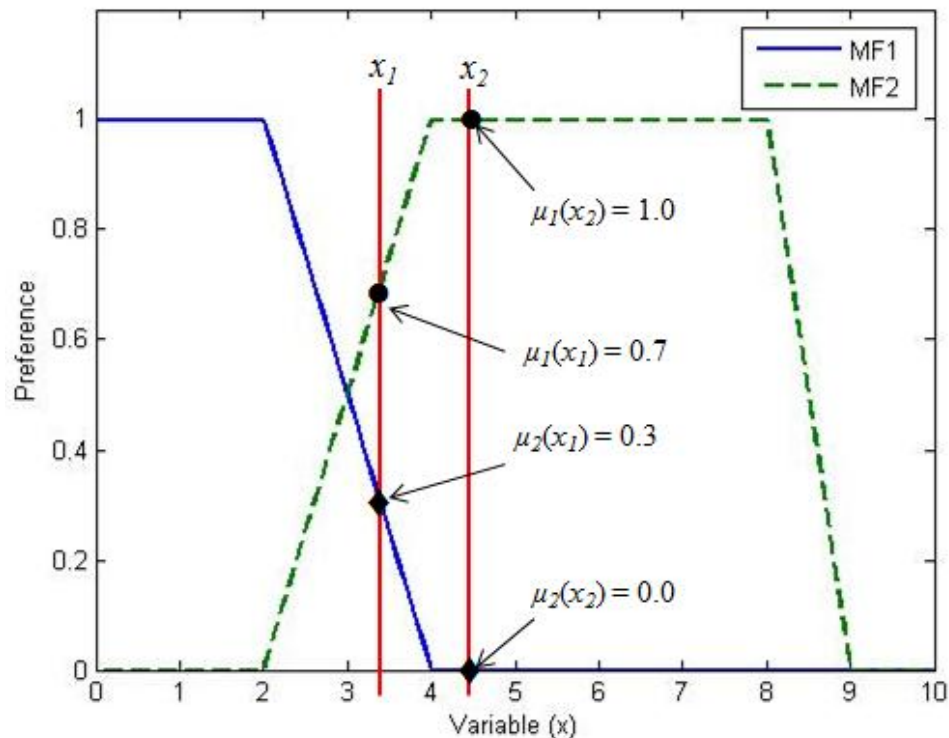


Figure 3.1 T1 Trapezoidal MFs

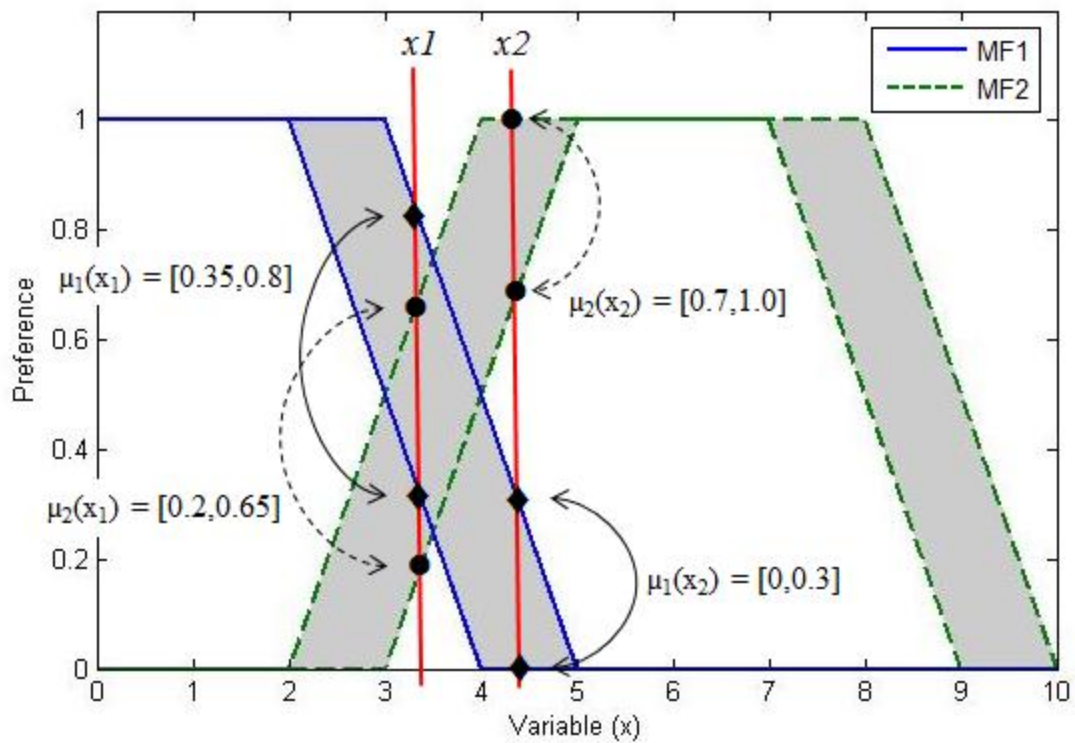


Figure 3.2 Interval T2 Trapezoidal MFs

By comparing the variable value of x_2 in the T1 and IT2 fuzzy sets, Figure 3.1 & Figure 3.2 respectively, the second key effect of T2 MFs is seen. With the T1 MFs, a FL rule involving only the dashed curve would be activated. The rule activation would be at a preference value of $\mu_2(x_2) = 1.0$. However, for the same value of x_2 in the IT2 fuzzy set, a rule involving both MFs would now be activated, resulting in a range of possible preference values; $\mu_1(x_2) \approx [0.0, 0.225]$ and $\mu_2(x_2) \approx [0.775, 1.0]$. Changes in rule activation can have a profound effect on the resulting outputs of a FLS. The IT2M approach utilizes randomization of “defining” MF data points to model the key effects of true IT2 MFs.

The experimental FLS SBD tool used only trapezoidal and triangular MFs. When using trapezoidal MFs, there are four points considered as “defining” points. The defining MF curve points are necessary to describe the shape of a trapezoidal MF. For the trapezoidal and triangular MFs, the defining curve points are abbreviated as $x-ll$, $x-lu$, $x-ru$, and $x-rl$, for left-lower, left-upper, right-upper, and right-lower, respectively. The defining curve points are shown on the labeled trapezoidal MF in Figure 3.3.

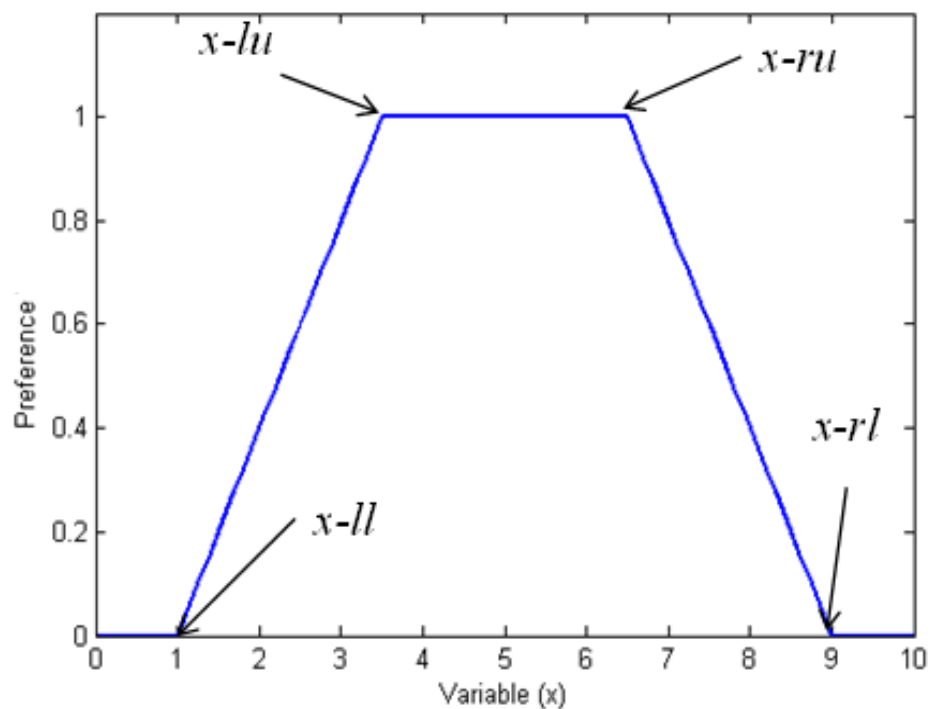


Figure 3.3 Defining Curve Points for Trapezoidal (and Triangular) MFs

To define a triangular MF, the x-coordinate values of the $x-lu$ and $x-ru$ defining curve points were simply set equal to each other. Note that in the SBD FLS, the upper defining curve points always have a preference value of one and the lower points a preference value of zero.

The newly developed IT2M FL SBD environments work by allowing human design agents to define uncertainty bounds on their T1 MFs. The shapes of the T1 MFs are then randomly altered within the defined uncertainty bounds to create new T1 MFs. The IT2M FLS then uses T1 FL to sweep across the range of values for the negotiated variable, resulting in a Joint Output Preference (JOP) curve describing the overall preference level for the entire set-range.

The process of randomizing the T1 MFs was then repeated for a specified number of iterations to produce a composite of JOP curves; example Figure 3.4. By plotting all JOP curves in the same figures it was possible to represent the uncertainty associated with the JOP solution [Gray and Singer, 2008] [Gray, Daniels, and Singer, 2010]; Sections 5.3.1 and 5.3.2 go into further details of this assertion. Four different randomization schemes for IT2M FL were developed by the author and are discussed in detail in the remainder of Chapter 3.

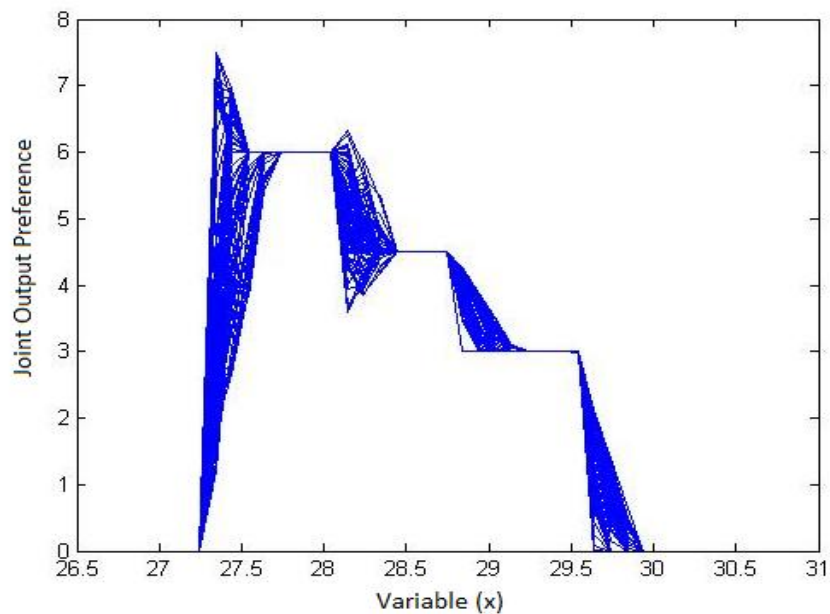


Figure 3.4 JOP Curve Plots for IT2M FLS Example

3.2 Yrand IT2M FLS

Of the four different IT2M FLSs developed to facilitate SBD, the Yrand IT2M FLS was the first attempt at uncertainty modeling. The Yrand IT2M FLS works by randomizing the preference value, $\mu(x_i)$, for all set values, x_i , of the design agents' input MFs. When using FLSs for engineering applications, it is often desirable to maintain a normalized [0,1] preference scale [Cox, 1999]. Therefore, during the IT2M FLS Yrand randomization process the maximum allowable preference level was set to a value of one, corresponding to 100% or a preference level of one. Any preference values that were randomized to a value greater than one were rounded back down to one. Similarly, preference values that randomized below zero, were rounded back up to zero.

To achieve Yrand randomization of the design agents' T1 MFs using a SBD FLS, a human agent was required to input a σ value to describe his/her degree of uncertainty; the actual data entry process is discussed in Chapter 6. Sigma represented a percent of standard deviation about the MF preference value of $u(x_i)$. The FLS then converted the provided σ (%) to a decimal equivalent and randomly selected a value from the decimal interval of $[-\sigma, \sigma]$ to add to the T1 MF preference value, resulting in an altered preference value $\mu'(x_i)$. The basic Yrand randomization process is shown in Eqn. (3.1). The term *rand()* in Eqn. (3.1) represents the process of randomly selecting an σ value from the interval $[-\sigma, \sigma]$ and is based on a Uniform distribution.

$$\mu'(x_i) = \mu(x_i) + rand([-\sigma, \sigma]) \quad (3.1)$$

The actual IT2M Yrand computational process utilized the following steps at each set value, x_i , to calculate the randomized MF preference values, $\mu'(x_i)$:

- 1) The entered $\sigma(\%)$ value was converted to a decimal value using:

$$\sigma_{decimal} = \sigma(\%)/100$$
- 2) A pseudo-random number was generated from a Uniform set of values $[0,1]$,
 using: $x_{randU} = rand([0,1])$
- 3) The pseud-random number was converted to a number between, $[0, (2 * \sigma)]$,
 using: $x_{rand\sigma1} = x_{randU} * 2 * \sigma$
- 4) This value was then converted to a number between, $[-\sigma, \sigma]$, using:

$$x_{rand\sigma2} = x_{rand\sigma1} - \sigma$$
- 5) Finally, the randomized MF preference value was calculated, using the current MF preference value $u(x_i)$ and the converted pseudo-random number $x_{rand\sigma2}$,
 using: $\mu'(x_i) = \mu(x_i) + x_{rand\sigma2}$

Figure 3.5 shows an example of two trapezoidal T1 MFs and the resulting Yrand IT2M MFs after one iteration of IT2M Yrand randomization. The randomized MFs represent the uncertainty in the original definition of the MFs' preference values $\mu(x_i)$. Notice that there are no preference values below zero or above one, which maintains the desired $[0,1]$ preference scale.

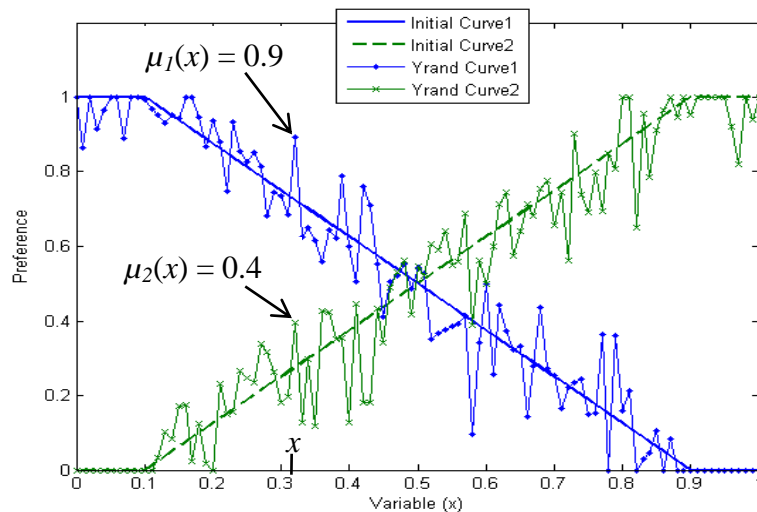


Figure 3.5 Two Trapezoidal MFs After Yrand Randomization Process

3.3 Parametric Linking

After examining randomized MFs which had passed through the IT2M Yrand randomization FLS process it became clear that, in a break from traditional FLSs designed for engineering applications, the randomized MFs were not maintaining the summation of membership grades equal to a total value of one. This fact is demonstrated by the two data points labeled in Figure 3.5, where the sum of $\mu_1(x) = 0.9$ and $\mu_2(x) = 0.4$ is equal to 1.5 total. The summation of MF preference values to a total value of one is not a requirement for FLSs. However, from a practical standpoint it makes logical sense that the membership grades (preference values) of the MFs should sum to one, to represent a total membership of 100%. Therefore, a process of parametrically linking the MFs was developed to ensure that the summation of preference values to a total value of one was maintained between adjacent MFs. For the Yrand IT2M FLS the parametric linking occurred between the preference values $\mu(x_i)$, of adjacent MFs. The results of parametrically linking the IT2M Yrand randomized MFs is discussed in Chapter 5, Section 5.3.1.

For the remaining IT2M FLS methods, xRU, xRL, and Slopes, as the name implies, the parametric linking process created a linked relationship between defining curve points of adjacent MFs. For two MFs the linked relationships were formed between the defining points, $x-ru$ of MF1 and $x-ll$ of MF2 indicated by “*”, and $x-rl$ of MF1 and $x-lu$ of MF2 indicated by “◇”; Figure 3.6 After the MFs were parametrically linked, any movement of a linked defining point during the randomization of the MFs would result in the point’s

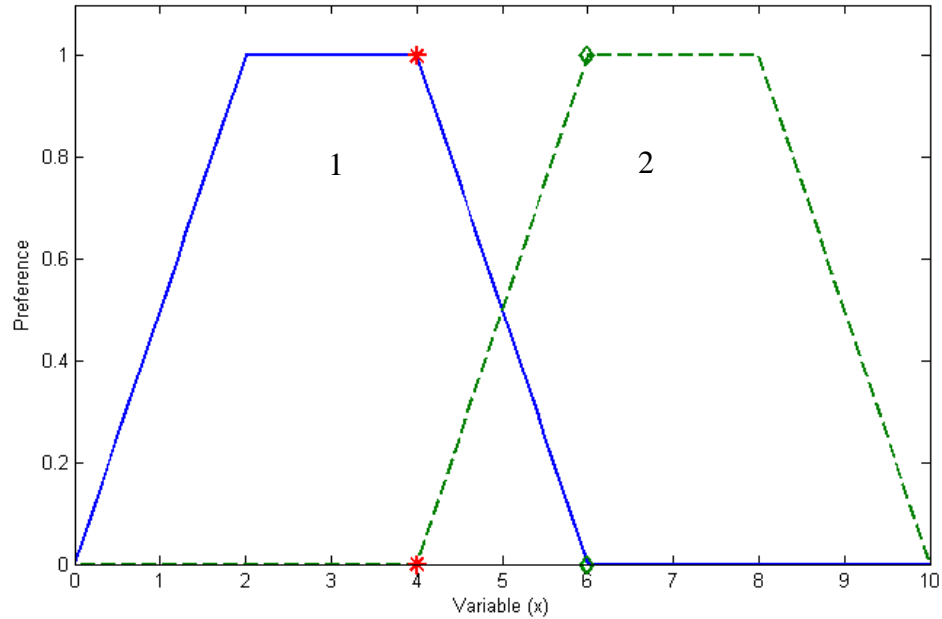


Figure 3.6 Parametrically Linked Defining Points of MFs

parametric partner being moved by an identical amount, and in the matching direction. The parametric movement of linked defining curves points enabled the software to maintain the desired summation of MFs; Eqn. (3.2). The remaining IT2M FLSs, described in following sections, utilized the parametric linking process during the randomization procedure.

$$\mu_1(x_i) + \mu_2(x_i) = 1.0 \quad (3.2)$$

In the SBD software developed by the author, the randomization process and parametric linking would take place from the left-to-right, or right-to-left, based on a simulated coin flip. The coin flip step was included to eliminate any leftward or rightward bias that could form by the randomization and parametric linking of MFs.

3.4 xRU, xRL, and Slopes IT2M FLS

Each of the remaining IT2M FL randomization methods employed the use of parametric linking to maintain the summation of MF preference values to a total level of one throughout a variable's set-range. The three IT2M FLS methods were each created to represent what the author felt were the most logical methods remaining for the randomization of a MF curve shape.

The xRU randomization process was created to allow a design agent to describe uncertainty in the definition of the upper-right, $x\text{-}ru$, defining trapezoidal curve point. The design agent defined positive and negative epsilon values, $\pm\epsilon$, which were used to establish the upper and lower bounds of uncertainty surrounding the $x\text{-}ru$ defining curve point; Eqns. (3.3) & (3.4). The $+\epsilon$ value did not have to be equal to the $-\epsilon$ value. The units of epsilon matched the dimensional units of the variable that the design agent was negotiating.

$$upper_{bound} = x\text{-}ru + \epsilon \quad (3.3)$$

$$lower_{bound} = x\text{-}ru - \epsilon \quad (3.4)$$

To achieve the randomization of the xRU MF defining points Eqn. (3.5) was used. In Eqn. (3.5), the $upper_{bound}$ and $lower_{bound}$ terms refer to the x-coordinate for the maximum and minimum uncertainty bounds as established by the design agent, and Rnd was a randomly generated number chosen from a Uniform distribution between [0,1].

$$x_{new} = (upper_{bound} - lower_{bound}) * Rnd + lower_{bound} \quad (3.5)$$

Figure 3.7 shows examples of the xRU randomization method as applied to a fuzzy set of T1 MFs. The figure shows examples of positive and negative movements of the x -ru defining MF curve points that could be produced by the xRU randomization method. Although not shown, the randomized points fall within the uncertainty bounds that would have been defined by a design agent. The circular symbols “○” in Figure 3.7 indicate the defining MF curve point that was independently randomized, while the triangular symbols “▸” indicate the parametrically moved (dependent) MF curve points.

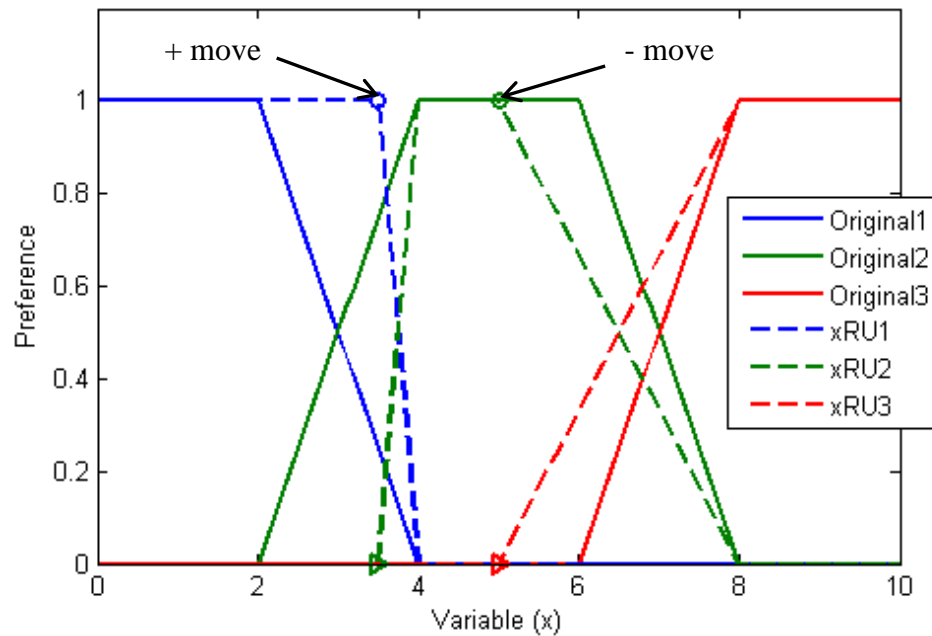


Figure 3.7 xRU IT2M Randomization Method Examples

In fuzzy logic theory, it is typical that a MF does not overlap itself. This is particularly important for T1 MFs, as each MF should be designed to possess only a single preference value $\mu(x_i)$, for each input value, x_i ; represented by Eqn. (3.6).

$$y_i = \text{preference}_i = \mu(x_i) \quad (3.6)$$

A T1 MF that does overlap itself is considered to have an improper curve shape because the shape simultaneously represents more than one preference value. Figure 3.8 shows an example of an improper T1 MF curve shape. In a T1 FLS, if a MF were to simultaneously possess multiple preference values for a single input, x , then the overlapping MFs would represent a preference of over 100% and violate the summation rule; Eqn. (3.2).

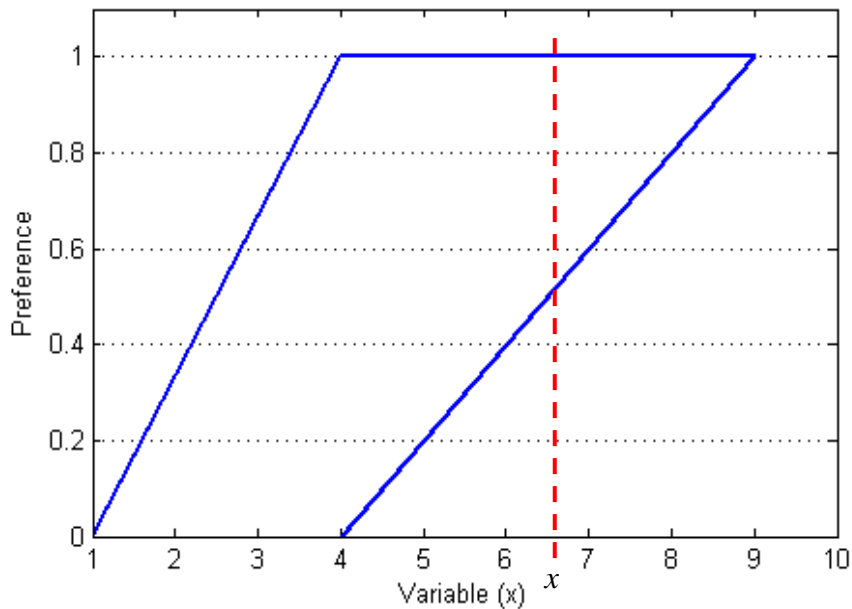


Figure 3.8 Improper Trapezoidal Curve Shape

To avoid the formation of improper MF curve shapes during the randomization process it was necessary to create limitations on the bounds of uncertainty that could be defined by a design agent for the IT2M MFs. The limits helped to ensure that only acceptable trapezoidal curve shapes would be created during each of the IT2M FL randomization processes.

Figure 3.9 & Figure 3.10 show the MF curve shapes resulting from extending the trapezoidal MFs of Figure 3.6 to the extreme bounds of the xRU IT2M FLS uncertainty limits.

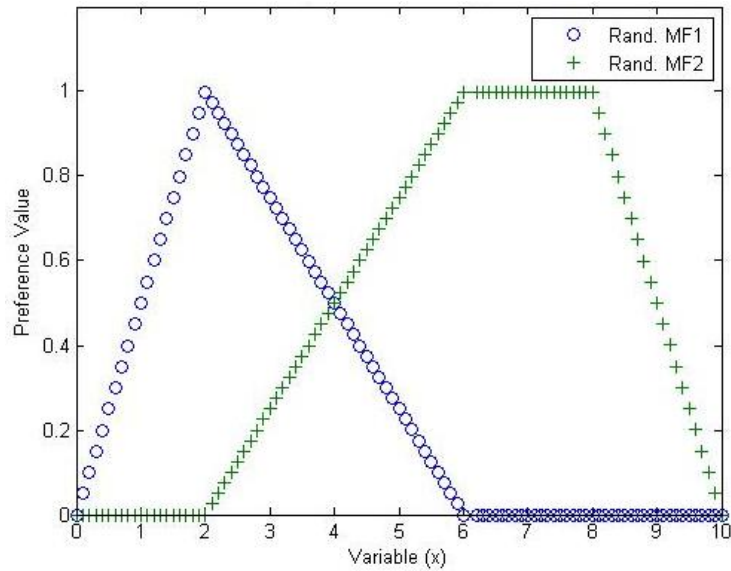


Figure 3.9 MF Curve Shapes for Maximum Negative Uncertainty, xRU IT2M

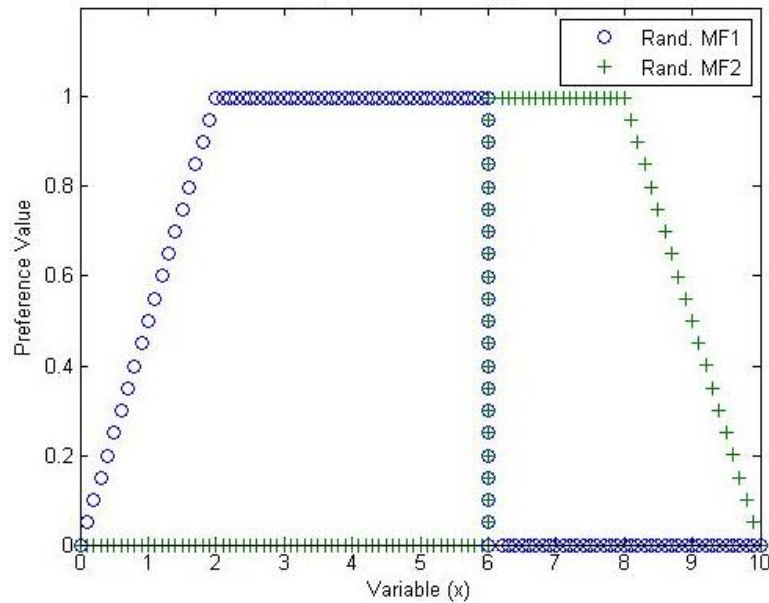


Figure 3.10 MF Curve Shapes for Maximum Positive Uncertainty, xRU IT2M

In each of the figures, the independently randomized curves were represented by the “○” symbols and labeled “Rand. MF1”, the dependent (parametrically linked curve) was plotted using “+” symbols and labeled “Rand. MF2”. When using the xRU randomization method, the randomization of the right-upper defining point, $x-ru$, was limited to move between $x-rl$ and $x-lu$ of the MF being independently randomized.

Maximum negative xRU randomization resulted in the independently randomized curve collapsing into a triangular function, Figure 3.9, while maximum positive randomization resulted in the formation of virtual step function where the two curves meet, Figure 3.10. The word “virtual” was used to describe the step function MF curve shape since the MF was not allowed to fully expand to a step function; this ensured that the MF would not simultaneously represent more than one preference value at the same time.

The next logical step after development of the xRU IT2M randomization method was the creation of an xRL IT2M randomization method. As the name implies, the xRL IT2M randomization method allowed a design agent to enter $\pm\varepsilon$ units to describe the uncertainty in the location of the right-lower $x-rl$, trapezoidal defining curve point. Again, the $\pm\varepsilon$ value did not have to be equal in magnitude. Figure 3.11 shows examples of positive and negative xRU randomizations for a fuzzy set of T1 MFs. Again, the circular symbols “○” in Figure 3.11 indicate the defining MF curve points that were independently randomized, while the diamond symbols “◈” indicate the parametrically moved (dependent) MF curve points. The xRL IT2M randomization was accomplished using Eqns. (3.3) – (3.4) with the $x-rl$ point in place of the $x-ru$ point.

Like the xRU IT2M FL randomization method, the xRL IT2M randomization method also required the application of rules to enforce limitations on the maximum positive and negative uncertainty values that could be input into the IT2M FLS. Figure 3.12 & Figure 3.13 show the curve shapes resulting from extending the trapezoidal MFs to the extreme

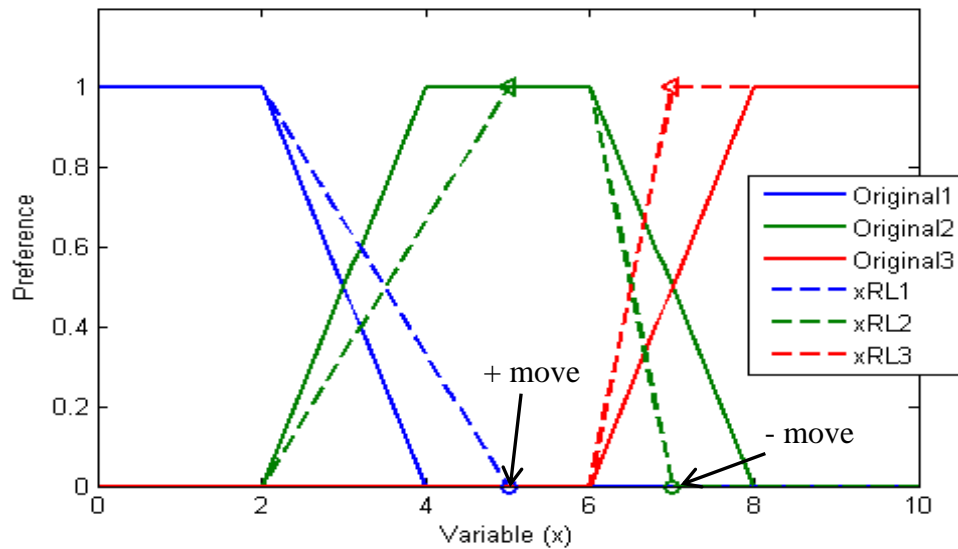


Figure 3.11 xRL IT2M Randomization Method Examples

bounds of the xRL IT2M FL randomization uncertainty limits. In the xRL IT2M method, the randomization of the right-lower point, $x-rl$, was limited to fall between $x-ru_1$ and $x-ru_2$; the subscripts are used to indicate MF1 versus MF2. The value $x-ru_1$ was the right-upper point on the independent MF being randomized and $x-ru_2$ was the right-upper point on the dependent MF immediately to the right. Maximum negative xRL IT2M randomization produced the virtual step function again, while maximum positive xRL randomization collapsed the dependent MF to a triangular curve.

The xRL and xRU IT2M FL randomization methods allow a user to define uncertainty in the slope of the MFs. Both the xRL and xRU IT2M randomization methods represent the

idea that a design agent is uncertain about where the transition between preference MFs should occur and at what rate the transition should occur. The Slopes IT2M randomization method was created to allow for a different viewpoint of MF uncertainty.

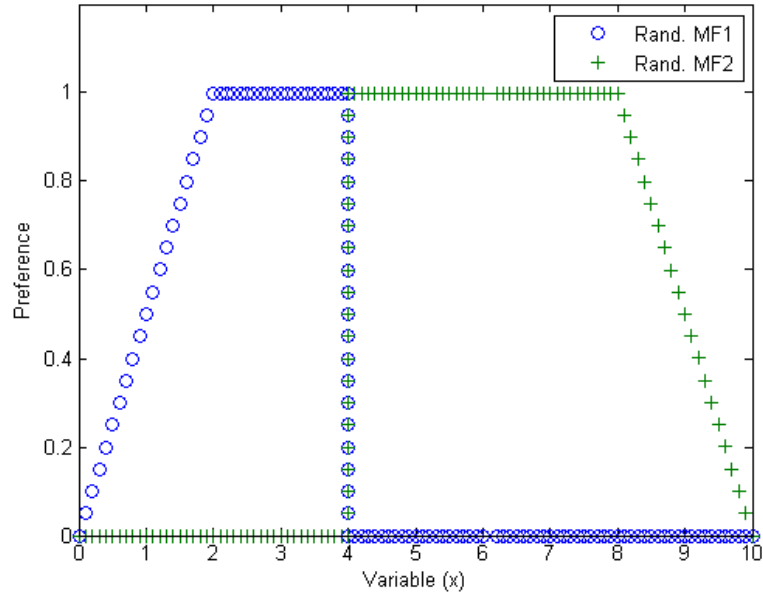


Figure 3.12 MF Curve Shapes for Maximum Negative Uncertainty, xRL IT2M

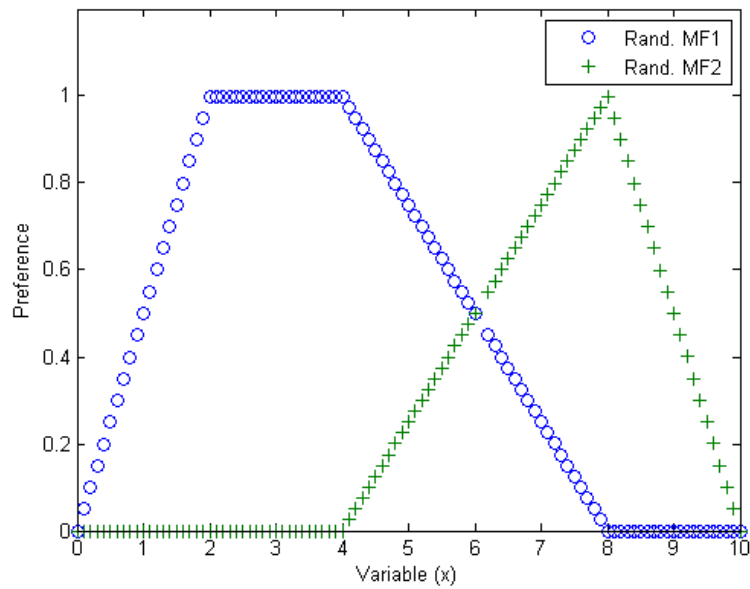


Figure 3.13 MF Curve Shapes for Maximum Positive Uncertainty, xRL IT2M

In the Slopes IT2M method the right-upper and right-lower defining curve points, x_{-ru} and x_{-rl} , are simultaneously randomized by an equal amount and in the same direction.

Figure 3.14 shows examples of the IT2M FLS Slopes randomization independently applied to two of the MFs, with one randomization in the positive x -direction and the other the negative x -direction. The independently randomized MF defining curve points are represented by the circular symbols “○” in Figure 3.14, while the parametrically moved (dependent) MF curve points are represented by the triangular symbols “△”. ▷

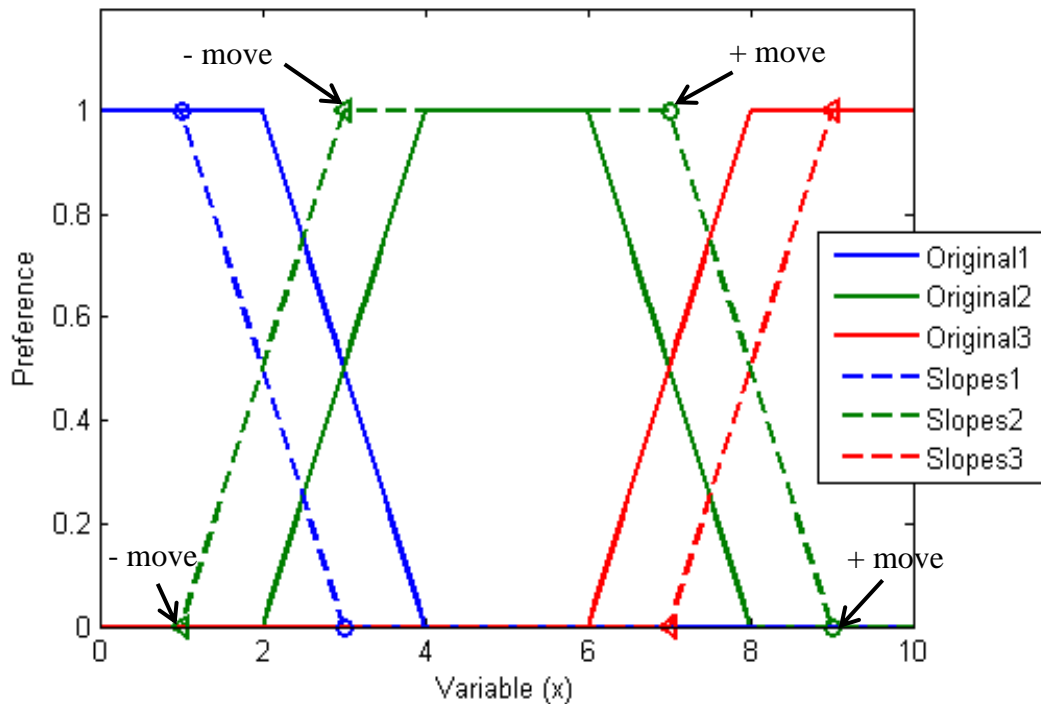


Figure 3.14 MF Curve Shapes for Maximum Positive Uncertainty, Slopes IT2M

The Slopes randomization process allowed the actual slope of the initially defined T1 MF to be maintained throughout the entire randomization process. With the Slopes method, a design agent could express confidence in the shape of the transition region between MFs, but uncertainty as to where the transition region should begin and end. The uncertainty

was described using $\pm\varepsilon$ values; the values did not have to be equal. During randomization of the MFs the Slopes IT2M FL randomization method affected the overall width of the MF, specifically the region of preference level equal to one, thereby expanding or contracting the MF in the region of 100% membership.

As with the xRL and xRU IT2M FLSs, the Slopes IT2M FLS also required rules to govern the maximum allowable uncertainty bounds an agent could establish for their MFs. Figure 3.15 & Figure 3.16 show the curve shapes resulting from extending the trapezoidal MFs to the extremes of the Slopes IT2M FLS uncertainty limits. Throughout the Slopes IT2M FL randomization, the maximum uncertainty bounds were limited to allowing the independent MF to be contracted by moving x_{-ru} to x_{-lu} (Figure 3.15) and thus collapsing the independent MF, or expanded by moving x_{-rl} up to x_{-ru_2} , collapsing the dependent MF (Figure 3.16). By restricting the allowable uncertainty bounds for each of the IT2M FLS randomization methods, it was possible to avoid the formation of any impractical MF curve shapes while still being capable of modeling the key effects of T2 FL MFs.

The impacts of the different randomization methods for IT2M FLS are discussed in detail in Chapter 5, Section 3. Computer software was created to facilitate the actual process of defining MFs, entering uncertainty bounds, and specifying linguistic preference for design variables. Chapter 6 provides information about the software and the human/machine interfaces that were developed to facilitate the SBD process.

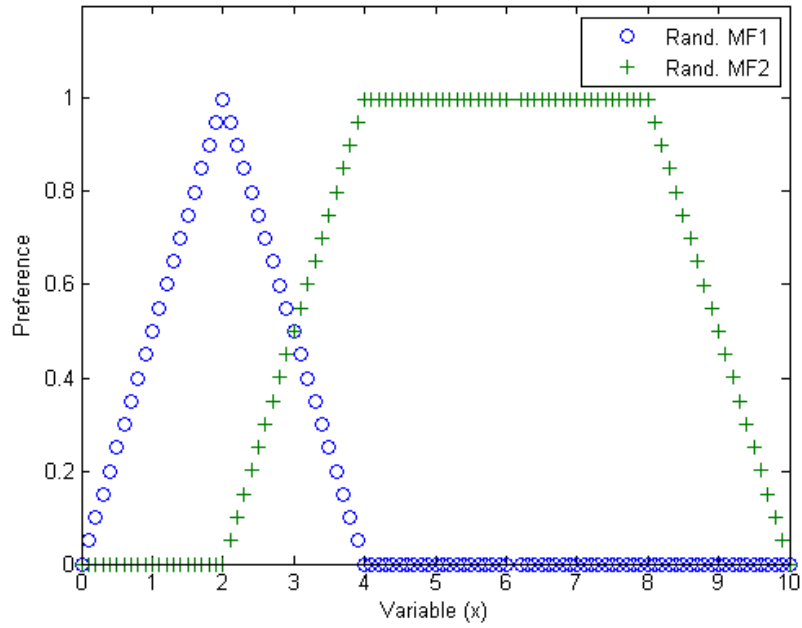


Figure 3.15 MF Curve Shapes for Maximum Negative Uncertainty, Slopes IT2M

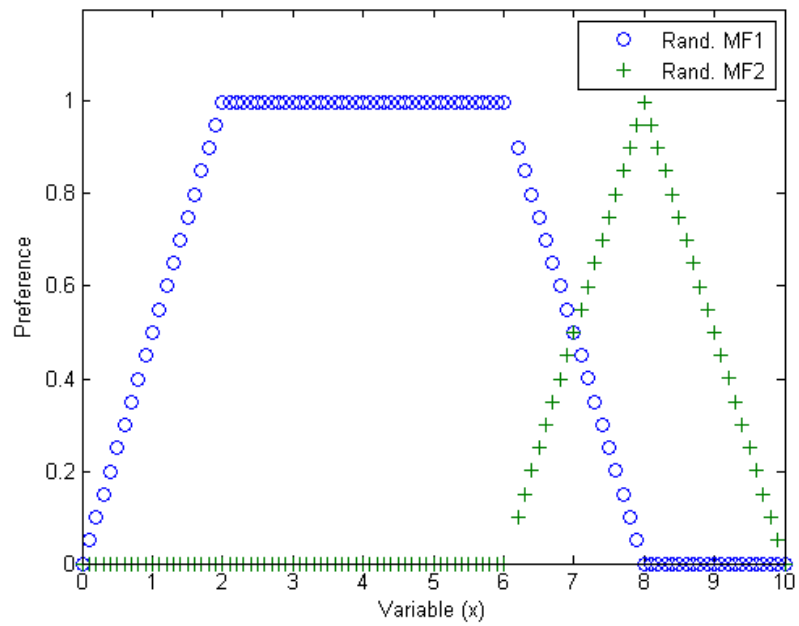


Figure 3.16 MF Curve Shapes for Maximum Positive Uncertainty, Slopes IT2M

CHAPTER 4

GENERAL TYPE-2 FUZZY LOGIC SYSTEM

4.1 Type-2 Membership Functions

A T1 FLS utilizes well-defined MFs in an attempt to model uncertainty. Because the MFs of a T1 FLS are known functions, the T1 FLS cannot truly model uncertainty. Type-2 FLSs were created in order to represent true uncertainty. The MFs of T2 FLSs can be used to describe the uncertainty of linguistic and numeric values, as well as the uncertainty associated with the definition of a MF. Interval type-2 (IT2) FLSs represent the uncertainty in a uniform manner using a footprint of uncertainty (FOU); Figure 4.1 shows the FOUs for two trapezoidal IT2 MFs. With IT2 MFs, like those shown in Figure 4.1, it is possible that at any x -location a MF possesses a set of preference values. This is in direct contrast of T1 MFs which are designed to possess only one preference value for each input value x . In an IT2 FLS, each preference value in the set of values has a uniform chance of occurring; there is no opportunity to express if one preference value is more likely to occur than another.

General type-2 (GT2) MFs utilize a third dimension to allow the expression of a non-uniform distribution for the set of preference values at each x -location. The GT2 MFs are thought of as adding a weighting value to each of the preference values within the entire set of possible values. The weighting values of the third dimension are more commonly referred to as the secondary preference values. There are an infinite number of possible

T1 MFs embedded in a T2 MF. A GT2 MF uses the secondary preference values to describe which function(s) are the most likely to occur.

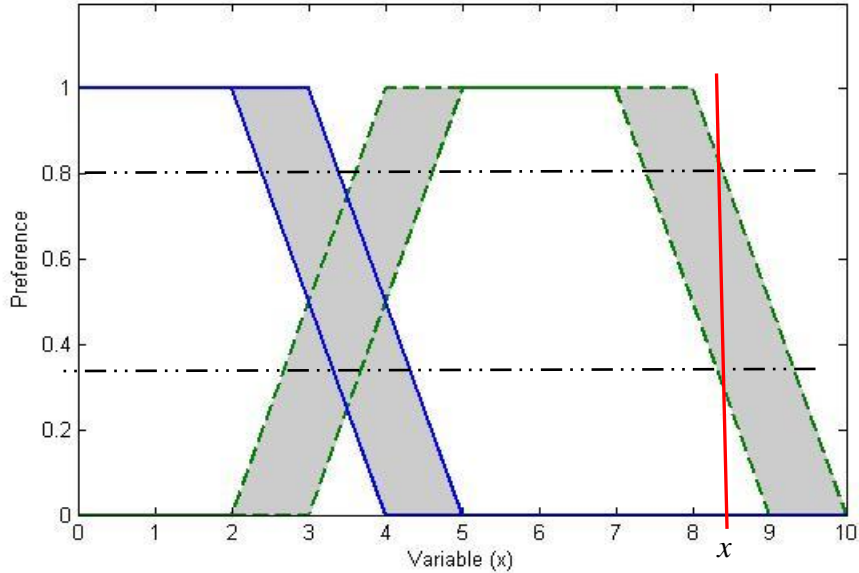


Figure 4.1 Footprint of Uncertainty Example for Two Trapezoidal MFs

If the T2 MF was vertically sliced at x , in Figure 4.1, the slice for an IT2 MF would show a uniform distribution for the secondary preference values. The same slice for a GT2 MF might show any type of function, such as Gaussian, triangular, trapezoidal, sigmoidal, etc..., to describe the secondary preference levels of the T2 MF's primary preference set. To further illustrate the difference in the IT2 and GT2 MFs, Figure 4.2 shows an example of secondary preference MFs for the vertical slice at x in Figure 4.1. Notice that the IT2 secondary MF is of a uniform distribution while a triangular secondary MF is used to describe the distribution of the GT2 MF's set of primary MF values. A triangular MF was arbitrarily chosen for this example. In reality, any assortment of function types could have been used to describe the secondary preference levels of the primary preference set for the GT2 MF.

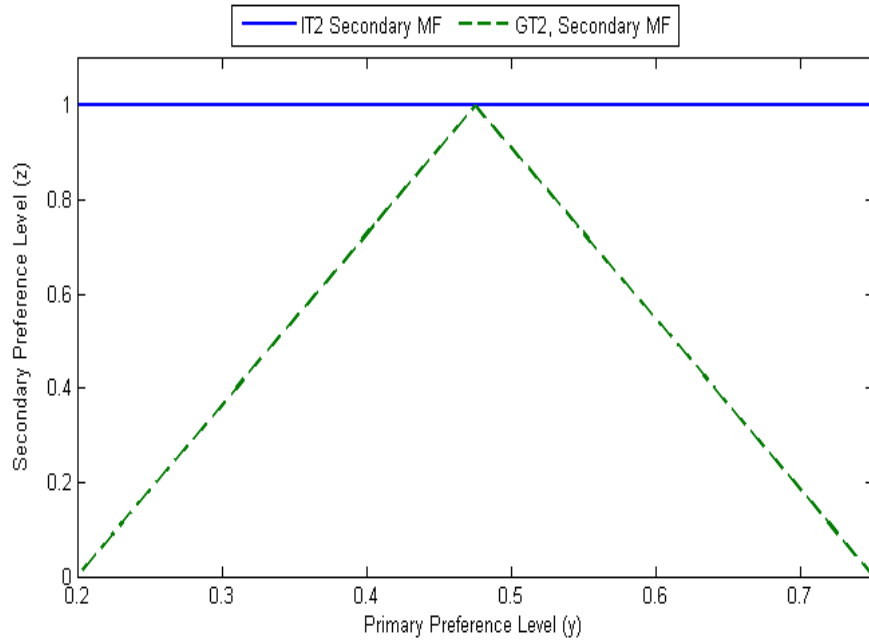


Figure 4.2 Secondary Membership Functions for IT2 and GT2 MFs

There are numerous ways to represent a T2 fuzzy set [Mendel, 2001]. Each representation provides a different method to decompose the three-dimensional fuzzy set into parts which are, individually, easier to work with than the whole. Some examples of these GT2 fuzzy set representations include the point-valued, vertical slice, wavy-slice, horizontal slice, α -plane, and z-slice representations [Mendel and Liu, 2008] [Mendel, Liu, and Zhai, 2009] [Wagner and Hagrass, 2008].

To create GT2 MFs with a SBD FLS it was initially thought that a design agent would need to define a secondary MF at each of the x_i locations within the set of values for a design variable. This meant if a set-range for a design variable was discretized into one hundred individual values then a design agent would have to create one hundred secondary MFs, plus the upper and lower bounds of uncertainty for the primary MF. In addition, a design agent would be required to view the MFs in three dimensions.

From a spatial standpoint humans are much more accustomed to viewing graphical data using only two-dimensional figures, and many people have difficulty thinking of data from a three-dimensional point-of-view. Because of the difficulties people have with cognitive processing three-dimensional data, concern arose that the process of defining GT2 MFs in three dimensions would be too cumbersome for the design agents, resulting in a time consuming and frustrating experience for the design tool users. To avoid frustrating and confusing the users of the SBD FLS and negatively impacting SBD experiments a simplified method for the creation of GT2 MFs was developed.

4.1.1 Simplified GT2 MF Definition Process

The simplified process for GT2 MF definition required a design agent to first define the T1 primary MFs of a fuzzy set. The design agents were instructed to identify the T1 primary MF as the MF that was “most likely” to describe their preference for the values of a variable’s set-range. After creating the T1 primary MFs, the second step was to define the upper and lower bounds of uncertainty for each T1 primary MF. When creating the uncertainty bounds for the primary MF, the design agents could enter $\pm\epsilon$ uncertainty values on either, or both, the right-upper and right-lower, x_{-ru} and x_{-rl} , defining MF curve points. The $\pm\epsilon$ values used to describe the MF uncertainty were not required to be of equal value. This method of uncertainty definition allowed for more flexibility in defining uncertainty bounds than that of the IT2M FLS methods. Figure 4.3 shows an example of a simplified GT2 MF from the perspective of a design agent.

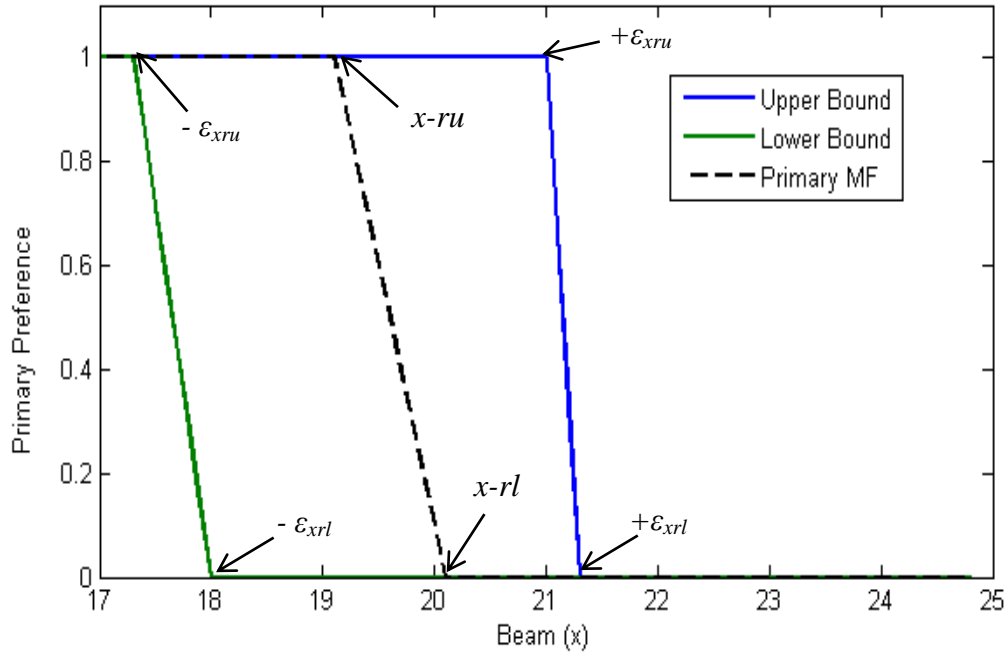


Figure 4.3 Example of User Defined, Simplified GT2 MF

After defining the primary MF and associated uncertainty bounds, the design agent's role in defining the GT2 MFs was finished. From this point on, the SBD FLS took control by creating data for the three-dimensional GT2 MFs. The FLS utilized the preference values of the upper bound, primary T1 MF, and lower bound to create triangular secondary MFs at each x_i for the entire set-range of discretized design values. For demonstration purposes only, the fully 3-D GT2 MF created from the simplified GT2 MF of Figure 4.3 is shown in Figure 4.4. Looking closely at Figure 4.4, the individual vertical slices used to create the 3-D MF can be seen. It is easy to understand how a human design agent could easily become overwhelmed had they been required to individually define each of the secondary MFs seen in Figure 4.4. With the use of a color scale, the same GT2 MF can be viewed in 2-D; Figure 4.5. The 2D color representation of the GT2 MF, Figure 4.5, contains the same information as the simplified GT2 MF of Figure 4.3.

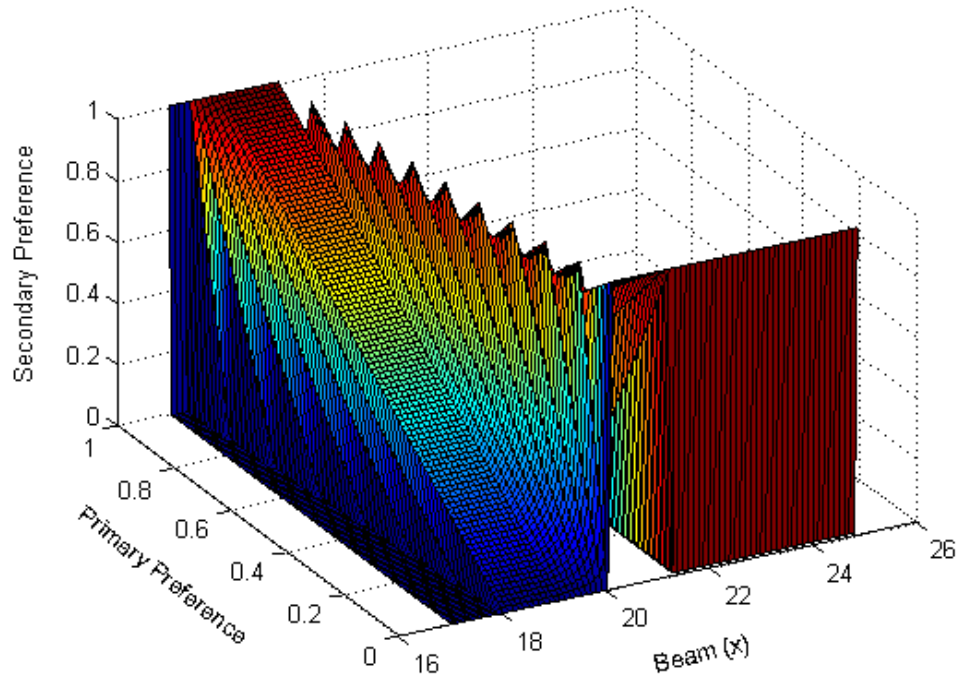


Figure 4.4 Example of 3-D GT2 MF Based on Simplified GT2 MF of Figure 4.3

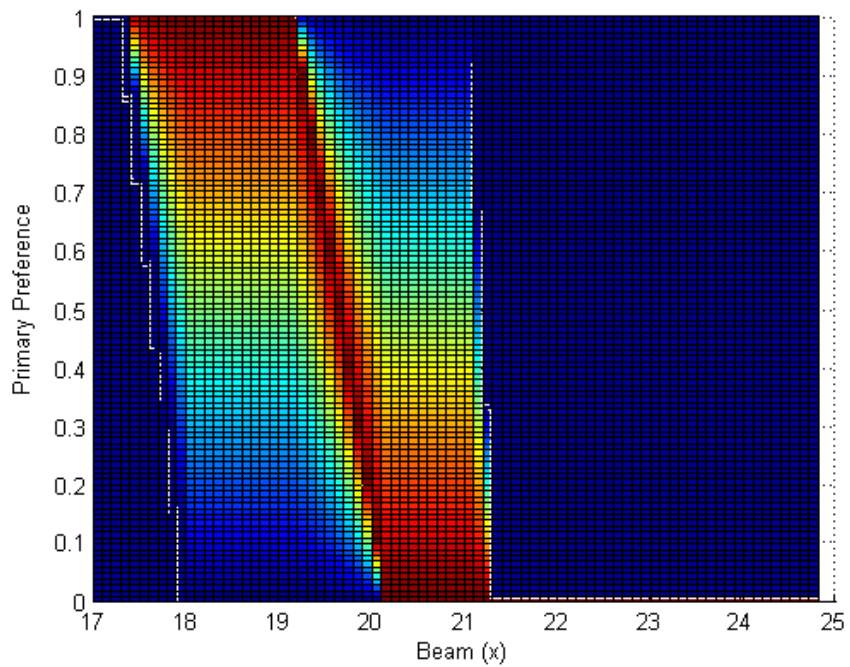


Figure 4.5 2-D Representation of the GT2 MF of Figure 4.4

When creating the secondary MFs from the simplified GT2 MF, the preference values of the primary T1 MF were used as the apex for each of the triangular secondary MFs. From the apex of a triangular secondary MF, the secondary preference values gradually decreased, eventually becoming zero at the points of the upper and lower uncertainty bounds. In some cases the apex of the secondary MF was equal to the upper or lower uncertainty bound resulting in the formation of right triangles. The secondary MFs for three vertical slices of the GT2 MF (Figure 4.4) were taken at $x = [18.5, 19.5, 20.5]$, and the triangular secondary MFs for each slice were plotted in Figure 4.6. Note how right-triangles were created for the secondary MFs at $x = 18.5$ and $x = 20.5$, where the primary MF was aligned with an uncertainty bound. At $x = 19.5$, the primary MF was between the uncertainty bounds, resulting in the secondary MF shown in Figure 4.6. The secondary preference levels assign a weighting value or “likelihood of occurrence” to the primary MF values within the FOU.

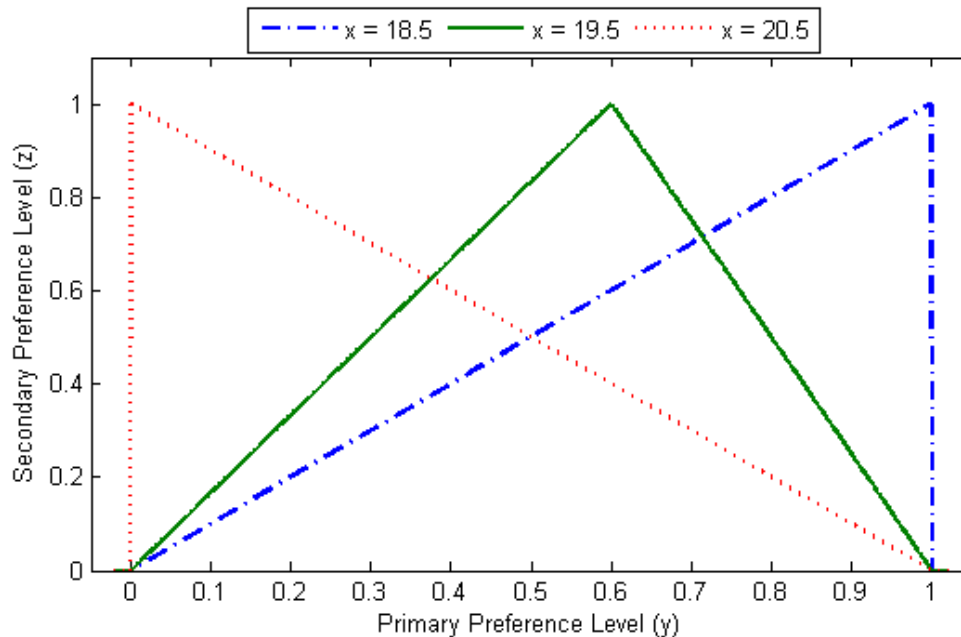


Figure 4.6 Slices of the GT2 MF Example of Figure 4.3 - Figure 4.5

4.2 General Type-2 FLS Type-Reduction

Once the GT2 MFs were created via the simplified two-step GT2 process, a type-reduction method was needed to reduce the T2 fuzzy sets to T1 fuzzy sets before finally defuzzifying the data into a format useful for the SBD process. As mentioned in Chapter 3, Section 1, there are several methods by which to achieve type-reduction of T2 fuzzy sets. For the SBD FLS the type-reduction process had to work quickly to avoid adding significant computational time. More importantly, the type-reduced data-set had to be formatted in a manner that was useful for set-based analyses in the hybrid agent FLS negotiation process.

An extensive literature search was performed to determine what type-reductions methods were available, which were most commonly used, and which was purported to be the fastest. The literature search led to the use of centroid type-reduction, employing the Enhanced Karnik-Mendel (EKM) algorithms [Wu and Mendel, 2009] for the GT2 FLS SBD tool. Centroid type-reduction was chosen since it “is one of the most popular methods in applications” [Liu, 2008]. The EKM algorithms were chosen because of the algorithm’s speed and computational simplicity.

A set of historical data was used to run tests to determine if the EKM algorithms were appropriate for use in the SBD hybrid agent FLS. The historical data utilized three design agents, Resistance, Cargo, and Stability, to negotiate the beam (*B*) variable of a containership design. Original MFs from the historical data were extended to GT2 MFs, and then type-reduced using the EKM algorithms. The Resistance agent’s GT2 fuzzy set input is shown below; Figure 4.7 & Figure 4.8 show the GT2 MFs in 3-D and 2-D,

respectively. Human design agents were allowed to describe their preference for design set-values by using linguistic terms Preferred (P), Marginal (M), and Unpreferred (U). The Resistance design agent preferred a ship with a small beam length, which explains the logic behind the linguistic preference choices of P , M , and U , in that order.

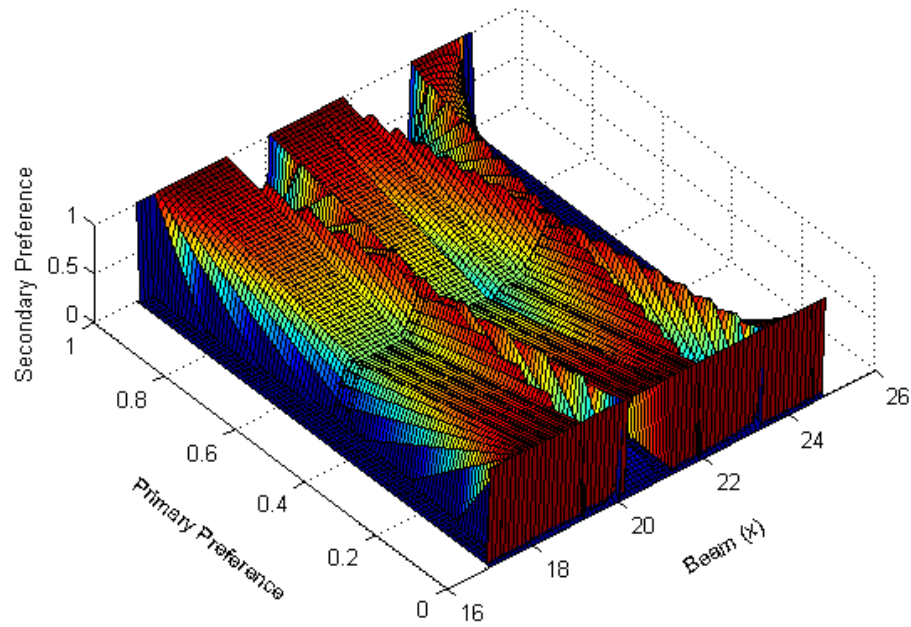


Figure 4.7 Resistance Agent's GT2 Fuzzy Set from Historical Data

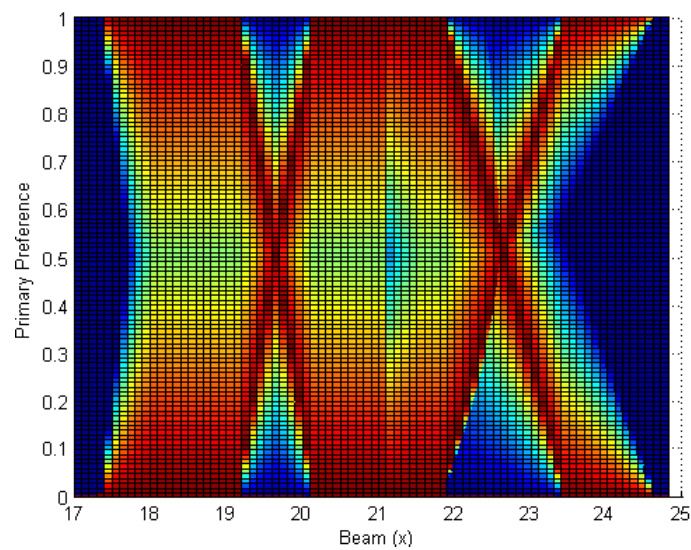


Figure 4.8 2-D View of Resistance Agent's GT2 Fuzzy Set

To represent the GT2 fuzzy sets, the author first tried using the α -plane representation. An α -plane is a horizontal (x-y plane) slice of a GT2 MF. “The two-dimensional α -plane, denoted \widetilde{A}_α , is the union of all primary membership(s) whose secondary grades are greater than or equal to the special value α ”, and is represented mathematically using Eqn. (4.1), [Liu, 2008],

$$\widetilde{A}_\alpha = \bigcup_{x \in X} (x, y) | \mu_{\widetilde{A}}(x, y) \geq \alpha \quad \text{where } \alpha = \bigcup_{x \in X} (\mu_{\widetilde{A}}(x))_\alpha \quad (4.1)$$

The $\alpha = 0$ plane corresponds to the FOU of a GT2 MF [Mendel and Liu, 2008]. The α -value is equivalent to the z -value, called the secondary preference value and the y -value is equal to the primary preference value. Equation (4.1) simply implies that a GT2 MF can be represented by summing all the individual α -planes from $[0,1]$. An example of different α -planes for a GT2 MF is shown in Figure 4.9. In Figure 4.9 Liu [2008] uses the u symbol to represent y -axis primary preference values and the α symbol to represent z -axis secondary preference values.

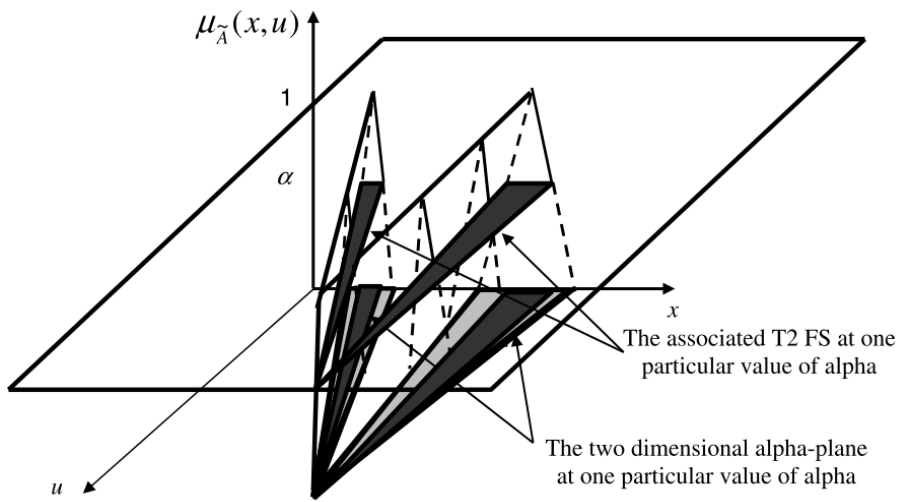


Figure 4.9 Example of α -planes of a GT2 MF [Liu, 2008]

Using the α -plane representation of GT2 MFs, the centroid of each α -plane was then found by means of Eqn. (4.2), which reduces the GT2 MF to a T1 MF consisting of the centroid values of the α -planes from $\alpha = [0,1]$ [Mendel, Liu, and Zhai, 2009] [Mendel and Liu, 2008] [Liu, 2008]. The T1 fuzzy MF could then be defuzzified to a crisp output.

$$Y_c = \int_{y_1 \in J_{x_N}} \dots \int_{y_N \in J_{x_N}} \mu_{\tilde{A}}(x_1, y_1) \times \dots \times \mu_{\tilde{A}}(x_N, y_N) / \left(\frac{\sum_{i=1}^N x_i y_i}{\sum_{i=1}^N y_i} \right) \quad (4.2)$$

In Eqn. (4.2), $\mu_{\tilde{A}}(x_N, y_N)$ is an α -plane, there are $i = 1 \dots N$ values in each α -plane, and, \times , represents the fuzzy logic operation of t -norm. For centroid type-reduction, only minimum t -norm is considered appropriate. In a simpler form, Eqn. (4.2) can be written as Eqn. (4.3) which states that, “For minimum t -norm operations, centroid type-reduction for a type-2 fuzzy set \tilde{A} is the union of the centroids of its associated type-2 fuzzy sets $\tilde{A}(\alpha)$, with $\alpha \in [0,1]$.” [Liu, 2008].

$$Y_c = \int_{\alpha \in [0,1]} \text{Centroid}(\tilde{A}(\alpha)) = \int_{\alpha \in [0,1]} \alpha / \text{domain}(\text{Centroid}(\tilde{A}(\alpha))) \quad (4.3)$$

The theory for centroid type-reduction of the α -planes of GT2 fuzzy sets was applied to the GT2 MFs that were created from the historical FLS data. As an example, the α -plane, centroid type-reduced, T1 fuzzy set of the Resistance agent is displayed in Figure 4.10.

The SBD hybrid agent FL design tool utilized a fuzzy logic rule bank that relied upon the MFs of the fuzzy set maintaining the summation of preference values to a total of one. It was evident from Figure 4.10 that the α -plane centroid type-reduced fuzzy set did not maintain this relationship. The fuzzy sets of other design agents’, Cargo and Stability, produced similar results as those seen for the Resistance agent.

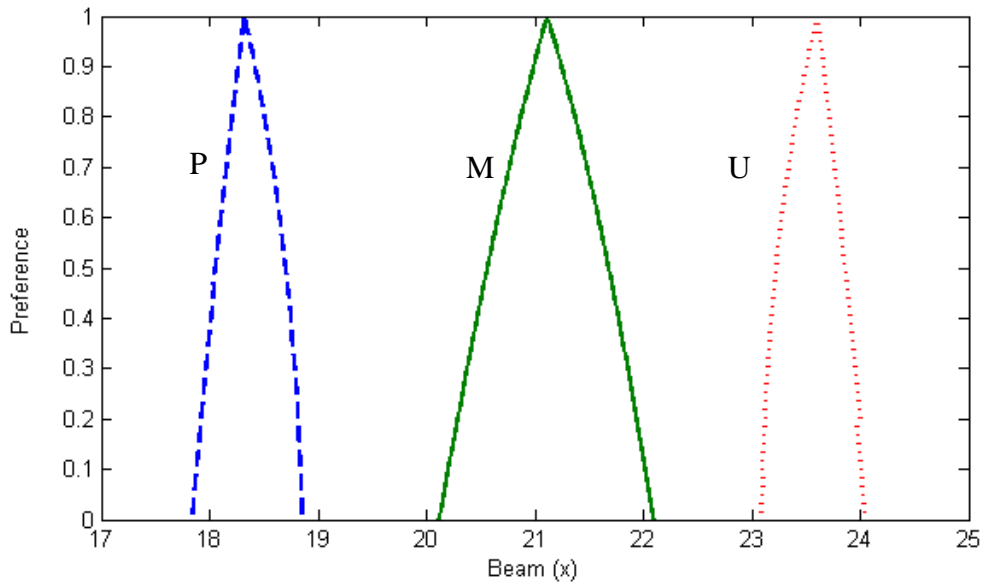


Figure 4.10 α -Plane, Centroid Type-Reduced, MFs of Resistance Agent's GT2 Fuzzy Set

If the MFs of Figure 4.10 were defuzzified, the JOP curve would contain incomplete information about the set values due to the gaps wherever the type-reduced MFs did not cross. Because of these results, the α -plane representation of the GT2 MFs could not be utilized in the SBD environment. Since the type-reduced data from the α -plane representation proved not to be useful for the SBD hybrid agent FLS, another type-reduction method needed to be selected for the GT2 FLS.

After trying several more methods of GT2 fuzzy set representation and type-reduction, the combination that proved to be the best for use in the FL SBD tool was the vertical slice representation [Mendel, 2007] [Liu, 2008] [Mendel, Liu, and Zhai, 2009] [Mendel and Liu, 2008] [Mendel and John, 2001], combined with centroid type-reduction [Karnik and Mendel, 2000] [Liu, 2008], and the EKM algorithms [Wu and Mendel, 2007] [Wu and Mendel, 2009].

A GT2 MF can be represented mathematically using Eqn. (4.4). In the vertical slice representation a GT2 MF, Eqn. (4.4), is comprised of the sum of slices taken vertically at each value, x_i , within the domain of the variable; Eqn. (4.5). A vertical slice is referred to as a secondary MF, $\mu_{\tilde{A}}(y)$; represented by Eqn. (4.6). In Eqn. (4.6) the secondary MF is a function of the secondary preference value, $f_x(y)$, which itself is a function of the primary preference value, y . Equations (4.4) – (4.6) are adapted from [Mendel, Liu, Zhai, 2009].

$$\tilde{A} = \{((x, y), \mu_{\tilde{A}}(x, y)) | \forall x \in X, \forall y \in J_x \subseteq [0, 1]\} \quad (4.4)$$

$$\tilde{A} = \int_{\forall x \in X} \mu_{\tilde{A}}(x)/x \quad (4.5)$$

$$\mu_{\tilde{A}}(x) = \mu_{\tilde{A}}(y|x) = \int_{\forall y \in J_x \subseteq [0, 1]} f_x(y)/y \quad (4.6)$$

The vertical slice representation was chosen for the SBD FLS since the simplified method employed by the FLS to create triangular secondary MFs of the GT2 MFs, was equivalent to the creation of vertical slices. The centroid type-reduction method was chosen for its computational simplicity. The method worked by calculating the location of the centroid of each triangular vertical slice along the primary preference y -axis. Also, as demonstrated by Figure 4.11, the method produced type-reduced fuzzy sets that maintained the desired overlap of type-reduced MFs thereby providing sufficient preference data for defuzzification throughout the entire set-range.

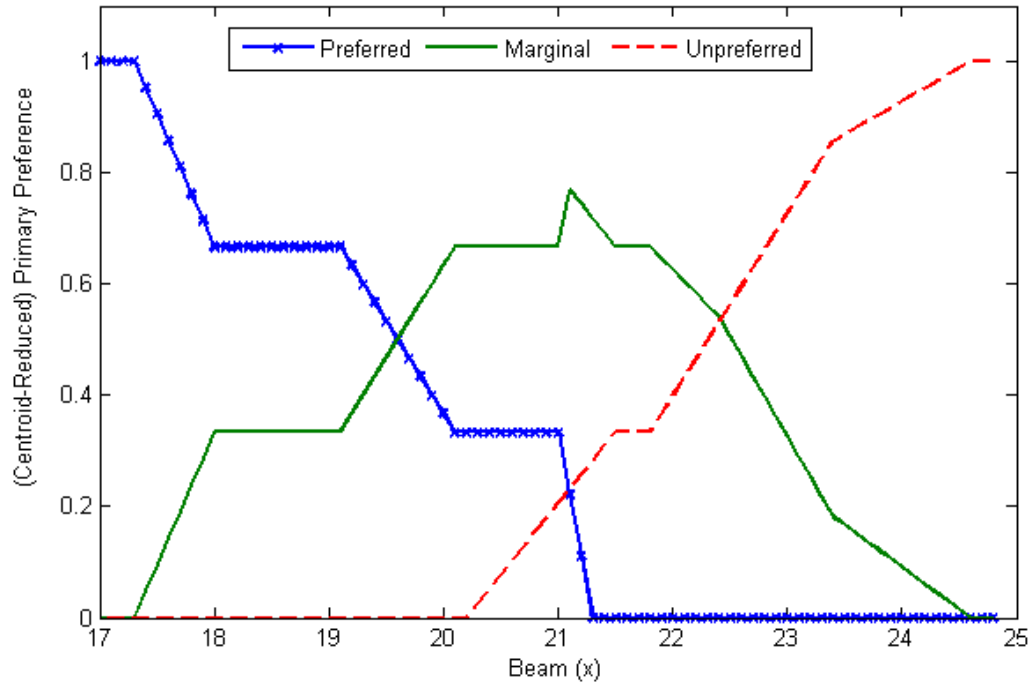


Figure 4.11 Vertical Slice, Centroid Type-Reduced, MFs of Resistance Agent's GT2 Fuzzy Set

CHAPTER 5

INITIAL TESTING OF FUZZY LOGIC SYSTEMS & RESULTS

5.1 Primer on the Structure of the Set-based Fuzzy Logic Design Environment

Before continuing discussion of the IT2M and GT2 FLS tests and results, it is pertinent to first understand the structure of the set-based design environment. The current research was based upon a hybrid agent T1 FL SBD tool developed by David J. Singer [2003]. Dr. Singer's original FLS SBD experimental data, referred to as the baseline data from here on, were used to provide input data for the IT2M and GT2 FLSs while the systems were in the initial research and development stage.

The original T1 FLS was utilized to perform set-based preliminary ship design experiments. In the construct of the SBD environment, the ship designers were modeled as domain agents in charge of describing their individual preference for the negotiation of a particular ship design parameter. The agents' preference information was described using any combination of three linguistic values of Preferred (*P*), Marginal (*M*), and Unpreferred (*U*). For the SBD experiments, design agents were instructed that the *U* linguistic preference should be used only when trying to convey that a design value could not be used to satisfy the agent's functional design goal. The linguistic values were represented by trapezoidal and triangular FL MFs that were created by the human design agents.

The entire SBD process was overseen by a Chief engineering design agent. The Chief engineering agent's responsibilities included the selection of a design parameter for negotiation, setting the amount of time allowed for the negotiation process, and guiding the narrowing of set-ranges of negotiated design variables. Figure 5.1 shows a graphical representation of the design agents that are involved during the use of the set-based FLS design tool for a ship design. The diagram also represents the lines of communication between the FLS and the hybrid design agents.

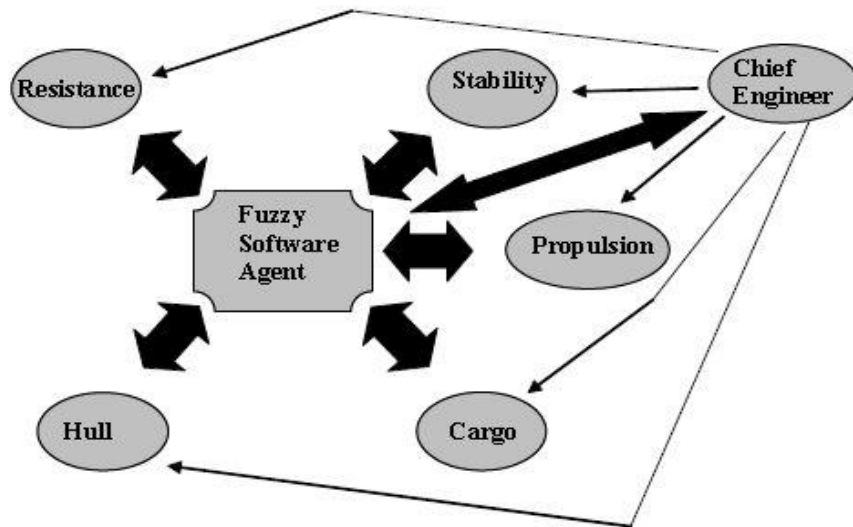


Figure 5.1 Diagram of Agent Communications Paths for FL SBD Environment

The FL SBD tool process began with the Chief engineer submitting a request for negotiation of a ship design variable. Negotiating design agents would then input their preference information for the set-values of the negotiated design variable as provided by the Chief engineering agent. After all negotiating design agents input a fuzzy set of MFs describing their linguistic preference for the negotiation of the design parameter, the FLS swept across the set of possible design values, $[x_{min}, x_{max}]$, concurrently considering each agent's preference information for the design variable. The FLS then produced a joint

output preference (JOP) curve describing the results of the combined preference information from each design agent. The JOP curve was comprised of crisp output preference values, $J(\mu(x_i), x_i)$. The JOP curve possessed one joint output preference value for each discretized set-range input value x_i , in the entire negotiation set-range, $[x_{min}, x_{max}]$. The Chief engineer and design agents would use the information from the JOP curve to narrow the design space for the next round of set-based negotiation of the design parameter.

Figure 5.2 shows an example of this SBD process utilizing only two design agent inputs. In the example shown in Figure 5.2, the FLS read the linguistic preference inputs from the two design agents, resulting in the activation of various rules in the FL rule matrix as the FLS swept across the set-range. After rule activation, the data passed through the steps of fuzzy inference and defuzzification resulting in the JOP curve values for the negotiated variable. The JOP curve was then used by the Chief engineering agent to trim (reduce) the set-range for additional negotiation.

One aspect of the current research involved the promotion of the set-based practice of concurrent design. To accomplish this task, all the SBD FLSs used minimum-correlation inference to concurrently consider each agent's input preference information as the system swept across the set of possible design values within the design space. Minimum-correlation inference selects the minimum preference value among the $1 \rightarrow j$ activating MFs; Eqn. (5.1).

$$\min\{\mu_1(x_i), \mu_2(x_i), \dots, \mu_j(x_i)\} \quad (5.1)$$

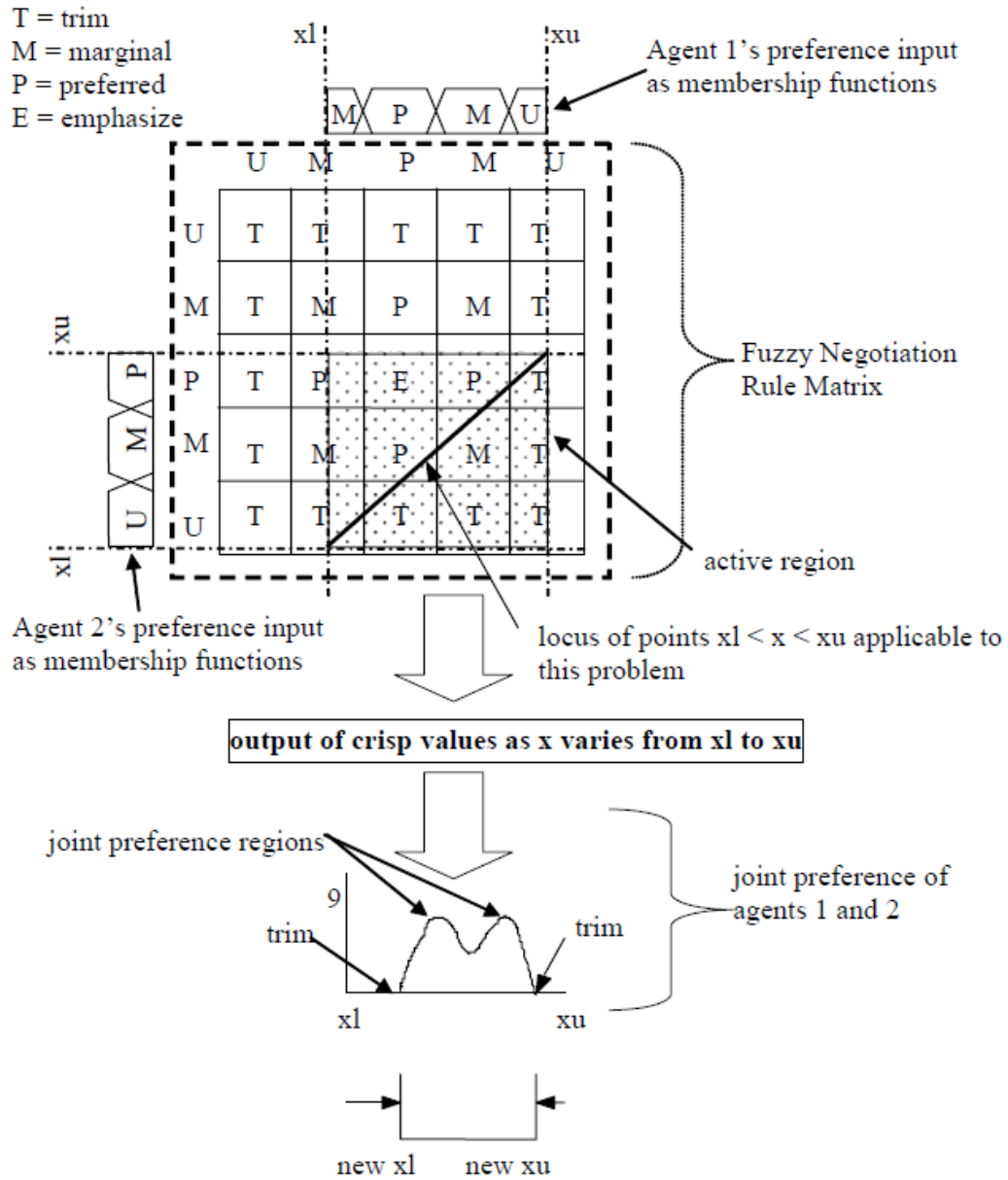


Figure 5.2 FLS Design Environment Process from Inputs to Output

As with the original set-based FLS design tool, Singer's meta-rule concept [2003] was used to create a rule matrix that governed the size and activation of an output preference function. After the inference process, centroid defuzzification was used to reduce the output preference function to a single crisp value for each set value x_i , resulting in a JOP curve for the negotiated variable. The centroid defuzzification equation is shown in

Eqn. (5.2). The subscript j represents the $1 \dots N$ rules that were activated at a particular location x_i along the x -coordinate axis. The term x_{ej} represented the centroid for the activated preference function that was a known value based on the number of negotiating design agents; [Singer, 2003]. The area of the activated preference function, which was clipped during the inference step, was represented by, a_j , and $J(x_i)$ represented the resulting preference (utility) value for the JOP curve at x_i ; Eqn. (5.2) matches Eqn. (2.8) but with slightly different notation.

$$J(x_i) = \frac{\sum_{j=1}^N a_j \cdot x_{ej}}{\sum_{j=1}^N a_j} \quad (5.2)$$

5.2 Initial Fuzzy Logic Systems Tests – T1 FLS Base Data

While developing and testing the IT2M and GT2 FLSs for the SBD environment, it was desirable to have a consistent set of data to use for the FLS inputs. As the new SBD FLSs were derivatives of the hybrid agent T1 FLS SBD tool developed by Singer [2003], it was natural to use historical data from one of the set-based ship design experiments performed by Singer during his research.

The example outlined here shows the baseline MF input data and the resulting JOP curve data that was obtained from the original T1 SBD process. This baseline data was utilized as input data in the research and development of the IT2M and GT2 FLSs. The resulting output for the beam negotiation was later used for comparison to the IT2M and GT2 FLSs' JOP curve results. In this simplified example, the beam negotiation was performed by three design agents: Cargo, Resistance, and Stability; their input preference

MFs are shown in Figure 5.3. Note that in the SBD tool, the FLS required the first and last MF of a fuzzy set to have a preference value equal to one. This was done to ensure the preference values summed to a total of 1.0 at the extremes of the set-range.

The actual roles of each functional design agent are discussed in Chapter 6. For now, Figure 5.3 provides insight into the motivations of each design agent when defining linguistic preference MFs for the beam design variable. The first fuzzy set in Figure 5.3 was created by the Cargo design agent. The Cargo agent chose to use triangular and trapezoidal MFs to emphasize that at discrete set-values an exact number of containers could be placed across the beam of the ship. The second fuzzy set was created by the Resistance design agent and third fuzzy set by the Stability agent.

When trying to reduce the resistance of a ship, a designer typically prefers the smallest beam possible. This preference was reflected in the Resistance agent's fuzzy set. To increase the stability of a ship, the ship's beam can be increased. The Stability agent's fuzzy set, Figure 5.3, mirrored this preference for larger beam values. Notice that at the upper end of the beam variable set-range the Resistance agent used the *U* MF to indicate that these set-values resulted in a resistance that was unacceptably large. In opposition, the Stability agent used the *U* MF at the lower end of the beam set-range indicating that these beam values could not supply the ship with the required stability. The SBD FLS is unique in its ability to handle competing and conflicting preference inputs, such as those expressed by the Resistance and Stability agents.

Based on Singer's meta-rule concept [2003], having three negotiating design agents input preference information into the FLS resulted in the creation of five output preference

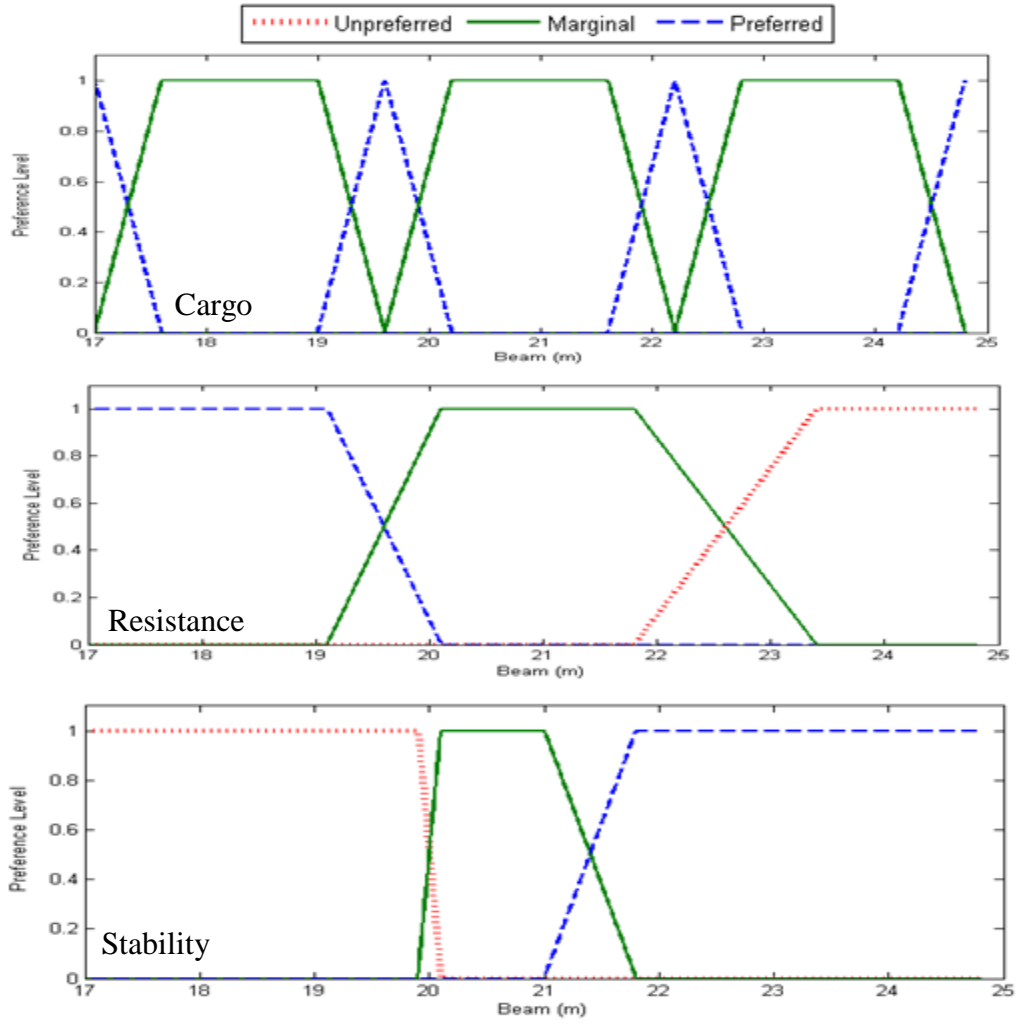


Figure 5.3 Design Agents' Preference T1 Fuzzy Sets for Beam Negotiation

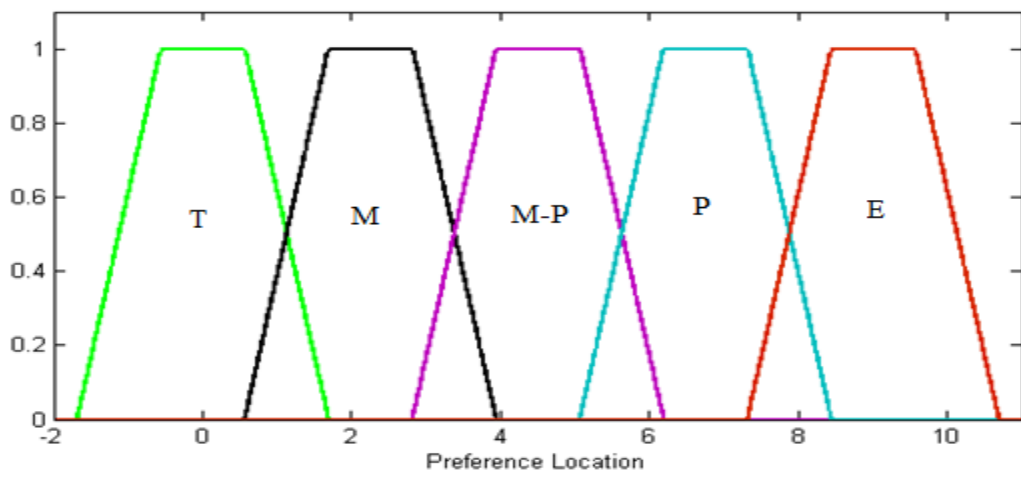


Figure 5.4 Output Preference Functions

functions; Figure 5.4. Associated with these output preference functions was a set of antecedent (IF...) and consequent (THEN,) actions for the fuzzy rule set listed in Table 5.1. Table 5.1 also lists the centroid value for each of the output preference functions.

Table 5.1 Fuzzy Rule Set for the Beam Negotiation Example, Antecedents and Consequents Based on Three Negotiating Design Agents

Rule #	IF...	THEN, Activate Output Preference Function...	Centroid of Output Preference Function
1	Any MF Unpreferred	Trim (T)	0.00
2	All MFs Marginal	Marginal (M)	2.25
3	Marginal, Marginal, Preferred	Marginally-Preferred (MP)	4.50
4	Marginal, Preferred, Preferred	Preferred (P)	6.75
5	All MFs Preferred	Emphasize (E)	9.00

After preference input, the T1 FLS swept across the set-range for the beam variable, from minimum to maximum, performing each of the four FLS processes for all set-values, x_i . To briefly illustrate this process, examine the specific beam set-value of $x = 21.5$ m in Figure 5.3. At the set-value of $x = 21.5$ m, the Cargo and Resistance agents each had one active MF of the Marginal linguistic type. Since both of these agents had only one active MF, the preference level for each of the agent's MFs was equal to $\mu_{C-M}(21.5) = \mu_{R-M}(21.5) = 1.0$, or linguistically 100% Marginal.

The Stability agent had two active MFs at the set-value of $x = 21.5$ m. The Stability agent's two active MFs had associated preference levels of $\mu_{S-M}(21.5) = 0.375$ and $\mu_{S-P}(21.5) = 0.625$ for the linguistic preferences of Marginal and Preferred, respectively.

These values are equivalent to 37.5% and 62.5% membership in the Marginal and Preferred fuzzy sets, respectively. Note how the MFs maintain the desired summation of set-membership to 1.0, or 100% for the fuzzy sets. Based on the activated MFs at $x = 21.5$ m (Figure 5.3), for the three negotiating design agents, two different fuzzy logic rules were activated:

- Rule #2, “All agents Marginal”,
- Rule #3, “Marginal, Marginal, Preferred”.

Each fuzzy rule had a consequent that instructed the FLS what output preference function to activate. The activated output preference functions corresponding to Rule #2 and #3 were “Marginal” and “Marginally-Preferred”, respectively. Using minimum-correlation inference, the height of the activated output preference function was then clipped, and the new area of the clipped output preference function was determined for use in the centroid defuzzification process. For the FLS input $x = 21.5$ m, the minimum-correlation on rule #2 resulted in a clip height of $\mu_{min-corr1}(x) = 0.375$, and for rule #3 $\mu_{min-corr2}(x) = 0.625$. The area of each clipped output preference function was equal to $a_1(21.5) = 1.107$ and $a_2(21.5) = 1.670$ squared units, for rules #2 and #3, respectively. The subscripts 1 and 2 represent the two activated fuzzy rules.

Each of the activated output preference functions had a centroid value, x_{c_j} , that was used during the centroid defuzzification process, $j = 1 \dots n$ for the n activated rules; for this example $n = 2$. The centroid value for output preference function Marginal, activated by rule #2 was, $x_{c_1} = 2.25$, and for Marginally-Preferred, activated by rule #3, $x_{c_2} = 4.5$. The centroid and clipped output preference areas were then input into the centroid

defuzzification formula Eqn. (5.2) to determine the final JOP value for the beam set-value of $x = 21.5$ m. The resulting JOP curve value was $J(x = 21.5) = 3.603$. The maximum obtainable JOP value is $\mu(x) = 9.0$. The data for the entire FLS process utilizing the example point $x = 21.5$ m is summarized in Table 5.2 and Table 5.3.

Table 5.2 Active MFs and Preference Levels for FLS Analysis of Beam Set-Value $x = 21.5$ m

$x = 21.5$	Active MF(s)		Preference Level(s)	
Cargo	Marginal	-----	1.0	-----
Resistance	Marginal	-----	1.0	-----
Stability	Marginal	Preferred	0.375	0.625

Table 5.3 Defuzzification Data for FLS Analysis of Beam Set-Value $x = 21.5$ m

Activated Rules	Minimum-Correlation	Clip Height	Clipped Output Area	Centroid
#2, All M	$\min(1,1,0.375)$	0.375	1.10742	2.25
#3, MMP	$\min(1,1,0.625)$	0.625	1.66992	4.50
Defuzzified Value =				3.60285

As the FLS swept through the entire set-range, the process generated a JOP value for each beam value in the set-range, resulting in the JOP curve shown in Figure 5.5. Notice how the JOP curve of Figure 5.5 has zero preference values in the ranges of approximately $x = [17,19.8]$ and $x = [23.5,25]$. Looking back at the fuzzy sets input by the design agents, Figure 5.3, notice that in the region, $x = [17,19.8]$, the Stability agent had input a MF with linguistic preference of Unpreferred, at a preference level of one. In the second region, $x = [23.5,25]$, the Resistance agent had input an Unpreferred linguistic preference, with a preference level of one. Since, design values were 100% Unpreferred

in these two regions, through minimum-correlation inference and centroid type-reduction, the FLS negotiation resulted in JOP curve values equal to zero within these two set-ranges. JOP values of zero indicated to the Chief engineering agent that these set-values were unacceptable for the design.

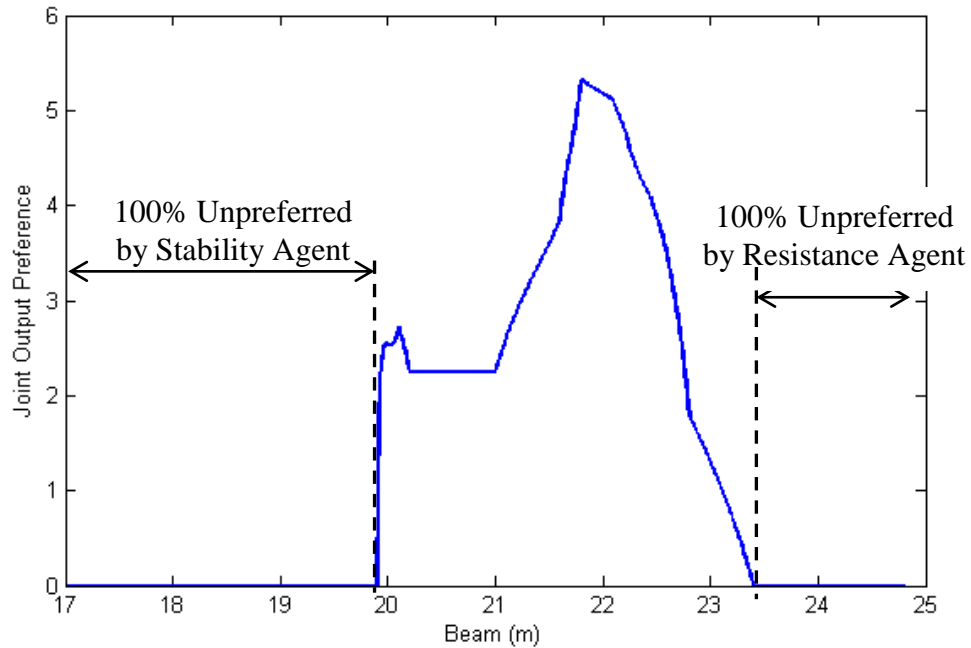


Figure 5.5 JOP Curve from T1 FL SBD Negotiation of Beam Set Values

Following SBD protocol, a Chief engineering agent viewing the JOP curve would be able to reduce the set of beam values to between $B = [20, 23.5]$ m for the subsequent negotiation round. The JOP curve in Figure 5.5 is used throughout Chapter 5, Section 3, to aid in the illustration of the changes elicited by introducing uncertainty modeling into the SBD tool through use of IT2M and GT2 FLSs. This T1 FLS beam negotiation JOP curve is often referred to as the “base” JOP curve throughout this thesis.

All JOP curves had a joint preference scale with minimum and maximum obtainable values of $J_{min}(x) = 0.0$ and $J_{max}(x) = 9.0$. This was a result of how the FLS used the

output preference MFs and centroid defuzzification process to compute the JOP values. The first and last output preference MFs always possessed centroid values of $x_{c_j} = 0.0$ and $x_{c_j} = 9.0$, respectively. To obtain a JOP value of $J(x) = 0.0$, based on the meta-rule concept [Singer, 2003], one or more design agents must have input a linguistic preference of Unpreferred, at a preference level of one (100% Unpreferred). This would result in activation of rule #1 only, with a centroid of $x = 0.0$, which in turn resulted in a JOP value of zero after centroid defuzzification.

To obtain the maximum JOP value, all negotiating agents must have input the linguistic preference of Preferred, at a preference level of one (100% Preferred). This would result in the activation of the final rule in the fuzzy rule bank, “All agents Preferred”. The output preference function for this rule had a centroid at $x = 9.0$, which based on input preference values of one and using Eqn. (5.2) for centroid defuzzification, would result in the maximum JOP value of $J(x) = 9.0$.

5.2.1 Ideal Iteration Level

The IT2M FLS models uncertainty through the randomization of T1 MFs. To achieve the uncertainty modeling, the randomization of the T1 MFs and the FLS steps, input to output, must be applied iteratively. Figure 5.6 shows an example of an IT2M MF that has been created from a T1 MF that has been processed through fifty iterations of xRU randomization. To run the IT2M FLSs efficiently, it was necessary to determine an ideal number of iterations that would be suitable for use with all of the IT2M FLS methods. With the IT2M FLS there is a tradeoff between the time required to perform a set of iterations and the amount of uncertainty represented in the JOP solution space.

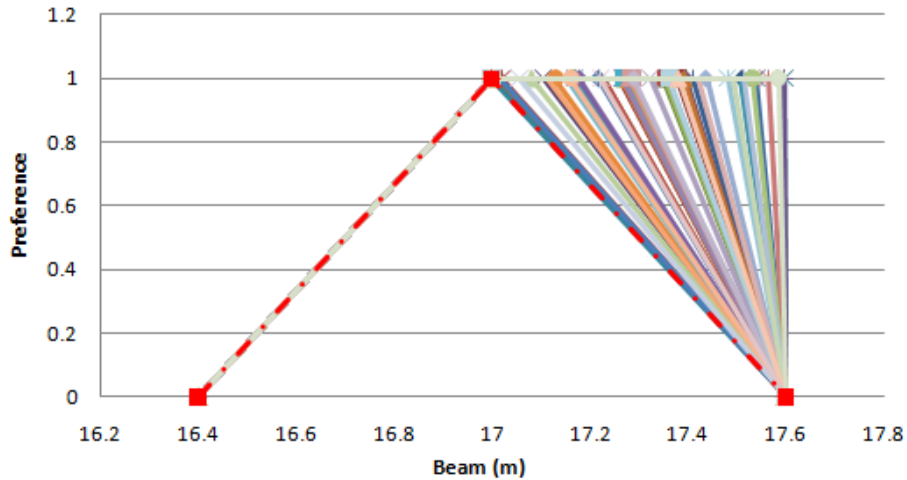


Figure 5.6 Fifty Iterations of a Randomization Process

To highlight the tradeoff between time and uncertainty representation, Table 5.4 lists the required average run times based on several different iteration levels when utilizing the IT2M FLS with the Yrand randomization method. Note that if the program run-times look rather long, correct function was the overall goal when designing the program and the algorithms have not been optimized for speed.

Table 5.4 Iterations and Average Program Run Time Data for IT2M FLS Using the Yrand Randomization Method

Number of Iterations	Average Run Time (sec)
10	5
100	42
1000	604
1000000	33000

To further demonstrate the tradeoff of uncertainty modeling obtained via different iteration levels, the JOP histogram data representation is introduced in Figure 5.7 & Figure 5.8, showing the changes in uncertainty modeling using the xRU randomization method, having been run for ten iterations and one thousand iterations, respectively.

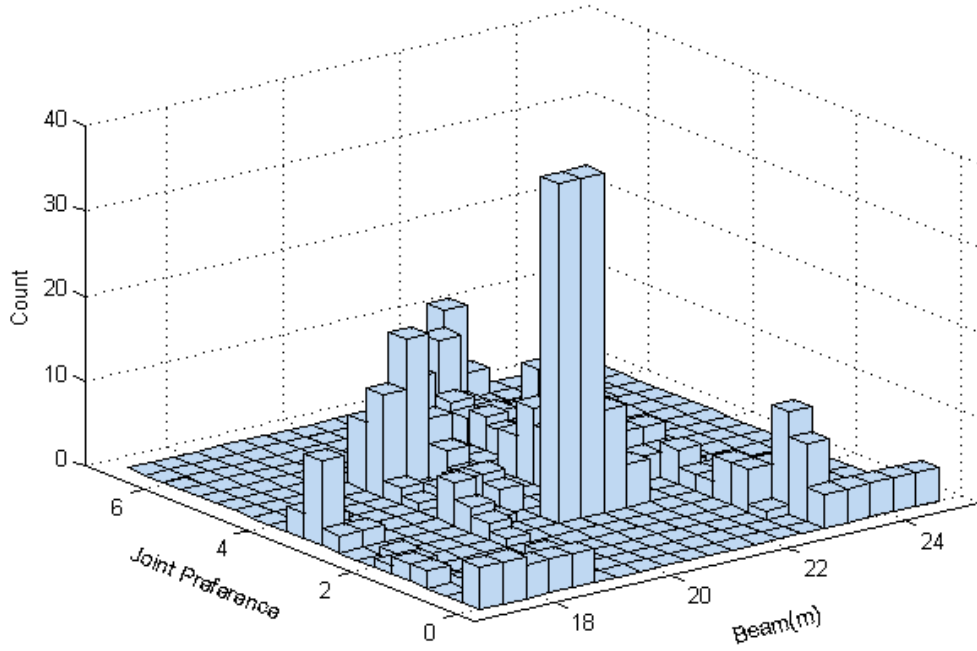


Figure 5.7 xRU IT2M FLS JOP Histogram After 10 Iterations

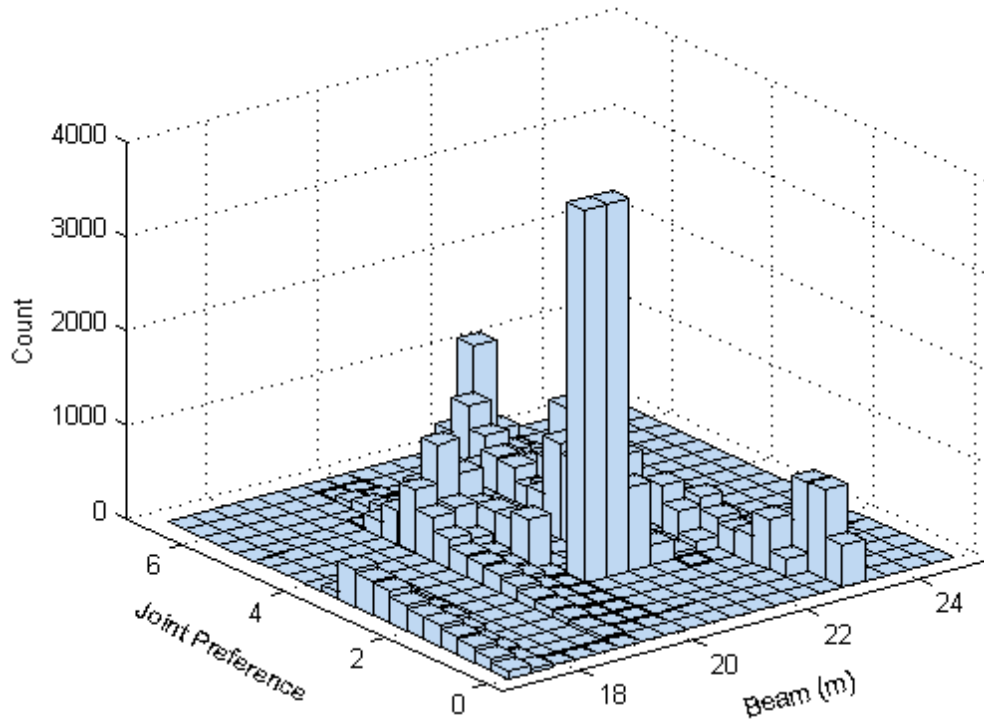


Figure 5.8 xRU IT2M FLS JOP Histogram After 1000 Iterations

The JOP histograms were developed by dividing the cumulative JOP plots into a grid and counting each time a JOP curve point fell inside one of the grid bins; Chapter 5 provides a detailed discussion on the development of the JOP histograms. Figure 5.7 and Figure 5.8 have many similarities. However, looking at the region near the beam value of, $x = 17$ m, in the one thousand iteration JOP histogram, the counts in this area make a much smoother transition as the joint preference value increases from $J(\mu(17),17) = 0$ up to $J(\mu(17),17) \approx 4$. In comparison, the bins in the same region of the ten iteration JOP histogram appear sporadic and choppy; Figure 5.7. By using a greater number of iterations, there is an increased understanding of the uncertainty in the design space.

Increasing the number of iterations used during each run of the IT2M FLS allowed one to gain confidence in the choice of certain design values. This confidence was gained by interpreting the data presented in the JOP histograms. For instance, if a design value was highly preferred and had a high count of occurrence on the JOP histogram an engineer could feel confident in choosing to use this value for their design. A value that was less preferred but also had a high number of counts on the JOP histogram may be worth investigating as an alternative design solution. Using the IT2M FLS JOP histogram information when exploring the JOP solution space, helped promote SBD practices by reducing uncertainty and increasing the amount of information available for making design decisions.

The JOP histogram data proved to offer an additional source of data analysis that was not present in either the T1 or GT2 SBD FLSs. Using the IT2M JOP histogram, one could identify the design values that were robust in the presence of design uncertainty. The robust design values would be those that possessed both a high level of preference and a

high count of occurrence in the JOP histogram. The JOP histogram data could be utilized in optimization routines and to set a “threshold of robustness” criterion for set-reduction. This threshold would allow the Chief engineering agent to narrow the design space to include only design values that had a JOP histogram count above a specified level. The full impacts and benefits of the JOP histogram for SBD are discussed in further detail in the results; Chapter 8.

From preliminary test results (Figure 5.7, Figure 5.8, Figure 5.9) it was clear that the iteration level affected the IT2M FLS’s ability to represent uncertainty in the design space. As such it was necessary to determine how many iterations were needed to gain a suitable representation of the uncertainty in the JOP solution space. To determine the ideal iteration level, the historical T1 FLS base-data was used to perform a tradeoff analysis between time required to perform a set number of iterations and the total representation of the solution space.

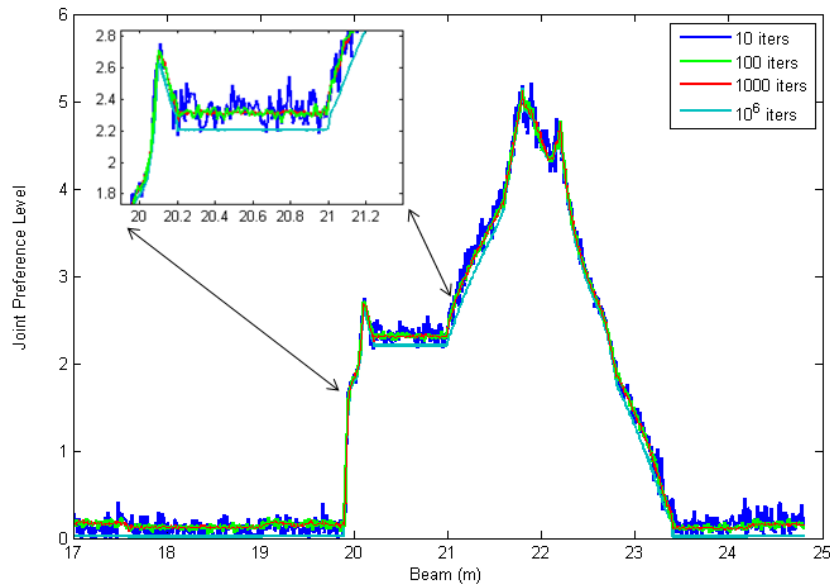


Figure 5.9 Averaged-Value JOP Curves for 10, 100, 1000, and 10⁶ Iterations of the Yrand IT2M FLS method

Different iteration levels were tested in incremental steps for the IT2M SBD FLS. Each set of IT2M FLS JOP curve data was then averaged into a single, averaged-value JOP curve. The averaged-value JOP curve, created from the set of iterations, was then compared to an averaged-value JOP curve created from one million iterations. The one million iterations averaged-value JOP curve was used to provide a baseline of comparison between the results of the different iteration levels; Figure 5.9. From Figure 5.9, it is observed that the averaged-value JOP curves of one hundred and one thousand iterations resemble the averaged-value JOP curve of 10^6 iterations quite closely.

To further analyze the different iteration levels, the length-squared (L-squared) distance between an averaged-value JOP curve, $J_{avg}(x)$, for a particular iteration level and the averaged-value JOP curve from one million iterations, $J_{mill}(x)$, was calculated for each set-value x , using Eqn. (5.3).

$$d^2 = \left(J_{avg}(x) - J_{mill}(x) \right)^2 \quad (5.3)$$

Figure 5.10 shows a plot of L-squared distances between the averaged-value JOP curves for one million iterations and the iteration levels of ten, one hundred, and one thousand iterations. It is apparent from Figure 5.10 that the averaged-value JOP curve for one thousand iterations was most similar in shape to that of one million iterations, followed by the averaged-value JOP curves of one hundred and ten iterations, respectively.

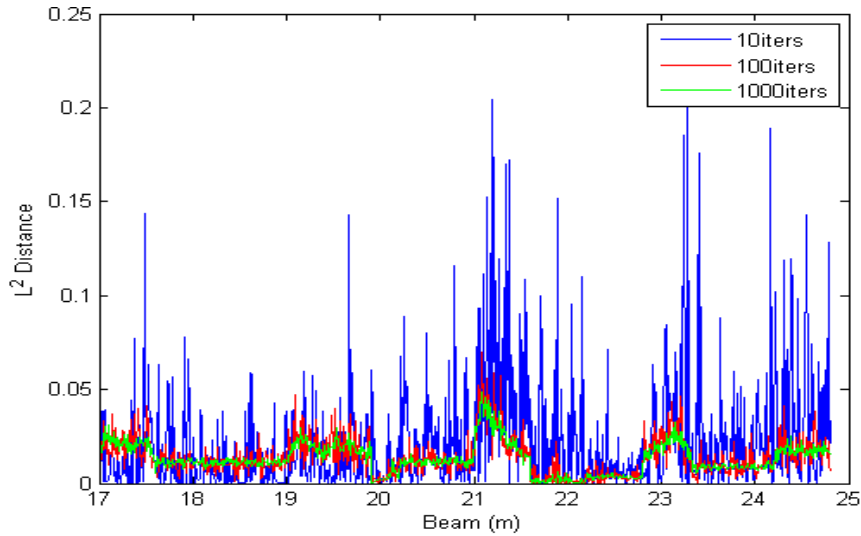


Figure 5.10 Plot of L-Squared Distances for Different Iteration Levels of the Yrand IT2M Method Compared to the Maximum of 10^6 Iterations

Since all JOP curves contained the same number of set values, x_i , it was possible to calculate the average L-squared distance for each iteration level data set. The average L-squared distance provided a single value, which could be used to easily compare each of the iteration-level data sets; Table 5.5.

Table 5.5 List of Averaged L-Squared Distances Between Averaged JOP Curve Values for Different Iteration Levels of Yrand IT2M FLS Method

Number of Iterations	L-Squared Distance to 10^6 Average JOP Curve
10	17.65
100	10.90
1000	10.44

Besides the uncertainty modeling provided by the iteration levels, the time required to complete all iterations was also of great importance. In fact, time to complete all iterations had a great influence on the final choice of an ideal iteration level. The time required to complete one thousand iterations versus one hundred iterations was rather significant; Table 5.4. Visually the one thousand iterations averaged JOP curve appeared

to be the most similar to the averaged value JOP curve of one million iterations. However, the average L-squared distance values, Table 5.5, showed that overall, the difference between the averaged value JOP curves of one hundred and one thousand iterations, when compared to one million iterations was quite low.

After comparing JOP curves and histogram data, L-squared plots and average L-squared values, and the time to complete all iterations, it was decided that one hundred iterations was the ideal iteration level. One hundred iterations were chosen over higher iteration levels because it provided an excellent balance between uncertainty modeling capabilities and the amount of time required to complete all iterations.

Although most of the examples and data shown in this section were results of the Yrand randomization method, the same analyses were done for the remaining IT2M FLS randomization methods. After extensive tradeoff analyses utilizing test data from all the IT2M FLS randomization methods, it was determined that one hundred iterations was the most suitable iteration level to use for all the IT2M FLSs based on uncertainty modeling capabilities and required run time.

5.3 Results of Initial Tests

5.3.1 Yrand IT2M FLS

The T1 FLS historical data was used to provide the design agent input preference MF data for the Yrand IT2M FLS preliminary tests. Using the ideal iteration level, one hundred iterations of the IT2M FLS Yrand randomization method were completed using the historical input data. For the preliminary tests, the sigma value of Eqn. (3.1) was set

to a value of 0.1, equivalently 10%. Figure 5.11 shows the composite plotting of all one hundred JOP curves, as well as the average JOP curve and the baseline T1 JOP curve.

After examining the results of the Yrand process in Figure 5.11, it was seen that the Yrand method failed to invoke the second key principle effect of IT2 MFs:

2) Opportunities for changes in rule activation due to MF curve uncertainty are now possible.

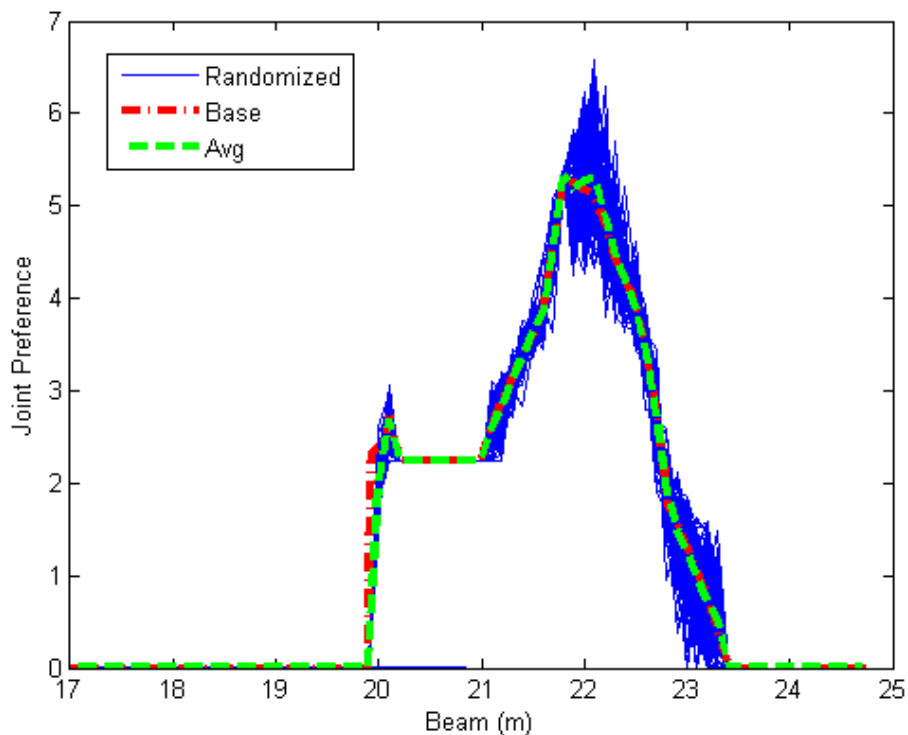


Figure 5.11 Yrand IT2M FLS JOP Curve Results Using 100 Iterations

The Yrand randomization method clearly affected only the JOP level and did not result in the creation of new non-zero preference values from additional rule activation. Since, the Yrand randomization method affected only the preference value of the T1 MFs, and not the width or shape of the MFs, there was no opportunity for changes in rule activation

due to the modeling of uncertainty. In addition to this problem, as mentioned in the previous chapter, the Yrand IT2M FLS did not maintain the summation of MF preference values to 100% or 1.0. Although a FLS is not required to enforce MFs to sum to one, typical FLSs for engineering applications do strive to maintain the logical summation of MF preference values to one [Cox, 1999].

Before abandoning the Yrand IT2M FLS, an investigation was performed to determine how the FLS JOP curve results for the Yrand method would change if the MFs of the design agents' fuzzy sets were parametrically linked. For the Yrand IT2M FLS, the parametric linking occurred at the preference level for all MF data points. One MF would be independently randomized, the adjacent MF's preference values would be parametrically adjusted so that the summation of preference values would remain equal to one at each $\mu(x_i)$. Figure 5.12 shows a set of MFs for the Cargo design agent before parametric linking, while Figure 5.13 shows the change in the MFs when the curves are parametrically linked. The parametric linking in Figure 5.13 began with the leftmost MF, but as with the parametric linking for the other IT2M FLS methods, a simulated coin flip was used to determine if parametric linking began with the leftmost or rightmost MF.

The Yrand IT2M FLS was updated to provide parametric linking of the MFs and the historical T1 data was again used to provide the FLS input MFs. Figure 5.14 shows that parametrically linking of the MFs for the Yrand IT2M FLS did result in the activation of new fuzzy rules. The additional rule activation resulted in the new, non-zero, preference values in the regions before $x \approx 20$ and after $x \approx 23.5$; these regions are labeled in

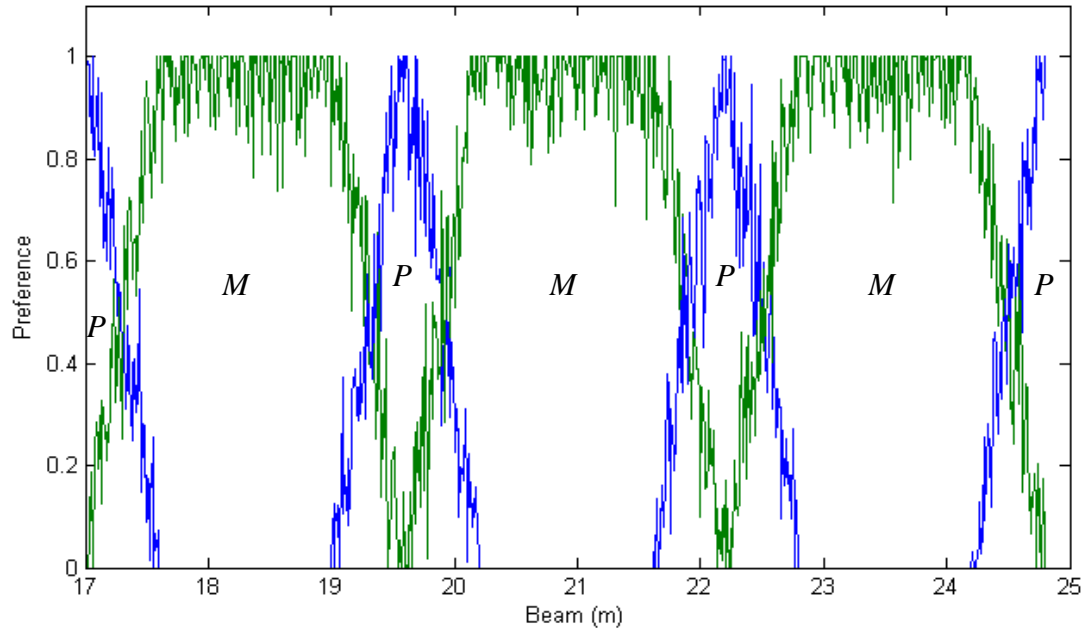


Figure 5.12 Cargo Agent's Fuzzy Set for Yrand IT2M FLS without Parametric Linking of MF Preference Values

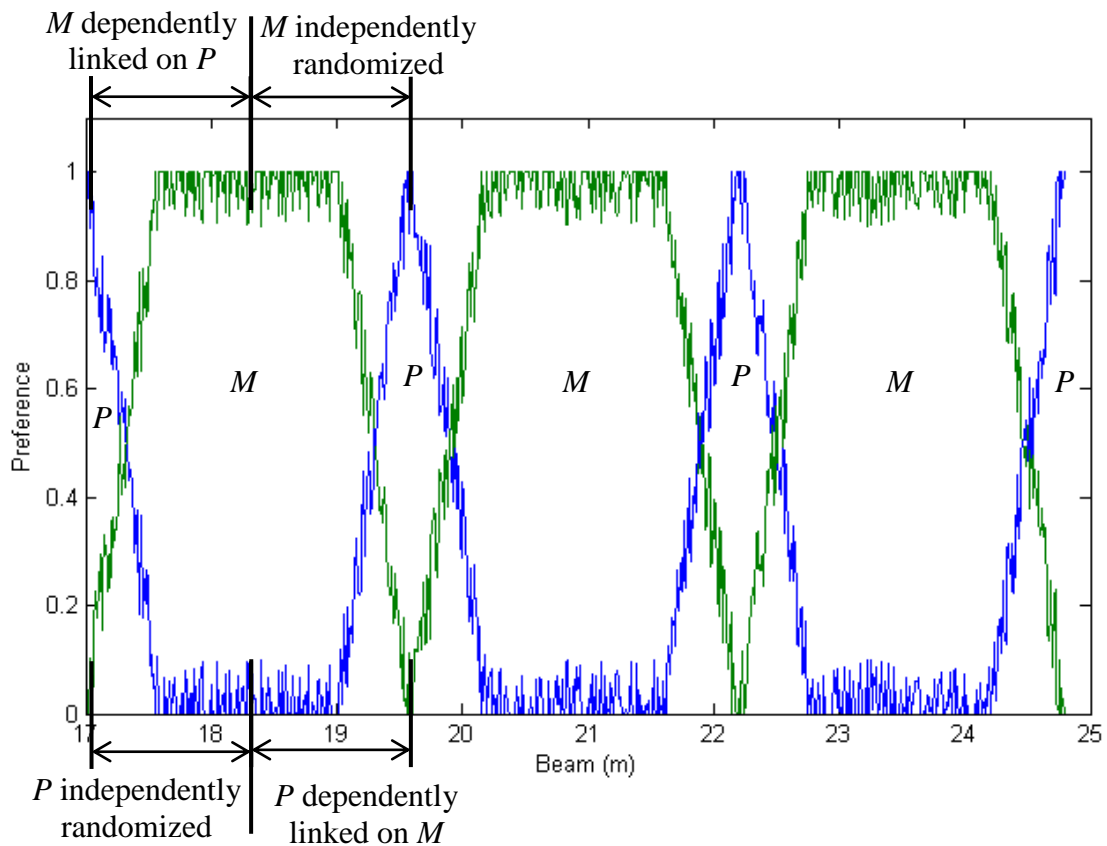


Figure 5.13 Cargo Agent's Fuzzy Set for Yrand IT2M FLS With Parametric Linking of MF Preference Values

Figure 5.14. Previously, the average JOP curve from the non-parametrically linked FLS, Figure 5.11, had joint preference values of, $J(x) = 0.0$, in these regions.

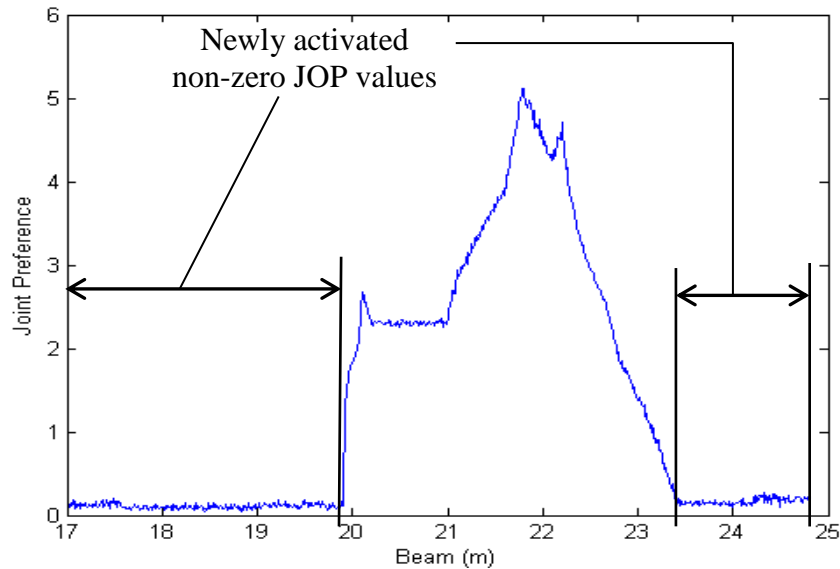


Figure 5.14 Average JOP Curve of the Yrand IT2M FLS When Input MFs Were Parametrically Linked

As a Chief engineer, the minor changes in the JOP values would not be considered significant enough to warrant continued analysis and investigation. Therefore, the Chief engineering agent would have reduced the set-range by the same amount in both the parametric and non-parametric cases for the following negotiation round; for this example.

By parametrically linking the membership functions for the Yrand IT2M FLS method no additional design insight was gained and the ability to model uncertainty was not affected. The information obtained from the two Yrand IT2M FLS tests led the author to conclude that modeling of the uncertainty for both the preference level and the locations of the MF curve defining points was needed to fully invoke the two key benefits of T2 MFs.

Since the Yrand method of randomization did not produce MFs that satisfied both key effects of IT2 MFs, this randomization method was not pursued any further for the IT2M FLS process. Although the Yrand randomization method was deemed not fully appropriate for the IT2M FLS SBD uncertainty modeling process, the Yrand IT2M FLS tests did provided data that helped in determining what aspects of randomization needed to be changed in order to model both of the key effects of T2 MFs. The conclusions drawn from the Yrand IT2M FLS preliminary tests led to the eventual development of the xRU, xRL, and Slopes IT2M FLSs.

5.3.2 xRU, xRL, and Slopes IT2M Results

As mentioned in Chapter 3, the xRU, xRL, and Slopes IT2M FLS methods of randomization were developed to model the key aspects of T2 MFs, stated again below:

- 1) The preference value of an active (T2) MF is represented by a set of possible values as opposed to a one single value and,
- 2) Opportunities for changes in rule activation due to MF curve uncertainty are now possible.

The historical T1 FLS design data for the negotiation of a ship's beam was again utilized as input data for the preliminary testing and development of the IT2M FLS randomization methods of xRU, xRL, and Slopes. As shown in Chapter 5, Section 2, the beam negotiation was performed utilizing preference inputs from three design agents, Cargo, Resistance, and Stability. Each of the three IT2M FLS methods, xRU, xRL, and Slopes, was tested using one hundred iterations for the IT2M FLS randomization process. The use of one hundred iterations was made based on the analyses done to determine the

ideal iteration level, Chapter 5, Section 2.1. When testing each of the IT2M FLS methods, the maximum allowable uncertainty was added to the MFs of the design agents' fuzzy sets. The maximum allowable uncertainty bounds for each method were described in Chapter 3, Section 4.

Figure 5.15 - Figure 5.17 show the composite graphing of all one hundred JOP curves created by the iterative process of the IT2M FLS for the xRU, xRL, and Slopes randomization methods, respectively. Each figure also displays the JOP curve resulting from taking the average JOP value at each individual set-value, x_i . To illustrate how the uncertainty modeling effects the JOP curves, the figures also show the T1 historical "base" JOP curve data. The average-value JOP curve was created in order allow for a more direct comparison between the IT2M FLS results and, the T1 and GT2 FLS results, which are each comprised of only a single JOP curve.

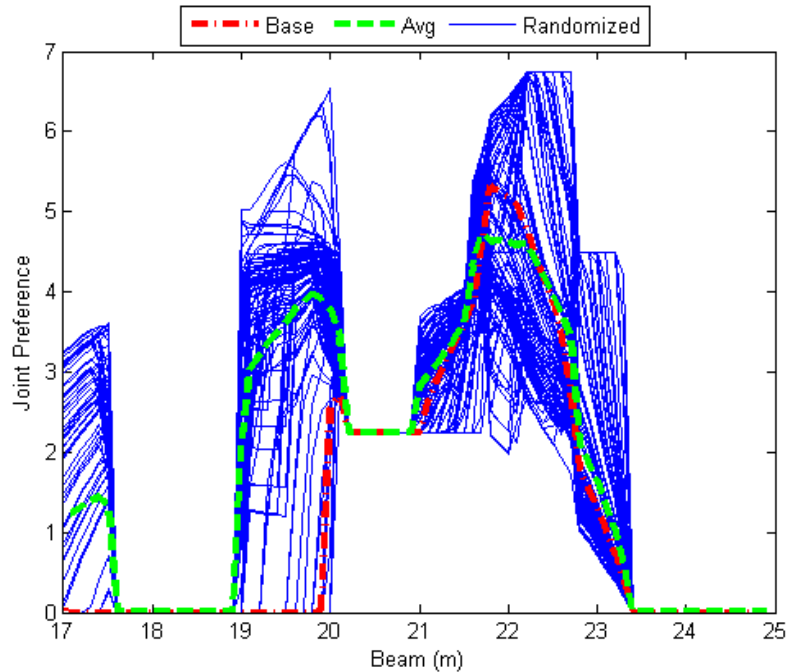


Figure 5.15 xRU IT2M FLS JOP Curve Results

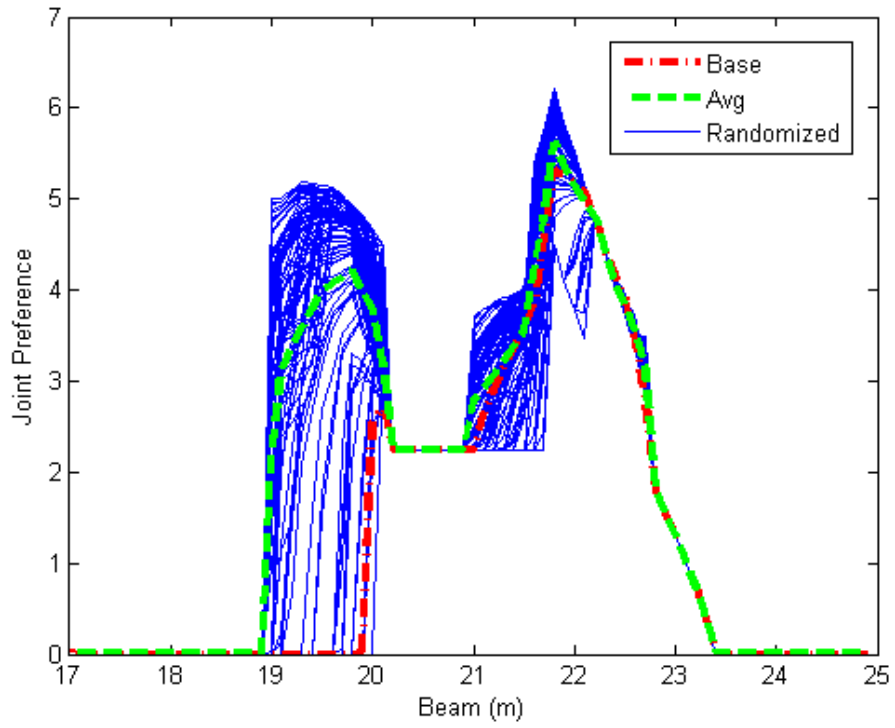


Figure 5.16 xRL IT2M FLS JOP Curve Results

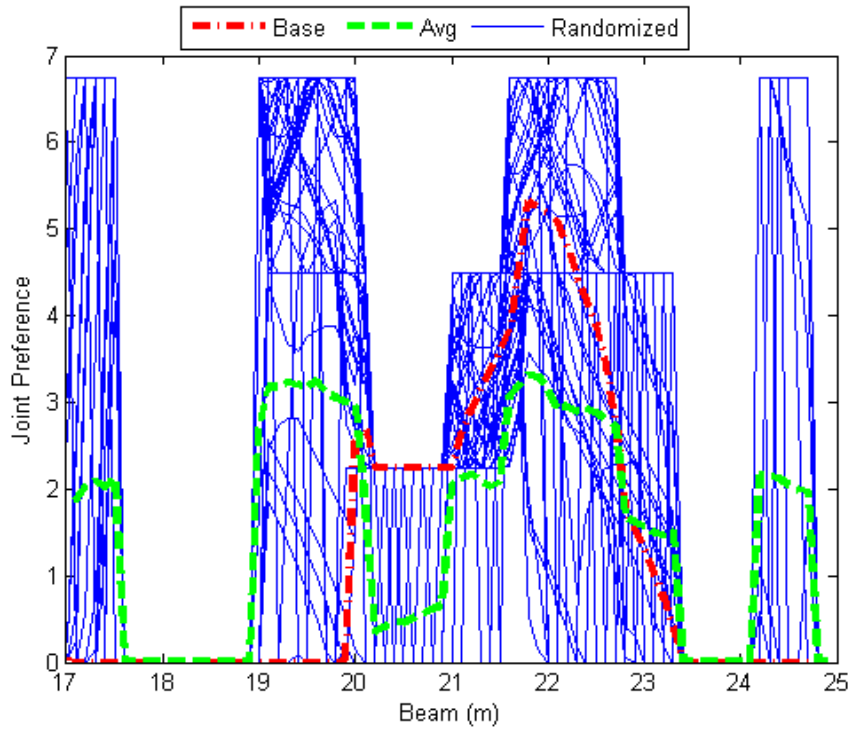


Figure 5.17 Slopes IT2M FLS JOP Curve Results

The results of Figure 5.15 - Figure 5.17 showed that the IT2M FLSs permitted the modeling of the uncertainty associated with a JOP curve solution produced by use of the T1 FLS. From the figures, it was apparent that the two key effects of T2 MFs were being correctly modeled by the IT2M FLSs. For example, in Figure 5.15, at $x \approx 21.5$ m, there exists a range of possible JOP values, and at $x \approx 17.25$ m, there were non-zero preference values created from rule activation that did not occur in the JOP curve of T1 FLS. The IT2M FLSs represented the design agents' MFs as having a set of possible preference values for each input value, x_i . As a result, changes in the JOP curve shape occurred due to the activation of new or different fuzzy rules.

Often, a complex design problem will not possess one optimal answer. The IT2M FLSs used the representation of uncertainty to show a more realistic depiction of a design space. From a design and engineering point-of-view, the composite graph of the randomized JOP curves was useful because it showed the formation of an upper and lower bound of uncertainty associated with the JOP solution space. By viewing the multiple JOP curves it was possible to search the solution space for alternative design solutions and observe the effects of uncertainty on the FLS JOP curve solution.

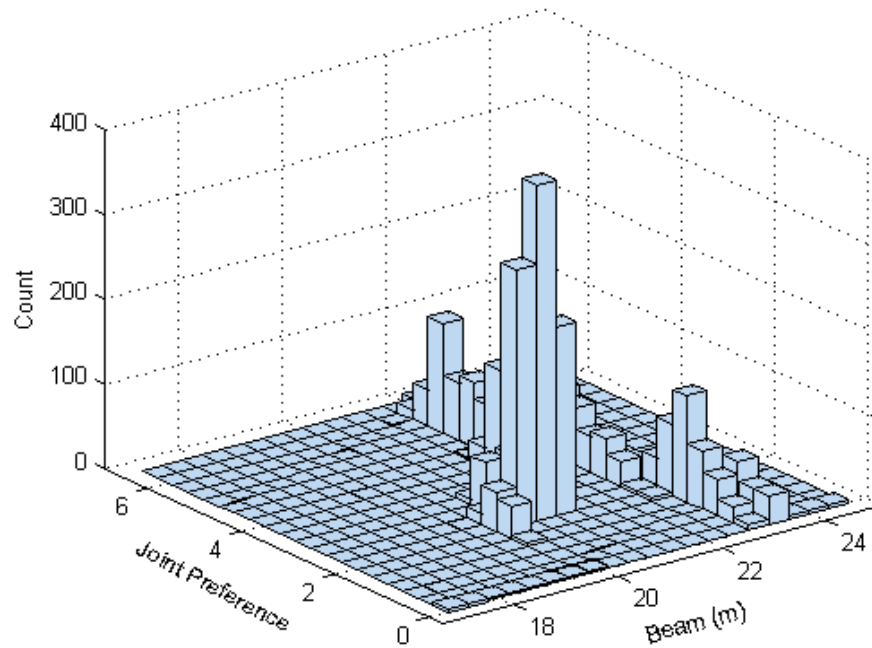
The averaged JOP curve provided a general sense of the overall preference for each design value taking into consideration the often conflicting preferences of the design agents. It was also possible to gain a general understanding of how the introduction of uncertainty into the design environment affected the JOP values in the solution space. The data from the randomized and averaged JOP curves provided information beyond what was present in the T1 FLS. One of the key principles of SBD is to delay design decisions until uncertainty has been reduced. By modeling the uncertainty in the design

space the IT2M FLS was increasing the information available for making informed design decisions. For instance, the IT2M FLS JOP curves provided a means to visually inspect the level of uncertainty from one round to the next and to determine if levels of uncertainty were reducing as the SBD process continued.

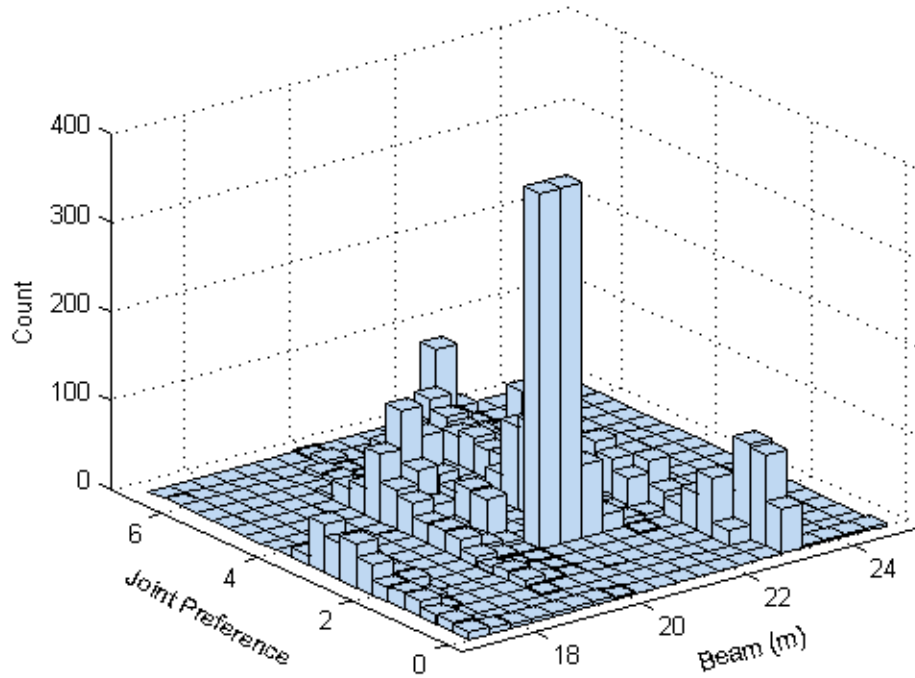
To further utilize the IT2M FLS results JOP histograms were created by dividing the JOP design space into a 20x20 grid. The 20x20 grid size was chosen arbitrarily based on the desire to offer enough fidelity to provide useful information that could be easily interpreted visually. Smaller and larger grid sizes were tried, but it was decided that the grids were either too coarse or too fine. Each time a JOP curve point passed through a bin in the grid, the total bin count for that bin was increased. The JOP histogram bin counts related how frequently a JOP curve passed through a particular bin and a design agent to determine if a JOP value occurred frequently, or if the JOP value was simply an outlier.

By using the JOP histograms to convey the uncertainty of the solution space, designers could understand which solutions were robust in the presence of uncertainty. If a preference value occurred frequently, a designer could have a greater sense of confidence, meaning reduced uncertainty, when choosing the value to analyze in further detail. The additional analysis of the JOP solution space using a JOP histogram provides a method to further reduce design uncertainty (a core SBD principle) when making critical design decisions, hence providing additional promotion of SBD beyond the capabilities of the T1 and GT2 FLS. The enhancements provided by the JOP histograms are discussed further in the results, Chapter 8.

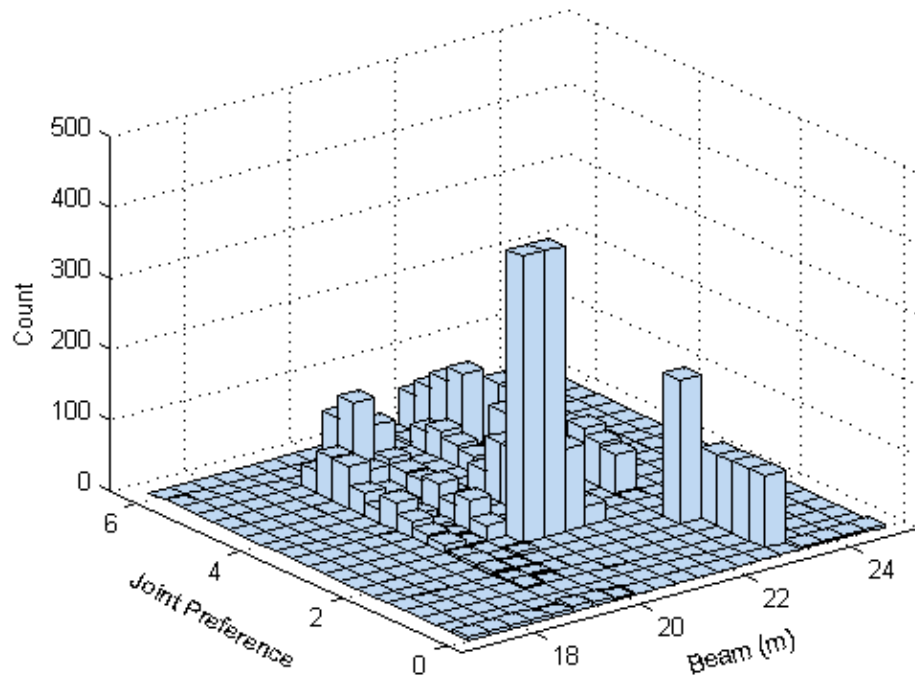
In the initial design and development phase, the JOP histograms were created and displayed in 3-D; as in Figure 5.18 - Figure 5.21. Later on when refining the IT2M FLS for the SBD preliminary ship design experiments, it was decided that the same information could be conveyed using a much simpler 2-D color plot. As such, the IT2M FLS JOP histograms for the set-based preliminary ship design experiments are displayed in 2-D using a gray-scale to indicate bin counts; examples are shown in Chapter 6. The JOP histograms of Figure 5.18 - Figure 5.21, were based on the results shown in Figure 5.11 - Figure 5.17, using one hundred iterations during each run.



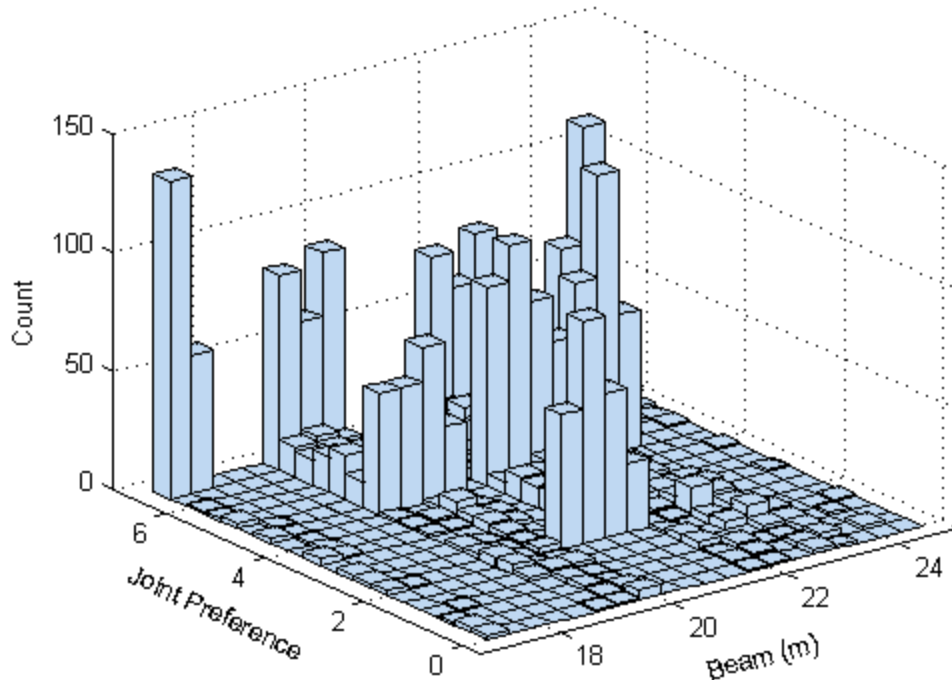
**Figure 5.18 Yrand IT2M JOP Histogram,
Based on Historical Beam Negotiation Inputs**



**Figure 5.19 xRU IT2M JOP Histogram,
Based on Historical Beam Negotiation Inputs**



**Figure 5.20 xRL IT2M JOP Histogram,
Based on Historical Beam Negotiation Inputs**



**Figure 5.21 Slopes IT2M JOP Histogram,
Based on Historical Beam Negotiation Inputs**

A few notes need to be made in regards to the JOP histograms shown above. Firstly, the counts for the zero preference values have been removed from the histogram data. The data was removed because in certain regions all one hundred JOP curves passed through the same bins of zero preference; example $x \approx [17,19]$ in Figure 5.16. Since it was clearly evident from the JOP curve plots that all preference values are zero for certain regions, the bin counts for zero preference values added no additional information in the JOP histograms. In some cases the bin counts for the zero preference values resulted in bin counts so large that useful interpretation of results was quite difficult; Figure 5.22. From a design and engineering standpoint, the non-zero preference counts provided more value in the JOP histograms than the zero preference counts. Although the zero value preference bin counts were removed from the JOP histograms, the zero preference JOP data was kept in the JOP curve plots for use by the Chief engineering and design agents.

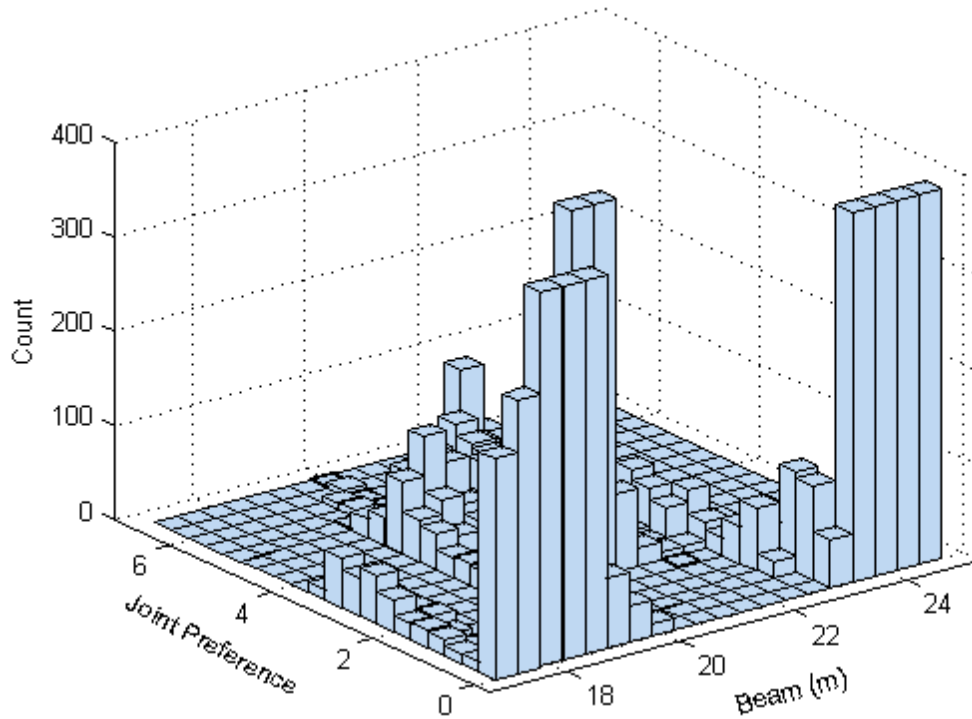


Figure 5.22 xRU IT2M JOP Histogram, Including Zero Preference Counts

Another point of interest was that some of the JOP histogram counts exceeded a value of one hundred, which was the total number of IT2M FLS iterations run. The cause for these bin counts was a result of how the variable set-range was discretized into individual set values, x_i . The historical beam variable set-range for the preliminary tests was, $B = [17, 24.8]$ m. The data was discretized using a step size of 0.1, resulting in approximately seventy-eight individual set values. Dividing the set values by the grid length of twenty resulted in approximately four set-values per bin width. It was possible that a group of four set-values could have had JOP values that were similar enough in quantity to each other that they would have fallen within the same bin. If this were to happen for every iteration, then the total bin count could be as high as 400. Because of the large variation in total bin counts for the JOP histograms of the IT2M FLS SBD

results, it was not possible to choose a single scale for the z-axis “count” without losing fidelity in some of the JOP histograms; hence the varying scales for the JOP histogram counts.

Effects of Randomization Methods

By inspection of the JOP and average JOP curves, Figure 5.11 - Figure 5.17, and the JOP histograms, Figure 5.18 - Figure 5.21, it was seen that each of the four different IT2M FL randomization methods produced distinctly unique output results. The different FLS outputs were products of how the design agents designed their input MFs and the IT2M FL randomization method used. However, since the preliminary tests all used the same base data for the FLS inputs, the differences in JOP curves seen in these figures were due to the different IT2M FL randomization methods. Changing the shape of the MFs through randomization could cause a drastic change in rule activation. This drastic change was clearly evident in Figure 5.15 & Figure 5.17 for xRU and Slopes randomization methods.

The average JOP results for the Yrand randomization method, showed only minor deviations that were centered about the baseline JOP curve. This result was sensible since the Yrand method used a uniform random distribution centered about the original base MFs to perturb the preference levels of the MFs, thereby forming upper and lower bounds of uncertainty. Because the Yrand IT2M FLS did not alter the width of the preference MFs, it was incapable of activating new fuzzy rules that could have potentially resulted in new, non-zero, JOP values. That activation of additional fuzzy rules and the resultant output of new, non-zero JOP values did occur when utilizing the other IT2M FLS randomization methods.

The xRU, xRL, and Slopes IT2M averaged JOP results each showed that the uncertainty in the set-range of $x \approx [19,20]$, Figure 5.15 - Figure 5.17, resulted in a new JOP curve shape. A similar result was seen for the set-range of $x \approx [17,17.75]$, Figure 5.15 & Figure 5.17, for the xRU and Slopes method. Looking specifically at the xRU randomization, the JOP curves showed non-zero preference values over the region of approximately $x \approx [17,17.75]$. The cause for this dramatic change in JOP curve shape was directly related to the change in shape of the Stability agent's Unpreferred (U) MF.

When the Stability agent's U MF decreased in width due to randomization it became possible for other fuzzy rules to be activated; rules which yielded non-zero preference levels. To demonstrate this result, Figure 5.23 shows the Stability agent's original historical fuzzy set. In Figure 5.24, the Stability agent's U MF has been xRU randomized using the maximum negative deviation allowed for the x -ru defining point of the U MF; x -ll of the M MF has been parametrically moved as well.

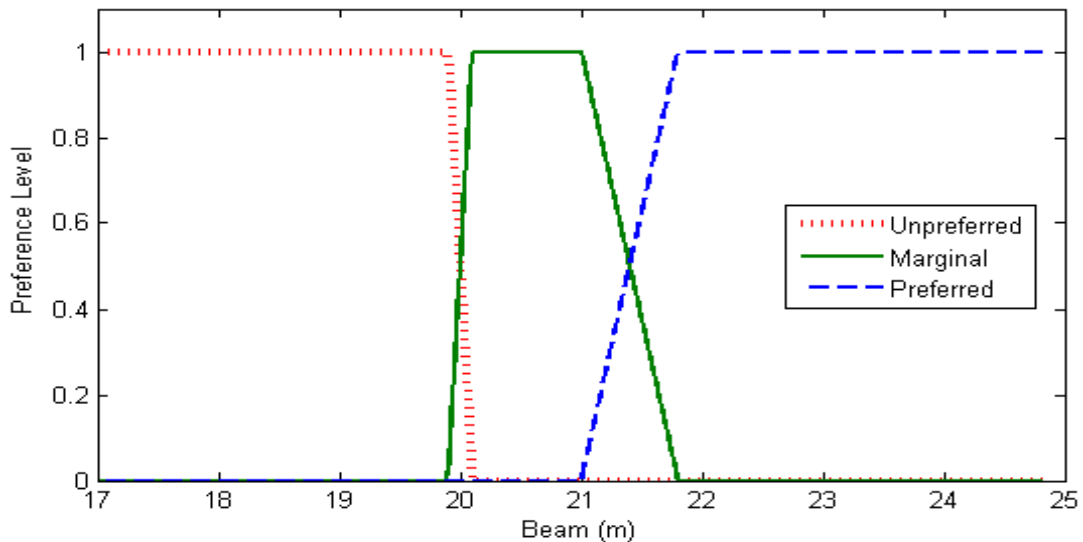


Figure 5.23 Original Historical Fuzzy Set for Stability Agent

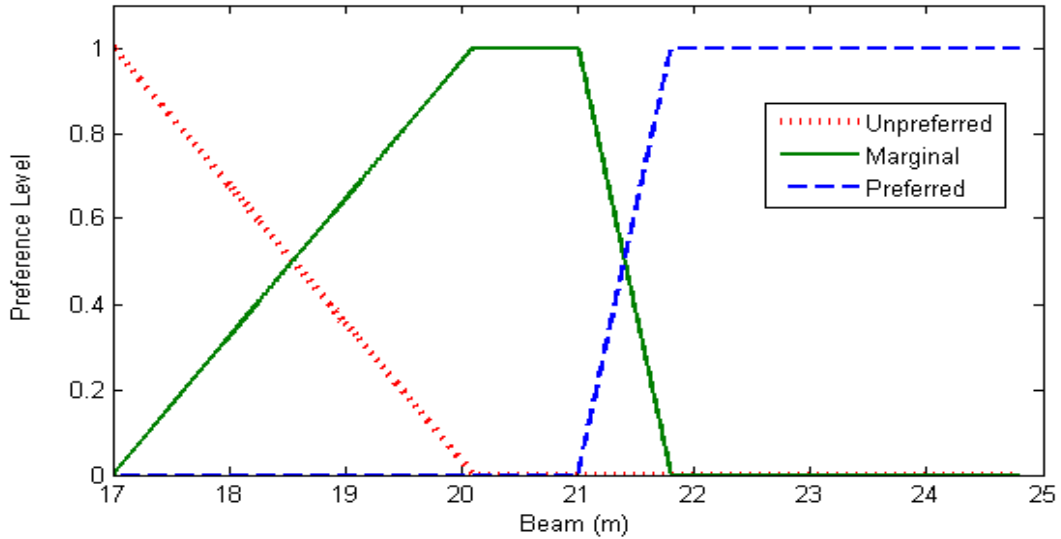


Figure 5.24 Stability Agent's Fuzzy Set After Single xRU Randomization of the *U* MF

From Figure 5.23, it is seen that in the original T1 fuzzy set the only active rule from $x \in [17, 19.9]$ was, “IF any agent unacceptable, THEN activate output preference function *Trim*”, because in this region only the *U* MF was active and it was active at a preference level of one; see FL rules Table 5.1. The activated *Trim* output preference function and centroid defuzzification produced only zero values for this region, since the centroid of the *Trim* output preference function centroid was located at zero.

Looking at Figure 5.24, xRU randomization allowed for additional rule activation because of the change in MF curve shapes. After the single xRU randomization, the Stability agent had a fuzzy preference that was both Unpreferred and Marginal to varying degrees in the range in the range $x \in [17, 19.9]$. After all one hundred xRU iterations the randomized FLS T1 MFs repeatedly resulted in additional rule activation and non-zero JOP levels for the set-range of approximately $x \in [17, 17.75]$, as seen in Figure 5.15. A similar explanation applies for the changes in JOP output for both xRL and Slopes IT2M FLS randomization results.

Comparison of IT2M FLS Randomization Methods

It is inappropriate to state that one IT2M FLS method of randomization truly performed better than another IT2M FLS method. From a designer's perspective, each IT2M FLS method possessed unique benefits for uncertainty modeling. The IT2M FLSs produced different resulting JOP curves as was shown previously in Figure 5.11 - Figure 5.17. The Yrand IT2M randomization method does not alter the width of a MF, and as a result there was no change in rule activation within the FLS. The JOP curves produced by the IT2M FLS Yrand randomization method all possessed approximately the same range of non-zero preference values. Only the uncertainty in the preference value for the negotiation variable could be modeled using the Yrand IT2M FL randomization method. The remaining three methods of randomization were capable of altering both the shape and preference levels of the baseline T1 MFs in order to model the key effects of true T2 MFs.

Using the xRU randomization method for the IT2M FLS, a drastic change in the shape of the JOP curve in terms of the range(s) of non-zero preference values resulted. This result was caused by additional rule activation in the FLS that stemmed directly from the uncertainty modeling provided by the IT2M FLS SBD tools. As discussed previously, when using the historical T1 MF data for the beam negotiation, up to an x -value of, $x \approx 20$, the only rule activated was one that resulted in JOP values of zero only. The xRU randomization method altered the width of the design agents' preference MFs, which directly caused further FL rule activation. As a result of the new/additional rule activation, a new range of non-zero preference values evolved from the uncertainty representation, in the approximate set-range of $x \in [17, 17.75]$; Figure 5.15.

The xRL IT2M FLS randomization method was capable of producing the same types of rule activation changes as seen in the xRU IT2M FLS example. However, because of how the design agents defined the input linguistic preferences in the historical T1 FLS for the beam negotiation, additional rule activation did not occur in this particular case.

The Slopes IT2M FLS randomization method elicited a change in the JOP curve shape when compared to the historical T1 FLS JOP curve. Figure 5.17 showed that as a result of changes in rule activation due to the IT2M FL Slopes randomization method, the JOP curves possessed two additional regions of non-zero preference values.

The results discussed so far were based on the initial IT2M FLS SBD tool tests which themselves were dependent upon the historical preference input MFs of design agents and the corresponding fuzzy logic rule bank. The purpose of using the historical data was to allow the author to gauge if the FLSs were working as predicted and to ensure that the IT2M FLS randomization methods were capable of representing uncertainty in the JOP solution space. It was quite logical to expect similar trends in uncertainty modeling capabilities when using the IT2M FLSs for different applications; such as the negotiation of a different design variable.

The conveyance of information directly relates to how the IT2M FLS represented uncertainty of the design variable and of the resulting JOP curves. As a designer trying to choose a particular IT2M FLS randomization method, it would be best to ask, “What properties of my system do I feel are uncertain?”, “What properties do I have confidence in?”, and “How do I want to convey the uncertainty of my preference MFs?” These questions can help a design agent to choose the most appropriate IT2M FLS

randomization method for the representation of design uncertainty. The author offers the following suggestions when trying to decide which IT2M FLS randomization method to choose for your own FLS.

The xRU randomization method should be used for the IT2M FLS if, when designing a MF, there is uncertainty about where to locate the $x-ru$ MF defining point, but not the $x-rl$ point. With the xRU IT2M FL randomization method, a design agent can express uncertainty in the range of membership grades possessing a value of one in the MF. In example, the range $x \in [17, 19.9]$ for the U MF of Figure 5.23. When using the xRU IT2M FL randomization method, a design agent should be fairly certain about the location of the $x-rl$ defining MF curve point, as only the location $x-ru$ point is independently randomized.

Conversely, the xRL IT2M FL randomization method should be used when there is uncertainty about the location of the $x-rl$ MF defining curve point, but not the $x-ru$ point. When using the xRL IT2M FL randomization method, a design agent should be fairly certain about the location of the $x-ru$ defining MF curve point. The xRL IT2M FL randomization method places an emphasis on the uncertainty associated with the rate of transition from a membership grade of one to zero, which is equivalent to the slope of the MF. For example, transition region of $x \in [21, 21.8]$ of the M MF in Figure 5.23.

Both of the xRU and xRL IT2M FLS SBD randomization methods allow a design agent to model uncertainty in the width of a MF, while simultaneously modeling uncertainty in the rate of transition from a MF of one linguistic type, to that of another linguistic type. The Slopes IT2M FL randomization method was different than the xRU and xRU

randomization methods because, it allowed the user to represent uncertainty in the width of the MF, while simultaneously representing a sense of certainty in the rate of transition from one linguistic preference, to a MF of a different linguistic preference. The Slopes randomization method would be best utilized when one desires to model uncertainty in the location and overall width of the MF, but not the rate of transition between the MFs.

Additional recommendations for when to use each IT2M FLS randomization can be made based solely on the JOP curve data, Figure 5.11 - Figure 5.17, for each of the randomization methods. The Yrand IT2M FLS randomization method displayed the least amount of T2 MF uncertainty modeling due to the fact that it cannot model uncertainty in the width of a MF or the locations of the MF defining points. The xRU and xRL IT2M FLS randomization methods appeared to have relatively similar uncertainty modeling capabilities, while the Slopes randomization appeared to represent a large degree of uncertainty. Therefore, it would be suggested to use the Slopes IT2M FLS randomization method at the earliest stages of design when uncertainty is the greatest, followed by the use of the xRU or xRL IT2M FLS randomization methods, and lastly the Yrand IT2M FLS randomization method during the latest stages of design when uncertainty has been greatly reduced.

CHAPTER 6

FUZZY LOGIC SET-BASED DESIGN TOOL

6.1 Set-based Hybrid Agent Design Tool Structure & Agent Roles

The hybrid agent fuzzy logic software was created for the purpose of testing facilitation of SBD theories and methodologies. For this research, the set-based hybrid agent FL software was configured to perform set-based preliminary containership designs. To achieve this goal, human design agents were organized into a design group and each agent was assigned one of five functionally independent design roles. The design agent roles for the preliminary ship designs were the Cargo, Resistance, Stability, Hull, and Propulsion; this is similar to what has been done historically for preliminary ship designs [Singer, 2003]. In addition to the functional hybrid design agent roles, at the highest level of the set-based hybrid agent structure was the Chief engineering agent controlling the entire SBD process.

In the hybrid agent FL SBD tool, two-way communications existed between the design agents and the Chief engineering agent, between the FL software and the Chief engineering agent, and between the FL software and the design agents. The back-and-forth communications allowed the Chief engineering agent to send requests for information from the design agents and to then receive their responses. Two-way communications also served as the input-output pathways to the SBD tool FLS software.

The communication paths between the Chief engineering agent, functionally independent design agents, and the FLS SBD tool software are shown in Figure 6.1.

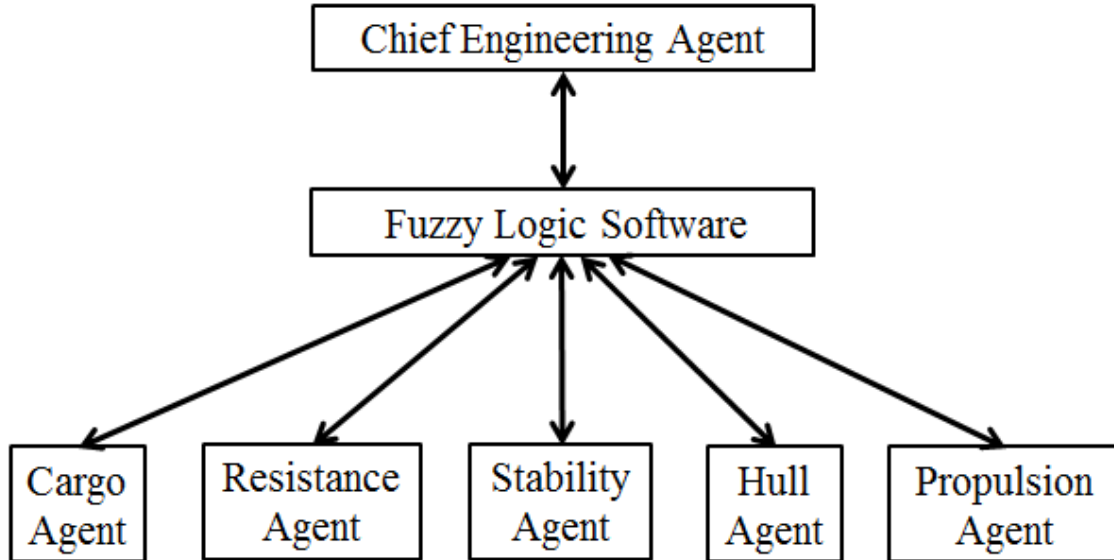


Figure 6.1 Lines of Communication Between Hybrid Agents and Fuzzy Logic Software in SBD Tool

The SBD tool software also provided some one-way communication paths. The paths were not shown in Figure 6.1 to retain clarity in the diagram. The one-way communication lines were set up so that a design agent could receive information regarding auxiliary variables. In the SBD hybrid agent FL software tool an auxiliary variable was defined as a ship design variable that was required by a design agent as an input for an analysis tool, but for which the design agent was not involved in the negotiation of the design variable. An example of an auxiliary variable in the preliminary ship design was, C_{wp} , waterplane coefficient. This variable was controlled by the Hull agent, since it directly affected the form of a ship and hence had a great impact on the total displacement of the ship. The Stability and Resistance design agents were not

significantly affected by the choice of C_{wp} , however the agents still needed the set-range of the variable to perform set-based analyses using their individual analysis tools. Hence, C_{wp} was an auxiliary variable for the Stability and Resistance agents.

During the set-based preliminary ship design, the Chief engineering agent was responsible for setting the pace of set-based communications. To facilitate communication of design variables in a set-based manner the hybrid agent FL SBD software provided the Chief engineering agent a graphical user interface (GUI) with tools to control variable set-ranges and request negotiations of design variables. The GUIs for the Chief engineering agent and design agents are discussed in Section 2 of this chapter.

Each of the functional design agents had an independent goal for the preliminary ship design. Outlined below are the specific design goals for each of the independent, functional design agents:

- Cargo Agent – Responsible for ensuring the required number of twenty-foot equivalent units (TEU), a.k.a containers, fit into the ship's hull and onboard the ship's deck in order to meet the owner's design requirements.
- Resistance Agent – Responsible for calculating the thrust necessary to achieve the required ship speed, V_k , in order to meet the owner's design requirements.
- Stability Agent – Responsible for guaranteeing transverse stability of the ship by ensuring that the transverse metacentric height, GM_t , was satisfactory. Simply put, ensure that the ship floats upright.
- Hull Agent – Responsible for assuring that the ship's displacement was greater than or equal its weight, so that the ship floats.
- Propulsion Agent – Responsible for determining the required installed engine power to meet the design speed requirement, and to pick an engine that could supply this power.

With each agent working to satisfy its own goal, it was likely that the design agents would have conflicting preferences for the same design values. The hybrid agent FL SBD tool was developed to deal specifically with the competing and conflicting constraints found in all complex system design scenarios and to facilitate the SBD process.

6.2 Hybrid Agent Fuzzy Logic Software Language and Development

The hybrid agent SBD tool was developed using the Java™ programming language to create GUIs that allowed the human design agents to interact with the FLS SBD tool by inputting preference information for set-ranges of ship design variables. The Java™ GUIs allowed design agents to use fuzzy logic MFs to describe linguistic preferences of Unpreferred (*U*), Marginal (*M*), and Preferred (*P*). After design agents input preference information for a design variable's set-range values, the FLS performed a negotiation of the input data to produce a single joint output preference (JOP) curve that describes the overall preference for each of the set values for the design variable. For the FL SBD tool, the JOP values, $J(x_i)$, range in scale from [0,9]. A JOP value of zero indicated the design value was completely unacceptable for at least one design agent, while a JOP value of nine indicated all design agents were completely certain that they preferred the design value.

The Java™ platform was chosen for the development of the SBD design tool because the “technology's versatility, efficiency, platform portability, and security make it the ideal technology for network computing” [ORACLE, 2011]. Using Java™ programming, the software was developed with an object oriented structure, calling upon Java™ Remote

Method Invocation (RMI) to allow the software to operate as a networked-based system. The network-based system allowed the hybrid FL design agents to work independently on their own personal computers (PCs) and in different locations, all while being connected to a central host computer that acted as a networked server. The Java™ RMI enabled the communications between the Chief engineering agent, design agents, and the SBD FLS tool. Information on the set-based communications and SBD process was stored in data files on the host computer for further analysis.

The original T1 FLS SBD tool theory and mathematics for the hybrid agent T1 FLS were created by David J. Singer [2003], with the Java™ programming outsourced to a consultant, Dr. J. Eric Ivancich. The author's research has focused on the investigation of the effects of adding uncertainty modeling to the SBD process via newly developed IT2M FLSs, and a GT2 FLS hybrid agent design tools. The theory and mathematical processes for the new SBD FLSs were developed by the author and initially coded using MATLAB programming software.

Since the goal of this research was to determine the effects of adding uncertainty to set-based communications, not to test the author's programming efficiency, help was sought for development of the newly developed hybrid agent IT2M FL and GT2 FL SBD tools. Outside programming help was necessary to avoid negatively impacting the SBD experiments and skewing results due to limitations of the software and functionality of the GUIs.

With permission from Dr. David Singer, the original T1 FLS hybrid agent SBD tool code was updated to include uncertainty modeling capabilities by way of IT2M and GT2 FLSs.

Because of his intimate knowledge of the T1 FLS hybrid agent software, Dr. J. Eric Ivancich was again consulted for the updating of Singer's T1 FL hybrid agent SBD tool Java™ research code.

6.2 Software Interfaces

There are two main sets of GUIs in the hybrid agent SBD FLS tool, those for use by the Chief engineering agent and those for the design agents. The agents' GUIs were developed to facilitate simplistic and intuitive data input and to aid in set-based communications.

6.2.1 Chief Engineering Agent Interfaces

The Chief engineering agent's GUIs were identical for the T1, IT2M, and GT2 FLSs. The Chief engineer agent was in charge of controlling the entire SBD process. The Chief agent had a "Main Interface" GUI that displayed information about the design agents' status and the ship design variables; Figure 6.2.

Note that in Figure 6.2, as well as many of the following figures, there were references to a variable *Dave_B*. This variable name was created for the sole purpose of differentiating between negotiations of the design variable beam (*B*), which were based on inputs from the historical T1 FLS data versus new negotiations for the *B* variable using human agents' preference inputs. In addition, for simplicity during the design and preliminary test stages the *Dave_B* variable was negotiated by only three design agents: Cargo, Resistance, and Stability. The true beam variable, *B*, was negotiated by all five design agents.

Modeling Method: Type 1

Agents

Name	Status
Cargo	Disconnected
Stability	Disconnected
Resistance	Disconnected
Propulsion	Disconnected
Hull	Disconnected

Disconnect

Variables

Name	Units	Min	Max	Status	Due In
Dave_B	meters	17.00	24.80	completed 0 round(s)	
Vk	knots	14.50	18.50	completed 0 round(s)	
GMt	meters	3.00	7.00	controlled by Stability	
KGm	meters	0.0	0.0	completed 0 round(s)	
KGc	meters	150	350	completed 0 round(s)	
KGo	meters	0.0	0.0	controlled by Stability	
KGs	meters	100	350	completed 0 round(s)	
TEU	units	500	1000	controlled by Cargo	
Threqd	kn	10.0	20.0	completed 0 round(s)	
LWL	meters	103.9	152.9	completed 0 round(s)	
T	meters	2.60	7.50	completed 0 round(s)	
Cb	nd	0.00	1.00	completed 0 round(s)	
B	meters	14.0	37.5	completed 0 round(s)	
Wm	tonnes	500	1500	completed 0 round(s)	
Lm	meters	100	350	completed 0 round(s)	
Lc	meters	50.0	250.0	completed 0 round(s)	
D	meters	7.50	14.00	completed 0 round(s)	
Wm	tonnes	1000	3000	completed 0 round(s)	

New Negotiation Round...
 Get Values/History
 Get Agent Status

Quit

Figure 6.2 Chief Engineering Agent's Main Interface GUI

In the “Main Interface” GUI, the design agents’ status referred to whether or not a design agent was connected or disconnected to the SBD tool software. A data table provided information about a design variable’s name, units, set minimum and maximum values, status, and “Due In” time. There are three status states for a design variable,

- 1) Status Completed – This state indicated the variable was not involved in an active negotiation and informed the Chief engineering agent exactly how many negotiations have been completed for the design variable.
- 2) Status In Progress – This state indicated that the design variable was currently being negotiated. Information was also provided to the Chief engineering agent as to how many design agents were still working on entering preference information for the negotiation of the design variable. When the system was waiting for only two design agents, the GUI would display the names of the design agents.
 - a. If the design agent(s) failed to submit preference information before the allotted time limit, the status would read “In Progress/Overdue”.
- 3) Controlled by ... Status – This status was reserved for design variables that were not negotiated. The set-ranges of these variables were controlled by the agent listed in the “Controlled by ...” status window.

The Chief engineering agent initiated the SBD negotiation process by requesting the negotiation of a design variable using the “New Negotiation Round...” button on the “Main Interface” GUI. Clicking this button opened a new dialog window, the “Negotiation Set-Up” GUI; Figure 6.3.

When sending the design agents a request for negotiation, the Chief engineering agent specified the set-minimum and -maximum values for the design variable and provided a time limit for the set-based negotiation. The time limit for the negotiation of the design variable appeared in the “Due In” column on the Chief engineer’s “Main Interface” GUI.

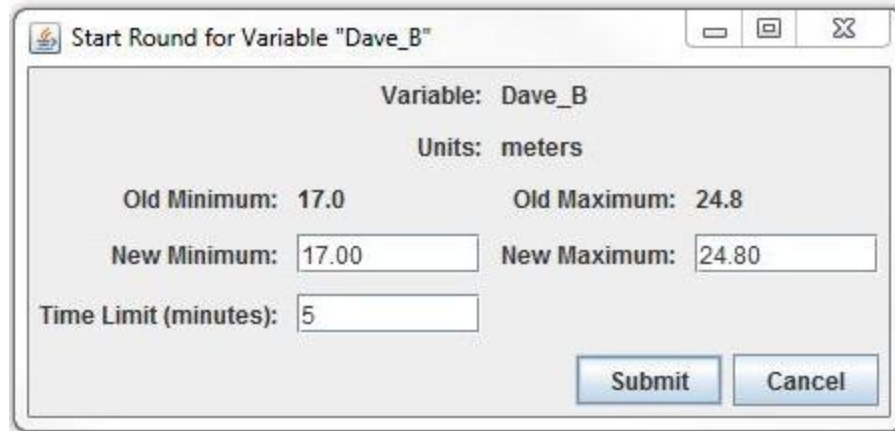


Figure 6.3 Chief Engineering Agent's Negotiation Set-Up GUI

Once submitted, the time limit began to count down to zero, and the count-down was displayed on the “Main Interface” GUI. The time limit was used to try to maintain a constant takt time throughout the SBD. Takt time is defined as, “the average time between outputs”, and is, “a German word used to describe a Japanese system that indicates a precise interval of time” [Hopp and Spearman, 2008].

The time limit was provided to the design agents with the intention that it be used to help gauge how much time the agent should allot to perform design analyses before finally entering preference information. No penalty was assessed if a design agent failed to enter preference data before the time limit expired. However, the “Due In” status would change from a time value, to a status statement of “Overdue”.

Depending on the FLS being used for the SBD process, the “Get Values/History” button would display different FLS results. When using the T1 or GT2 FLSs, after first selecting a design variable by clicking on the variable name, clicking on the “Get Values/History” button resulted in a new display window; the “FLS Results” screen. The

“FLS Results” screen displayed the JOP curve result for the most recent negotiation round. After the first negotiation round, the “FLS Results” screen contained two tabs, one displayed the most recent JOP curve only, while the other tab displayed a plot of the current and previous JOP curve results together; Figure 6.4 and Figure 6.5.

The “FLS Results” screen also displayed the set-minimum and -maximum from the most recent negotiation round; labeled the “Old Minimum” and “Old maximum”. The “FLS Results” screen could also be opened by double-clicking the left-mouse button on the variable name in the table of the Main Interface screen.

After the first round of negotiation, when the Chief engineering agent went to request a new negotiation round, the “Negotiation Set-Up” GUI opened with an addition to the previous information shown in Figure 6.3. The GUI now included a display of the JOP curve results similar to those in Figure 6.4 and Figure 6.5. When starting a new negotiation round, the Chief engineering agent used the additional JOP curve information to determine how to trim the set-range, thereby establishing a reduced set-range for the new negotiation round. As an alternative to using the “New Negotiation Round ...” button, double-clicking the right-mouse button on a variable name also opened the “Negotiation Set-Up” GUI.

When using the IT2M FLS, the “FLS Results” screen displayed the unique JOP curve results for this particular FLS; that being the cumulative plotting of all JOP curves, one curve per iteration, and the averaged value JOP curve. The IT2M FLS used additional post processing of the JOP curve results to create a JOP histogram data for each negotiation round. For the IT2M FLS, the “FLS Results” screen also contained tabs for

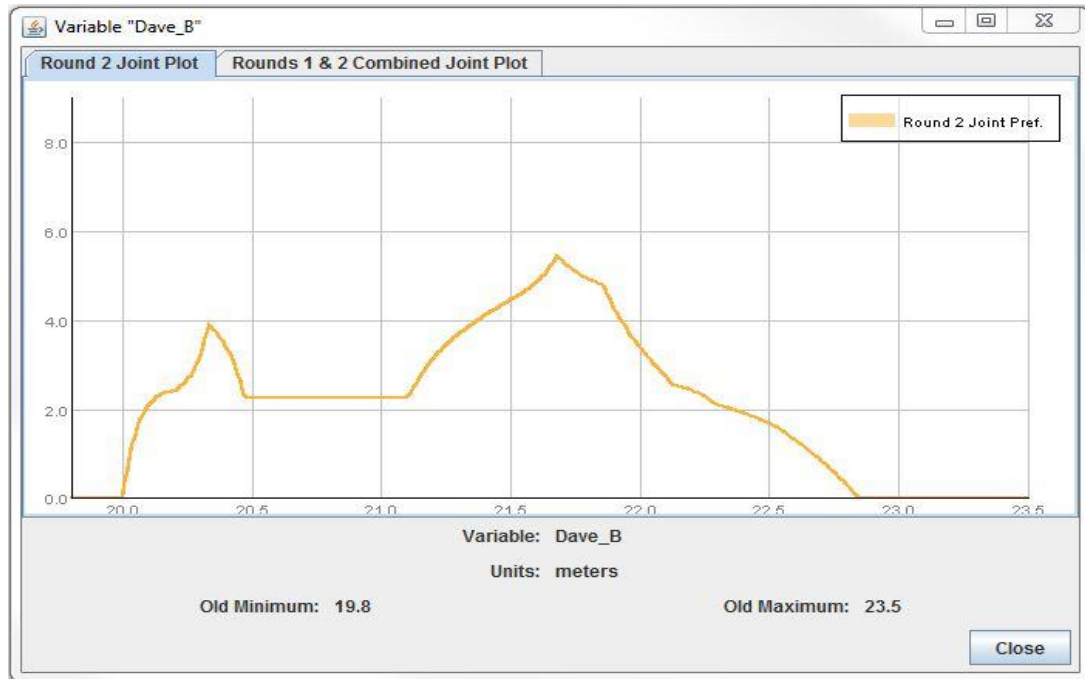


Figure 6.4 FLS Results Screen for T1 and GT2 FLSs, Displaying Current JOP Curve Only

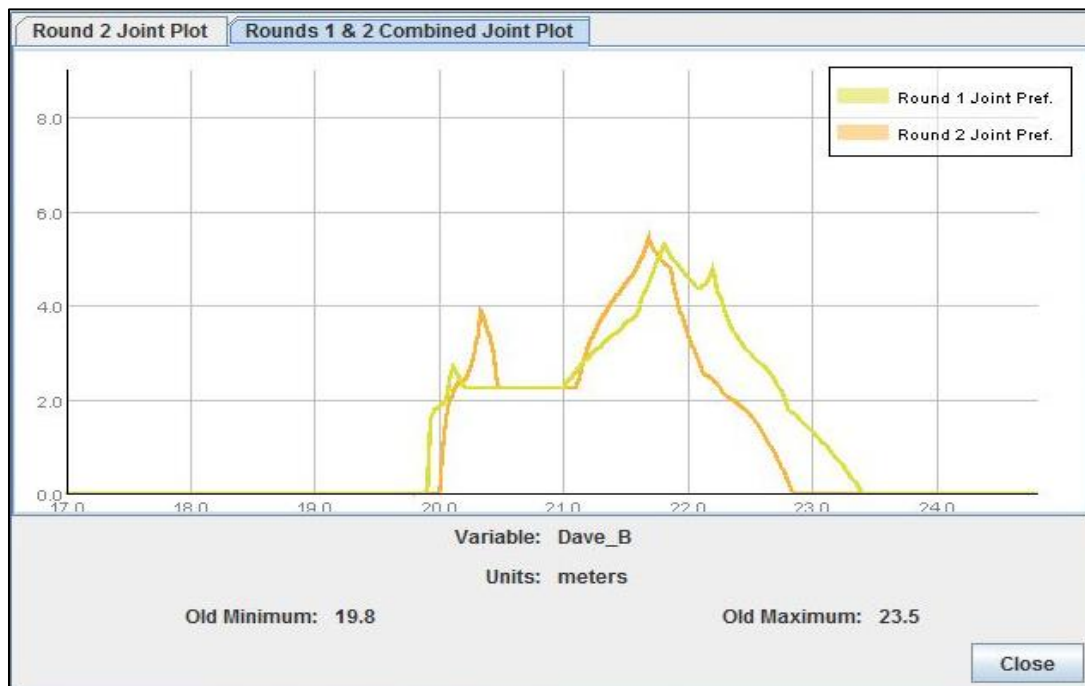


Figure 6.5 FLS Results Screen for T1 and GT2 FLSs, Displaying Current and Previous JOP Curves Simultaneously

the JOP histogram displays; one with zero preference values included and a one for the JOP histogram without the zero preference values. All four tabs are shown in the screenshot of the “FLS Results” screen for the IT2M FLS; Figure 6.6. For comparison, the JOP histogram results based on the JOP curve data of Figure 6.6 are shown in Figure 6.7 and Figure 6.8.

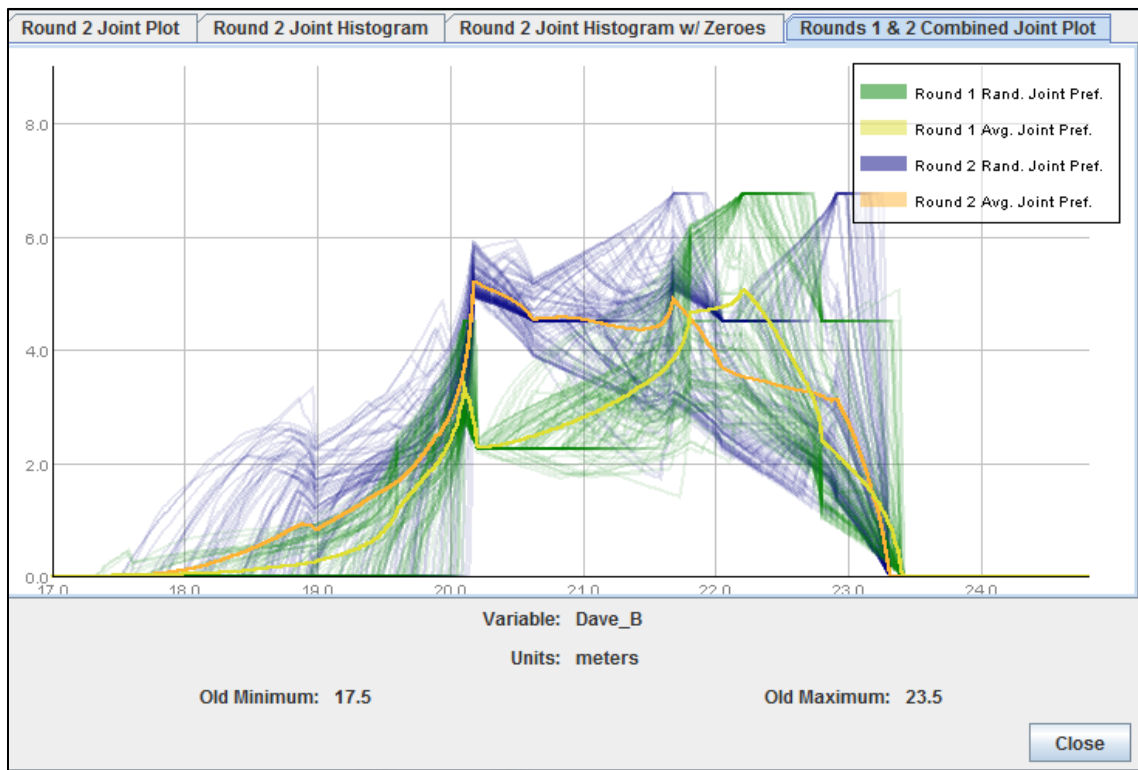


Figure 6.6 IT2M FLS JOP Curve Results Display in the New Negotiation Set-Up GUI for the Chief Engineering Agent

Similar to the T1 and GT2 FLSs, when starting an additional negotiation round, the Chief engineering agent was provided the JOP curve negotiation results for the most recent negotiation. The displayed IT2M FLS results included a cumulative plot of JOP curves, averaged value JOP curves for previous and current negotiation rounds, and current JOP

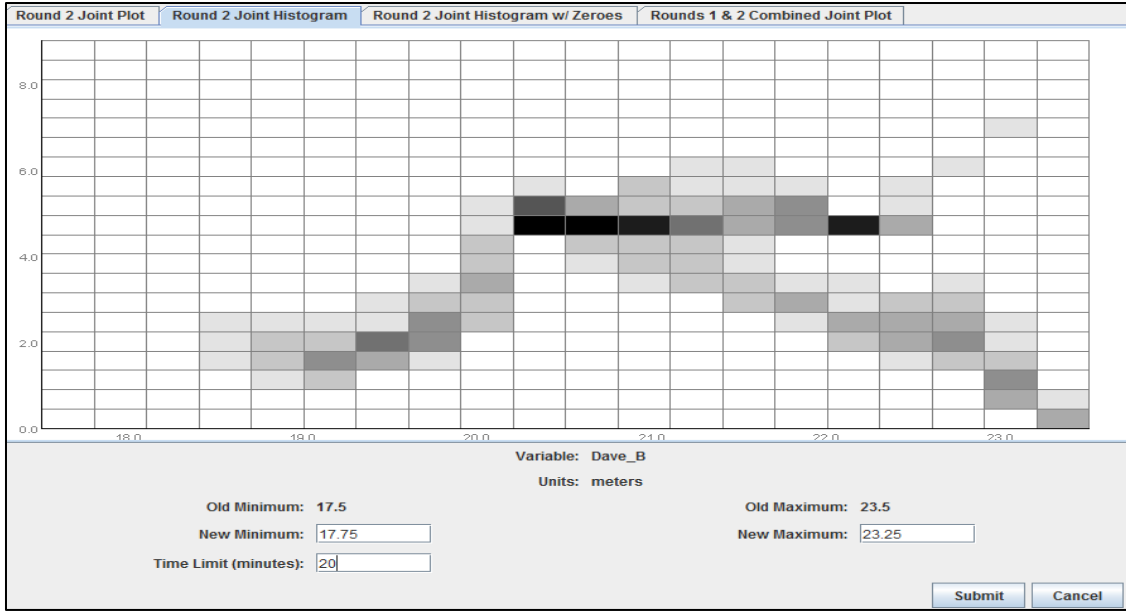


Figure 6.7 IT2M FLS JOP Histogram Data Based on JOP Curve Data of Figure 6.6, With Zero Preference Values Removed

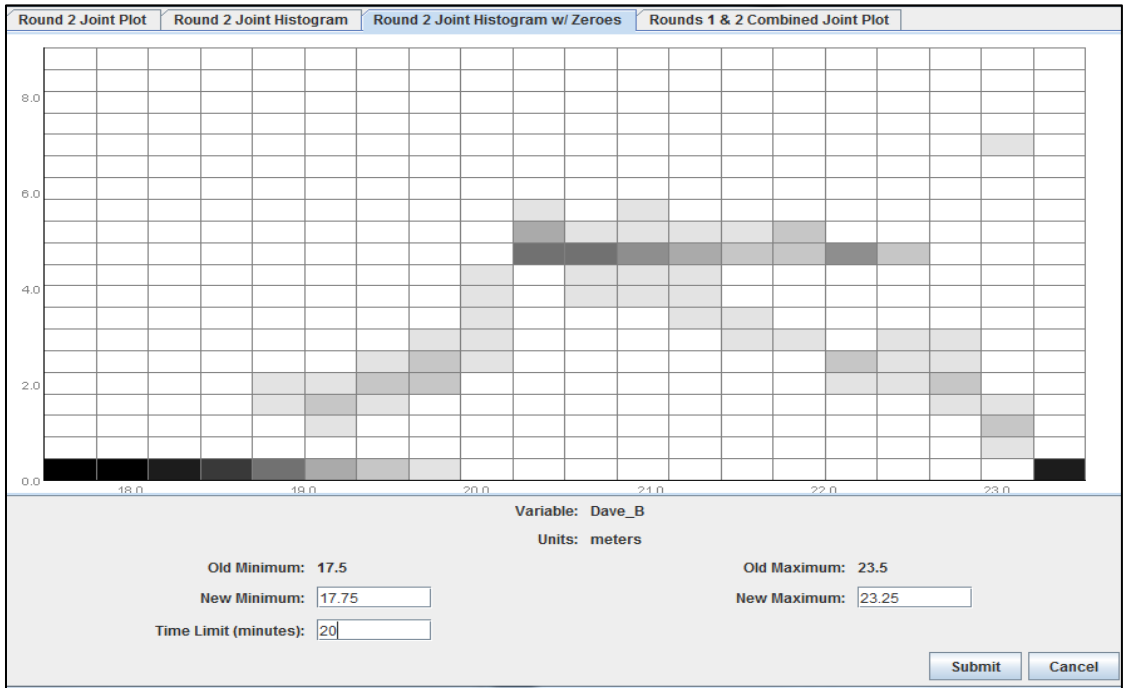


Figure 6.8 IT2M FLS JOP Histogram Data Based on JOP Curve Data of Figure 6.6, Including Zero Preference Values

histograms with and without zero preference values. The Chief engineering agent used the JOP curve data to make informed decisions as to how to reduce the set-range for the new negotiation round.

The Chief engineering agent's "Main Interface" GUI also had a "Get Agent Status" button. The "Get Agent Status" button was used by the Chief engineering agent to view the status of the design agents in reference to specific design variables. After selecting a variable name from the table and then clicking the "Get Agent Status" button, a new window would open displaying the names of the negotiating agents; the connection status, "connected" or "disconnected"; and the preference status for negotiation, "submitted", "un-submitted" (if negotiation in progress), or "nothing pending". This information was used by the design agent to control the flow of the SBD negotiations.

The final button found on the Chief engineer's Main Interface screen is the "Disconnect" button. This button was used at the end of a SBD to properly disconnect a design agent from the networked software. The program recorded all instances of connection and disconnection from the program while a SBD was in progress.

6.2.2 Design Agent Interfaces

Design Agents' Main Interface

A design agent's "Main Interface" GUI was identical for all hybrid agent SBD tool FLSs. Figure 6.9 shows an example of the Resistance agent's "Main Interface" GUI for the FL SBD tool. All of the design agents' "Main Interface" GUIs had the same general layout. Many of the same features that were present on the Chief engineering agent's "Main Interface" GUI were also found on the design agents' "Main Interface" GUI.

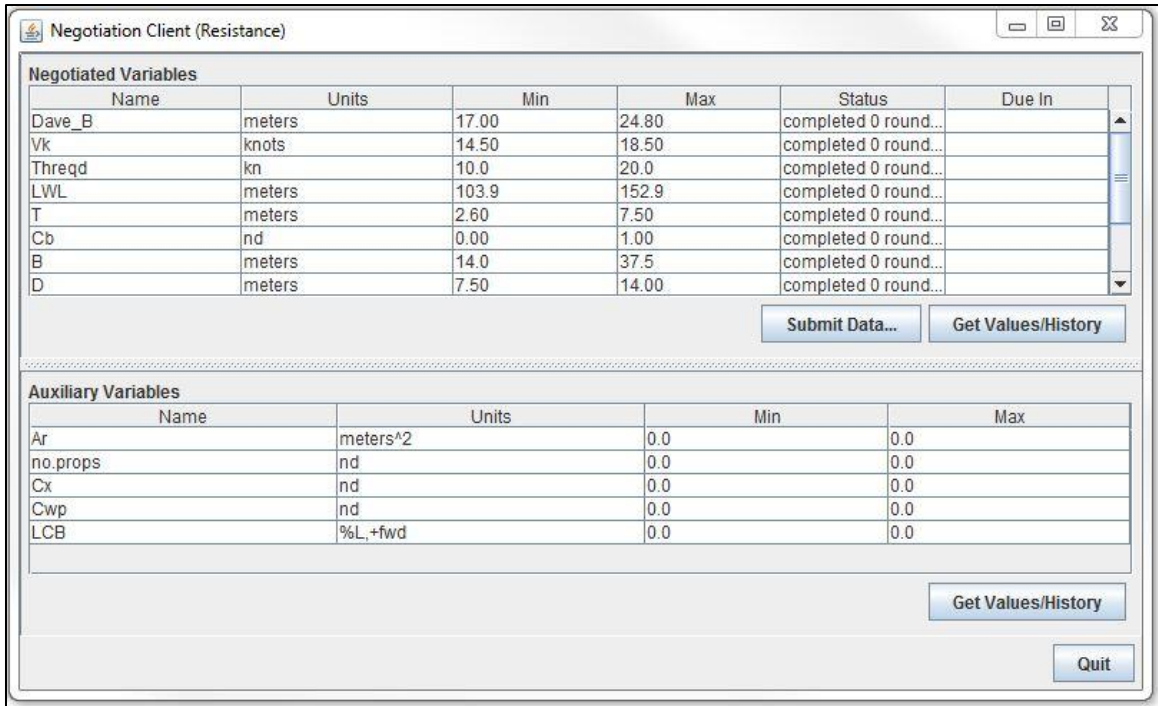


Figure 6.9 Example of Design Agents' Main Interface

For the negotiated design variables, the “Get Values/History” button provided the same information that the Chief engineering agent was able to view for the JOP curve results of each of the SBD tool FLSs. The JOP curve data of previous negotiation rounds was used by design agents to aid in performing SBD analyses of design variables and for the development preference information for set-based negotiations.

The design agents also had an “Auxiliary Variables” table in their “Main Interface” GUI. As mentioned previously, auxiliary variables were ship design variables that a design agent needed as an input into one of their analysis tools, but which were not negotiated by the design agent. The set-ranges for these variables were automatically updated as they were reduced through set-based negotiations by other design agents. Selecting a variable in the “Auxiliary Variables” table and then clicking the “Get Values/History”

button opened a pop-up window displaying the current set-minimum and -maximum values for the variable; labeled as the “Old” minimum and maximum.

Using the left-mouse button and double-clicking on the variable name would display the historical values for the negotiated or auxiliary variables. Double-clicking a negotiated design variable with the right-mouse button opened the design agent’s “Preference Data Input” GUI; the GUI could also be opened using the “Submit Data ...” button on the agent’s “Main Interface” GUI. The “Preference Data Input” GUI was used by the design agents to define the individual MFs that describe linguistic preferences for different ranges within a set of values for a design variable.

When the Chief engineering agent requested the negotiation of a design variable, the negotiating design agents were notified via a pop-up window; example Figure 6.10. The pop-up window displayed the date, time, variable name, and notification of a requested negotiation. The window also notified a design agent when negotiations were completed. Design agents could use the pop-up notifications window and the “Main Interface” GUI to determine which variables needed to be negotiated and to assign a priority to the negotiation requests.

To determine linguistic preferences for the different set values of a design variable, the design agents used individualized analysis tools. These tools consisted of computer programs separate of the SBD tool software; for example, specially designed Microsoft Excel© spreadsheets and C++ programs. Once a design agent had determined linguistic preferences for set values, the “Preference Data Input” GUI was used to create the MFs which represented the agent’s linguistic preferences.

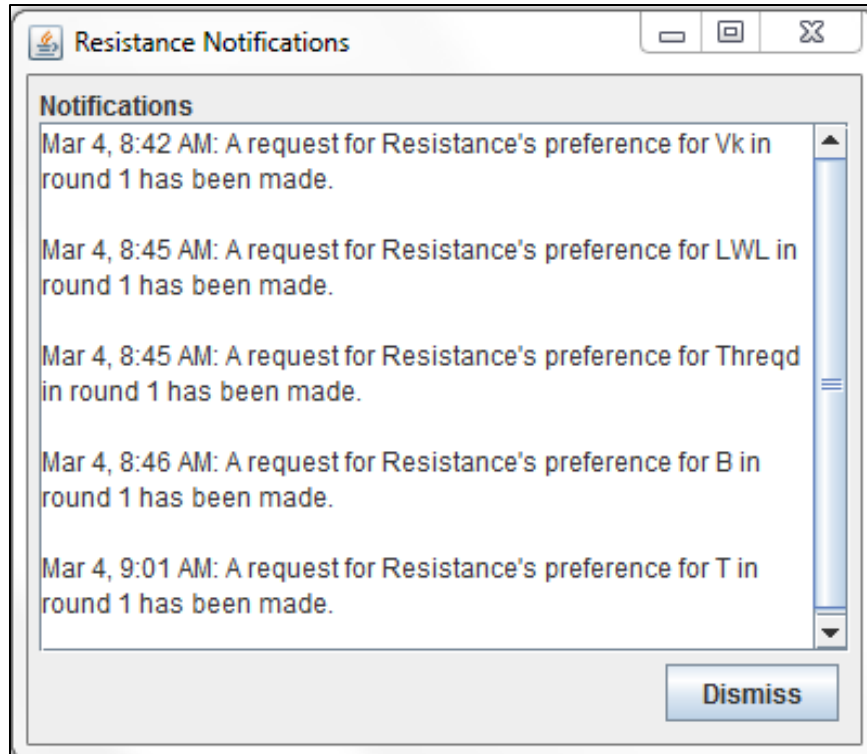


Figure 6.10 Example of Design Agents' Notifications Pop-Up Window

Design Agents' Preference Data Input GUIs for T1, IT2M, & GT2 FLSs

The "Preference Data Input" GUI was used by the design agents to create the MFs for the modeling of linguistic preference and design uncertainty. As mentioned previously, all the FLSs used trapezoidal and triangular MFs. The MFs were described by four defining curve points, left-lower (x_{ll}), left-upper (x_{lu}), right-upper (x_{ru}), and right-lower (x_{rl}); reference Figure 3.3. At all times the upper defining curve points had a preference value of one, while the lower points maintained a preference value of zero.

The appearance of the "Preference Data Input" GUI changed depending on which FLS was being used for the set-based negotiations. However, overall the GUI maintained the same general appearance and functionality between the different FLSs. The Type-1 FLS was used as the basis for which the other FLSs were designed. In a similar manner the

“Preference Data Input” GUI for the T1 FLS was the basis for the “Preference Data Input” GUI of the IT2M and GT2 FLSs.

When the “Preference Data Input” GUI opened, by default, the design agent was automatically presented with five MFs of linguistic preference, *U*, *M*, *P*, *M*, and *U*, in that order. An example of the T1 FLS default “Preference Data Input GUI” is shown in Figure 6.11 for the first round of negotiation. The GUI lists the number of MFs and the associated set values for each of the defining MF curve points, as well as the linguistic preference of the MF. An additional MF was added by clicking on the row in the “Trapezoid Table” and then clicked on the “Split Trapezoid” button. To remove a trapezoid, the user pressed Ctrl+mouse-click to select two adjacent MFs from the “Trapezoid Table”, and then clicked the “Join Trapezoids” button. The addition and subtraction of MFs allowed design agents to define as few or as many MFs as needed to linguistically describe preference of the set-range values for a design variable.

There were two methods to change the location of the MF defining curve points and linguistic preference of a MF. The most accurate method for defining the MF curve points was to enter exact set-values into the “Trapezoidal Table”. The simplest method for changing the MF curve shape and location of the defining curve points was to use the drop-and-drag points positioned at each of the defining curve points located on the MFs in the “Preference Plot”. After defining the location of a MF defining curve point for one MF, the parametrically linked MF defining curve point of the adjacent MF was automatically updated in the “Trapezoidal Table” and in the “Preference Plot”; refer to Chapter 3, Section 3 for a review of the parametric linking concept.

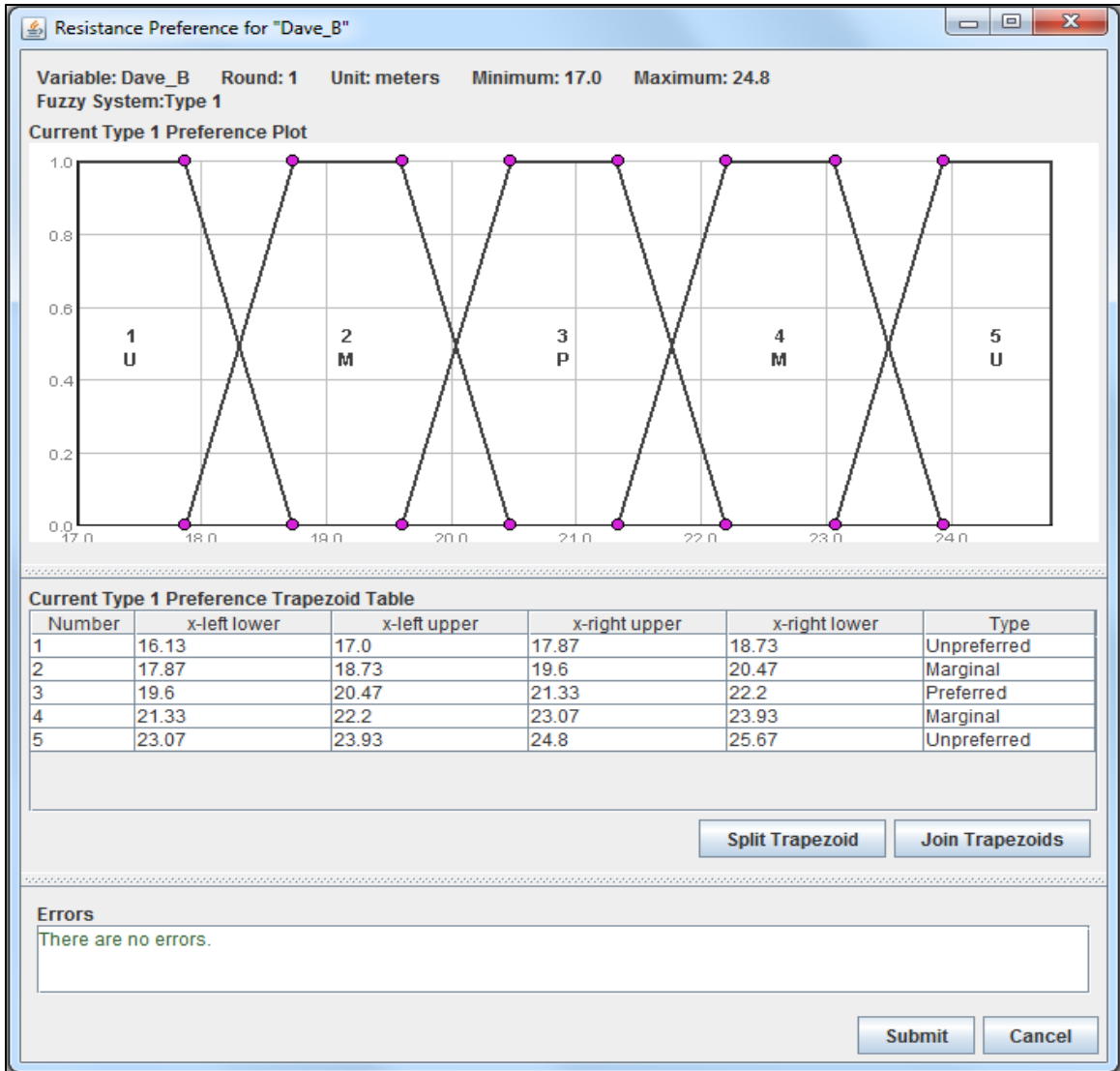


Figure 6.11 Initial State of Design Agent's Preference Data Input GUI for T1 FLS

Java™ code was in place to try and limit a user from defining an improper MF curve shape. In the event an improper curve shape was created by a design agent, the program contained error checking code that notified the design agent to the presence of an error in the fuzzy set. The code then described which MF was causing the error and what the error was in the “Errors” box of the “Preference Data Input” GUI. Design agents were not allowed to submit preference information until all errors were corrected. Besides the

MF curve shape errors, a design agent also received an error message when attempting to place two MFs of the same linguistic type side-by-side.

The linguistic preference of a MF could be changed by clicking the MF's type label in the "Trapezoidal Table" and then selecting the desired linguistic preference type from a drop-down menu; again linguistic preference choices were Unpreferred (*U*), Marginal (*M*), and Preferred (*P*). The linguistic preference of a MF could also be changed by clicking on the symbol for the linguistic preference of the MF in the "Preference Plot" and then selecting the desired preference type from the drop-down menu.

After splitting, joining, and altering the MFs of a fuzzy set the "Preference Plot" of a design agent's fuzzy preference data may look something like that of Figure 6.12.

Once the first round of set-based negotiation was complete, the "Preference Data Input" GUI changed appearance to include a display of the design agent's fuzzy set and the JOP curve(s) from the previous negotiation round. Since a computer display has a limited amount of space for applications and windows, tabs were used to switch between views of the agent's previous MFs or the JOP curve(s); Figure 6.13 and Figure 6.14. Note that the figures have been cropped and formatted to fit onto a single page.

From one round of negotiation to the next round, the Chief engineering agent would have reduced the set-range of the design variable. To highlight this fact, and to help differentiate the set-ranges of the current and previous negotiation rounds, the eliminated set-values were grayed-out in the plots of the previous fuzzy set and JOP curve data. This action can be seen in the screen shots of the "Preference Data Input" GUI, Figure 6.13 & Figure 6.14, for a subsequent negotiation round.

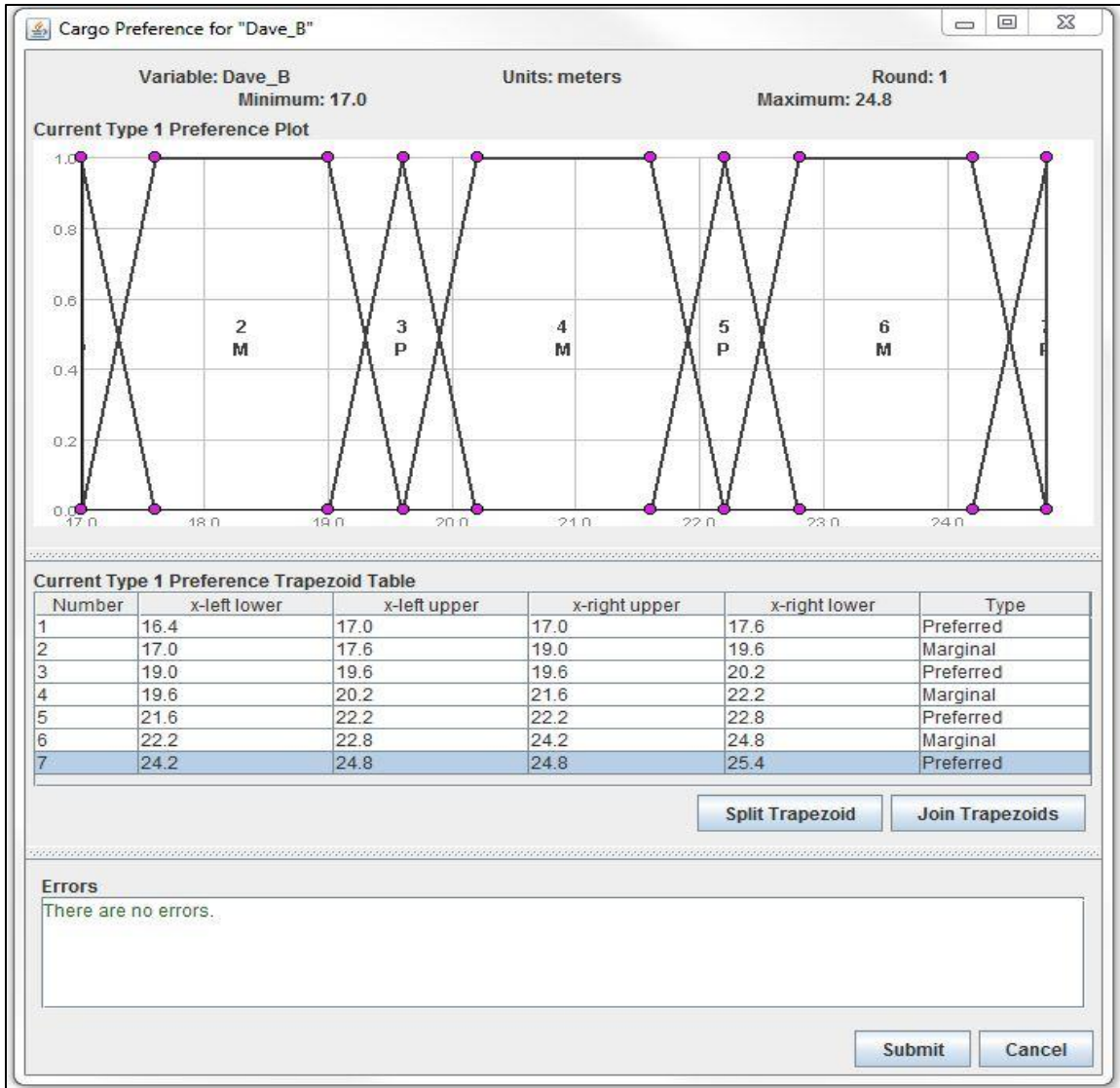


Figure 6.12 Example of Design Agent's T1 FLS Preference Data Input GUI for Beam Negotiation, Round 1

All of the characteristics of the design agents' T1 FLS "Preference Data Input" GUIs discussed so far were also found in the GUIs of the IT2M and GT2 FLSs. Because of the added uncertainty modeling capabilities of the IT2M and GT2 FLSs, the "Preference Data Input" GUIs for these FLSs also include methods for defining the uncertainty associated with the definition of the primary MFs.

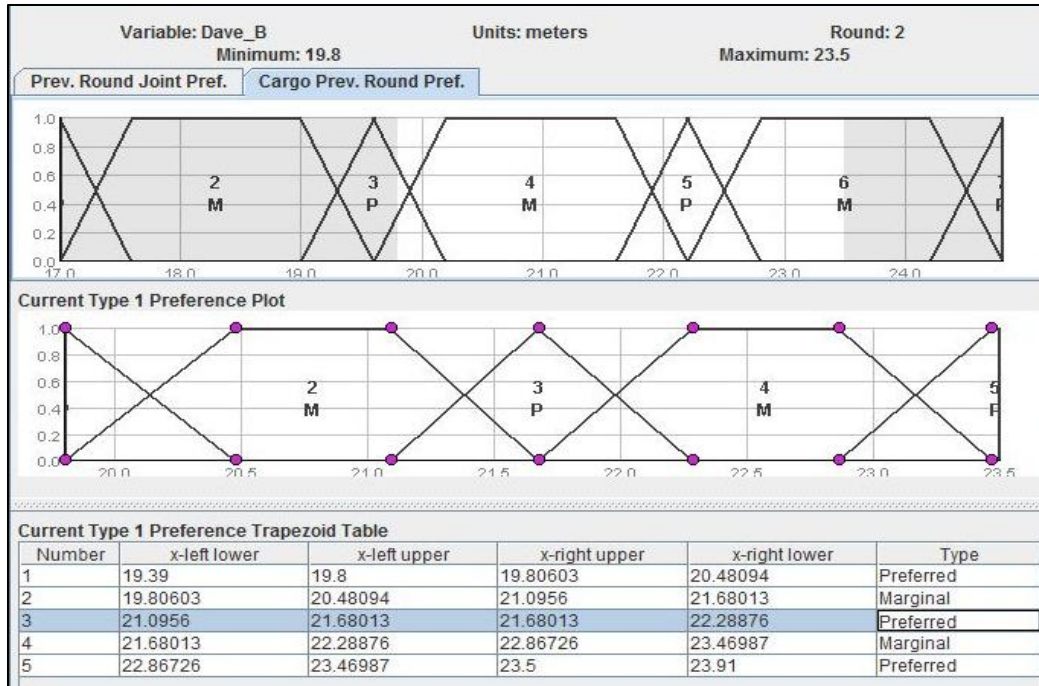


Figure 6.13 T1 FLS Design Agent's Preference Data Input GUI after Round 1 Negotiation, Showing Previous Round's Fuzzy Set

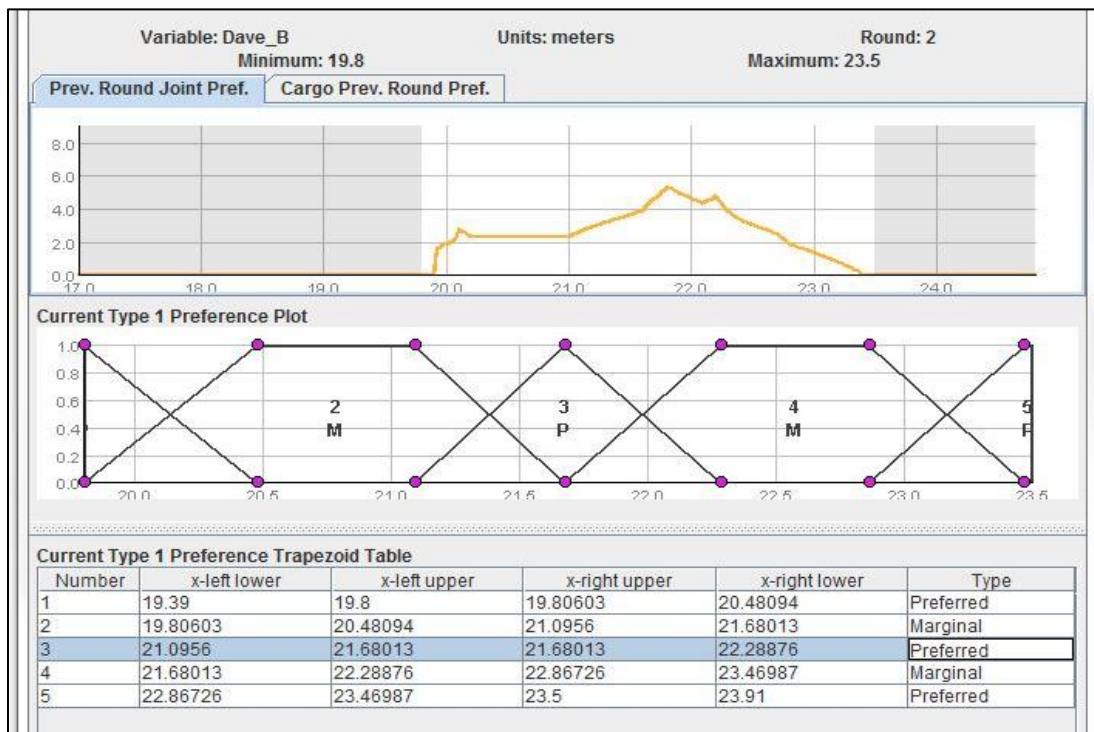


Figure 6.14 T1 FLS Design Agent's Preference Data Input GUI after Round 1 Negotiation, Showing Current JOP Curve Result

As discussed in Chapter 3, the author has created several unique randomization methods for the representation of uncertainty via an IT2M FLS. Each of the IT2M randomization methods required additional columns in the “Trapezoidal Table” to allow for the definition of precise $\pm\epsilon$ uncertainty values. As an alternative, the design agents were given the ability to define the uncertainty bounds using drop-and-drag points that were added to the MF “Preference Plot”. The additional columns and the uncertainty bound drop-and-drag points for the xRU, xRL, and Slopes IT2M FLS randomization methods are shown in Figure 6.15 - Figure 6.17. To save space each of the “Preference Data Input” GUI screen shots were taken during the first negotiation round, which does not include the additional JOP curve data, JOP histogram data, or fuzzy set data from the previous negotiation round.

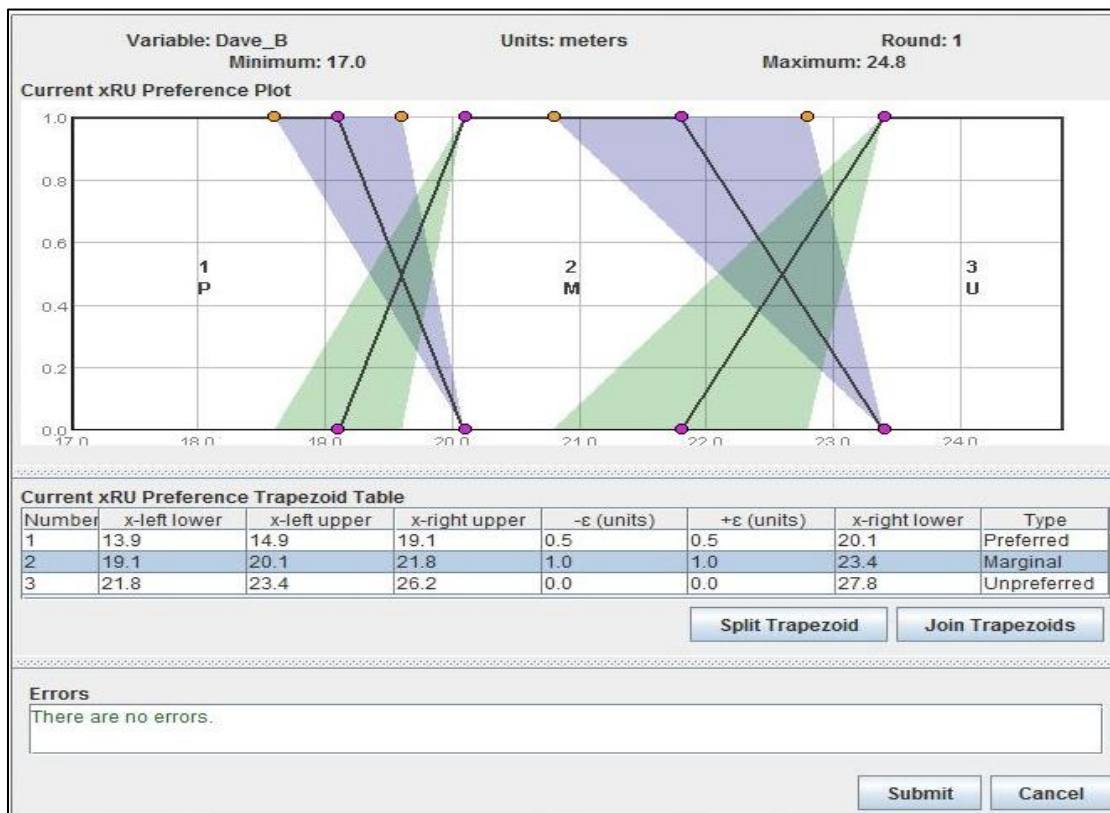


Figure 6.15 xRU IT2M FLS Preference Data Input GUI Example, Round 1

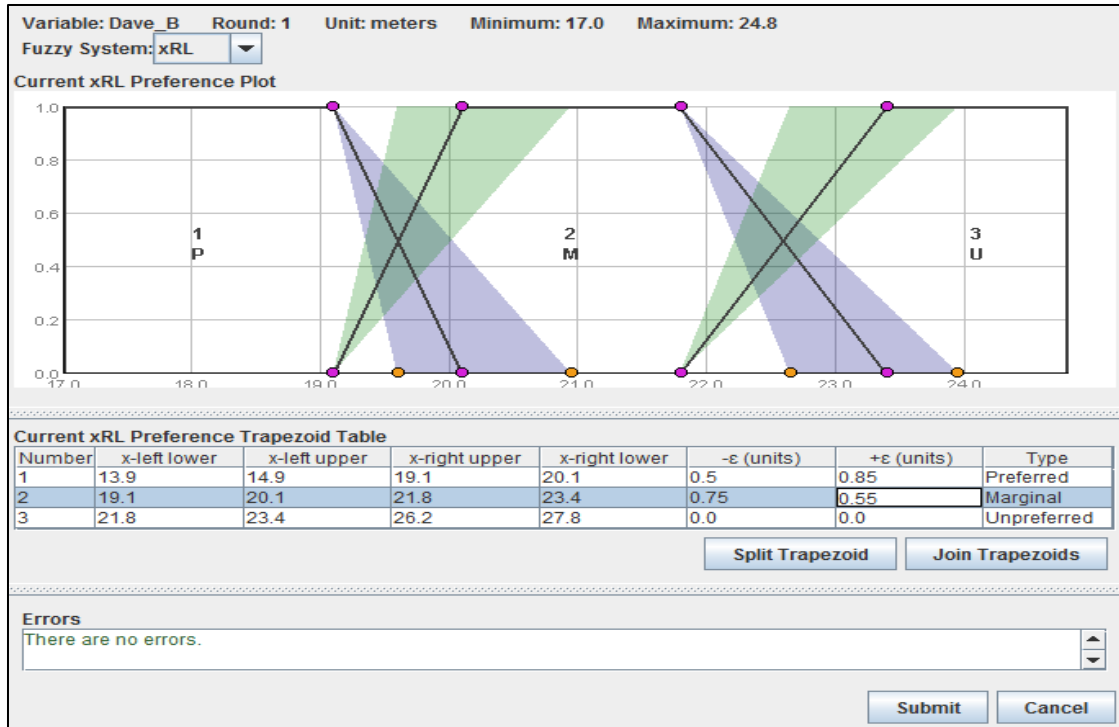


Figure 6.16 xRL IT2M FLS Preference Data Input GUI Example, Round 1

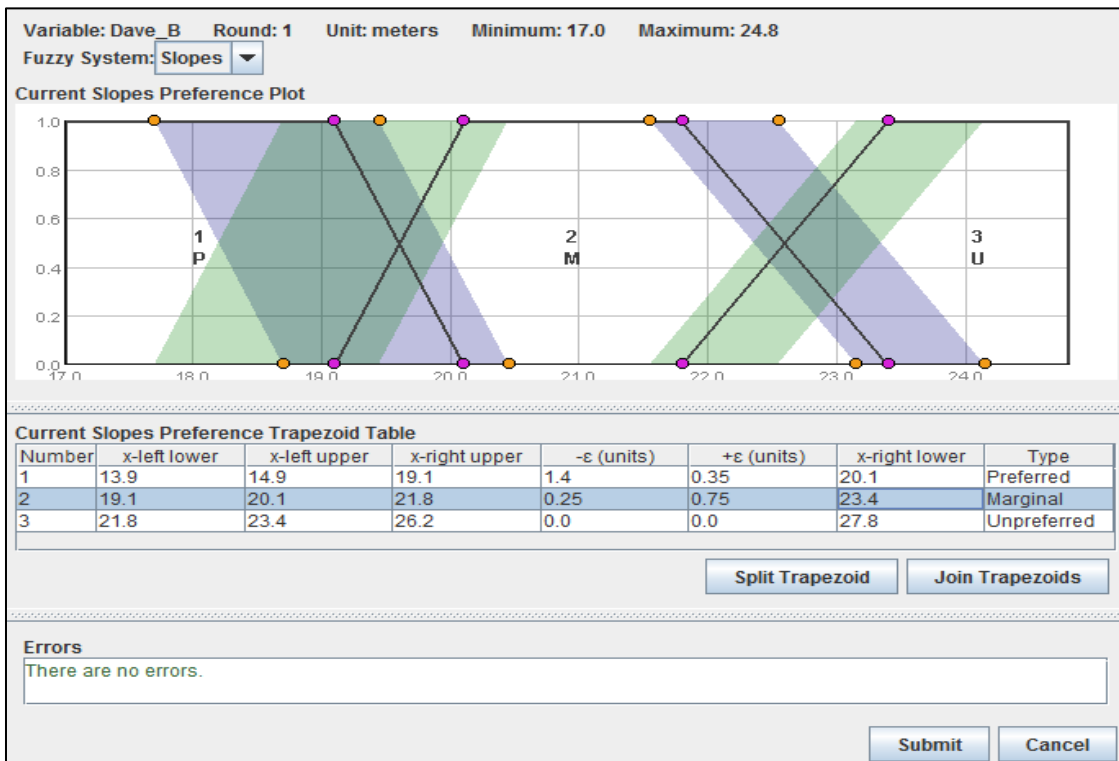


Figure 6.17 Slopes IT2M FLS Preference Data Input GUI Example, Round 1

As demonstrated in the IT2M FLS “Preference Data Input” GUI examples, the $\pm\varepsilon$ uncertainty units do not have to be of equal value. The design agents were allowed to define the uncertainty bounds as small, or as large, as deemed appropriate as long as the bounds did not exceed the maximum limits which were discussed in Chapter 3, Section 4. If a design agent attempted to define an uncertainty bound that exceeded the maximum allowable limits, an error message would be displayed in the “Errors” section of the “Preference Data Input” GUI and the uncertainty bound would change to a red color. Preference data could not be submitted until all errors were corrected.

After the first round of negotiation the design agents’ “Preference Data Input” GUI for the IT2M FLS updated to include tabs which allowed the design agent to switch between views of all JOP curves plots for the IT2M FLS iterations or the agent’s MFs from the set-range of the previous negotiation round. Figure 6.18 shows an example of the “Preference Data Input” GUI for the IT2M FLS after the first negotiation round. A plot of the JOP curves for the IT2M FLS has been selected for viewing in Figure 6.18.

The GT2 FLS design agent “Preference Data Input GUI” was designed to be similar in style and functionality to the GUI of the IT2M FLS. The “Trapezoid Table” in the “Preference Data Input” GUI, for the GT2 FLS, had two additional columns for the definition of the $\pm\varepsilon$ uncertainty values associated with the upper and lower trapezoidal defining curve points, x_{-ru} and x_{-rl} . The $\pm\varepsilon$ values for the defining curve points could be entered independently of one another, and, as with the IT2M FLS, the positive and negative epsilon uncertainty values were not required to be equal quantities. The $\pm\varepsilon$ uncertainty values could also be set by using the associated drop-and-drag points on the MFs located in the fuzzy set “Preference Plot”.

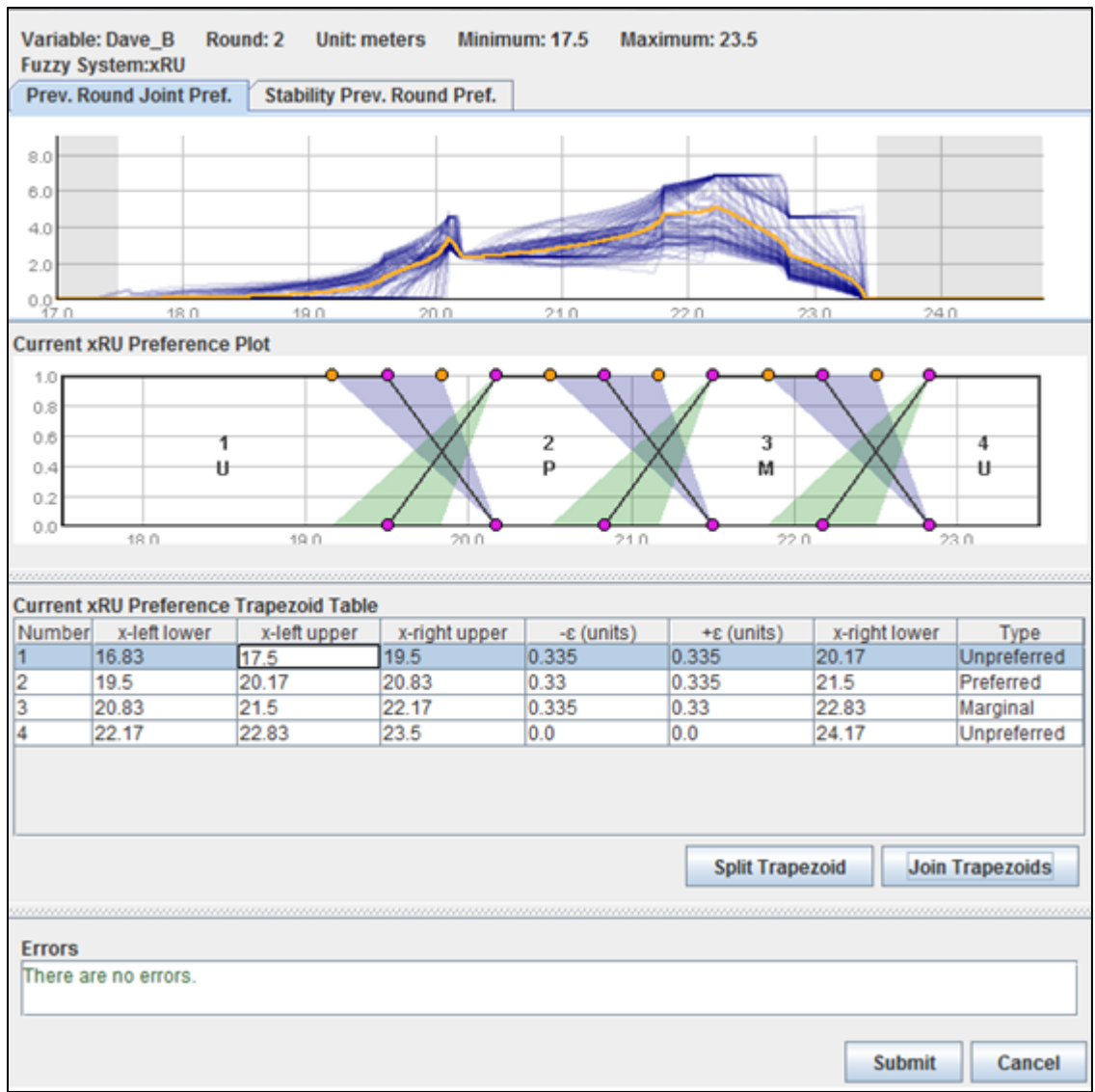


Figure 6.18 Example of IT2M FLS Design Agents' Preference Data Input GUI for Additional Negotiation Rounds, Previous Round's JOP Curve Data Shown

When using the GT2 FLS, design agents could use the “Preference Data Input” GUI to “Split” (add) or “Join” (remove) Preference MFs, select linguistic preference type, and enter or set MF defining curve points, in the same manner as the T1 and IT2M FLSs. After the first round of negotiation, the Preference Data Input GUI of the GT2 FLS included tabs to enable viewing of the most recent JOP curve result and the design agent's preference MFs of the previous round. Note that because of the extra T2 FLS

process of type-reduction, the JOP result of the GT2 FLS was a single curve, much like that of the T1 FLS, but ultimately of a different shape due to the modeling of the inherent design uncertainty. Figure 6.19 shows an example of the “Preference Data Input” GUI when using the GT2 FLS for the SBD process.

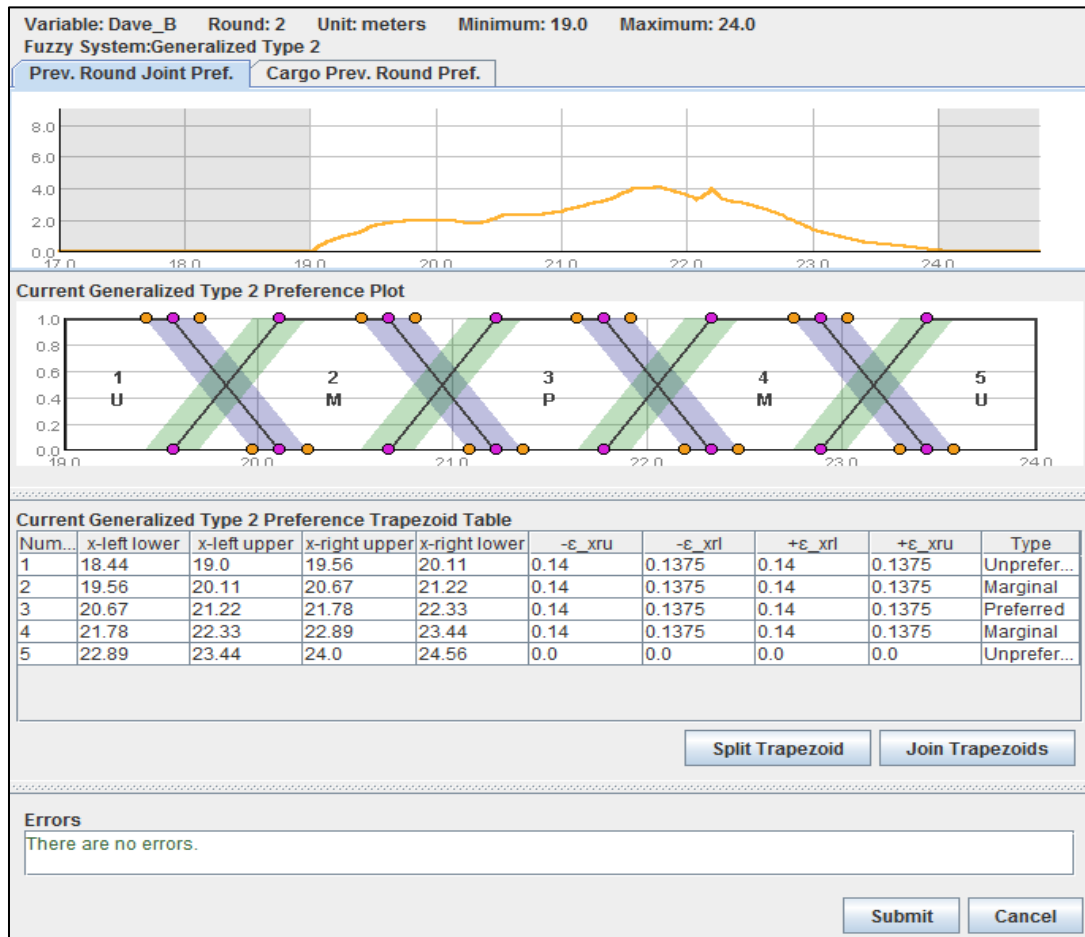


Figure 6.19 Example of GT2 FLS Design Agents’ Preference Data Input GUI for Additional Negotiation Rounds, Previous Round’s JOP Curve Data Shown

Post-Preference Data Input Survey

In order to collect insightful data from the human design agents that was not evident from the raw design data, such as the design agents’ motives for specific choices that were made when creating and defining a preference fuzzy set, the author created a post-

preference data input survey. The survey contained twelve questions, ten multiple choice and two short answer. The design agents were required to answer each question in order to complete the final step of the preference data input process. Many of the SBD survey questions used in the post-preference data input questionnaire were adapted from questions used by Chang and Tien [2006] in, “Quantifying Uncertainty and Equivocality in Engineering Projects”. The post-preference data input survey is shown in Figure 6.20. All survey questions and answer choices are located in Appendix A.

1. How would you rate your overall level of uncertainty for this negotiation round?	unanswered
2. How many membership functions did you use to describe your preference for the negotiated set of values?	unanswered
3. What was your motivation for using x# of membership functions for the negotiation of the values set?	unanswered
4. Did you utilize this variable's Joint Output Preference (JOP) curve data from the previous negotiation round to make preference decisions for this negotiation round?	unanswered
5. Did you utilize JOP curve data from other variables to make preference decisions for this negotiation round?	unanswered
6. Did you utilize your preference curve data (MFs) from the previous negotiation round to design your preference functions for this negotiation round?	unanswered
7. What were your reasons for choosing the +- epsilon (or sigma %) values for each membership function? (Enter "N/A" if using Type-1 System)	unanswered
8. Compared to previous negotiation rounds for this variable, How many membership functions (MFs) did you use to describe your preference?	unanswered
9. Compared to previous negotiation rounds for this variable, How would you describe the uncertainty bounds for your membership functions?	unanswered
10. Compared to previous negotiation rounds for this variable, How would you rate your level of design uncertainty for this negotiation?	unanswered
11. When describing your membership functions for the negotiation of the design variable this round, do you feel that you had ___ information, than previous rounds?	unanswered
12. The time you were given to perform design analyses before entering your membership function data to describe your preference for the design variable was ___ ?	unanswered
<input type="button" value="Submit Preference & Questionnaire"/> <input type="button" value="Cancel & Return to Preference"/>	

Figure 6.20 Post-Preference Data Input Survey Questions GUI

CHAPTER 7

SET-BASED EXPERIMENTAL DESIGN & DETAILS

7.1 Experimental Design

The goal of the SBD experiments was to test the effects of introducing uncertainty modeling into the SBD process. It was hypothesized that adding uncertainty representation to the design process would positively enhance SBD facilitation. To test the author's hypothesis preliminary ship designs were completed using the T1, IT2M, and GT2 FLS SBD tools. The results of these set-based ship design experiments are discussed in detail in Chapter 8.

To ensure successful scientific experiments, it was crucial to design the experiments in such a way as to avoid the introduction of bias and to eliminate as many sources of variability as possible. To avoid experimental bias the author created two different ship designs for the SBD experiments. One ship design, referred to as Ship E, was established with loose design constraints. The second ship design was developed with rigid design constraints and referred to as Ship D. Both preliminary ship designs were of the standard containership type. The use of the two different ship designs with varying degrees of difficulty in the design constraints allows this research to also test for the robustness of the FL SBD tool applications. If a FL SBD tool method is robust, it should easily facilitate the SBD process for both Ship E and Ship D. Testing the robustness of the FL

SBD environment in this manner was something that Dr. Singer failed to illustrate in his dissertation [2003].

To create the different ship designs and associated design constraints, the author analyzed a database of approximately 1,000 container ship designs to develop regression equations for *LWL*, *B*, and *T* based on constraints of TEU capacity and service speed. The criteria that constituted the preliminary ship designs as easy or difficult relates to the design constraints and producibility of the designs. The Ship E design was less difficult because the design constraints were rather loose. Therefore, there were many satisfactory ship designs solutions, and these solutions had principle design characteristics that were all well below the maximum allowable values of the design constraints. Although Ship D was a smaller containership design, in terms of TEU capacity, the maximum allowable principle design constraints were set to such a low tolerance, that there was only a very narrow range of values that would produce a feasible design solution; making Ship D a very difficult design.

Several principle ship design characteristics were used as governing constraints for the preliminary ship designs. The ship design characteristics directly affected the difficulty of each design; these design constraints are listed in Table 7.1. Some constraints and principle ship design characteristics were equal for both ship designs, these constraints are not listed in Table 7.1.

The complete list of ship design requirements for Ship E and Ship D are found in Appendix B and C respectively. Although it may appear as though the Ship E design

would be more difficult because many of the constraint values for the design were much larger than those of Ship D, naval architecturally this was not the case.

Table 7.1 Principle Ship Design Constraints

<i>Design Constraint (units)</i>	<i>Ship E</i>	<i>Ship D</i>
TEU Capacity	4,000	8,000
Avg. TEU Weight (t)	14.0	13.5
Endurance Range (nm)	4475	2000
Service Speed @ 85% Maximum Continuous Rating (knots)	22-26	Speed \geq 25
Endurance Days	26	18
Complement: Officers and Crew	25	22
Maximum Length of Waterline, LWL (m)	360	300
Maximum Beam, B (m)	51	33
Maximum Draft, T (m)	25	12.75

Since the SBD process required the participation of human subjects, the experiments were subject to the requirements of the University of Michigan’s Institutional Review Board (IRB) process. To comply with the requirements of the IRB, each human subject that participated in the SBD experiments was randomly assigned an anonymous identification number (ID#). The design agents used the ID# when logging into the SBD software. By using the ID#’s, the software was able to anonymously tag all set-based communications with a design agent’s ID#, which facilitated post-processing of data.

The design agents were asked to answer pre-experiment and post-experiment surveys to gauge their individual design experience and familiarity with the concepts of SBD before and after the experiments. To maintain anonymity the design agent ID#’s were also used when filling out the pre- and post-experiment surveys. The questions for the pre-

experiment survey and post-experiment survey can be viewed in Appendix D and E respectively.

The use of human subjects introduced an unavoidable source of variability into the design experiments due to the different levels of education, design experience, intelligence, and familiarity with SBD concepts. In addition, one must account for the learning curve associated with the use of computer software. To minimize the effects due to uncontrollable sources of variability, the following steps were taken:

- A human subject was allowed to participate in only two SBD experiments, and during each experiment the human subject was randomly assigned a design agent role.
 - Done to minimize the effects due to a learning curve.
- A human subject was never assigned the same design agent role.
 - Done to minimize the effects of a learning curve and account for variability in subject experience, design knowledge and intelligence.
- Human subjects were randomly assigned to participate in the design experiments for Ship E and Ship D.
 - Done to account for variability in subject experience, design knowledge, and intelligence.
- Human subjects were randomly assigned to different FLS SBD experiments of T1, IT2M, and GT2.
 - Done to minimize the learning curve affects and account for variability of subjects' knowledge and experience.
- Order of experiments was randomized by ship design and FLS type.
 - Total of six possible test cases selected at random. Done to minimize the learning curve affects and account for variability of subjects' knowledge and experience.

One may notice that the random assignments for participation in a SBD experiment did not limit a subject from participating in experiments for the same ship design type, or the same FLS type. For instance, a subject may have been randomly assigned to participate on a Ship E design using the T1 FLS, and a different experiment with the same Ship E design, but using the IT2M FLS. The author felt that assigning subjects to the experiments in this way would help to account for variability in levels of education, experience, and intelligence. If a subject was randomly assigned to participate in two SBD experiments that were of the same ship design type, or the same FLS type, it was felt that the experience a subject may gain from the initial experiment would only help to level-out the potential inexperience of another designer.

In an ideal situation, the author would have performed a standard statistical hypothesis testing procedure using x number of participants and y experimental tests to achieve the desired level of statistical confidence to either accept or reject the null-hypothesis at a statistically significant level. The human subjects would have all had the same level of education and work experience and each subject would have randomly been assigned to participate in each of the possible experimental scenarios.

The author's situation was less than ideal. Because of the need for familiarity with ship design, the author was limited to the subject pool of students from within the Department of Naval Architecture and Marine Engineering, at the University of Michigan. Within that small subject pool, the author chose to select only students who had some prior design experience, seniors and graduate students, in an attempt to reduce variability in education and experience levels. The small subject pool size forced the author to use pair-wise comparisons between the different ship designs and FLS experiments, resulting

in a total of six individual SBD tool experiments; two ship designs, Ship E and Ship D, and three FLSs, T1, IT2M, and GT2.

All human subjects were required to attend a pre-experiment training session. The purpose of the training session was to provide the subjects with an equal opportunity to learn about SBD concepts, design agent roles and goals, and how to operate and interact with the SBD FL hybrid agent tool and the ship design analysis tools. The subjects were also instructed on the difference between the FLSs, how to create MFs, and how to define uncertainty bounds using the different FLSs.

7.2 Experimental Design Tool Set-Up

The FL SBD tool software was set up to run a set-based preliminary ship design using a Chief engineering agent, and five design agents of the Cargo, Resistance, Stability, Hull, and Propulsion design functionalities. This meant that each test required a total of six subjects. Since, the Chief engineering agent greatly affects the flow of the SBD, without a detailed familiarity of SBD principles the design process would be hindered. Therefore, it was thought best to maintain a consistent knowledge and experience level throughout all of the SBD tool experiments and as such, the author acted as the Chief engineering agent for all of the SBD experiments.

The design agents were in charge of negotiating the ship design variables for the preliminary set-based ship designs using a FL SBD tool to facilitate the SBD process. The complete list of negotiated design variables is found in Appendix F. To develop preference opinions for the negotiated variables, the design agents were each provided ship design analysis tools in the form of specially adapted spreadsheets or other naval

architectural and marine engineering computer software. Table 7.2 lists the tools utilized by each design agent to perform design analyses.

Table 7.2 List of Design Agents' Analysis Tools

<i>Design Agent</i>	<i>Design Analysis Tool(s)</i>
Cargo	Container Arrangements Spreadsheet
Resistance	Powering Prediction Program Hydrostatic Values Spreadsheet
Stability	Stability Estimate Spreadsheet Hydrostatic Values Spreadsheet
Hull	Hull Displacement Spreadsheet Hydrostatic Values Spreadsheet
Propulsion	Preliminary Power Estimation Spreadsheet Propeller Optimization Program Hydrostatic Values Spreadsheet

The goal of the preliminary set-based ship design experiments was not to prove the effectiveness of SBD for developing an optimal design, since this research hypothesis was previously investigated by Singer [2003]. Instead, the goal here was to investigate the effects of introducing uncertainty modeling into the SBD environment. Therefore, during the SBD experiments it was not critical for the set-ranges of the ship design variables to be narrowed down until a single design remained. As such, to focus on maintaining consistency in the experimental procedure, each SBD tool experiment was given a total of six hours to work towards set-reduction of the negotiation design variables for a preliminary ship design.

The six hour time span included time allowances, which provided the SBD team with occasional breaks. Since the design agents are tasked with entering their linguistic preferences for the design variables based solely on the analyses they conduct for their

independent functional design goal, the design agents were instructed not to discuss details of the experiment during their breaks so that they would not accidentally be influenced by the goals and preferences of the other design agents. For the same reason, verbal communications were also kept to a minimum during the SBD experiments.

Since the author's goal was to only test the hypothesis that uncertainty modeling would enhance the SBD process, it was not necessary to test each of the individual IT2M FLS randomization methods. Therefore, the Slopes IT2M FL randomization method was chosen for the initial SBD tool ship design experiments. It was thought that this method would allow the design agents to describe the largest variabilities in design uncertainty.

Later, after analyzing the experimental results, an additional experiment was run using the Ship E design requirements and the IT2M FLS. For this additional Ship E set-based preliminary ship design experiment, the IT2M FLS was set up so that the design agents could select one of the randomization methods, xRU, xRL, or Slopes, to represent the uncertainty of the preference MFs in their fuzzy set. The motivation for this additional test is discussed in the results section, Chapter 8.

CHAPTER 8

EXPERIMENTAL SET-BASED SHIP DESIGN RESULTS

8.1 Explanation of Set-Based Experimental Data and Analyzed Results

One of the main principles of SBD is the delaying of design decisions until there is a reduction in overall design uncertainty. The delaying of design decisions helps to avoid the design getting stuck in an infeasible solution space. For a FL SBD tool to be classified as aiding in the facilitation of SBD, it was expected that the set-ranges of the ship design variables would gradually narrow throughout the course of a preliminary ship design experiment. Set-based design relies on an increase in information and a reduction of design uncertainty before making the crucial early-stage design decisions. Therefore, it was also reasonable to expect that the levels of design uncertainty would decrease as the design process continued.

A total of six SBD experiments were initially run. These experiments included designs based on two unique containerships, which are referred to as Ship D and Ship E. The Ship D design possessed highly restrictive design constraints, making it difficult to find a feasible design solution, whereas the Ship E design constraints were very relaxed and several feasible solutions were known to exist. Each ship design was attempted using the T1, IT2M-Slopes, and GT2 FLS SBD methods. Singer [2003] has shown that a T1 FLS can facilitate the SBD process. Therefore, in the new experiments, the T1 FLS was used as a baseline of comparison when trying to investigate the effects of introducing

uncertainty modeling into the SBD process. After running the six initial design experiments, a seventh experiment was run in which design agents were allowed to choose which randomization method they used to represent the uncertainty of the MFs. This additional test, referred to by the label IT2M-Choice, was tested with the Ship E design, with the experimental goal of deciphering if further SBD enhancement could be achieved using this IT2M-Choice FLS.

Table 8.1 shows a summary of the overall SBD experimental results for the seven completed set-based ship designs. A SBD experiment was considered an overall success if it facilitated the basic SBD principles such as the gradual narrowing the solution space and set-variable ranges while leading to feasible design solutions. A design failure resulted when a feasible design solution did not exist within the design space or any of the design agents were unable to satisfy their functional design goal by the end of the set-based ship design experiment.

Table 8.1 Summary of SBD Overall Experimental Results

FLS Design Method	Ship Design	Experiment Result
Type-1	Ship D	Failed SBD
IT2M-Slopes	Ship D	Successful SBD
GT2	Ship D	Successful SBD
Type-1	Ship E	Successful SBD
IT2M-Slopes	Ship E	Successful SBD
GT2	Ship E	Successful SBD
IT2M-Choice	Ship E	Successful SBD

The remainder of this section is used to describe how the data was post-processed after the SBD experiments. Section 8.2 provides details into the results and conclusions based on the analyzed data. In Section 8.2.1 an assessment of SBD facilitation is provided and

discussion of general trends that were observed in all the SBD experiments is given. An analysis of the trade-offs, benefits, and drawbacks of each FLS SBD method based on the experimental results follows in Section 8.2.2 for the highly constrained (Ship D) SBD experiments and Section 8.2.3 for the loosely constrained (Ship E) SBD experiments.

Data on many different experimental variables was recorded during the SBD experiments with the goal of providing evidence to either support or reject the experimental hypothesis, “adding uncertainty modeling capabilities to the FL SBD tool functionality enhances the overall SBD process”. After post-processing the experimental data, it was determined that the magnitude of a set-range and the magnitude of the uncertainty bounds of a design variable were the most effective at illustrating the set-based properties of the FLS design tool environments. The magnitude of a set-range was calculated using Eqn. (8.1) and the magnitude of the uncertainty bounds, the distance between $\pm\varepsilon$ coordinate values, using Eqn. (8.2). In an ideal SBD one would expect these values to decrease with time.

$$set-range = set_max - set_min \Rightarrow x_{range} = x_{max} - x_{min} \quad (8.1)$$

$$\|uncertainty\| = |(+\varepsilon) - (-\varepsilon)| \quad (8.2)$$

Figure 8.1, showing a single, simplified GT2 MF for the beam design variable, can be used to explain the concepts of set-range magnitude and magnitude of uncertainty in further detail. As an example, the set-range magnitude is calculated in Eqn. (8.3) and illustrated in Figure 8.1 using the dash-dot double-arrow. Because the figure shows a GT2 MF, there are uncertainty bounds associated with both the x_{-ru} and x_{-rl} defining MF curve points. The calculated magnitude of uncertainty associated with x_{-ru} is shown in

Eqn. (8.4) and for $x-rl$ in Eqn. (8.5), and illustrated using the dotted double-arrows in Figure 8.1.

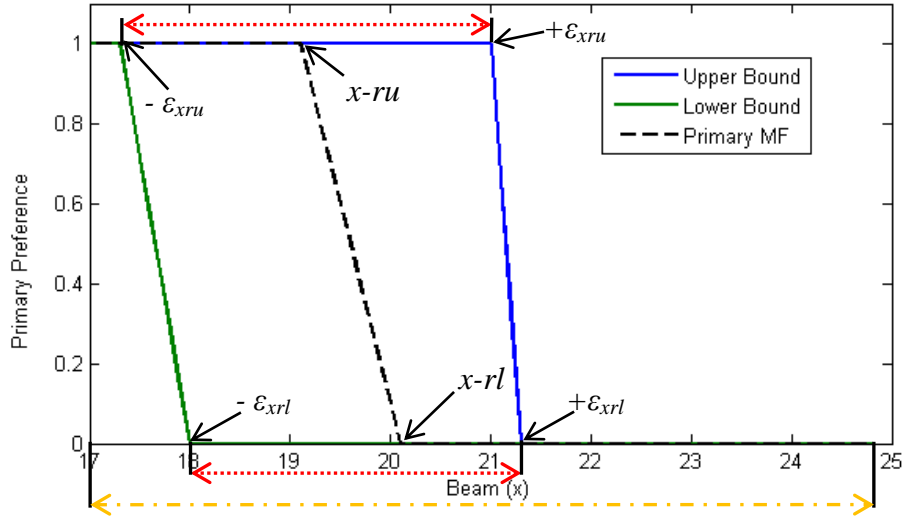


Figure 8.1 A Single, Labeled, Simplified GT2 MF from a Design Agent’s Fuzzy Set Describing Preference for Beam Set-Values

$$set-range = 24.8 - 17 = 7.8 \quad (8.3)$$

$$\|\varepsilon_{x-ru}\| = |21.0 - 17.25| = 3.75 \quad (8.4)$$

$$\|\varepsilon_{x-rl}\| = |21.25 - 18.0| = 3.25 \quad (8.5)$$

The magnitude of the uncertainty as was plotted in the results figures was derived by first calculating the magnitude of uncertainty associated with each individual MF in a design agent’s fuzzy set; as was done for the MF of Figure 8.1, using Eqn. (8.2). The values of magnitude of uncertainty for the entire fuzzy set were then used to create an average value for the magnitude of uncertainty for a design agent’s fuzzy set. The average magnitude of uncertainty was used as the, “magnitude of uncertainty”, as plotted in the results figures shown throughout Chapter 8, as well as in Appendix H and Appendix J for

the Ship D and Ship E set-based ship design experiments, respectively. Appendix G for Ship D, and Appendix I for Ship E, include all results of the set-range magnitude for each negotiated design variable and associated FLS SBD method plotted versus time.

In all the results figures, the experimental data was plotted versus time in order to judge the speed of set-reduction, to view the rate of uncertainty reduction, and to allow for quick comparison of the properties of one design variable to those of another. The x -axis was scaled with units of minutes and was held at a constant maximum value of 320 minutes for all Ship D SBD experimental plots, and 350 minutes for all Ship E SBD experiments plots.

Since, the negotiation rate of design variables in each experiment was subject to the working pace of the individual design agents, the negotiation rounds of each experiment did not occur at exactly the same time intervals. Also, the first negotiation of some design variables did not occur until well after the SBD experiment was begun. These two points are illustrated in Figure 8.2 where the set-range for the block-coefficient (C_b) design variable is plotted from start to end using the experimental time recorded for the individual SBD tests. Looking specifically at the first negotiation round of the C_b design variable, it was seen that each SBD experiment began the first negotiation round at a different time. Note that as shown in Figure 8.2, when the experimental time scale was used the phrase “Experimental Time” appeared on the x -axis.

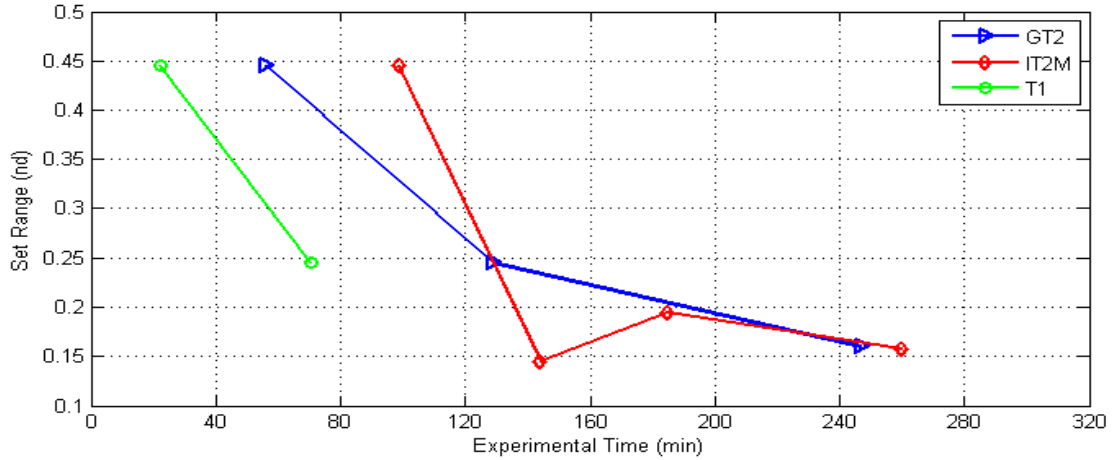


Figure 8.2 Ship D, Set-Ranges for C_b Negotiation vs. Experimental Time Scales

Since there was variability in the rate at which set-based negotiations occurred, as well as when the first round of negotiation occurred for each SBD experiment, the time data indicating when a negotiation round occurred was converted from the experimental time scale to an absolute time scale using Eqn. (8.6). In Eqn. (8.6), $i = 1 \dots n$ time steps, t is the experimental time in minutes, and $t(1)$ was the experimental time for the start of the first negotiation round. The $t(1)$ value was generally unique for each design variable. The purpose of the absolute time scale was to allow for more straightforward comparisons between the data gathered from each SBD experiment. For instance, by using the absolute time scale, the FLS SBD method which spent the most time negotiating the C_b design variable for the Ship D design is now easily determined in Figure 8.3, which displays the same C_b set-range data as was plotted in Figure 8.2, but the data was plotted using the absolute time scale instead.

$$absTime(i) = t(i) - t(1), \text{ for } i = 1 \dots n \quad (8.6)$$

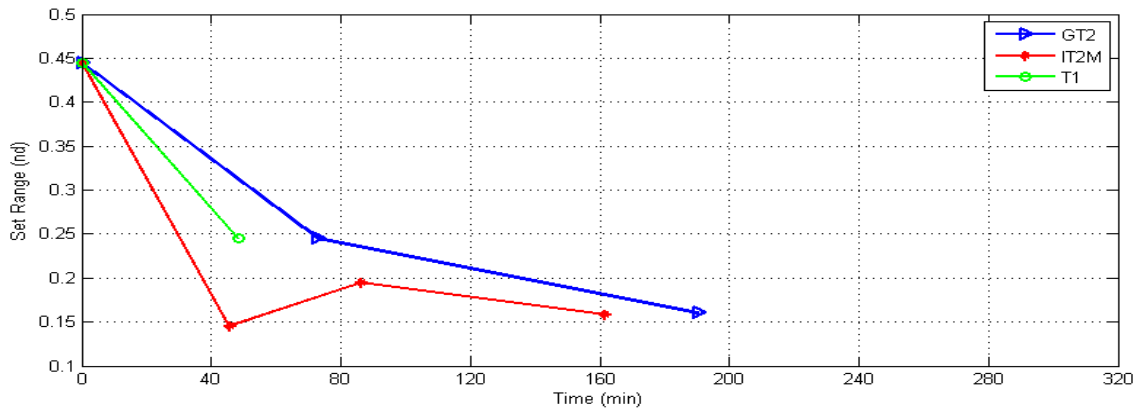


Figure 8.3 Ship D, Set-Ranges for *C_b* Negotiation vs. Absolute Time Scales

Since the absolute time scale allowed for quicker data comparison between the different SBD experiments, it was also used when plotting the magnitude of uncertainty versus time for the SBD experiment variables. The results and figures shown in this chapter, as well as in Appendix G – Appendix I, which utilized the absolute time scale are identifiable with the label “Time” appearing on the *x*-axis of the figures.

In all of the SBD experiments the principle design variables of length-of-waterline (*LWL*), beam (*B*), depth (*D*), and draft (*T*) were each used to begin the SBD process. That is, within the first five minutes of the SBD experiments beginning, the Chief engineering agent would have submitted a request for the negotiation of those principle design variables. These principle design variables were chosen to begin the set-based preliminary ship design process because they all significantly impact the final design solution. Figure 8.4 plots the magnitude of set-range data for the Ship D SBD experiments using the experimental time scale and it shows how the negotiation of the principle design variable, beam (*B*), began at approximately the same time in each experiment. As a SBD progressed, negotiations of the remaining design variables would

begin. For example, the C_b negotiations plotted in Figure 8.2 which were started well after the beginning of the first set-based negotiation round.

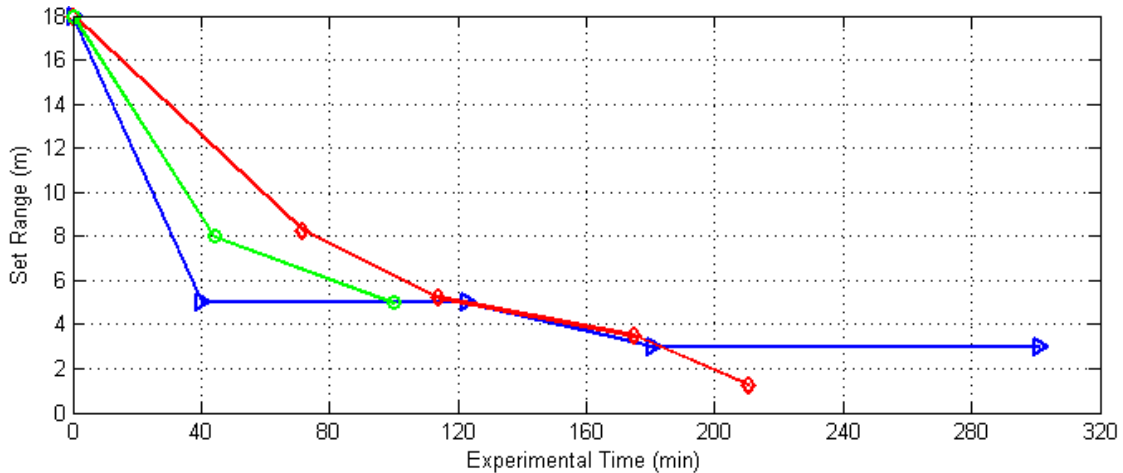


Figure 8.4 Set-Range Magnitude Plots for Ship D Experiments, B Negotiation, Experimental Time Scale

One limitation of the SBD experiments was that it was not possible to control the rate at which a design team conducted their set-based negotiations. The Chief engineering agent could suggest that a specific amount of time to be spent on analyses before the set-based negotiation, but a time limit was not specifically enforced. As a result, when starting the first negotiation round for any additional design variables, beyond the principle design variables, it was difficult to start these negotiations at the same time during each SBD experiment.

Efforts were made by the Chief engineering agent to try and ensure that the first negotiation round for the additional design variables began at the same time in each SBD experiment. Figure 8.5 shows one example in which the first negotiation of the cargo box length (L_c) occurred at approximately the same time during each of the Ship D SBD experiments. However, as was shown previously in Figure 8.2, it was not always

possible to achieve a consistency between the start of negotiation for all SBD experiments. The inconsistencies due to varying negotiation rates represent one limitation of the SBD experiments.

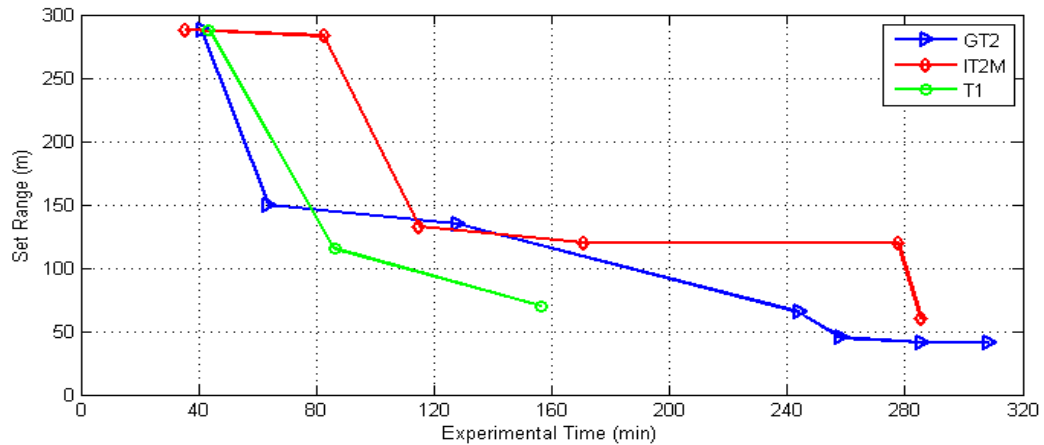


Figure 8.5 Magnitude of Set-Range for L_c vs. Experimental Time, First Negotiations Began at Approximately the Same Time

It was mentioned earlier that a consistent time scale, $[x_{min}, x_{max}]$, was used when plotting the Ship D design results and again for the Ship E design results. However, it was not possible to set a consistent scale for the y-axis in all plots of the set-range magnitude or the magnitude of uncertainty values for the SBD experiments since not all design variables had units on the same order of magnitude or same dimensional units. To maintain some degree of consistency, the maximum y-axis value was held consistent within experiments of the same ship type design; Ship D or Ship E. For example, the magnitude of uncertainty for the Ship D IT2M FLS experiment and the Ship D GT2 FLS experiment were both set to have the same y_{max} value in order to allow for quick comparisons between the results for the two unique SBD FLS methods when working on the same ship design.

Some of the negotiated design variables possessed non-dimensional coefficients. The abbreviation “nd” was used when plotting the coefficients’ data to indicate the variable was non-dimensional.

8.2 Set-Based Design Experimental Results

The goal of this research was to determine the effects of introducing uncertainty into the SBD procedure. The experimental hypothesis was that the introduction of uncertainty into the design space would aid in the enhancement of the SBD process. The core principles of SBD theory were used as guidelines to determine if the FL SBD tools were indeed facilitating SBD. Graphically, facilitation of SBD would be demonstrated by the following properties:

- 1) Gradual narrowing of the set-ranges for the negotiation variables of the ship design.
- 2) Frequent set-based communications, in the form of multiple negotiation rounds throughout the SBD process.
- 3) Gradual reduction of the magnitude of design uncertainty associated with a design variable.
 - As design agents gain information about design space, it was expected that uncertainty would decrease.

8.2.1 Assessment of Set-Based Facilitation by the Fuzzy Logic Systems

The first task after conducting the set-based ship design experiments was to determine if each of the FLS design environments were facilitating the principle components of SBD. Once facilitation of SBD practices was determined, the focus could then switch to the analysis of the experimental hypothesis. The results in this section were provided as

evidence to show that each FLS environment was indeed facilitating principle SBD practices.

By thoroughly examining the data from all seven set-based ship design experiments, several general trends were observed for both the Ship E and Ship D design experiments when utilizing the T1, IT2M-Slopes, IT2M-Choice, and GT2 FLS SBD environments. As opposed to showing the over ninety charts and graphs of the analyzed data for all experiments, a select sample of figures has been chosen for display in this chapter in order to facilitate the discussion of the general trends that were observed in all of the set-based ship design experiments. These figures represent the trends that were seen throughout the individually graphed experimental data in Appendix G – Appendix J, and these trends embody the principles of the SBD methodology.

The first general trend observed throughout the SBD experiments was the narrowing of the variable set-ranges as a SBD process continued. This trend was noticed for all of the FLS SBD environments in both the Ship E and Ship D design experiments. Figure 8.6, for the Ship D experiments, and Figure 8.7, for the Ship E experiments, each represent a sample of the general trend in set-reduction observed throughout the SBD experiments.

Figure 8.6 and Figure 8.7, as well as the figures of Appendix G (Ship D) and Appendix I (Ship E), demonstrate the facilitation of the core SBD principle of narrowing a set-range and eliminating infeasible values so that only feasible solutions remain. Although the T1 FLS was able to facilitate the act of SBD set-reduction, the method itself did experience difficulties remaining in the feasible design space when performing the set-reductions for

the highly constrained ship design, Ship D. These results, as well as other general observations for the Ship D experimental results are discussed in detail in Section 8.2.2.

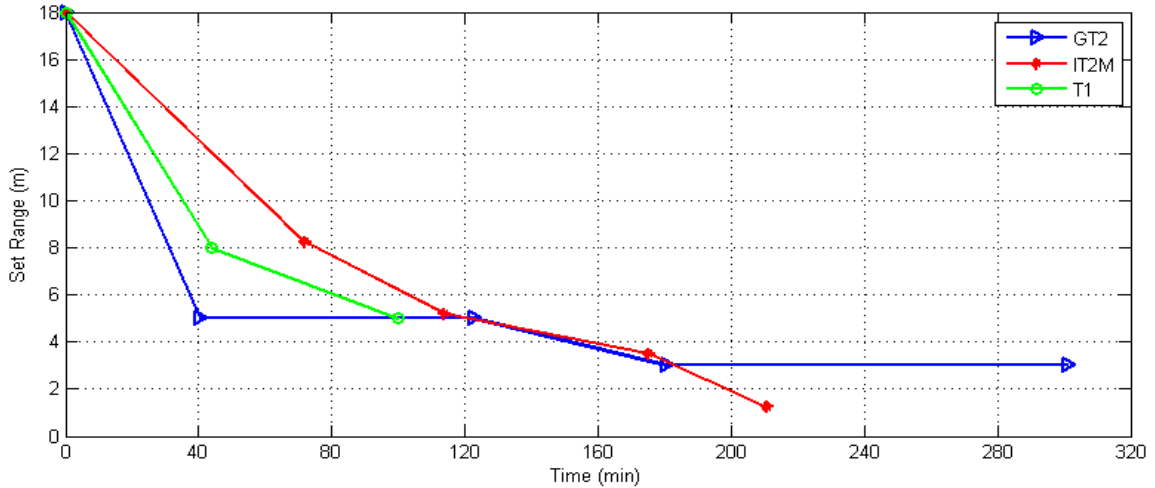


Figure 8.6 Narrowing of Set-Range for the *B* Design Variable During Ship D SBD Experiments, Plotted Versus Absolute Time

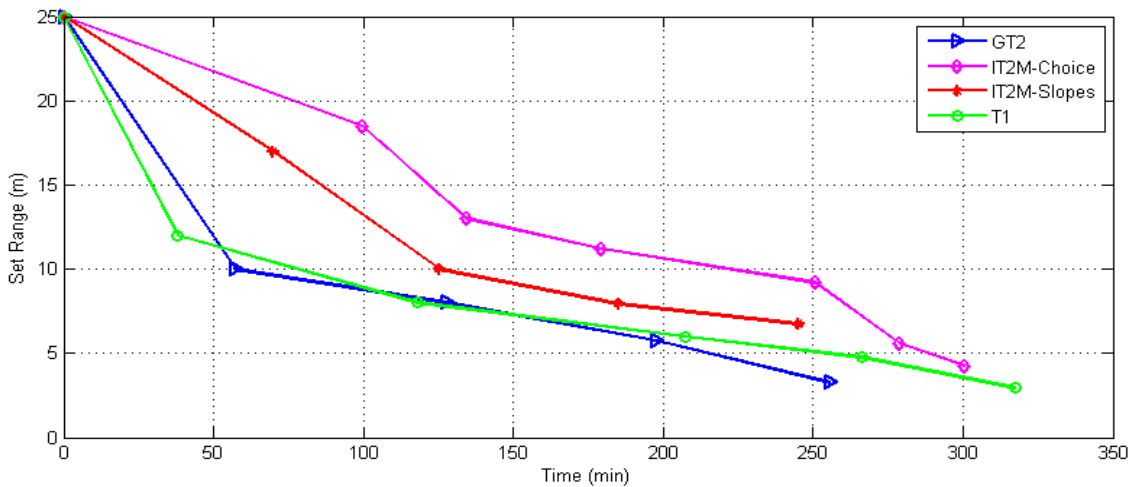


Figure 8.7 Narrowing of Set-Range for the *B* Design Variable During the Ship E SBD Experiments, Plotted Versus Absolute Time

Although there were some atypical results, the overall trends reflected in the set-range plots match the graphical properties that one would look for in a SBD process. For instance, Figure 8.6 and Figure 8.7 plot the magnitude of set-range of the beam variable

for the set-based experimental designs of Ships D & E, respectively. These figures exemplified the ideal gradual set-range narrowing that should be present in a SBD. Some atypical trends in set-reduction were witnessed, but in general these trends were simply outliers compared to the general trends observed for the whole set of SBD experiments. In many cases the atypical trends could be quite easily explained by looking at the experimental survey data.

An atypical set-reduction trend was frequently a result of the need to re-open a set-range at some point during the SBD. The re-opening of a set-range was both allowable and necessary when a set-range had been reduced to a point at which any of the negotiating design agents could no longer meet their functional goal(s) using values within the current set. Figure 8.8 shows how the set-range for the draft negotiation variable had to be re-opened for the T1 FLS after approximately 115 minutes and after approximately 180 minutes for the GT2 FLS Ship D experiments.

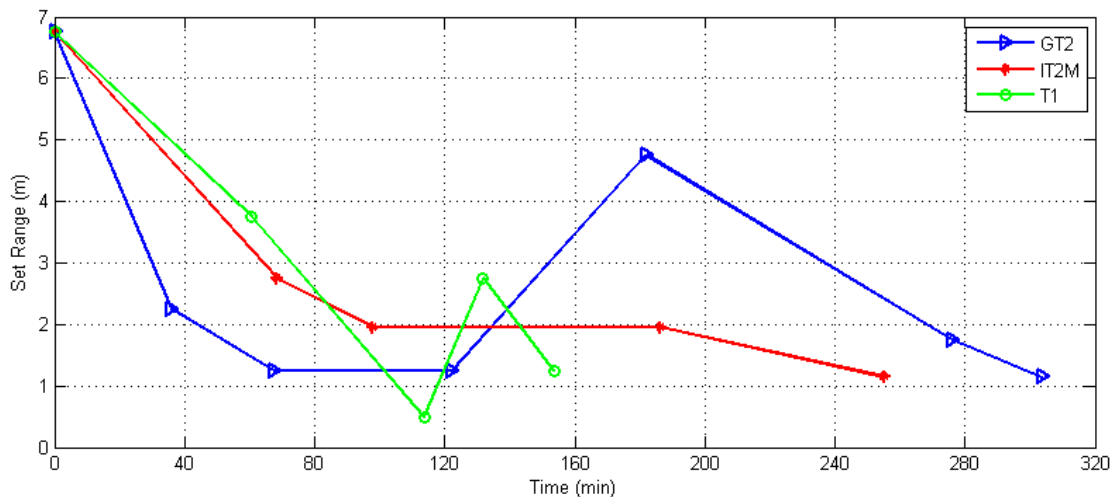


Figure 8.8 Ship D, Set-Ranges for *T* Negotiation vs. Absolute Time

Also demonstrated in magnitude of set-range plots, examples Figure 8.6 - Figure 8.8, was the frequent occurrence of set-based negotiations that was expected when facilitating the SBD process. In the figures, each line-marker indicates that a set-based negotiation took place at that point in time. The set-based negotiations were facilitated by use of the developed FLS SBD tools. Based on the collected experimental data, it was possible to determine the average number of set-based negotiations for each of the seven set-based ship design experiments conducted. The average number of negotiation rounds for a SBD experiment was determined by calculating the total quantity of negotiation rounds for all of negotiated design variables and then dividing the sum by thirteen, which was the total number of negotiated design variables for each SBD experiment. Table 8.2 lists the average number of negotiation rounds completed for each SBD experiment using the different FLS SBD environments.

Table 8.2 Average Number of Set-Based Negotiations Per SBD Experiment

FLS Type	Ship D	Ship E
T1	3.1	5.6
IT2M (Slopes)	4.5	4.2
IT2M (Choice)	N/A	6.4
GT2	5.1	3.9

Through utilization of the SBD FLS environments, design agents were given the means to communicate data in a set-based manner. As the list in Table 8.2 indicates, frequent set-based communications occurred during the SBD experiments, as each negotiation round required the use of set-based communication. In general, the results shown in this chapter and Appendices G – J, demonstrate that the set-based communications led to the

gradual reduction in the magnitude of each design variable set-range and overall levels of design uncertainty.

To also facilitate SBD the process there should be a gradual reduction in the overall design uncertainty as the design process continues. The reduction of uncertainty typically results from an increase in design information. In the SBD experiments each negotiation round helped to narrow the design space and increase the information about the remaining feasible design space through the process of set-based negotiations.

Unlike the T1 FLS SBD environment, the newly developed IT2M FLS and GT2 FLS SBD environments were capable of modeling design uncertainty. In these FLSs the design uncertainty was represented by the design agents describing upper and lower uncertainty bounds with the use of epsilon uncertainty points. The magnitude of design uncertainty was then calculated for each negotiation round of a SBD experiment using Eqn. (8.2) and the process described earlier in Section 8.2.1. Figure 8.9 show examples of the magnitude of uncertainty plotted versus the absolute time scale for the negotiation of the draft (T) design variable for the GT2 FLS Ship D SBD experiment; in Figure 8.9 both the uncertainty associated with the x_{-ru} and x_{-rl} MF defining curve points is shown.

Throughout the IT2M and GT2 FLS SBD experiments it was observed that the magnitude of design uncertainty closely reflected the magnitude of the set-range for a design variable. For instance, as shown in Figure 8.10 the set-range magnitude increased during the fifth negotiation round of the GT2 FLS Ship D SBD experiment, at approximately 180 minutes. At the same time the magnitude of design uncertainty

increased, as shown in Figure 8.9. This trend was reflected throughout all of the IT2M and GT2 FLS SBD experiments.

The ability to actually represent the levels of design uncertainty at each stage of the SBD process represents a significant enhancement to the overall facilitation of SBD practices. The enhancements to the facilitation of the SBD process are discussed in the following section.

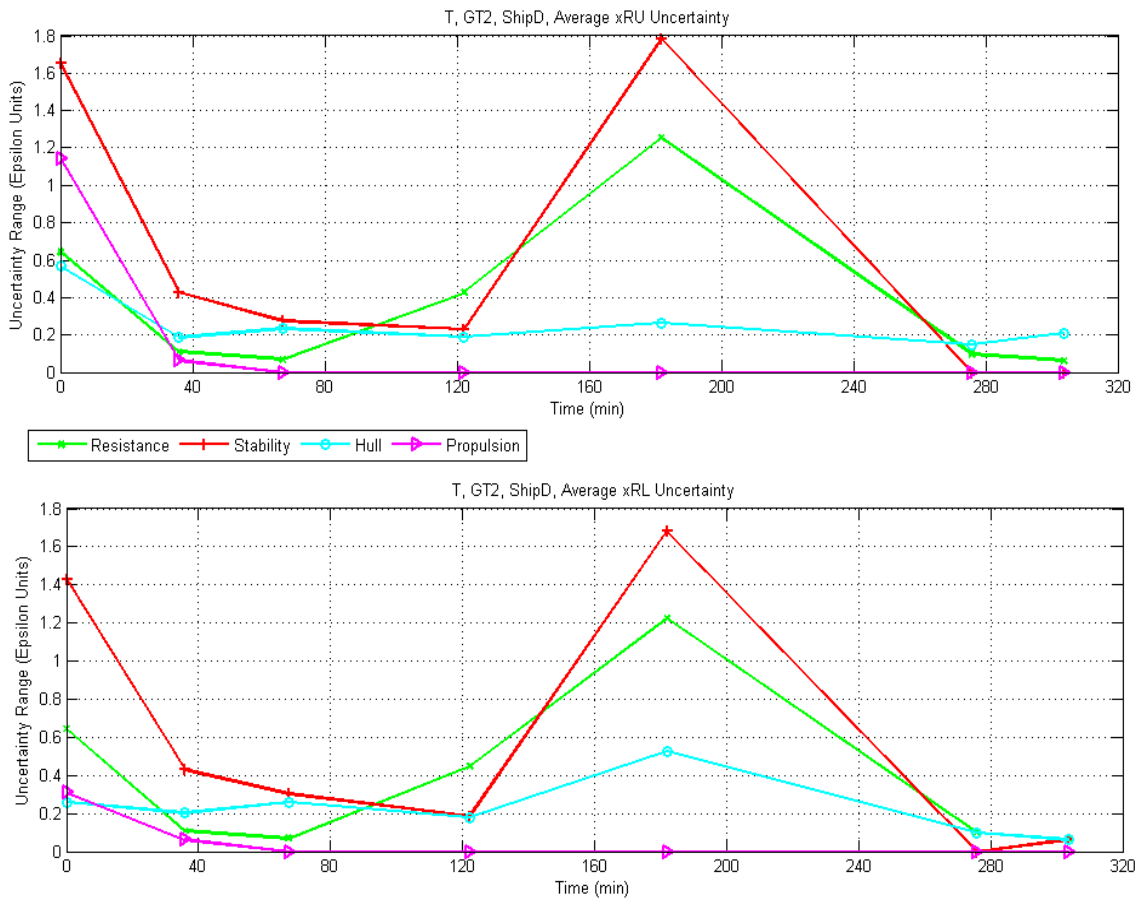


Figure 8.9 Magnitude of T Design Uncertainty for GT2 FLS Ship D SBD vs. Absolute Time Scale

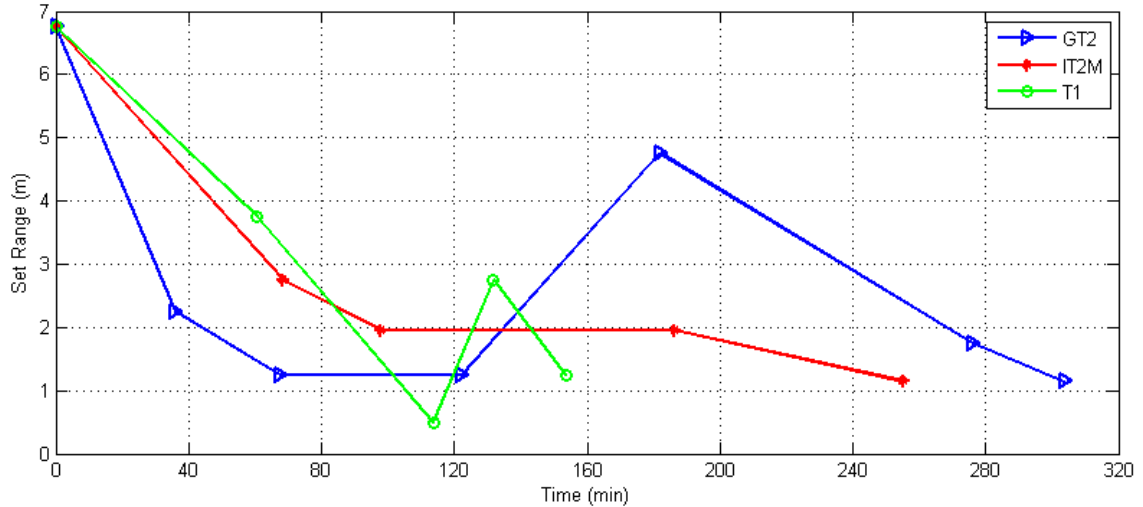


Figure 8.10 Magnitude of T Set-Range for Ship D SBD Experiments vs. Absolute Time Scale

8.2.2 Enhancement of SBD Through Introduction of Uncertainty Modeling

In the previous section it was shown that each of the FLS SBD methods was indeed capable of facilitating SBD practices. Now the focus may be turned to the main research goal, which was to determine if the IT2M and GT2 FLSs were able to enhance the SBD process through the modeling of design uncertainty when compared to the T1 FLS SBD environment. Analysis of the SBD results provided evidence in support of the research hypothesis that uncertainty modeling was able to enhance the SBD process. Unique insights into the performance of the FLS SBD methods were gained from separately examining the results for the highly constrained ship design and loosely constrained ship design experiments.

Results of Highly Constrained (Ship D) Set-Based Ship Design Experiments

The greatest evidence in support of the research hypothesis was seen by comparing the T1, IT2M-Slopes, and GT2 FLS SBD experimental results for the Ship D preliminary set-based ship designs. The set-range plots of the negotiated ship design variables

showed several important generalities for the T1 FLS SBD tool Ship D experiments as compared to the IT2M-Slopes and GT2 FLS SBD tool Ship D experiments.

- Overall, the T1 FLS had fewer negotiation rounds per ship design variable compared to both the IT2M and GT2 FL SBD tools.
- Overall, much less time was spent performing SBD negotiations of the ship design variables compared to that of the IT2M and GT2 FL SBD tools.
- Overall, the magnitudes of the final set-ranges for the T1 FLS were larger than those of the IT2M and GT2 FL SBD tools.

Evidence supporting these overall trends of the Ship D SBD experiments is listed in Table 8.3, as well as being shown in Figure 8.11 - Figure 8.13. Table 8.3 provides values for the average time spent negotiating a ship design variable and the average number of negotiation rounds performed for the SBD of Ship D using the T1, IT2M-Slopes, and GT2 FLS design environments. The table also lists the total number of minimal set-ranges for each of the FLS SBD Ship D experiments. The total number of minimal set-ranges was calculated by examining each of the negotiated design variables and then comparing the magnitude of the final set-range of each FLS type in order to determine which FLS had the smallest final set-range. The FLS with the smallest set-range was considered to have the “minimal” set-range for that negotiation variable.

Table 8.3 Analysis of Ship D Set-Based Ship Design Experimental Data

	T1	IT2M-Slopes	GT2
Average Negotiation Time (min)	107.7	200.8	244.2
Average Negotiation Rounds	3	5	5
Total Number of Minimal Set-Ranges	2	5	6

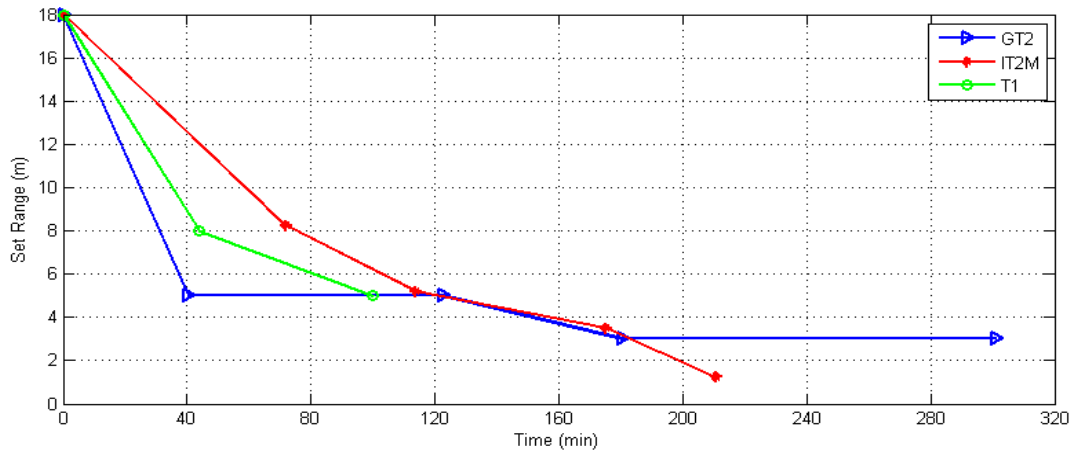


Figure 8.11 Ship D, Set-Ranges for *B* Negotiation vs. Absolute Time

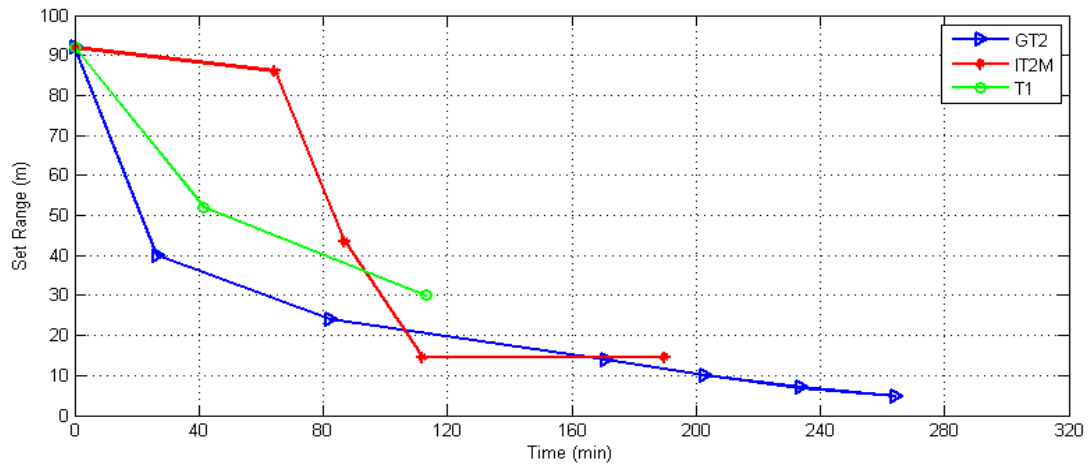


Figure 8.12 Ship D, Set-Ranges for *Lm* Negotiation vs. Absolute Time

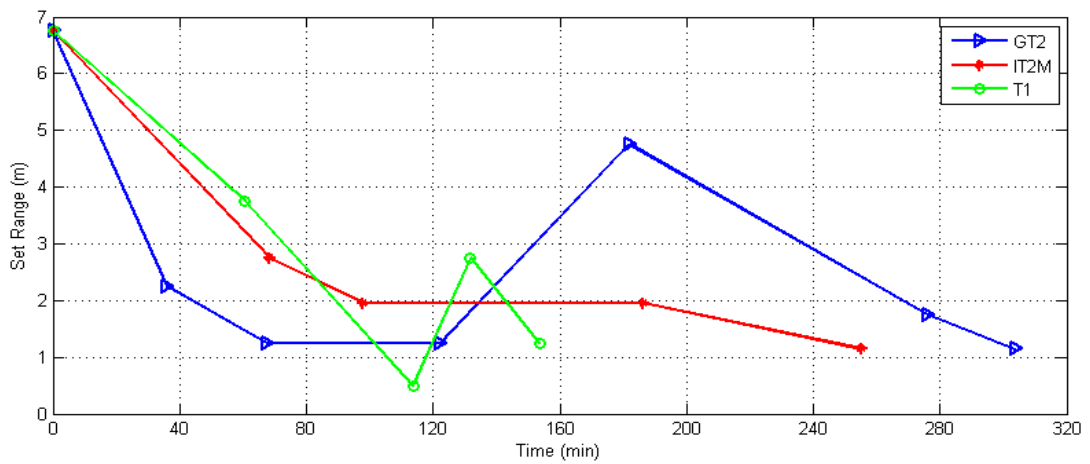


Figure 8.13 Ship D, Set-Ranges for *T* Negotiation vs. Absolute Time

Figure 8.11 shows the gradual set-based narrowing that was expected for a SBD process. Each of the individual FLS methods as plotted in Figure 8.11 was seen to have reduced the set-range for the beam (B) design variable. In the case of the Ship D design experiments, the IT2M-Slopes FLS managed to reduce the B set-range further than the T1 or GT2 FLS methods and would thus be considered to have the minimal set-range for the B variable in this case. Figure 8.11 also shows that there was very little reduction in set-range between the fourth and fifth negotiation rounds for the GT2 FLS Ship D experiments. The final observation was for the T1 FLS curve, which had only three negotiation rounds and did not reduce the set-range by as much as the IT2M-Slopes or GT2 FLS methods. A similar trend of gradual set-reduction is seen in Figure 8.12, which shows the magnitude of the set-range for the length of the machinery room (Lm) plotted versus absolute time. For the Lm negotiation the GT2 FLS achieved the minimal set-range, followed closely by the IT2M FLS, and at almost six times the set-range magnitude, the T1 FLS.

In general, most of the plots of set-range versus time showed trends of gradual set-reduction, similar to those of Figure 8.11 and Figure 8.12. In some instances however, it became necessary to re-open and re-negotiate a variable's set-range. This action was necessary when design values that were needed to develop a feasible solution were eliminated from the set-range making the design infeasible. A design would be considered infeasible, if for any reason, a design agent was unable to meet the functional design goal assigned to their agent role. For instance, as shown in Figure 8.13, during both the T1 and GT2 FLS experiments the draft (T) set-range needed to be re-opened for re-negotiation.

Records from the collected survey data indicated that during the GT2 FLS Ship D SBD experiment the Stability design agent was unable to meet their functional design goal with the set-range values at $t \approx 120$ minutes. As a result the Chief engineering agent re-opened the set-range for re-negotiation at this time. A similar course of action was taken during the T1 FLS Ship D SBD experiment. In the T1 FLS experiment, the set-range was reduced such that the Hull design agent could no longer meet their functional goal of ensuring the ship stayed afloat. Therefore, the Chief engineering agent re-opened the set-range and re-negotiation ultimately ending up with a set-range magnitude of 1.5 m.

When a set-range needed to be re-opened, it was because critical design values that were needed for a feasible design were eliminated. The pre-mature elimination of set-values can be a result of human input error or the complex interdependency of design variables. In example, if the current set-ranges were very narrow for the variable sets of length-of-waterline (*LWL*), *B*, and *T* yet provided for a feasible solution, further reduction in any one of the three sets may cause a design agent to no longer be able to satisfy their functional design goal. The Chief engineering agent does not know if the necessary set-values were eliminated from the top or bottom of the set-range, and must re-open the range in both directions. By doing so, the re-negotiation of the set-range based on new analyses and an increased amount of available design information, should result in a newly reduced feasible set-range that was shifted towards either the upper or lower range of values.

The process of re-negotiation can be explained by examining the GT2 FLS magnitude of set-range curve in Figure 8.14. Prior to re-negotiation ($t \approx 120$ min) the magnitude of the

GT2 FLS T set-range was 1.25 m based on $[x_{min}, x_{max}] = [11.5, 12.75]$ m. The set-range was then re-opened to a magnitude of 4.75 m, $[x_{min}, x_{max}] = [8, 12.75]$ m. Finally, the set-range was eventually reduced to a magnitude of 1.15 m, $[x_{min}, x_{max}] = [10.6, 11.75]$ m at around $t \approx 300$ min. Notice how after re-negotiation the set-range shifted to include smaller T values that had been previously eliminated from the set-range at $t \approx 120$ min.

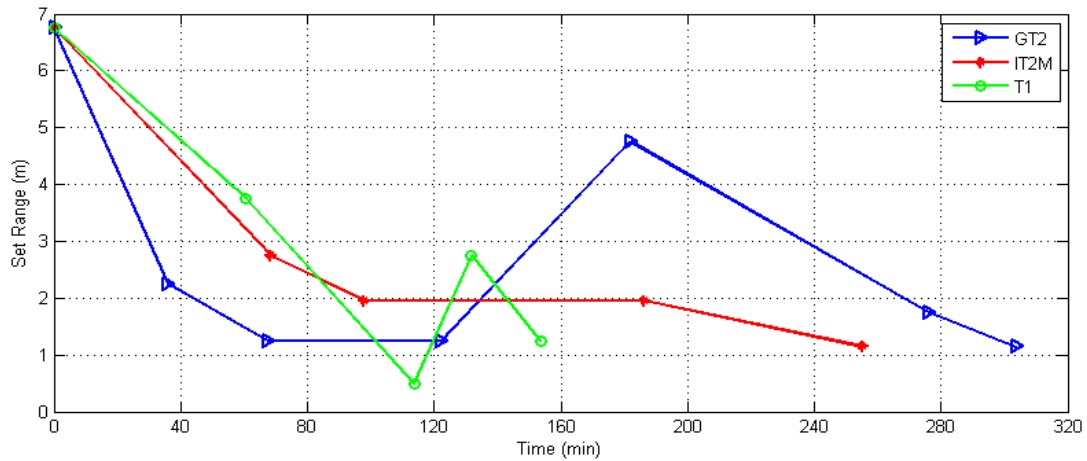


Figure 8.14 Ship D, Set-Ranges for T Negotiation vs. Absolute Time

The cause for re-negotiation was often the result of the complex interactions that occur between design variables of complex systems. It is possible that the set-reduction of a single set-range can affect the feasibility of values in other variable set-ranges. For instance, when the fourth negotiation of the T variable for the GT2 FLS SBD of Ship D began at $t \approx 120$ min, the design agents were performing analyses based upon depth (D) set-range data from the third D negotiation which occurred at $t \approx 100$ min; Figure 8.15. The JOP curve for the T negotiation resulted in JOP values of only zero, indicating that a design was infeasible for the entire set-range of T values and that the range needed to be re-opened.

Similarly, before the T set-range had been re-opened, a new GT2 FLS D negotiation was begun at $t \approx 160$ min. Since this negotiation was based on T set-range data which still needed to be re-opened for negotiation, the JOP data for the D negotiation resulted in only zero JOP values, indicating that the D set-range needed to be re-opened for negotiation. The complex relationship between the T and D design variables highlights just one of the many intricate relationships existing between design variables of a complex design. Eventually the T set-range and D set-range were simultaneously re-opened for negotiation at $t \approx 180$ min.

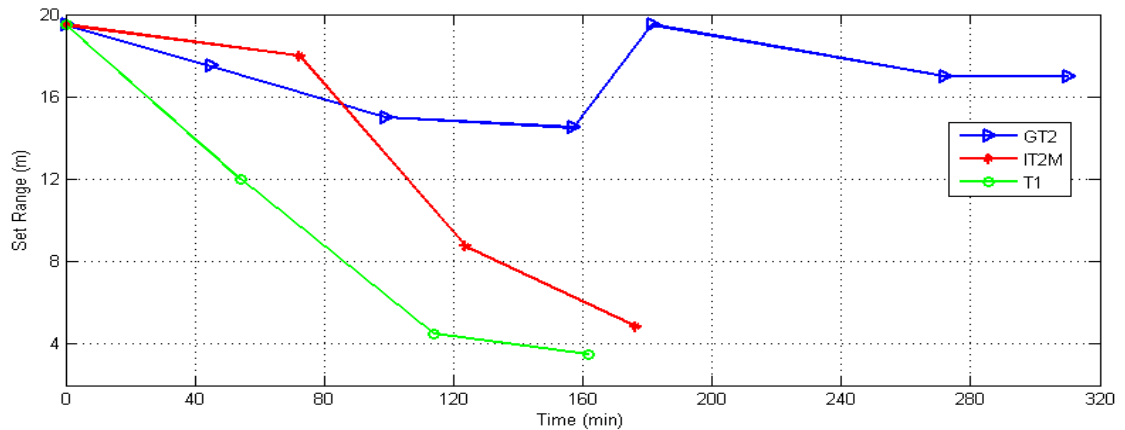


Figure 8.15 Set-Range Magnitude for D Negotiation of Ship D SBD vs. Absolute Time

This example also highlights another limitation of the SBD experimental methodology. It was not previously known if there was a benefit to negotiating every design variable during a single negotiation round or if the design variables could be continuously negotiated as needed. It was thought that negotiating every design variable would be more time consuming and continuing to negotiate a converged set-range would consume time that design agents could spend on analyses for other design variables. Since it was necessary to limit the experimental time for each SBD study, the method of allowing the

Chief engineering agent to submit negotiation requests for specific design variables at will was utilized in the SBD experiments, as opposed to requiring the negotiation of every design variable each round. The scope of these experiments was limited as the experiments were not designed to determine if one method of negotiation was better than the other. The example above, however, appears to indicate that there may be some benefit to negotiating every design variable during each round so that all design analyses would be based on the most up-to-date set-range data.

As discussed previously, T1 FLSs do not truly model uncertainty because the systems rely on fully known mathematical functions to represent data. However, the IT2M and GT2 FLSs have been shown to be capable of representing design uncertainty [Gray, Daniels, and Singer, 2010], [Gray and Singer, 2008].

For a single design variable there are several negotiating design agents. Therefore, in the magnitude of uncertainty plots, the uncertainty defined by each negotiating design agent was graphed individually. The GT2 FLS allowed for uncertainty inputs of $\pm\epsilon$ around the x_{-ru} and x_{-rl} defining MF curve points. Therefore, the magnitude of uncertainty for a negotiation variable of a GT2 FLS was represented using two separate plots. In one plot, the magnitude of epsilon uncertainty range was shown for the x_{-ru} MF defining curve points, and in the other plot, the x_{-rl} uncertainty magnitude was shown.

To properly facilitate the SBD concept of reducing design uncertainty in a highly constrained ship design, the magnitude of uncertainty plots of the Ship D SBD experiments should show a gradual reduction in the uncertainty associated with the design agents' MFs. Figure 8.16 and Figure 8.17 show the magnitude of uncertainty for

the design agents involved in the negotiation of the *B* ship design variable, for the Ship D experiments using the IT2M-Slopes and GT2 FLS methods, respectively.

Notice how in both of the figures the uncertainty of all the design agents gradually reduces over time. In Figure 8.16 the Resistance agent did have an increase in design uncertainty near $t \approx 120$ min, but the uncertainty was quickly reduced thereafter. Survey data indicated that the Cargo and Propulsion design agents felt very certain about the preference for *B* design values, which is why these design agents had no uncertainty associated with the definition of their MFs and thus a magnitude of uncertainty equal to zero for all negotiation rounds; Figure 8.16.

Overall, the plots for the magnitude of uncertainty for the design variables of the IT2M and GT2 FLS Ship D experiments displayed the general trend of a gradual reduction in the magnitude of uncertainty associated with the design agents' MFs. The plots provide evidence that the IT2M and GT2 FLSs offer enhancement of the SBD practice of delaying design decisions until there is a reduction of design uncertainty. The T1 FLS was not capable of representing the uncertainty in definition of linguistic preference and therefore cannot graphically represent the reduction of design uncertainty that occurs in a SBD process.

The values listed in time for the different FLS methods, it may appear that the T1 FLS method was superior in this category. However, with SBD the fastest method is not always the best method, as is the case here.

Table 8.4 provide strong evidence of the abilities of the IT2M-Slopes and GT2 FLS SBD tool methods to enhance the overall SBD process. The IT2M-Slopes and GT2 FLS

methods utilized more set-based negotiations and possessed more minimal-set ranges for the Ship D SBD than did the T1 FLS. Both of these properties indicate an enhancement in the facilitation of SBD practices. Looking at the average negotiation

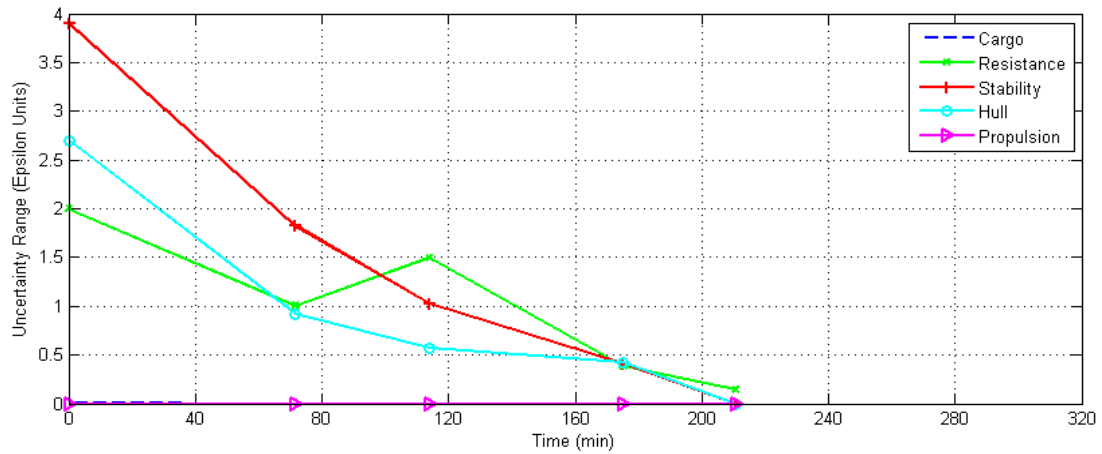


Figure 8.16 IT2M (Slopes), Ship D, Magnitudes of Uncertainty for B vs. Time

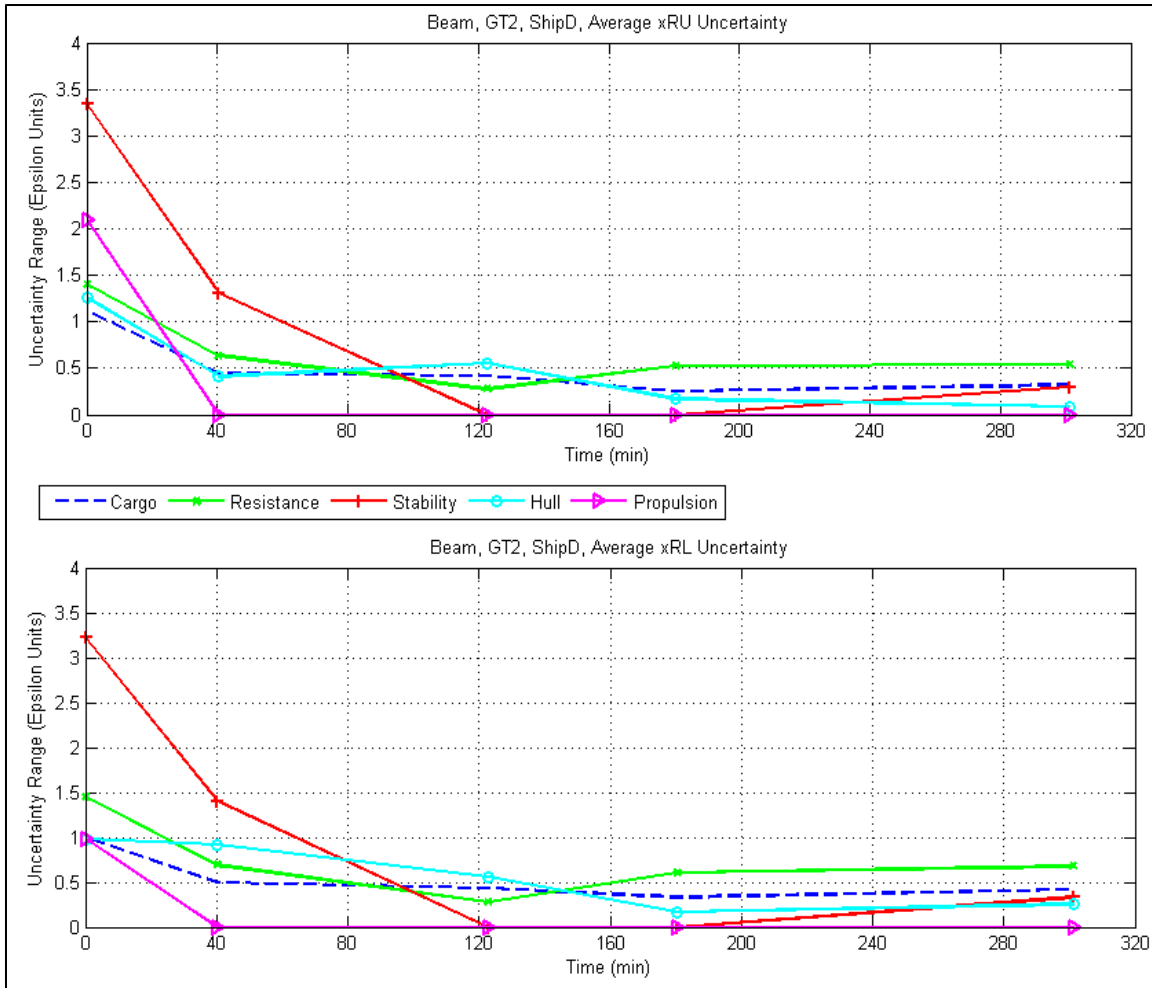


Figure 8.17 GT2, Ship D, Magnitudes of Uncertainty for *B* vs. Time

time for the different FLS methods, it may appear that the T1 FLS method was superior in this category. However, with SBD the fastest method is not always the best method, as is the case here.

Table 8.4 Analysis of Ship D Set-Based Ship Design Experimental Data

	T1	IT2M-Slopes	GT2
Average Negotiation Time (min)	107.7	200.8	244.2
Average Negotiation Rounds	3	5	5

Total Number of Minimal Set-Ranges	2	5	6
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The average negotiation time, listed in time for the different FLS methods, it may appear that the T1 FLS method was superior in this category. However, with SBD the fastest method is not always the best method, as is the case here.

Table 8.4, for the T1 FLS SBD tool was approximately half of the average negotiation time for the other FLS methods. The reason for this short negotiation time for the T1 FLS Ship D SBD experiment was that this experiment resulted in a catastrophic design failure. Normally during a SBD, if a design variable set-range was narrowed to the point where a design agent could no longer satisfy their functional goal, the set-range was re-opened by the Chief engineering agent and negotiations repeated.

In the case of the T1 FLS Ship D SBD experiment, the failure was considered to be catastrophic because the root cause of the design failure could not be traced to a single design variable or even several design variables. As a result, all of the negotiation variable set-ranges would have needed to be re-opened for re-negotiation. At the point in time when the design failure occurred, the T1 FLS SBD Ship D experiment had already utilized over half of the time that was allotted for the SBD experiment. Because so many of the design variable set-ranges needed to be re-opened, it would have been as if the design was starting over from the beginning.

With only a small portion of the allotted experimental time remaining, it would not have been possible to adequately narrow the set-ranges. Thus, the T1 FL SBD tool experiment for the Ship D design was terminated, and classified as a catastrophic design failure. This

explains why the small value for the average negotiation time of the T1 FLS was a negative aspect in this case.

Based on the plotted data for the magnitude of set-range and magnitude of uncertainty versus time for the IT2M and GT2 FL SBD experiments as compared to the T1 FLS SBD experiment, there was strong evidence that the quick convergence rate of the set-ranges for the T1 FLS experiment was the root cause of the catastrophic design failure. Without the presence of design uncertainty, the set-ranges for the T1 FLS Ship D experiment were quickly narrowed before the design tradeoffs were fully understood. It is hypothesized that the quick set-range convergence led to the elimination of design values that were needed to have a feasible ship design for the T1 FL SBD Ship D experiment. An examination of the depth variable for the Ship D design experiments shows evidence in support of this hypothesis.

The final set-minimum and -maximum values for the depth variable of the Ship D SBD experiments are listed in Table 8.5. Based on the Ship D design constraints, to produce a feasible ship design, it was necessary to have a depth value of less than the 17.5 m set-minimum possessed by the T1 FLS at the end of the Ship D SBD experiment. In both the IT2M and GT2 FLS SBD experiments, the set-minimum for the depth variable was 2.5 m lower than in the T1 FLS, at a value of 15 m and 15.85 m, respectively, by the end of the experiments.

Table 8.5 Set-Minimum and Set-Maximum Values for the Final Round of Depth Variable of the Ship D SBD Experiments

FLS Type	Set-Minimum (m)	Set-Maximum (m)
----------	-----------------	-----------------

T1	18	21
IT2M	15	18.4
GT2	15.85	18.25

The set-range plot for the negotiation of the Ship D depth (D) variable, Figure 8.18, showed that as early as (approximately) 115 minutes into the T1 FLS SBD experiment the depth set-range had converged to a magnitude lower than that of the IT2M and GT2 FLS final set-range magnitudes.

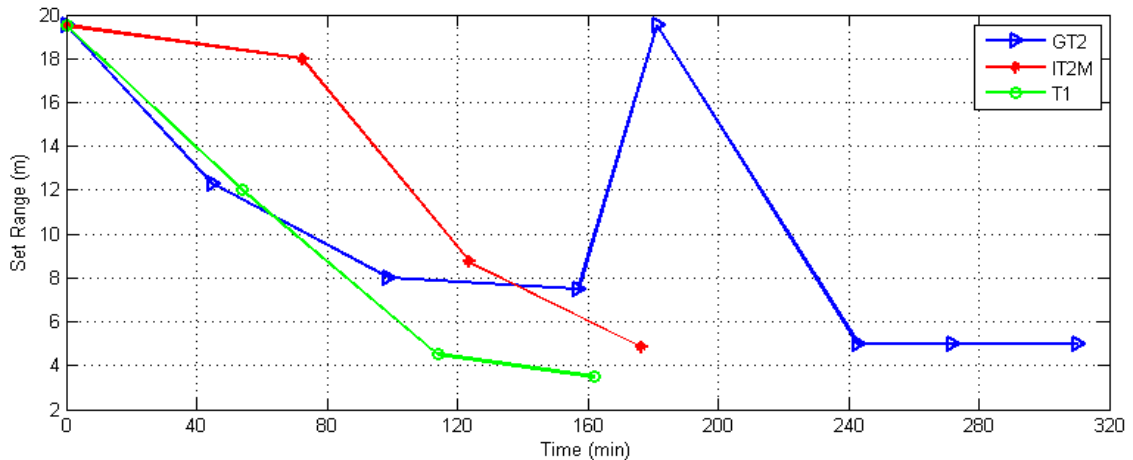


Figure 8.18 Ship D, Set-Ranges for D Negotiation vs. Time

Without design uncertainty modeling to aid in the purposeful delaying of the convergence process until uncertainty was reduced, the T1 FLS reached convergence of the depth set-range too quickly eliminating set-values needed for a feasible ship design. The IT2M FLS SBD depth set-reduction was more gradual and required approximately 60 minutes longer to negotiate than did the T1 FLS. The GT2 FLS SBD Ship D depth set-reduction required four more negotiation rounds and almost 150 minutes extra, to reach the final set-range as compared to the T1 FLS Ship D set-based depth negotiation.

Looking at the JOP curves resulting from the second round of depth negotiation during the Ship D SBD experiments, there was a striking difference in the range of non-zero JOP values; Figure 8.19 - Figure 8.21. As the figures show, the T1 FLS and GT2 FLS JOP curves indicate that the set-ranges should be reduced to approximately [17.5,22] m and [17,24.5] m respectively, for a third negotiation round.

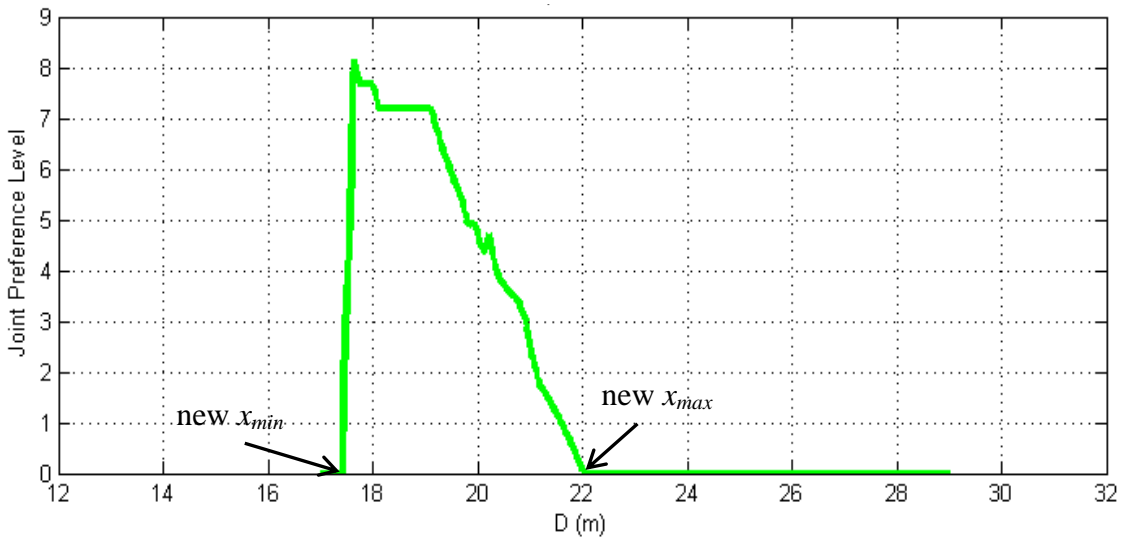


Figure 8.19 T1 FLS Ship D SBD, Round 2 Depth Negotiation JOP Curve

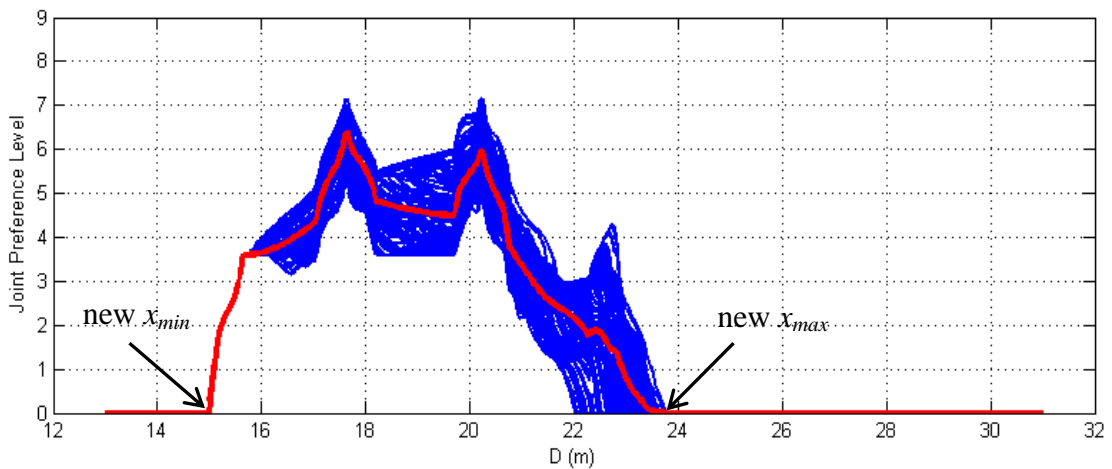


Figure 8.20 IT2M (Slopes) FLS Ship D SBD, Round 2 Depth Negotiation JOP Curve

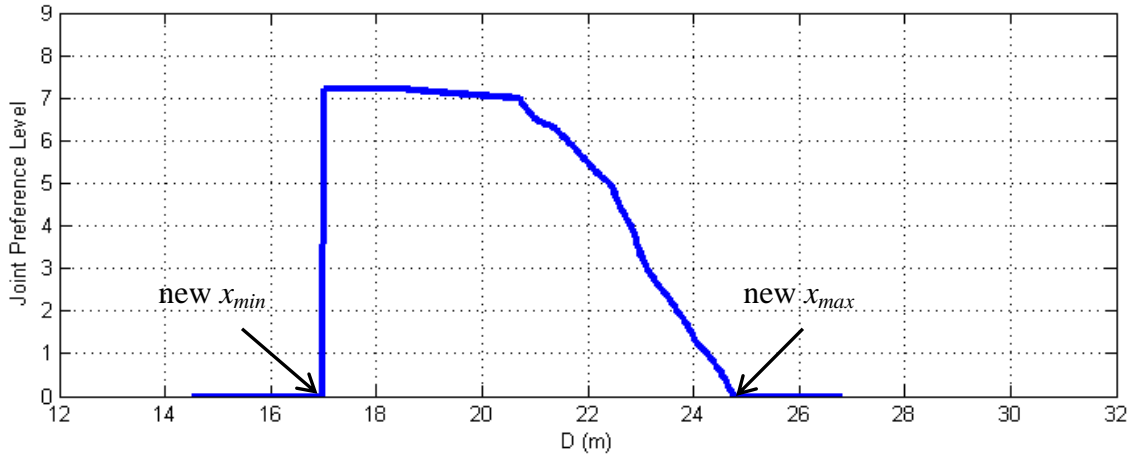


Figure 8.21 GT2 FLS Ship D SBD, Round 2 Depth Negotiation JOP Curve

Eventually the GT2 set-range was re-opened for re-negotiation and ultimately reduced to the set-range of approximately [15.85,18.25] m; Figure 8.22. The early set-reduction in T1 FLS experiment contributed to the catastrophic failure of the T1 FLS Ship D SBD as the set-range for D was further reduced to approximately [18,21], which excluded the depth value needed for a feasible design; Figure 8.23. The IT2M FLS depth set-range maintained a gradual set-reduction with final set values of $D = [15,18.4]$ m after the third negotiation round; Figure 8.24.

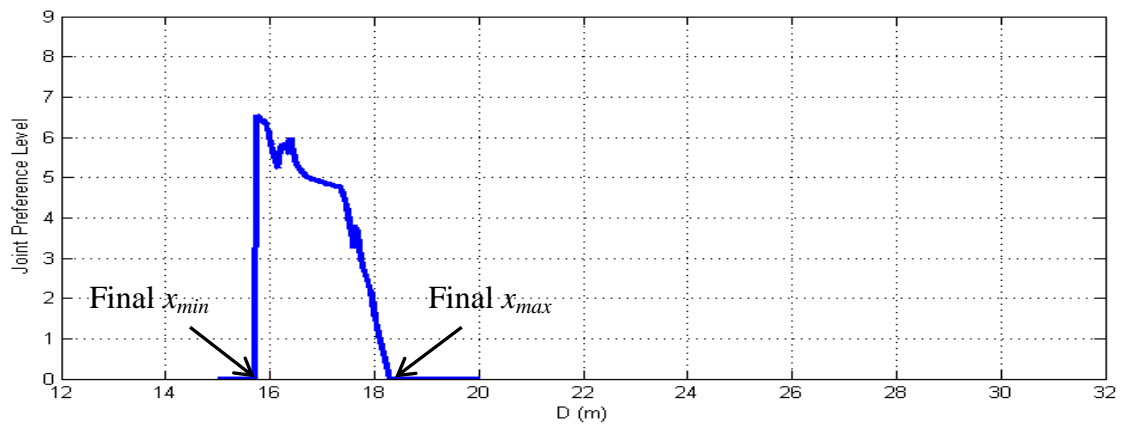


Figure 8.22 GT2 FLS Ship D SBD, Round 8 Depth Negotiation JOP Curve

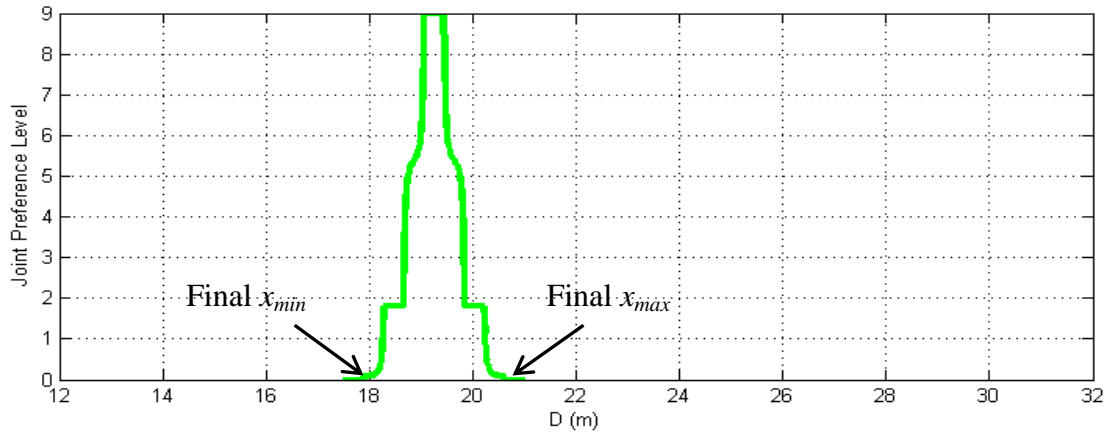


Figure 8.23 T1 FLS Ship D SBD, Round 4 Depth Negotiation JOP Curve

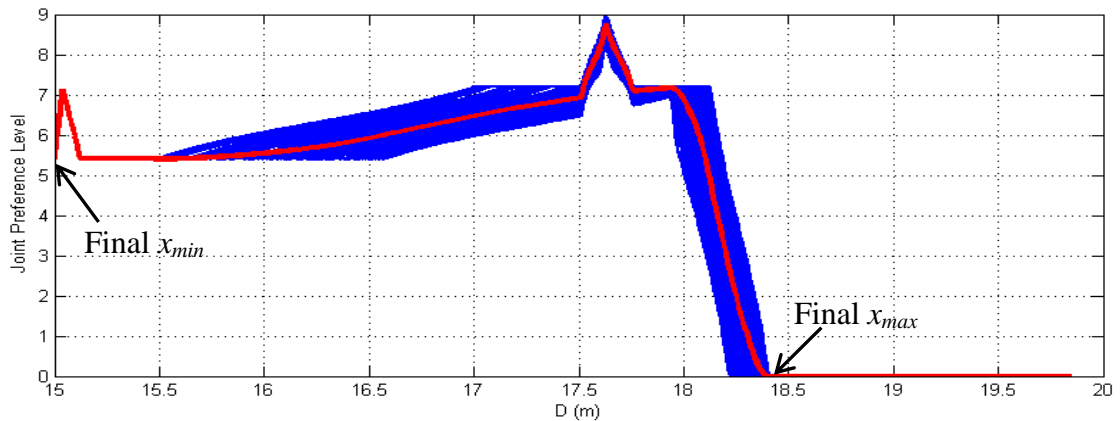


Figure 8.24 IT2M (Slopes) FLS Ship D SBD, Round 4 Depth Negotiation JOP Curve

The absolute time scale (described in Chapter 8, Section 8.1) was used to plot the set-range data shown in Figure 8.18. Because the time data was adjusted to the absolute time scale, the figure does not show the fact that just under an hour's worth of time remained in the T1 FLS SBD experiment by the final negotiation round. It was at this point in time when the T1 FLS ship design became infeasible. The interdependence of the design variables, discussed earlier in this section, meant that many design variable set-ranges would have had to have been re-opened for negotiation to try and search for a feasible solution. So, although it was possible to re-open the set-range during the GT2 FLS SBD

experiment, it was not possible to take the same course of action during the T1 FLS SBD experiment since meaningful analyses and negotiations could not take place within the limited experimental time remaining.

The general trends for the reduction of the set-ranges and the magnitudes of uncertainty show that the SBD process was enhanced by the use of uncertainty modeling. It was also shown that without uncertainty modeling to delay set-reduction, the T1 FLS Ship D SBD experiment failed for the highly constrained ship design. The IT2M and GT2 FLS Ship SBD experiments were capable of reducing the set-ranges without catastrophic failure during the Ship D design, a clear enhancement of the SBD process over the T1 FLS SBD environment. The GT2 FLS SBD experiment proceeded at a slower pace than the T1 FLS experiment. The slower SBD negotiations allowed the pre-mature set-reduction of the lower set-ranges values during second round negotiation of the depth variable for the GT2 FLS SBD experiment to be noticed before a catastrophic design failure occurred.

Results of Loosely Constrained (Ship E) Set-Based Ship Design Experiments

The main goal of the Ship E SBD experiment was to determine if introducing uncertainty modeling into the SBD process would enhance the overall SBD experience as hypothesized. Also of interest during the Ship E design experiments was to examine how the different SBD FLSs would function for a less constrained ship design. The Ship E design was a much simpler containership design because of the loose design constraints. Thus, within the solution space there were several feasible design solutions and as a result, there were no catastrophic design failures during the Ship E SBD experiments.

As with the Ship D SBD experiments, the Ship E experiments also showed gradual reduction of the magnitude of the set-ranges and magnitudes of uncertainty of the ship design variables. Excellent examples of gradual, set-based range reduction include the *B*, *D*, and *KGc* negotiations show in Figure 8.25, Figure 8.26, and Figure 8.27, respectively. Overall, the GT2 FLS SBD tool performed the best, followed by the T1 and IT2M FLS SBD tools. This assessment was based on the total number of minimum set-ranges, as well as the generally smooth and gradual reductions of the set-range of each design variable.

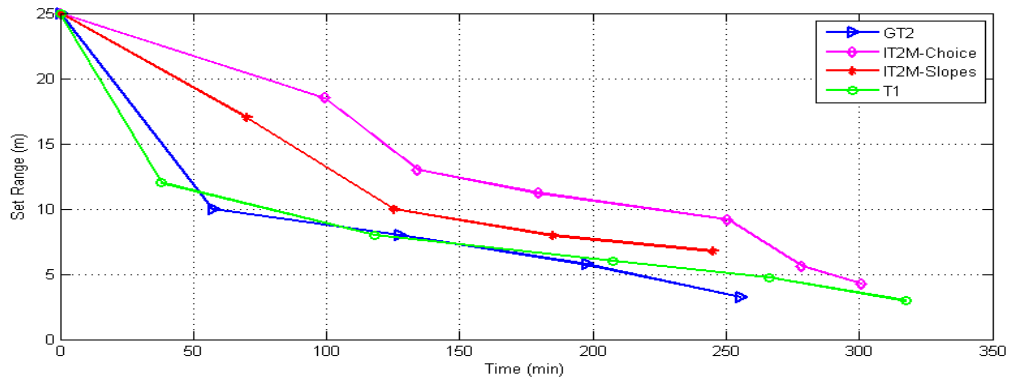


Figure 8.25 Magnitude of Set-Range for *B* Negotiations, Ship E SBD Experiments vs. Absolute Time Scale

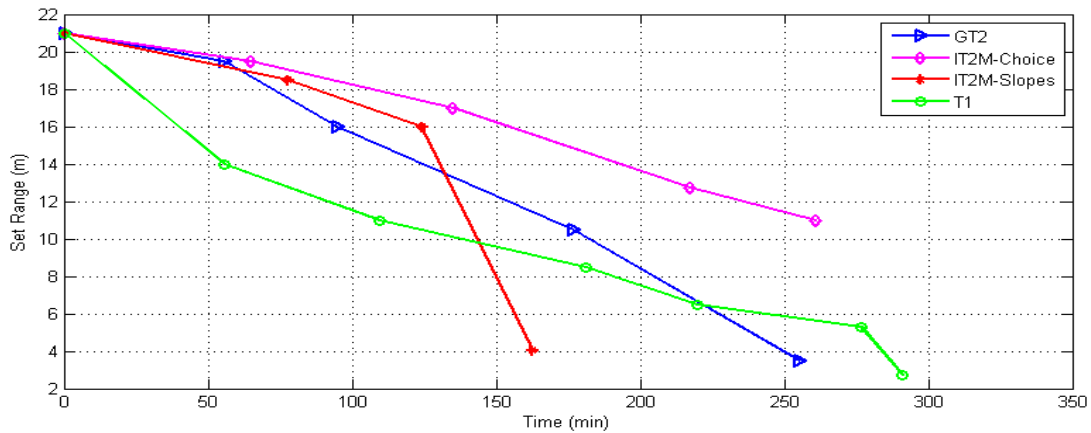


Figure 8.26 Magnitude of Set-Range for *D* Negotiations, Ship E SBD Experiments vs. Absolute Time Scale

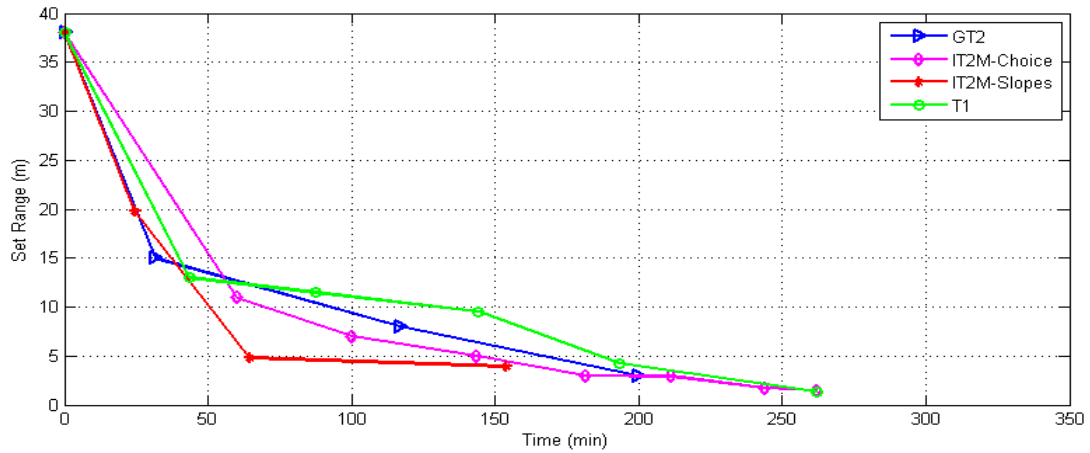


Figure 8.27 Magnitude of Set-Range for *KGc* Negotiations, Ship E SBD Experiments vs. Absolute Time Scale

Initially the Ship E design was completed using only the T1, IT2M-Slopes randomization method and GT2 FLSs. The results for the IT2M-Slopes FLS were unexpected, as the FLS underperformed for the Ship E SBD experiments compared to the other T1 and GT2 FLS methods. Figure 8.25 and Figure 8.28 demonstrate the meaning of “underperformance” for the IT2M-Slopes SBD FLS, where it is shown that the *B* and machinery vertical center-of-gravity (*KGm*) set-ranges for the IT2M-Slopes FLS had a much greater final magnitude than either the T1 or GT2 FLSs; especially for *KGm*.

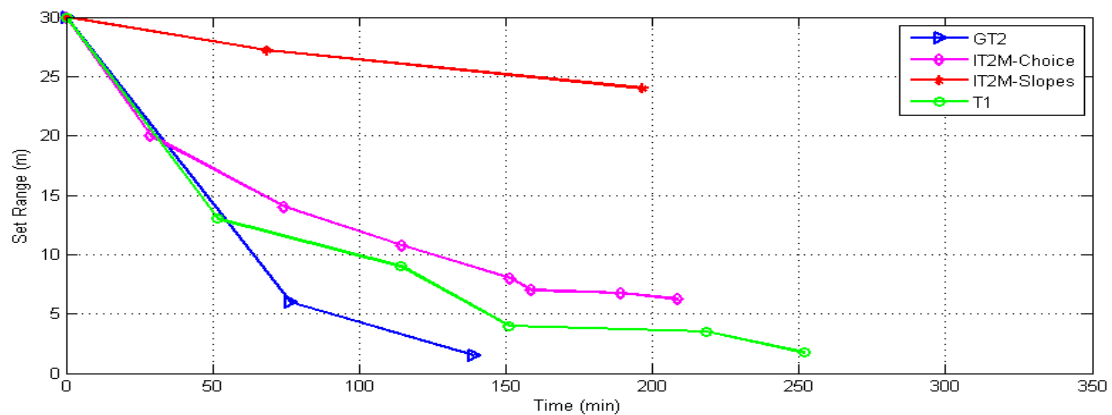


Figure 8.28 Ship E, Set-Ranges for *KGm* Negotiation vs. Time

Unlike the Ship D design experiments, the Ship E SBD experiments had only one instance in which a set-range needed to be re-opened for re-negotiation. The re-opening of the set-range occurred during the IT2M-Slopes FLS Ship E experiment; Figure 8.29. The Ship E design was a much simpler design than Ship D design because there were multiple feasible design solutions. This meant that within each set-range there were several set-values that could be chosen to produce a feasible solution and to satisfy the design agents' functional design goals. As such, it is understandable that the Ship E design would be less likely to reduce a set-range to the point at which there were no longer any feasible set-values, thus requiring the set-range to be re-opened for re-negotiation.

After reviewing the initial Ship E SBD experimental results, it was hypothesized that the IT2M FLS Slopes randomization method was too limited in its ability to model the uncertainty associated with the design agents' MFs, as compared to the GT2 FLS. This hypothesis led to the testing of an alternative, mixed method, IT2M FLS (IT2M-Choice).

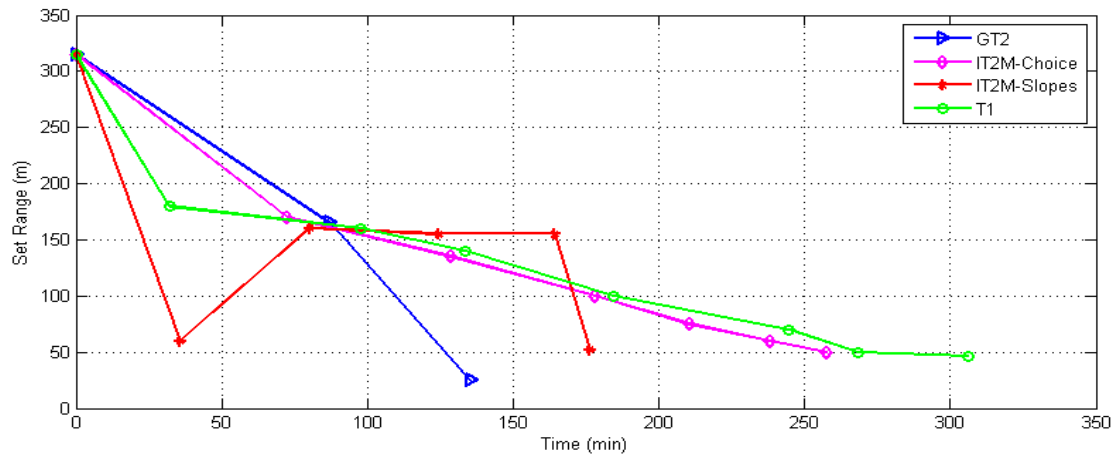


Figure 8.29 Ship E, Set-Ranges Magnitudes for L_c Negotiation vs. Absolute Time

In the IT2M-Choice FLS SBD Ship E experiment, the design agents were given the freedom to select one of three IT2M randomization methods, xRU, xRL, or Slopes, for the modeling of the uncertainty associated with the preference MFs of their entire fuzzy set. This meant that uncertainty modeling methods could be mixed on a per agent basis. For instance, the Cargo agent could choose to use the xRL randomization method for the MFs of its fuzzy set and the Resistance agent could choose to use the Slopes randomization method for the MFs of its fuzzy set.

Design agents were provided guidelines for choosing an appropriate IT2M FL randomization method for the modeling of the design uncertainty of their linguistic preference MFs. The advice provided was similar to the suggestions outlined at the end of Chapter 5, Section 3.2. The results from the mixed method IT2M FLS are labeled in the above set-range plots as “IT2M-Choice”, versus, “IT2M-Slopes” for the initial IT2M FLS experiment which utilized only the Slopes randomization method for uncertainty modeling. Although in some instances the IT2M-Choice FLS showed improvements in set-reduction over the IT2M-Slopes FLS, Figure 8.25 - Figure 8.28, the system still did

not produce set-reductions nearly as great in magnitude as those seen in the GT2 FLS experiments.

Upon further studying the magnitude of set-range versus absolute time plots for the Ship E SBD experiments, it was noticed that the IT2M-Choice FLS had consistently more negotiation rounds than did the GT2 FLS SBD experiment. Also, the set-reduction between negotiation rounds of the IT2M-Choice FLS was more gradual than that of the GT2 FLS. Figure 8.30 shows one of the many set-range plots that possessed the above mentioned qualities. There were several plausible causes for the performance of the IT2M FLSs during the Ship E experiments. Each cause was related to the representation of uncertainty when using the IT2M FLS SBD tool.

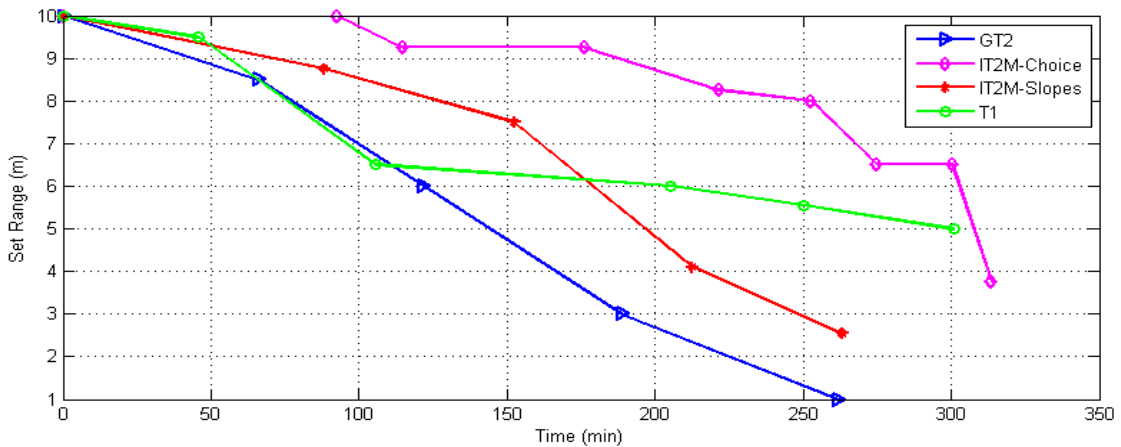


Figure 8.30 Ship E, Set-Range Magnitudes for T Negotiations vs. Absolute Time

It was possible that the design agents were unknowingly influenced by the default uncertainty bounds of the IT2M FLS SBD environment. The default uncertainty bounds for the IT2M FLS MFs were twice as large as the default uncertainty bounds of the GT2 FLS MFs. Figure 8.31 shows the default uncertainty bounds for the IT2M-Slopes FLS

SBD tool with $\pm\varepsilon = 0.435$ units by default, which were twice as large as the uncertainty bounds shown in Figure 8.32 for the GT2 FLS SBD tool with $\pm\varepsilon = 0.2175$. It was originally thought that the difference would not have a significant impact on the experimental outcomes since the design agents were given the freedom to change the uncertainty bounds as they deemed appropriate. However, after examining the magnitude of uncertainty plots and reviewing survey data, in most cases the initial magnitude of uncertainty for the IT2M FLSs was in fact greater than that of the GT2 FLS. This result indicates that the default uncertainty bounds may have actually influenced the design agents' choice of uncertainty bounds for their MFs.

With uncertainty bounds approximately twice as large as those of the GT2 FLS, the IT2M FLS would have needed to perform more negotiation rounds to reduce uncertainty to the same levels that the GT2 FLS began with. This affect was witnessed in the magnitude of uncertainty plots of the IT2M FLSs. The plots showed how the magnitude of uncertainty associated with a design agent's fuzzy set started out (in general) much larger than that of the GT2 FLS, requiring approximately one to two negotiation rounds before being reduced to uncertainty levels similar to that of the GT2 FLS.

Figure 8.33 - Figure 8.35 demonstrate this observation using the IT2M-Slopes, IT2M-Choice, and GT2 FLS SBD negotiations of the cargo vertical center of gravity (KGc) design variable. Notice how in Figure 8.33 and Figure 8.34 for the IT2M FLS experiments the magnitude of uncertainty at round one is approximately twice the magnitude of uncertainty for round one of the GT2 FLS experiment, Figure 8.35. By the second negotiation round the magnitude of uncertainty for the IT2M FLS methods had reduced to levels similar to what the GT2 FLS experiment began with.

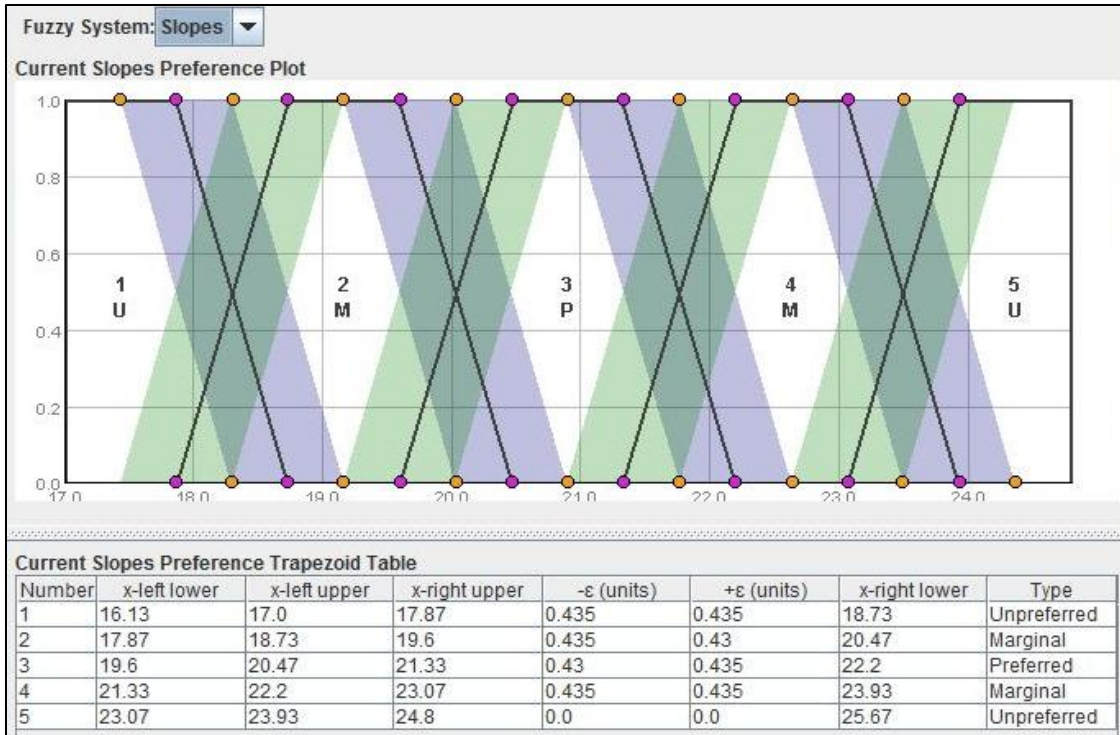


Figure 8.31 IT2M-Slopes FLS MFs Shown With Default Uncertainty Bounds

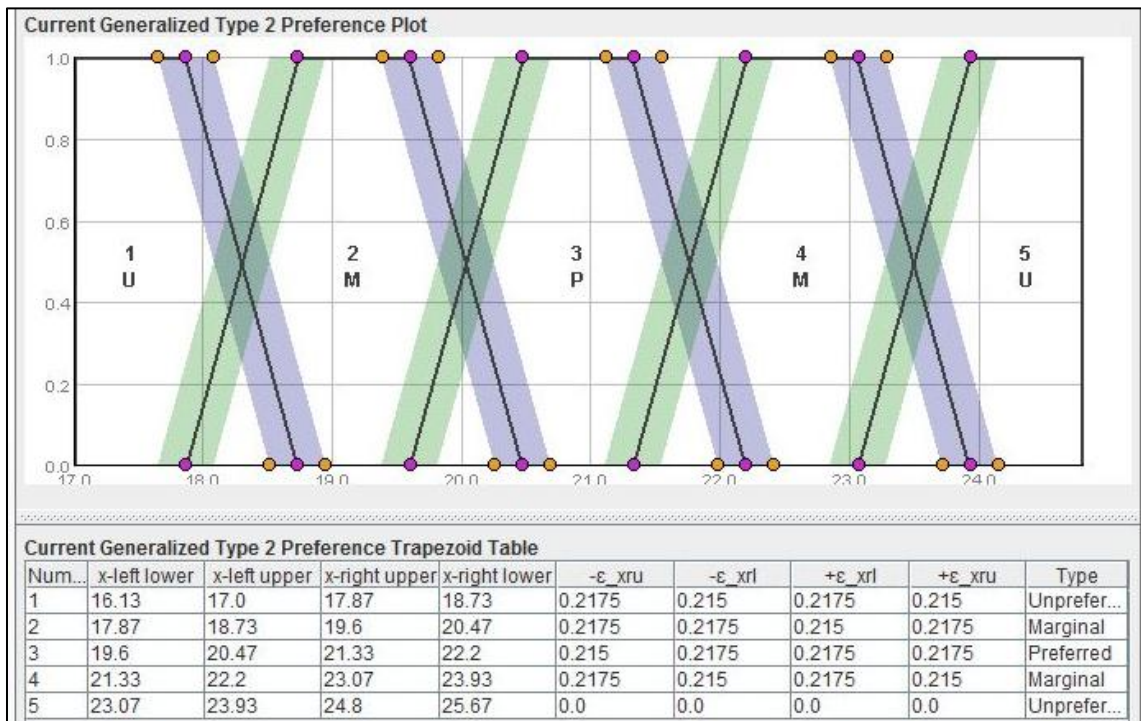


Figure 8.32 GT2 FLS MFs Shown With Default Uncertainty Bounds

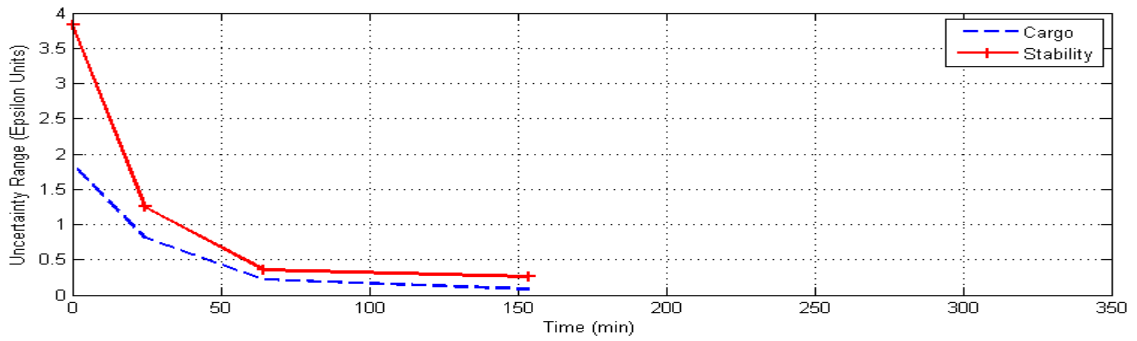


Figure 8.33 IT2M (Slopes), Ship E, Magnitudes of Uncertainty for KG_c vs. Time

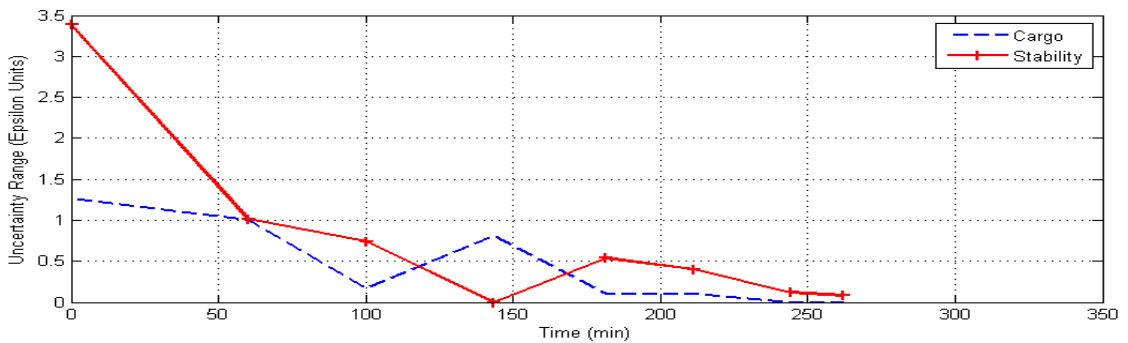


Figure 8.34 IT2M (Choice), Ship E, Magnitudes of Uncertainty for KG_c vs. Time

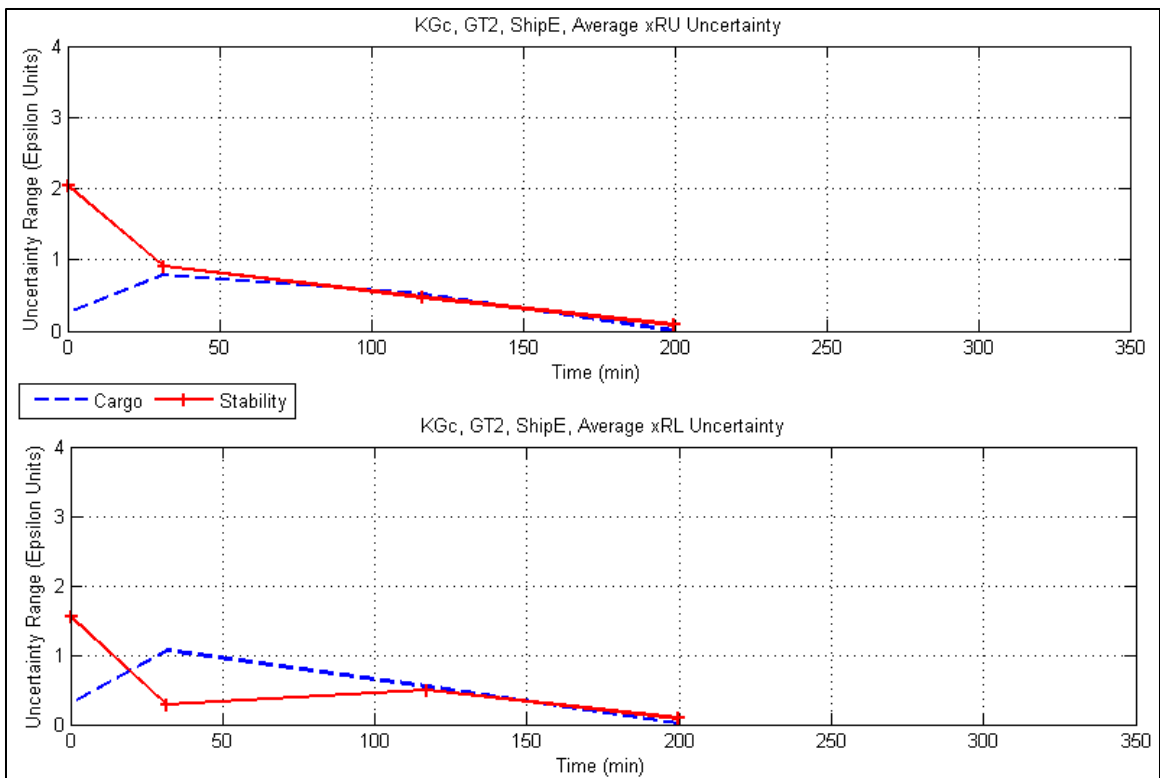


Figure 8.35 GT2, Ship E, Magnitudes of Uncertainty for KG_c vs. Time

The IT2M FLS JOP curve plots contained additional uncertainty information due to the plotting of the JOP curve resulting from each iteration of the IT2M FLS randomization; example Figure 8.36. This information contained a great deal of uncertainty as compared to the single JOP curves output by the T1 and GT2 FLS SBD tools. As the Chief engineering agent, the additional uncertainty information often made it difficult to determine a discrete point at which to trim the set-range for a subsequent negotiation round. To avoid elimination of plausible solutions, the Chief engineering agent took a cautious approach to the set-reduction process. The cautious set-reduction process further delayed the overall set-reduction of the set-ranges for the IT2M FLS SBD experiments as compared to the T1 and GT2 FLS SBD methods.

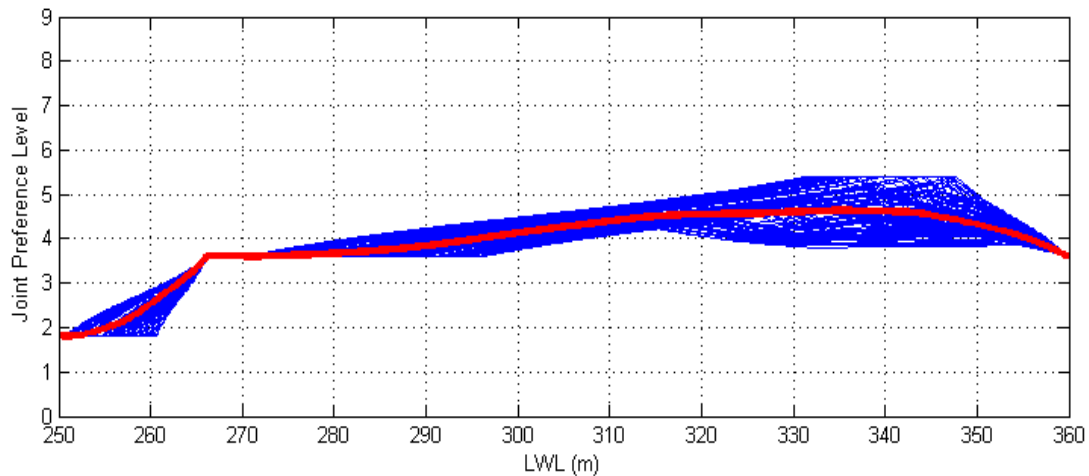


Figure 8.36 IT2M-Choice FLS, Ship E SBD, Round 1, LWL Negotiation JOP Curve

The output of the SBD experiments was directly related to the information input into the FLS by the human design agents. Upon review of the JOP curves for the Ship E SBD experiments, it was noticed that many of the JOP curves for the IT2M FLS SBD experiments contained no preference values of zero. Examples of this type of JOP curve

include Figure 8.36, which shows the IT2M-Choice FLS SBD JOP curve for the length of the waterline (*LWL*) Ship E negotiation and Figure 8.37, which shows the GT2 FLS SBD JOP curve, also for the Ship E *LWL* negotiation.

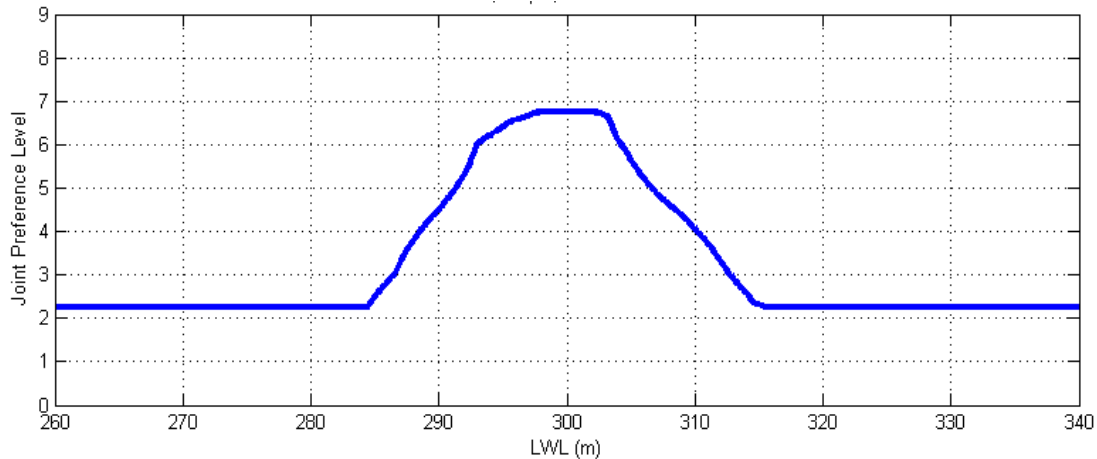


Figure 8.37 GT2 FLS, Ship E SBD, Round 3, *LWL* Negotiation JOP Curve

As a Chief engineering agent, JOP curves without zero preference values were particularly difficult to reduce because, a JOP curve without zero preference values tells the Chief engineering agent that all set-values are acceptable for the design. When faced with a JOP curve possessing no zero preference values, the Chief engineering agent had two courses of action:

- 1) Wait until other ship design variable set-ranges were reduced and then re-submit the set-range for negotiation to determine if a design agent's preference for set-values had changed as a result of other design variable set-ranges being reduced,
or
- 2) Make a best estimate of where to trim the set-range based upon the JOP values that were less-preferred.

The first option was the most preferable as it invoked the SBD principle of delaying design decisions until the design trade-offs were more fully understood. Typically, if the JOP curve was still without zero preference values after employing option (1), the Chief engineering agent would invoke option (2). This process can be seen in Figure 8.38 for the IT2M-Choice FLS SBD negotiation of the Ship E design variable T . As a result of the two step procedure that often occurred during the IT2M FLS experiments, the process took longer to reduce set-ranges for the ship design variables.

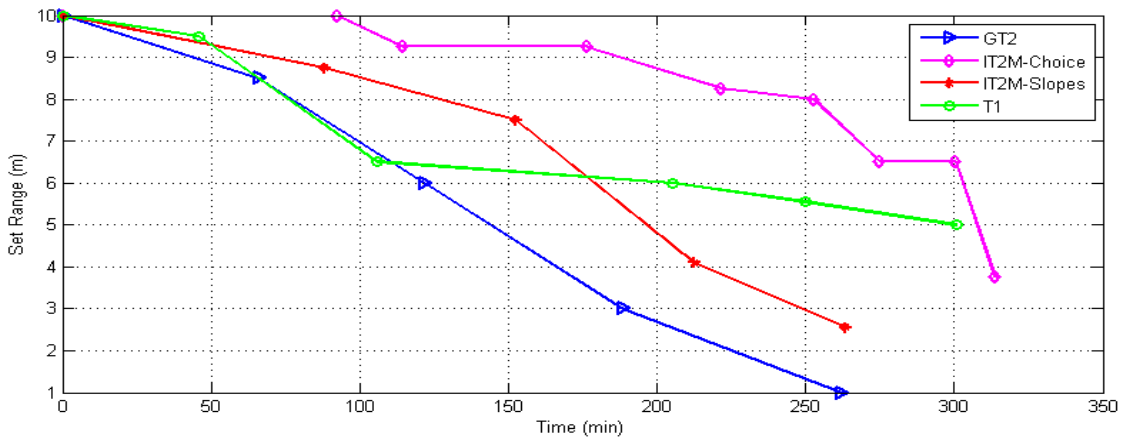


Figure 8.38 Ship E, Set-Ranges for T Negotiation vs. Time

In general, the Ship E SBD experiments as a whole resulted in more JOP curves that were without zero preference values than compared to the highly constrained Ship D SBD experiments. As there were many satisfactory solutions for the Ship E design, it was logical that the design agents would label set-values as *Unpreferred* far less than in the Ship D design. Without the use of the *Unpreferred* linguistic label by a design, a JOP curve would result in only non-zero preference values. The frequent occurrence of JOP curves without zero preference values for a simply constrained design would further delay the set-reduction process for a SBD. However, it is possible that the delay in set-reduction would be balanced out by the overall simplicity of a loosely constrained design.

Since the SBD experiments were not specifically designed to test this theory, it can only be hypothesized that for a simply constrained design it would be harder to reduce the set-ranges because of the lack of *Unpreferred* design values within the set-ranges for the design variables.

The use of uncertainty modeling was employed for the Ship E SBD via the IT2M-Slopes, IT2M-Choice, and GT2 FLS SBD environments. In general, the IT2M and GT2 FLS SBD methods showed the gradual reduction of design uncertainty that would be expected for the facilitation of SBD. As with the Ship D SBD experiments, the representation of design uncertainty for the loosely constrained Ship E SBD represents a clear enhancement of the SBD process over the T1 FLS SBD method that is incapable of representing true design uncertainty. Appendix J contains all plots of the uncertainty magnitude versus absolute time for the Ship E SBD experiments. Several examples of the uncertainty representation for the Ship E SBD experiments are shown in Figure 8.39 – Figure 8.41 for the *B* design variable.

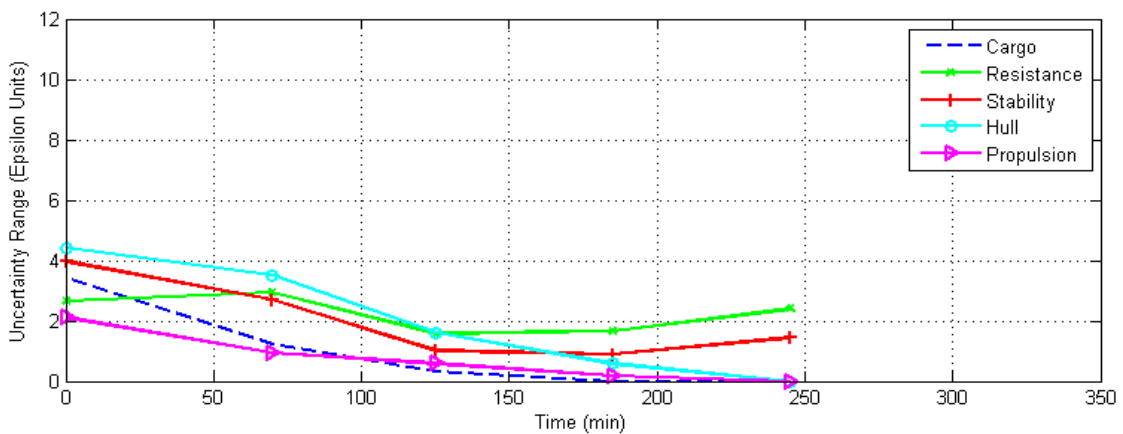


Figure 8.39 IT2M (Slopes), Ship E, Magnitudes of Uncertainty for *B* vs. Time

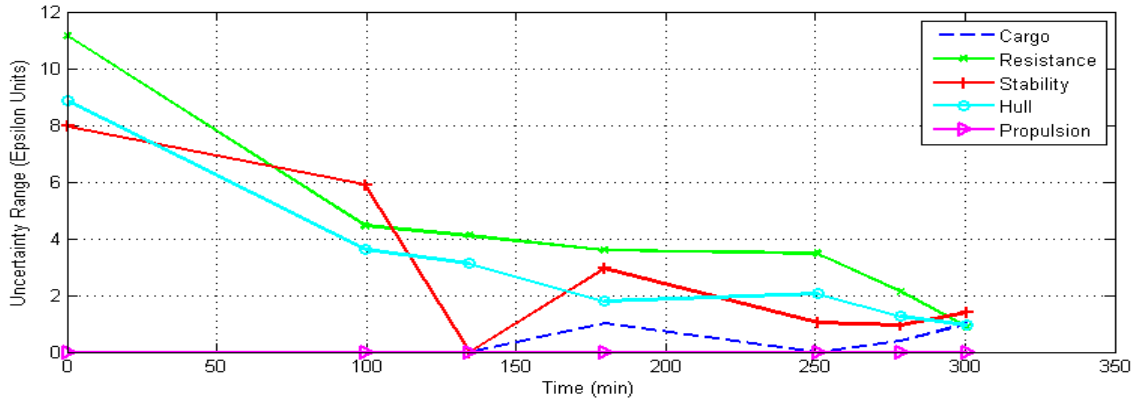


Figure 8.40 IT2M (Choice), Ship E, Magnitudes of Uncertainty for B vs. Time

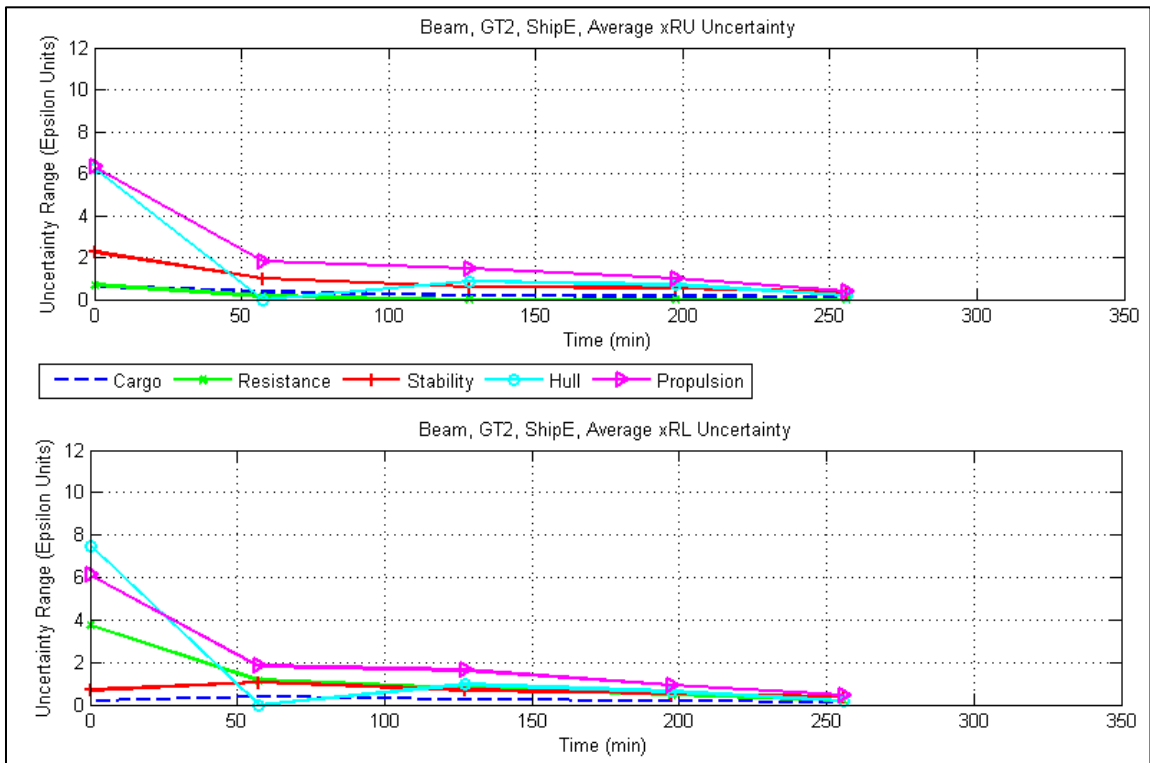


Figure 8.41 GT2, Ship E, Magnitudes of Uncertainty for B vs. Time

There were a few cases during the magnitude of set-range and the magnitude of uncertainty reduction for both the Ship D and Ship E SBD experiments that could not be directly explained through the need to re-open the set-range. Since, the majority of the results followed the SBD trends as expected, these few cases must be attributed to the

variabilities associated with human subjects. By examining the survey data it was possible to support this theory. For instance, in the IT2M-Choice Ship E SBD experiment a human subject was randomly assigned to the design role of Resistance agent, a role in which they later reported in the survey data they had very little previous experience. This led the subject to maintain a high degree of uncertainty throughout the entire design process, despite the narrowing of set-ranges and the increase in information as the design progressed. Figure 8.42 shows an example of this occurrence.

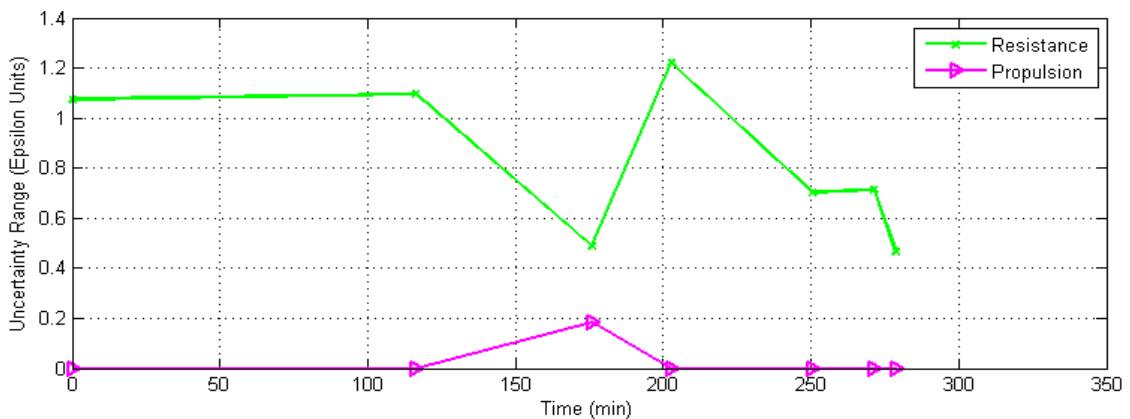


Figure 8.42 IT2M (Choice), Ship E, Magnitudes of Uncertainty for V_k vs. Time

In most cases the plot of uncertainty over time showed a gradual reduction in the magnitude of uncertainty for both the Ship D and Ship E SBD experiments. However, in some cases the magnitude of design uncertainty actually increased. It was explained in the previous section that the increase in uncertainty magnitude typically coincided with the re-opening of a set-range for re-negotiation; this was not always the case however.

In some cases the atypical trends could not be attributed to a design agent's inexperience with a particular agent role. Since the SBD experiments utilized human subjects for the design agents and the FLS linguistic preference inputs, the experiments were not without the inherent variability of human thought and cognition. This is to say that a human

design agent may change their level of uncertainty based on a feeling about the current direction of the design, based on their intuition, or based on some other intangible reason. Thus, some of the atypical trends in uncertainty may be attributed to the uncontrollable influence of human variability, cognition, and free will.

The purpose of collecting the post-preference input survey data from the design agents was so that any atypical trends could, potentially, be explained by the data provided by the design agents. For instance, the Stability and Hull design agents explained in the survey data that their design uncertainty increased for the structural vertical center of gravity (*KGs*) negotiations, Figure 8.43, because when they viewed the IT2M FLS JOP curve results they noticed the uncertainty associated with the JOP curve and started to feel uncertain about their linguistic preference inputs as well.

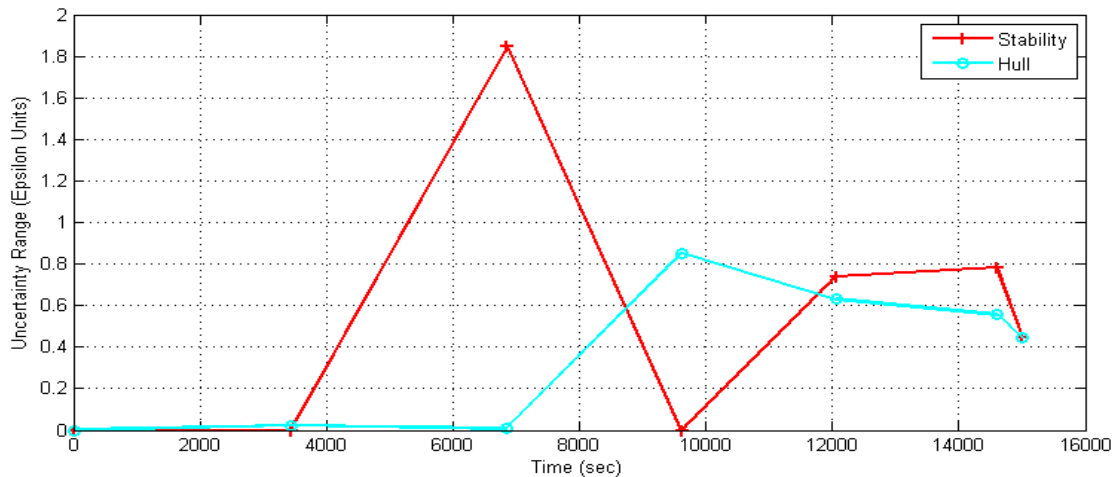


Figure 8.43 Magnitude of Uncertainty for *KGs* Negotiations vs. Absolute Time, Ship E, IT2M-Choice FLS

In addition to the variability of human cognition, the SBD experiments were also limited to be filled by a small group of naval architect and marine engineering students from within the University of Michigan. Not all students possessed the same level of design

experience. The subjects were randomly assigned to design roles and design teams in order to minimize the variability in subject intelligence and experience.

The figures in Chapter 8 showed examples of the general trends that were witnessed during the SBD experiments. In some instances atypical trends were witnessed, but in most cases the trends could be explained by graphical data or linguistic survey data. Using the results data and figures generated from the SBD experiments it was possible to make several conclusions as to the efficacy of each SBD FLS method for the facilitation of SBD and as to the capabilities of uncertainty modeling to further enhance the SBD process.

CHAPTER 9

CONCLUSIONS, RECOMMENDATIONS, & FUTURE RESEARCH

9.1 Conclusions

This research work was completed to test the hypothesis that representing uncertainty in the SBD space would enhance the facilitation of SBD and SBD principle practices. To test this hypothesis set-based experimental ship designs were conducted for both highly constrained and loosely constrained containership designs. Three different methods were used to facilitate the SBD process. These methods utilized T1, IT2M, and GT2 FLS environments to promote set-based practices such as, set-based communications and reductions in the set-ranges of design variables.

The T1 FLS SBD tool had previously been shown by Singer [2003] to be capable of facilitating SBD and reaching a global optimum. Type-1 FLS SBD experiments were performed in this research to provide a baseline of data when searching for enhancements to the facilitation of the SBD process through the uncertainty modeling provided by the IT2M and GT2 FLS SBD environments. The SBD experiments utilizing the T1 FLS revealed that the T1 FLS SBD environment was capable of facilitating SBD, to a degree. For the Ship E SBD in which there were numerous feasible design solutions as a result of having loose design constraints, the T1 FLS SBD tool performed well. The T1 FLS SBD tool was able to easily provide a means for reducing set-ranges and narrowing the solution space by eliminating less desirable solutions, hence facilitating the SBD process

for the loosely constrained ship design. However, the relatively quick rate of set-reduction during the T1 FLS SBD Ship D experiments, as compared to the set-reduction rate of the IT2M and GT2 FLS Ship D experiments, proved to be a weakness of the T1 FLS SBD tool.

The T1 FLS environment did not possess the ability to model design uncertainty and the Ship D SBD design experiment ended with a catastrophic design failure. The IT2M and GT2 FLSs SBD experiments however were able to gradually reduce the set-ranges of the Ship D design variables because these FLSs contained uncertainty modeling that helped to facilitate the SBD practice of purposefully delaying design decisions. The delaying of design decisions was particularly evident in the IT2M FLS SBD tool experiments. The extra information provided by the representation of uncertainty in the JOP curve solution space caused the Chief engineering agent to take a more gradual approach to the set-reduction process. The more gradual set-reduction during the IT2M FLS SBD experiments provided the time necessary for a more complete understanding of design trade-offs to develop, while simultaneously promoting the reduction of design uncertainty.

For the Ship D, highly constrained, SBD experiments the T1 FLS ended as a catastrophic failure since the system was not able to stay within the feasible design space. The IT2M and GT2 FLSs, however, were able to successfully reduce variable set-ranges and narrow the solution space while maintaining design feasibility. As such, the results of the SBD experiments illustrate that the representation of design uncertainty provides the following SBD enhancements:

- Enforcement of the SBD practice of delaying design decisions; especially when utilizing the IT2M FLS,
- Increase in the available information for decision making; in example the IT2M FLS cumulative JOP plots and JOP histograms,
- Improved understanding of the complex interactions between the ship design variables by both delaying design decisions and increasing available design information.
- A means to track the reduction of design uncertainty throughout the SBD process.
- Robustness to the level of design difficulty; the IT2M and GT2 FLS methods successfully facilitated SBD practices for both the loosely and highly constrained ship designs.

The enhancements provided by the addition of uncertainty modeling to the IT2M and GT2 FLSs were critical in preventing the pre-mature elimination of crucial design values from the set-ranges during a highly constrained ship design. A few set-ranges had to be re-opened during the GT2 FLS SBD Ship D experiment, however, the delaying of design decisions provided enough time to realize the set-reduction error and the sets were re-opened and the negotiation process continued smoothly.

Although the IT2M FLS did not achieve the same magnitude of set-reductions as seen in the GT2 FLS experiments, it can be argued that the more gradual set-reduction also prevented the IT2M FLS from pre-maturely reducing the set-ranges of the design variables during the Ship D SBD experiment. Analyses of the experimental results have shown that the IT2M FLS experiments may have possessed higher levels of initial design uncertainty due to the design agents being unintentionally influenced by the default uncertainty bounds of the IT2M FLS environment. The default uncertainty bounds for the IT2M FLS were in fact, twice as large as the GT2 FLS. The larger initial design

uncertainty for the IT2M FLS SBD experiments consequently resulted in a slower set-reduction process, which explains the smaller magnitudes of set-reduction observed for the IT2M FLS SBD experiments.

The experimental results have shown that, although beneficial for facilitating the SBD practices of delaying design decisions, the modeling of design uncertainty appeared less beneficial for a loosely constrained ship design. Since a loosely constrained ship design possess many feasible design solutions, it is easy to quickly reduce the set-ranges of design variables without the worry of eliminating critical design values needed for a feasible design.

It was also observed during the Ship E SBD experiments that because of the vast feasible solution space, many of the JOP curve results were without zero preference values that are typically used by the Chief engineering agent to identify how to reduce the set-range of a design variable for further negotiation. It was thought that the lack of zero JOP values and the resulting difficulties in set-reduction would have slowed down the set-reduction process for the simplistic Ship E SBD. However, analysis of the set-range data for the Ship E experiments showed that greater magnitudes of set-reduction were still achieved for the loosely constrained ship design as compared to the highly constrained ship design. Since the Chief engineering agent knew that many feasible solutions existed for the Ship E design, it was easy to reduce the set-ranges without the worry of prematurely eliminating design values needed to achieve a feasible solution, even without the presence of zero preference values.

Several measures were taken to reduce the experimental variability resulting from the use of human subjects. However, when using human subjects it is not possible to completely eliminate the variability in human nature and individual cognitive processing. As such, the experiments were limited in the capacity to control the levels of human variabilities. Despite the inherent variabilities associated with the involvement of human subjects in the SBD experiments, the overall the experimental data and figures provided evidence in support of the hypothesis that the SBD process can be enhanced through the introduction of uncertainty modeling. The magnitude of set-range and magnitude of uncertainty plots both demonstrated gradual reductions throughout the SBD process; thus, enabling the facilitation of the SBD principles of gradual elimination of infeasible solutions, the reduction of uncertainty, and the increase in design information for making crucial design decisions.

The development and creation of the JOP histogram provided a truly novel tool for the enhanced analysis of SBD negotiations. With any complex system robustness and design flexibility are always considered to be of great importance. The U.S. Navy is constantly trying to design ships with ever increasing flexibility to fulfill multiple mission roles. When designing for flexibility, a design must have situational robustness and cannot be optimized for a single mission only. The JOP histogram of the IT2M FLS allows a designer to determine not only the most preferred set-values from within a variable's set-range, but also the set-values that occur most frequently in the presence of design uncertainty, which indicates robustness. The designer can then choose to further investigate the set-values with the highest JOP rating, as well as set-values that have robustness to design uncertainty; a highly desirable characteristic for any design. It is

envisioned that the JOP histogram data could be used for optimization routines or as a “threshold of robustness” to provide additional criteria for set-reduction and trade-off studies.

The tools and methods developed for this research represent a significant contribution to the field and naval architecture and marine engineering (NA&ME). Through research the author has accomplished:

- 1) The representation of uncertainty in design and communication through the use of IT2M and GT2 FLSs,
- 2) The enhancement of SBD facilitation through,
 - a. Representation of design and communication uncertainty
 - b. Identification of robust design solutions (IT2M JOP histogram)
 - c. Delayed set-reduction resulting from uncertainty modeling
 - i. Avoided premature elimination of feasible solutions
 - ii. Provided robustness to SBD method
- 3) Development of new interval type-2 modeling methods
 - Yrand, xRU, xRL, and Slopes randomization methods
- 4) Creation of IT2M Joint Output Preference Histogram
- 5) Development of a simplified GT2 MF representation (2-D)

Although the methods and tools developed for this research were applied to the field of NA&ME for complex ship design, they could each be easily applied to the general field of complex systems design in order to facilitate SBD. For instance, the FLS SBD tools could be applied to mechanical or aerospace design to perform the SBD of either an automobile or airplane, respectively.

9.2 Recommendations for Future Work

The research conducted for this dissertation was not without limitations, as no one set of trials can test all experimental hypotheses. As such, there is room for further investigation on the facilitation of SBD. The results of this research also led to the formulation of several new hypotheses which require further, in depth, investigation. The areas envisioned for continued research include:

- 1) Conducting additional SBD experiments to identify the performance benefits of the IT2M FLSs compared to that of the GT2 FLS. This could be accomplished by using the SBD environments to produce a ship design with a known optimal solution and then comparing the SBD results of each SBD FLS to the known optimal solution.

- 2) This research has shown that the SBD tools indeed facilitated the SBD process and that the newly developed IT2M and GT2 FLSs were able to enhance the SBD process. However, the results were based on relatively few design experiments as there was a limited subject pool from which to draw acceptable experimental participants. It would be useful to create a simple design experiment that could allow the author to draw upon a much larger subject pool so that statistical hypothesis testing could be performed to further support the conclusions of this research.

- 3) A current limitation of the SBD environments is that each of the design agents has an equal preference weight when negotiating a design variable. That is to say, that no single design agent can influence the negotiation process more than the other design agents. In reality, when negotiating a design variable, although many design agents may be involved in the variable negotiation because they each have a preference for the values

within the set-range, the design agents should not all have an equal influence on the negotiation of the variable. There is a need to research and develop a methodology which allows for certain design agents to have more influence over the negotiation of a design variable than do the other negotiating design agents. It is possible that a weighting value could be provided for each negotiating design agent and this value would be incorporated into the FLS processes.

4) One of the main components of SBD is the set-based communications process. Currently the set-based communications between human design agents are facilitated through the use of a FLS software environment. It has long been thought that a computer cannot capture or reproduce the extensive range of knowledge of an experienced engineer. This thought was one of the main motivations for designing the SBD FLSs to include the linguistic inputs from human design agents. With continued research and development the human design agents could potentially be replaced by optimization codes which would represent each functional design discipline. It would then be possible to test the hypothesis that a SBD team of human design agents could outperform a strictly computational SBD tool.

It would be of interest to test the SBD process when utilizing the computerized design agents (optimization codes), versus human design teams comprised entirely of subjects with only college level education and design experience, subject groups with only 1 – 4 years of design experience, and subject groups with over 4+ years of design experience, and finally, groups with a mixture of design experience. This would allow the experiments to show if a SBD team of human design agents could outperform

computational design agents and demonstrate the influence of experience on the design process.

5) In the SBD experiments the Chief engineering agent was given the free will to submit a request for negotiation of a design variable at any time during the SBD experiment. This meant that some design variables were negotiated more than others. It also meant that a new negotiation request could be submitted while other design variables were still being negotiated by the design agents. The research did not test to see if negotiating every design variable each round would result in a more efficient SBD process. Therefore, there is an opportunity to investigate the advantages or disadvantages to the two different modes of SBD negotiation.

Appendix A
Post-Preference Data Input Survey
Questions & Answer Choices

1) How would you rate your overall level of uncertainty for this negotiation round?

- High
- Moderate-High
- Moderate
- Low-Moderate
- Low

2) How many membership functions did you use to describe your preference for the negotiated set of values?

- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 20
- More than 10

3) What was your motivation for using x# of membership functions for the negotiation of the values set?

Short Answer

- 4) Did you utilize this variable's Joint Output Preference (JOP) curve data from the previous negotiation round to make preference decisions for this negotiation round?
- Yes
 - No
 - N/A, first negotiation round
- 5) Did you utilize JOP curve data from other variables to make preference decisions for this negotiation round?
- Yes
 - No
 - N/A, first negotiation round
- 6) Did you utilize your preference curve data (MFs) from the previous negotiation round to design your preference functions for this negotiation round?
- Yes
 - No
- 7) What were your reasons for choosing the +- epsilon (or sigma %) values for each membership function? (Enter "N/A" if using Type-1 System)

Short Answer

- 8) Compared to previous negotiation rounds for this variable, How many membership functions (MFs) did you use to describe your preference?
- Fewer MFs
 - More MFs
 - Same MFs
 - N/A, first negotiation round
- 9) Compared to previous negotiation rounds for this variable, how would you describe the uncertainty bounds for your membership functions?
- Wider uncertainty bounds
 - Narrower uncertainty bounds
 - Approximately equal uncertainty bounds
 - N/A, first negotiation round
 - N/A, Type-1 FLS

10) Compared to previous negotiation rounds for this variable, how would you rate your level of design uncertainty for this negotiation?

- Greater design uncertainty
- Less design uncertainty
- Same level of design uncertainty
- N/A, first negotiation round

11) When describing your membership functions for the negotiation of the design variable this round, do you feel that you had ____ information, than previous rounds?

- a. more
- b. less
- c. same
- d. N/A, first negotiation round

12) The time you were given to perform design analyses before entering your membership function data to describe your preference for the design variable was ____ ?

- a. more than adequate
- b. adequate
- c. less than adequate

Appendix B

Design Constraints for Ship E

Primary Design Requirements:

Your company has been asked to respond to a request for a bid for a standard containership operating between ports located in Sydney, Australia and Hong Kong, China. The vessel needs to satisfy the following requirements:

- 1) Carriage of 8,000 TEU (Twenty foot Equivalent Units) with an average weight of 13.5 tonnes with a VCG at 45% of the container height in accordance with ISO standards.
 - There is no requirement for preferential loading control of the vessel; i.e. the ability to accommodate a uniform container weight vertically and longitudinally
- 2) Endurance range of 4475 nautical miles, at service speed for fuel and 26 days of provisions and water
- 3) Service speed at 85% Maximum Continuous Rating within the range of 22-26 knots, with 26 knots being preferred.
- 4) Vessel must be of all steel construction and be designed to commercial standards including the requirements for Safety of Life at Sea (SOLAS) and the Germanischer Lloyd classification society.
 - Specific attention should be given to the minimum GMt requirement
 - The vessel will be flagged in Australia, but operated with a U.S. crew
- 5) 26 days of endurance
- 6) Complement of 25 officers and crew
- 7) Maximum length of waterline (LWL): 360 m
- 8) Maximum beam (B): 51 m
- 9) Maximum draft (T): 25 m
- 10) Only one propeller is to be used
- 11) You may assume $LCG = LCB$, thus $trim = 0$, and $T_{aft} = T_{forward}$

The customer seeks a minimum after tax Required Freight Rate (RFR) vessel design based upon the following economic assumptions:

ship economic life	18 years
voyage length per round trip	4475 nm
min. average speed made good on voyages	22 knots
port calls of 2 <i>days</i> each per round trip	2
utilization (% containers paying on each voyage)	85%
operation days per year	340

Appendix C

Design Constraints for Ship D

Primary Design Requirements:

Your company has been asked to respond to a request for a bid for a standard containership for use along the U.S. Atlantic Coastline operating out of the Newport News Marine Terminal in Newport News, VA. The vessel needs to satisfy the following requirements:

- 1) Carriage of a minimum of 4,000 TEU (Twenty foot Equivalent Units) with an average weight of 14.0 tonnes with a VCG at 45% of the container height.
 - There is no requirement for preferential loading control of the vessel; i.e. the ability to accommodate a uniform container weight vertically and longitudinally
- 2) Endurance range of 2,000 nautical miles, at service speed for fuel and 18 days of provisions and water
- 3) Service speed at 85% Maximum Continuous Rating of no less than 25 knots
- 4) Vessel must be of all steel construction and be designed to commercial standards including the requirements of the American Bureau of Shipping and the U.S.C.G.
 - Specific attention should be given to the minimum GMt requirement
 - The vessel will be flagged in the United States and operate with a U.S. crew
- 5) 18 days of endurance
- 6) Complement of 22 officers and crew
- 7) Maximum length of waterline (LWL): 300 m
- 8) Maximum beam (B): 33.0 m
- 9) Maximum draft (T): 12.75 m
 - Based on size limitations of the ports of operation
- 10) Only one propeller is to be used
- 11) You may assume $LCG = LCB$, thus $trim = 0$, and $T_{aft} = T_{forward}$

The customer seeks a minimum after tax Required Freight Rate (RFR) vessel design based upon the following economic assumptions:

ship economic life	20 years
voyage length per round trip	2000 nm
average speed made good on voyages	25 knots (minimum)
port calls of 1 day each per round trip	8
utilization (% containers paying on each voyage)	85%
operation days per year	350

Appendix D

Pre-Experiment Design Agent Survey Questions and Answer Choices

Pre-Experiment Survey

Enter your assigned ID # here:

Answer the following questions below. Make estimates when necessary.

- 1) What is your level of design experience?

# of class/research design projects:		Total <-- numbers only
# of internships:		
# years of work experience:		

- 2) Current education level.

undergraduate		Year (1, 2, etc...) <-- numbers only
graduate		
		<input checked="" type="radio"/> masters <input type="radio"/> Ph.D

- 3) What is your assigned agent role and task, within the design group?

Enter text here

- 4) Please estimate how important you view your agent task/role for the ship design.
 1 not important --> 5 very important <-- DROP-DOWN menu

- 5) At this point in time, please estimate your group morale?
 1 low morale --> 5 very high morale <-- DROP-DOWN menu

- 6) How long do you estimate, in minutes, the ship design will take?
 <-- Enter time value

- 7) Please estimate the amount of work flow interactions that you think will take place between project members during the design process.
 Choices: light and sequential, heavy and sequential, light and reciprocal, heavy and reciprocal
 <-- DROP-DOWN menu

- 8) How much do you think your task depends on information obtained/provided by others within the group?
 1 very little --> 5 quite a lot <-- DROP-DOWN menu

- 9) How much do you think other tasks depend on the information you provide?
1 very little --> 5 quite a lot <-- DROP-DOWN menu
- 10) How often are the same work methods, analyses, or design tools used to complete your task?
1 seldom --> quite often <-- DROP-DOWN menu
- 11) To what extent is your task analyzable - via design tools, mathematical equations, formulas, etc...?
1 very little --> 5 quite a lot <-- DROP-DOWN menu
- 12) To what extent does your task require "engineering judgement", or knowledge based on experience?
very little --> quite a lot <-- DROP-DOWN menu
- 13) How easy is it to know if your task is done correctly?
1 very easy --> very difficult <-- DROP-DOWN menu
- 14) Rate the possibility of difficult situations arising for which there will be no immediate or apparent solutions when performing the design?
1 very low --> very high <-- DROP-DOWN menu
- 15) How frequently do you expect to encounter interruptions during your design task?
1 seldom --> very often <-- DROP-DOWN menu
- 16) Please provide a description of your personal attitude or typical role when working in a design group.

Enter text here

- 17) How familiar are you with the concepts of Set-based design?
1 not familiar --> 5 very familiar <-- DROP-DOWN menu
- 18) How familiar are you with the concepts of Point-based design (design spiral)?
1 not familiar --> 5 very familiar <-- DROP-DOWN menu

Appendix E

Post-Experiment Design Agent Survey Questions and Answer Choices

Post Experiment Survey

Enter your assigned ID # here:

*Answer the following questions below. Make estimates when necessary.
Some questions request additional explanations, others you may make additional comments.
You may extend explanations beyond the outlined text boxes if needed.*

- 1) Please estimate how important your task/role was for the ship design.
1 not important --> 5 very important <-- DROP-DOWN menu

- 2) What was your task/role in the design group?

- 3) How would you rate group morale during the design project?
1 low morale --> 5 very high morale <-- DROP-DOWN menu

- 4) How often did you have to explain your inputs to group members?
1 not often --> 5 very often <-- DROP-DOWN menu

- 5) How much time did your group take to prepare before beginning the design?
1 very little --> 5 quite a lot <-- DROP-DOWN menu

- 6) How would you categorize the level of uncertainty associated with your design task?
1 very little --> quite a lot <-- DROP-DOWN menu

- 7) Please rate the amount of work flow interactions between project members during the design process.
Choices: light and sequential, heavy and sequential, light and reciprocal, heavy and reciprocal
DROP-DOWN -->

- 8) How much did your design task depend on information obtained/provided by others?
very little --> quite a lot <-- DROP-DOWN menu

- 9) How much did other design tasks depend on your information?
very little --> quite a lot <-- DROP-DOWN menu

- 10) How often did you use the same work methods, analyses, or design tools to complete your task?
1 seldom --> quite often <-- DROP-DOWN menu

11) To what extent do you feel your task was analyzable - via design tools, mathematical equations, formulas, etc...?
1 very little --> 5 quite a lot <-- DROP-DOWN menu

12) To what extent do you feel your task required the use of "engineering judgement", or knowledge based on experience?
very little --> quite a lot <-- DROP-DOWN menu

13) How easy was it to know if your task was done correctly?
1 very easy --> very difficult <-- DROP-DOWN menu

14) How often do you feel that you ran into difficult problems for which there were no immediate or apparent solutions when performing your design task?
1 seldom --> very often <-- DROP-DOWN menu

15) How often did you encounter interruptions during your design task?
1 seldom --> very often <-- DROP-DOWN menu

16) How often did disagreements or conflicts occur among group members during the design process?
1 seldom --> very often <-- DROP-DOWN menu

17) Please provide an assesment of your personal attitude or assumed role during the ship design process.

Enter text here

Please comment on the ability of the design tool to allow you to represent uncertainty

18) during the design process.

Enter text here

How would you rate your familiarity with set-based design concepts?

19) 1 not familiar --> 5 very familiar <-- DROP-DOWN menu

Compared to before you used the design tool and performed the ship design, your

20) understanding of set-based design is now:

Choices: worse, same as before, slightly better, better, much better

<-- DROP-DOWN

Please comment on the Fuzzy Logic design tool you just used during your design task.

21) List any positives, negatives, interface issues, ease of use, difficulties, likes, dislikes, uncertainty representation, etc...

Enter text here

22) Please rate your satisfaction with the methods by which design data was represented via the design tool.

1 dissatisfied --> 5 very satisfied <-- DROP-DOWN menu

Please rate both your (a) satisfaction with, and (b) the level of, communication that

23) took place during the design process.

a) 1 dissatisfied --> 5 very satisfied <-- DROP-DOWN menu

b) 1 very low --> 5 very high <-- DROP-DOWN menu

Please rate your experience with using the Fuzzy Logic tool to facilitate the design

24) process.

1 frustrating --> 5 enjoyable <-- DROP-DOWN menu

a) Please rate the value added to the ship design process by using the Fuzzy Logic

25) design tool/method?

1 no value --> 5 very valuable <-- DROP-DOWN menu

b) Please comment on why you chose the above rating:

Enter text here

26) a) Do you feel the Fuzzy Logic design tool presented you with Choice information as compared: to a standard point-based design.

Choices: more, less, same

b) Compared to the other FL design tool method you used:

Choices: more, less, same Choice *leave blank if you have used only one Fuzzy Logic method

c) Please comment on the choices you have made:

Enter text here

27) Last method used:

Select

Previous method(s) Used: Select Select <-- DROP-DOWN menu

Selection Choices: Type-1, IT2M-Yrand, IT2M-xRU, IT2M-xRL, IT2M-Slopes, Gtype-2

28) Of the Fuzzy Logic design tool methods used,

a) which do you feel has been the most intuitive?

DROP-DOWN menu --> Choice *Leave blank if you have used only one Fuzzy Logic design tool method

Choices: Type-1, IT2M, GT2

b) which do you prefer for facilitation of design?

DROP-DOWN menu --> *Leave blank if you have used only one

Choices: Type-1, IT2M, GT2 Fuzzy Logic design tool method

c) Please comment on the choices you have made:

Enter text here

29) When using the design tool(s), what elements did you find most useful for decision making? For example, the graph of the Joint Preference Curves, or the average JOP curve, or JOP Histogram data, historical data, etc....

Enter text here

30) Any additional comments? Feel free to add them here.

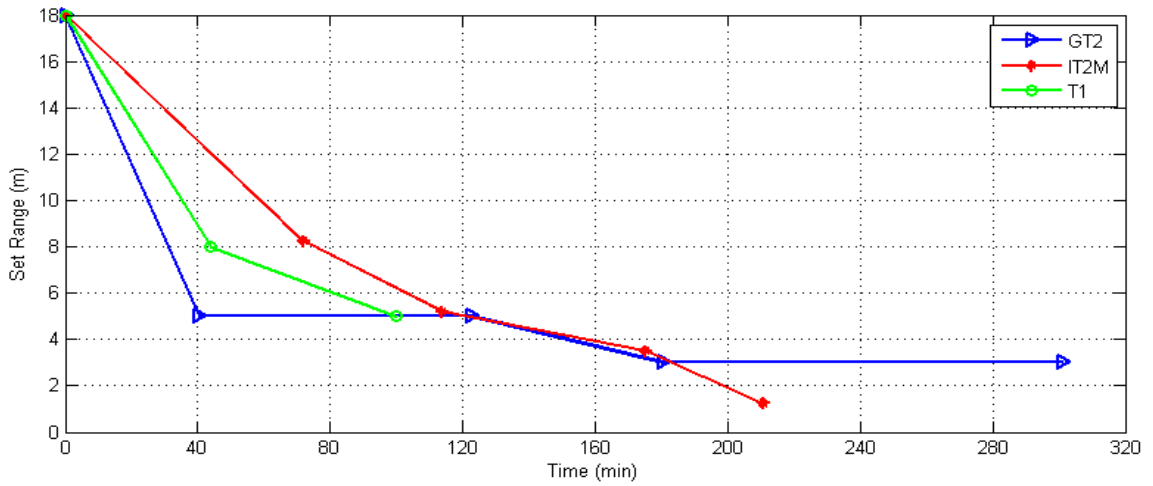
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Appendix F
SBD Tool Agent Variables Map

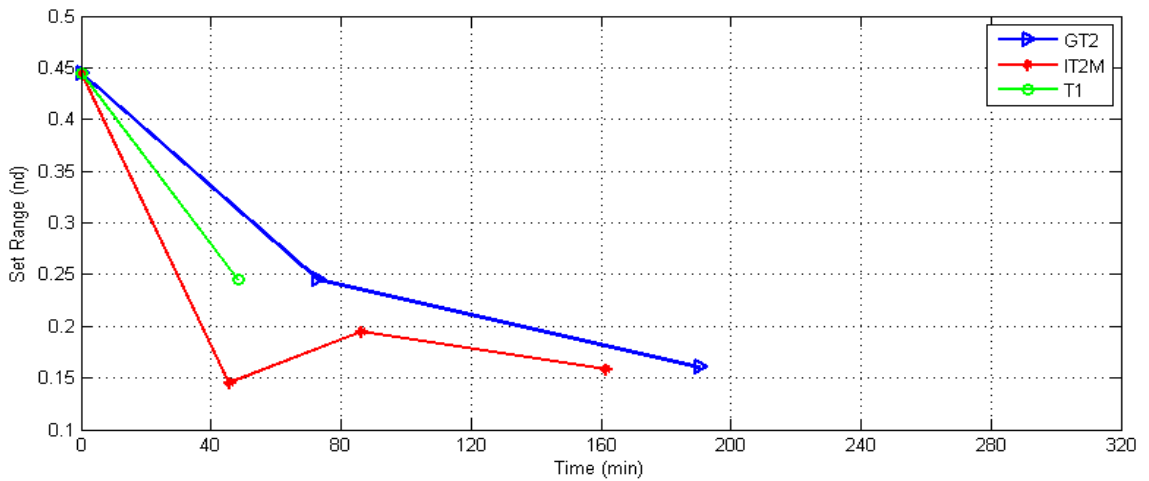
Variable	Units	Description	Customer/ Chief Engineer.	Cargo TEU model cargo layout	Resistance PPP resistance	Stability Weights (trans.) intact stab.	Hull Weights l (longl) sizing, trim	Propulsion POP, catalog prop., engine	Action for variable
Vk	knots	trials speed at (1-Ms) power	x	x	n	n	n	n	Negotiated
GMt	m	transverse metacentric height	x			o			Output
KGm	m	machinery related VCG	x					n	Negotiated
KGc	m	cargo VCG	x	n		n			Negotiated
KGo	m	ouftit VCG	x			x	o		Output
KGs	m	structure VCG	x			n	n		Negotiated
TEU		20' container count	x	o					Output
Threqd	kN	total req'd propeller thrust	x		n			n	Negotiated
LWL	m	waterline length	x	x	n	n	n	x	Negotiated
T	m	mean design draft	x		n	n	n		Negotiated
Cb		block coefficient	x	n	n	n	n	x	Negotiated
B	m	beam	x	n	n	n	n	n	Negotiated
Wm	tonnes	machinery related fuel, lube oil weight	x			x		n	Negotiated
Lm	m	length of engine room	x					n	Negotiated
Lc	m	length of cargo box	x	n				n	Negotiated
D	m	depth	x	n	x	n	n	n	Negotiated
Wc	tonnes	cargo weight	x	o		x	x	n	Output
w		longl wake fraction	x		o			x	Output
t		thrust deduction	x		o			x	Output
etar		relative rotative efficiency	x		o			x	Output
Ar	m^2	rudder area	x		x			o	Output
Ncrew		number of crew members	x			x	x		Given
Ndays		endurance days	x			x	x		Given
KB	m	vertical center of buoyancy, VCB	x			o	x		Output
hdb	m	double bottom height	x	o				x	Output
sfc	t/kW/hr	specific fuel consumption	x					o	Output
sloc	t/kW/hr	spec. lube oil consumption	x					o	Output
No. props.		number of propellers	x		x		x	x	Given
Dp	m	propeller diameter	x		x			o	Output
Pb	kW	installed kW	x					o	Output
Cm		midship coefficient	x		x	x	x	x	Calculated
Cwp		waterplane coefficient	x		x	n	n	x	Negotiated
LCB = LCG	%L, +fwd amid.	longl center of buoyancy	x		x	x	o		Assumed
Wo	tonnes	ouftit weight	x			x	o		Output
Ws	tonnes	structure weight	x			x	o		Output
LBP	m	length between perpendiculars	x				o		Output
Ae/Ao		expanded area ratio	x		o			x	Output
Total container Ties on deck		number of container tiers on deck	x	o					Output
Total container Columns on deck		number of container columns on deck	x	o		x			Output

o = output from agent for other use
n = negotiated between agents
x = input agent needs or views

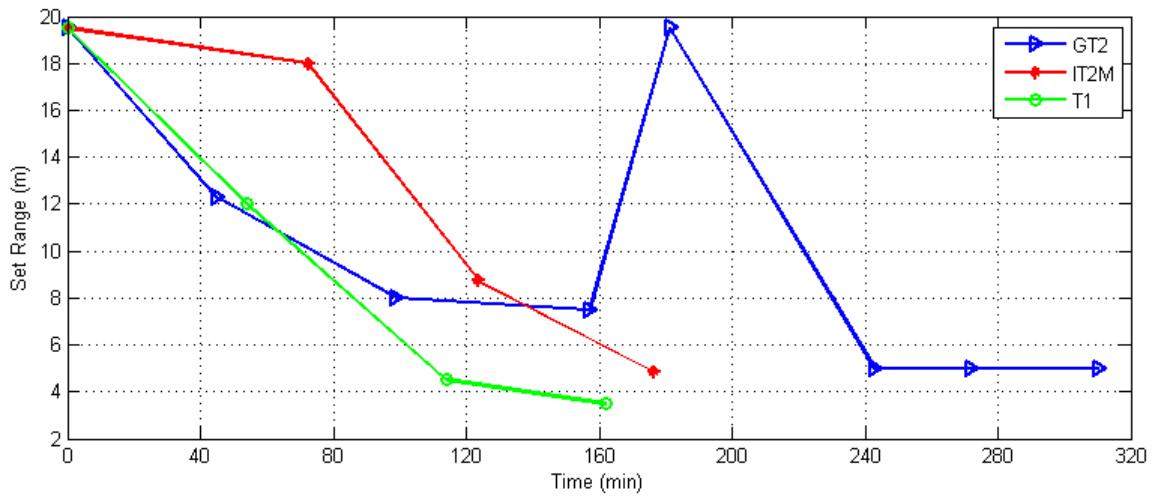
Appendix G
Magnitude of Set-Range vs. Time Plots
for Ship D SBD Experiments



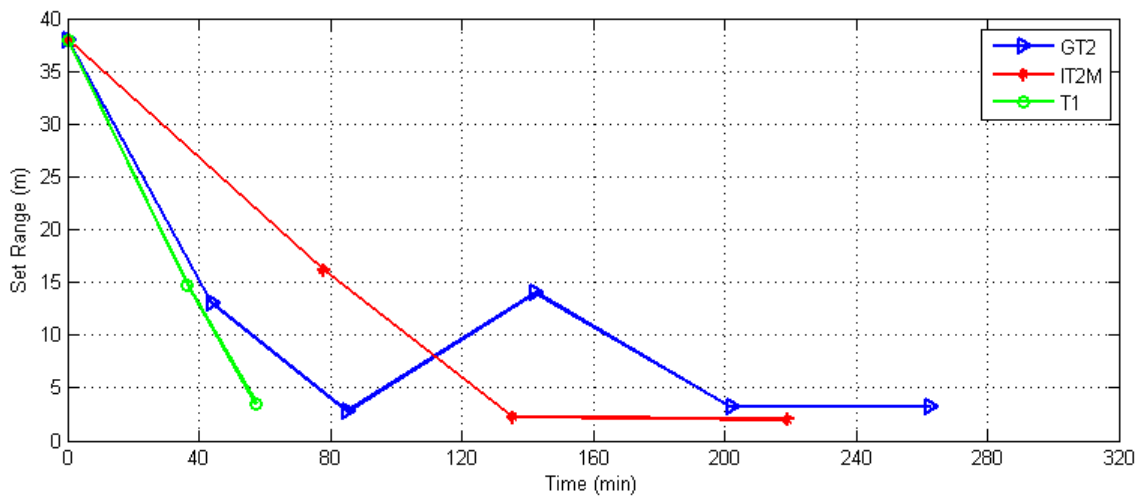
Ship D, Set-Ranges for *B* Negotiation vs. Time



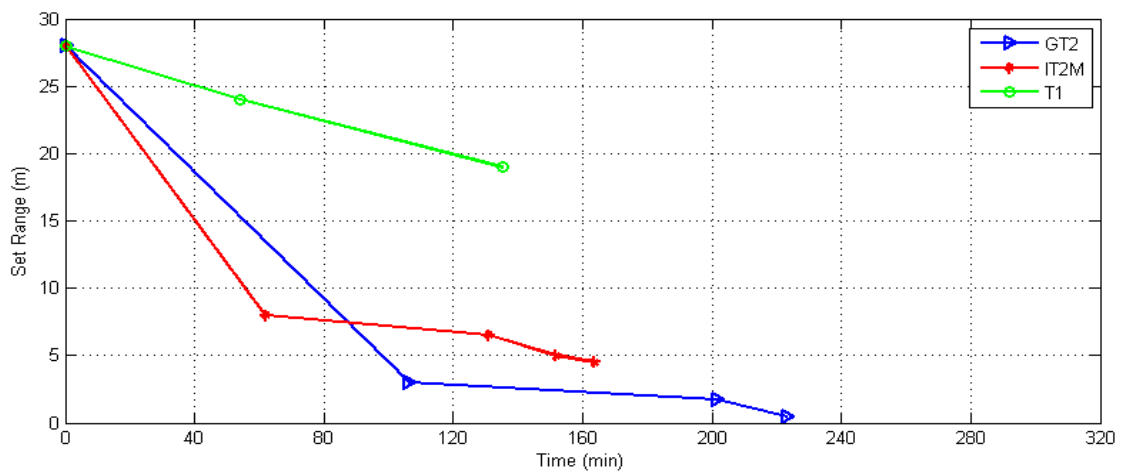
Ship D, Set-Ranges for *C_b* Negotiation vs. Time



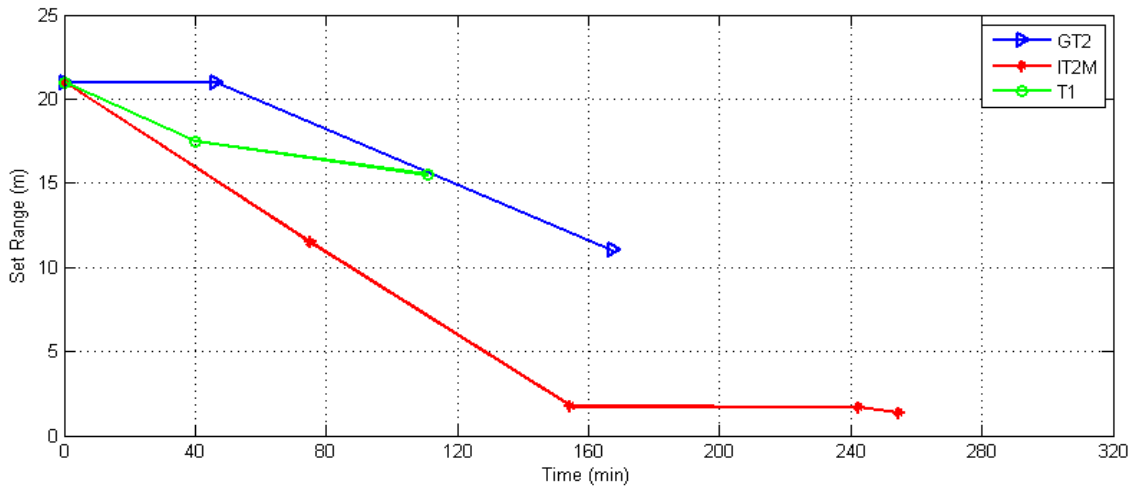
Ship D, Set-Ranges for *D* Negotiation vs. Time



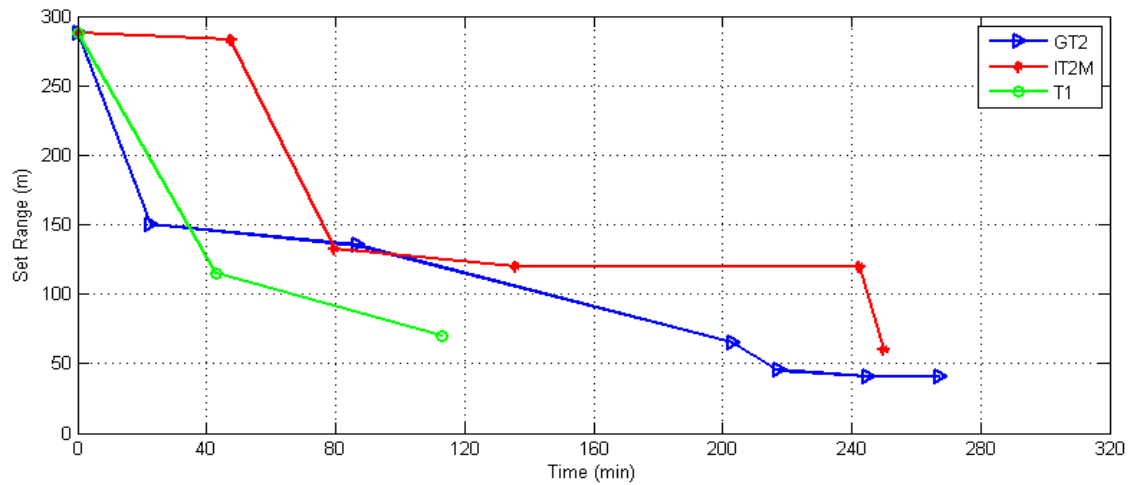
Ship D, Set-Ranges for *KGc* Negotiation vs. Time



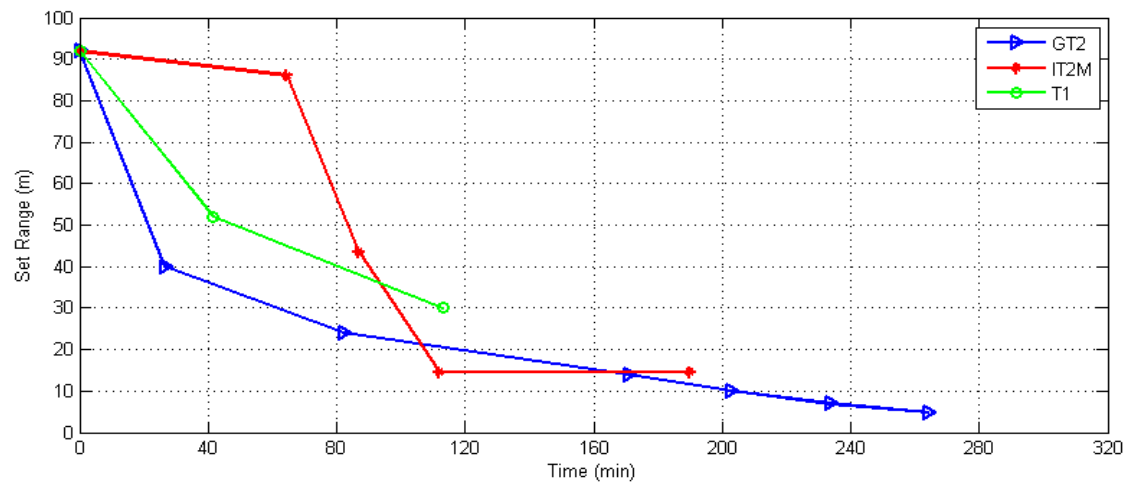
Ship D, Set-Ranges for *KGm* Negotiation vs. Time



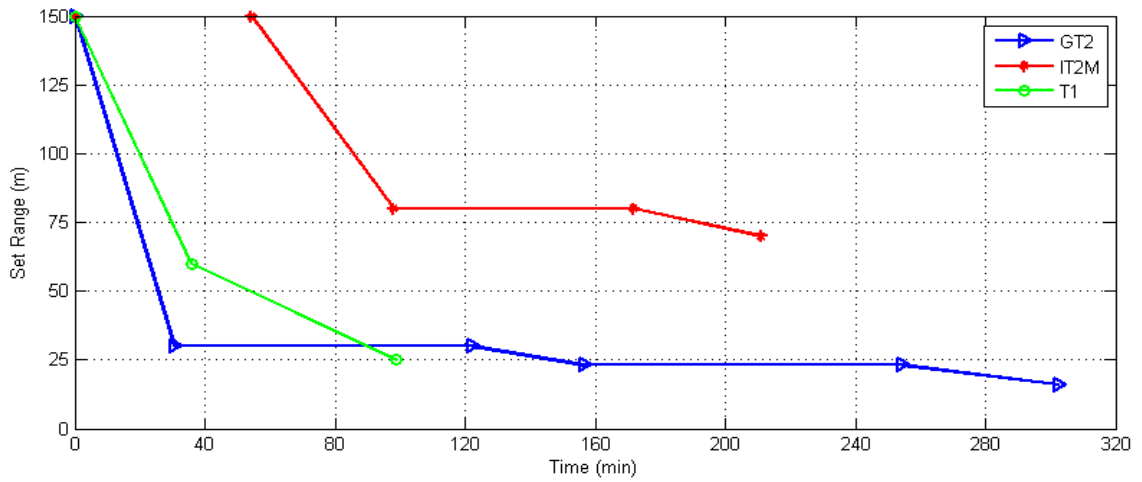
Ship D, Set-Ranges for *KGs* Negotiation vs. Time



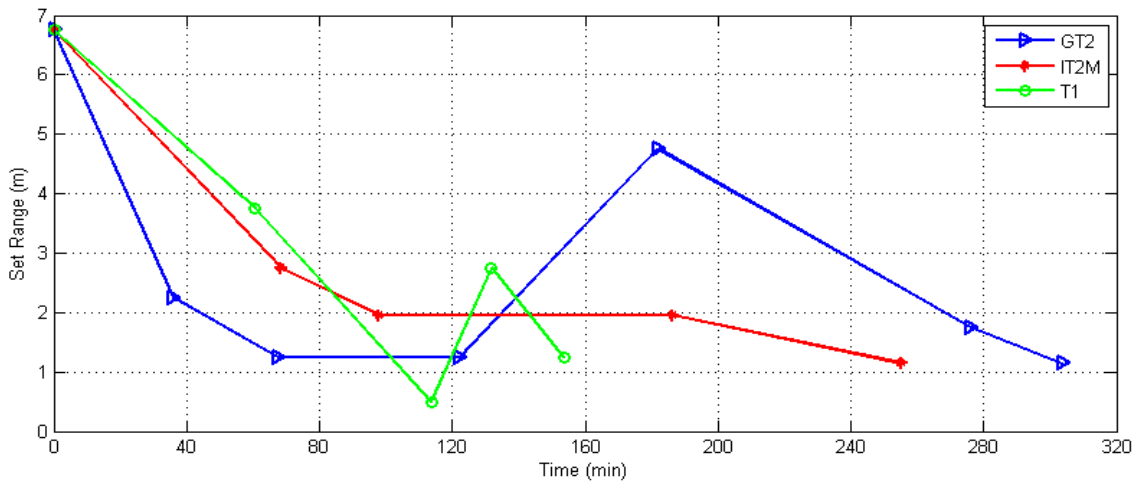
Ship D, Set-Ranges for *Lc* Negotiation vs. Time



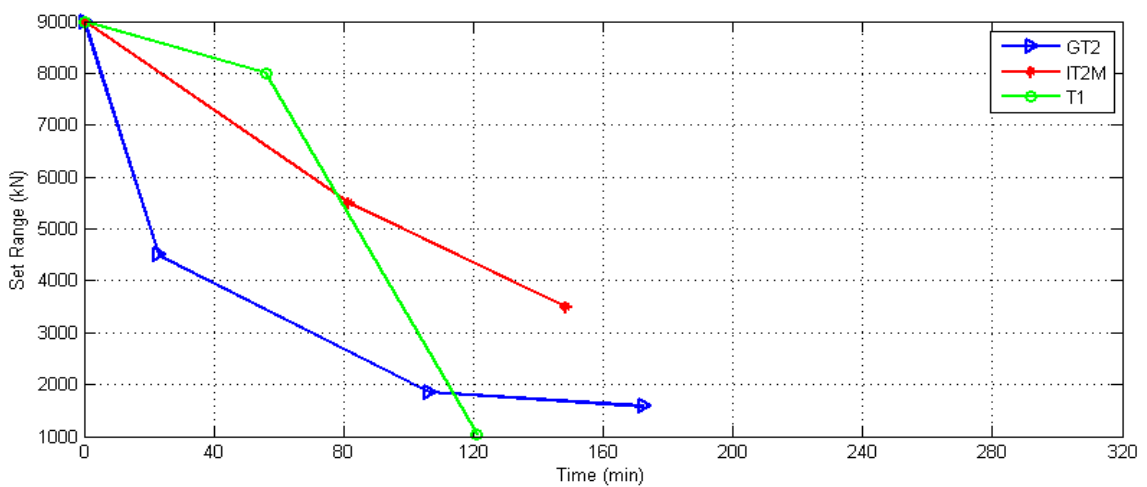
Ship D, Set-Ranges for *Lm* Negotiation vs. Time



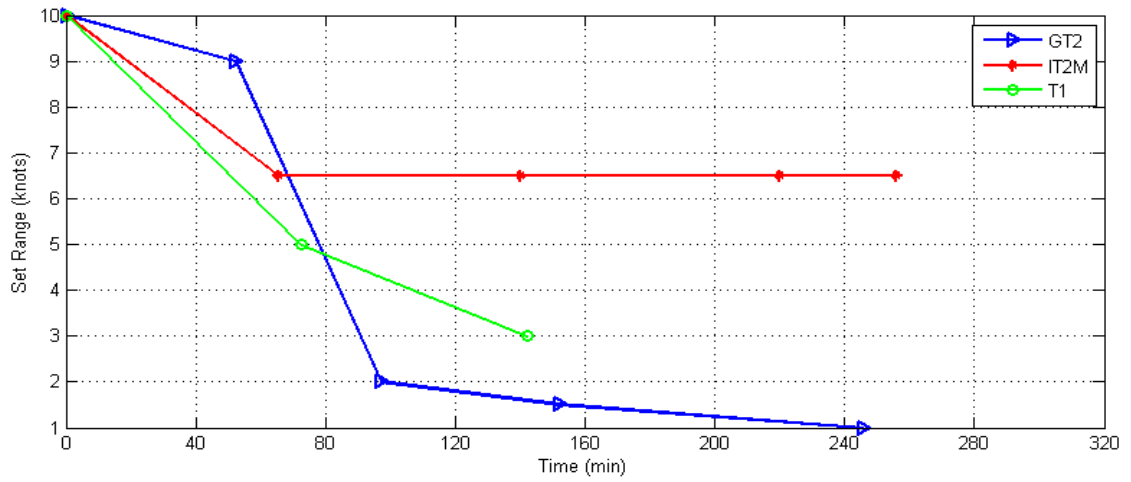
Ship D, Set-Ranges for *LWL* Negotiation vs. Time



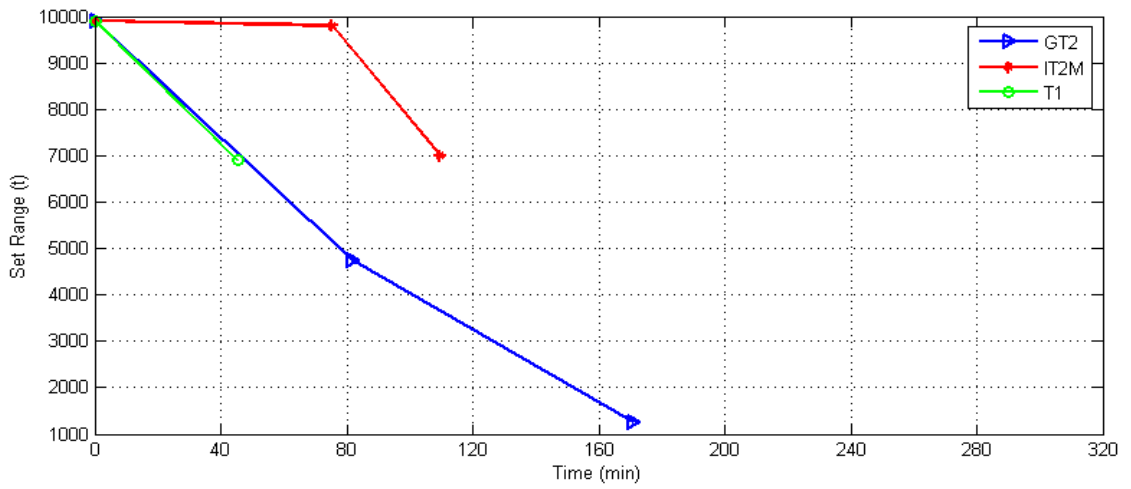
Ship D, Set-Ranges for *T* Negotiation vs. Time



Ship D, Set-Ranges for *Threqd* Negotiation vs. Time

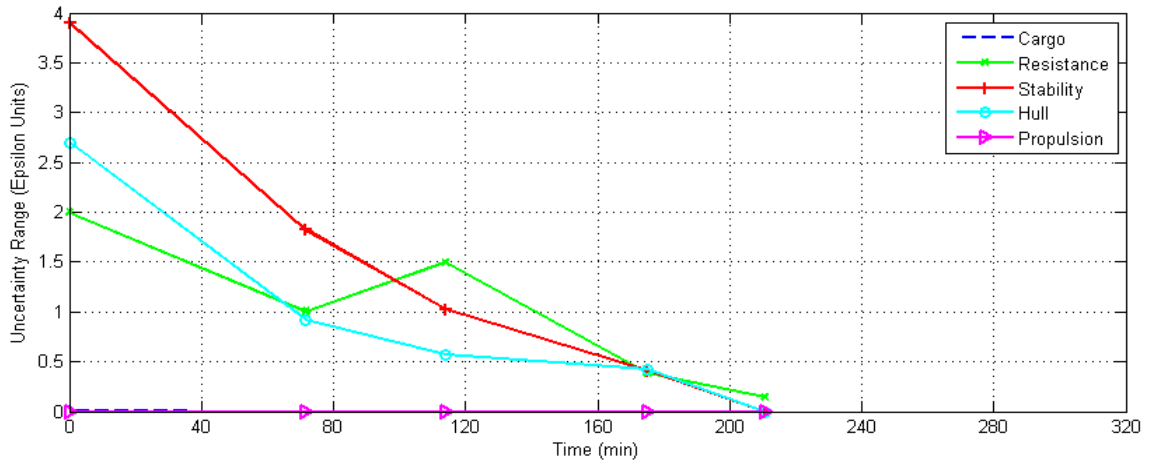


Ship D, Set-Ranges for V_k Negotiation vs. Time

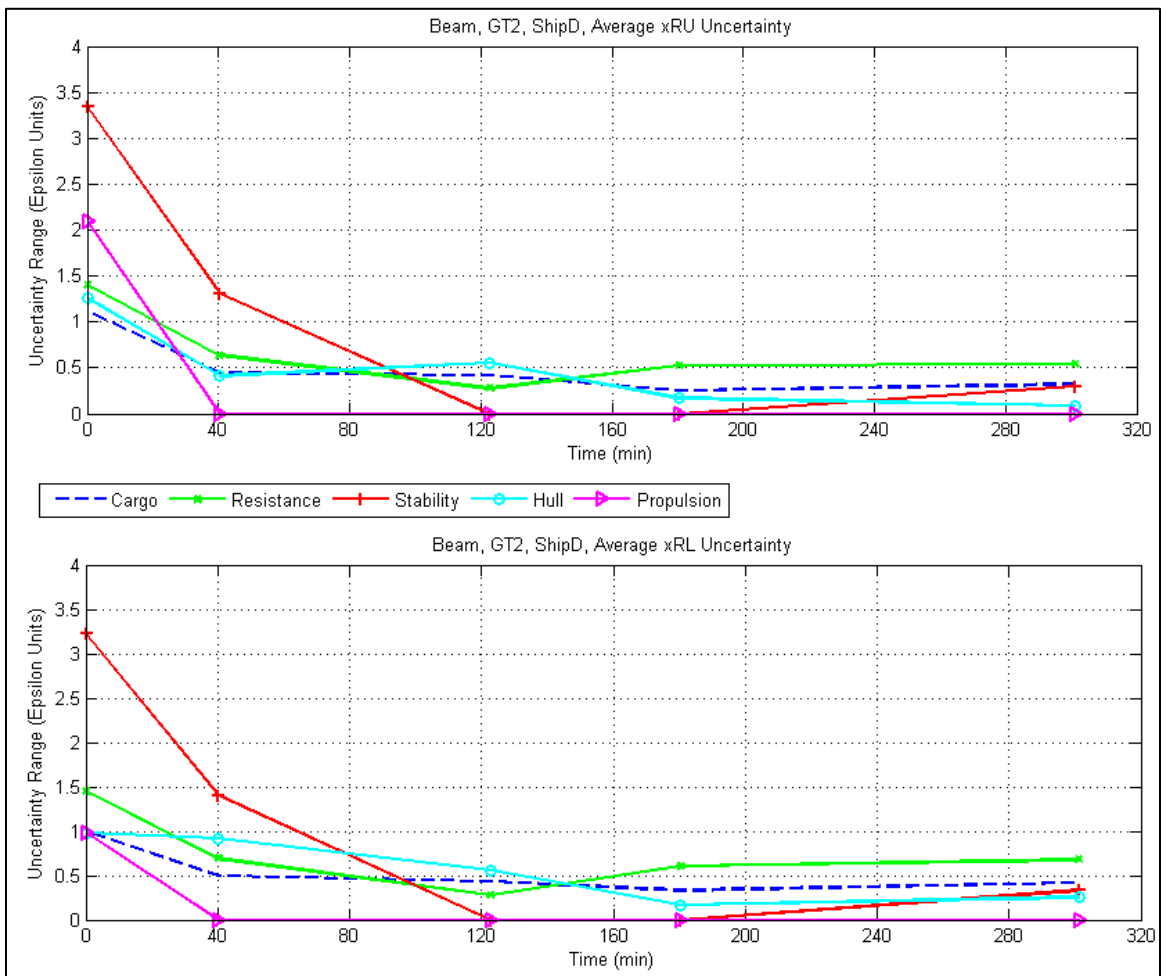


Ship D, Set-Ranges for W_m Negotiation vs. Time

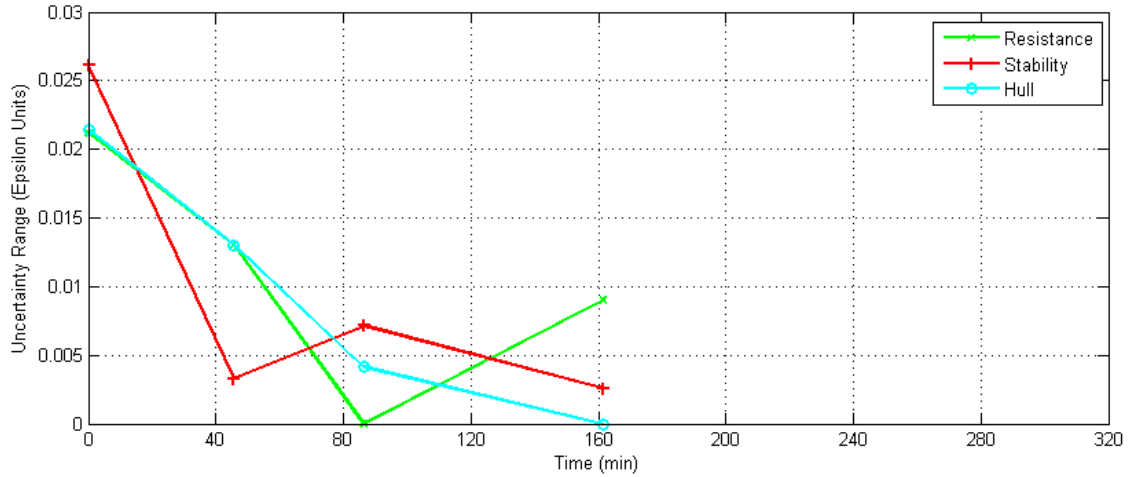
Appendix H
Magnitude of Uncertainty vs. Time Plots
for Ship D SBD Experiments



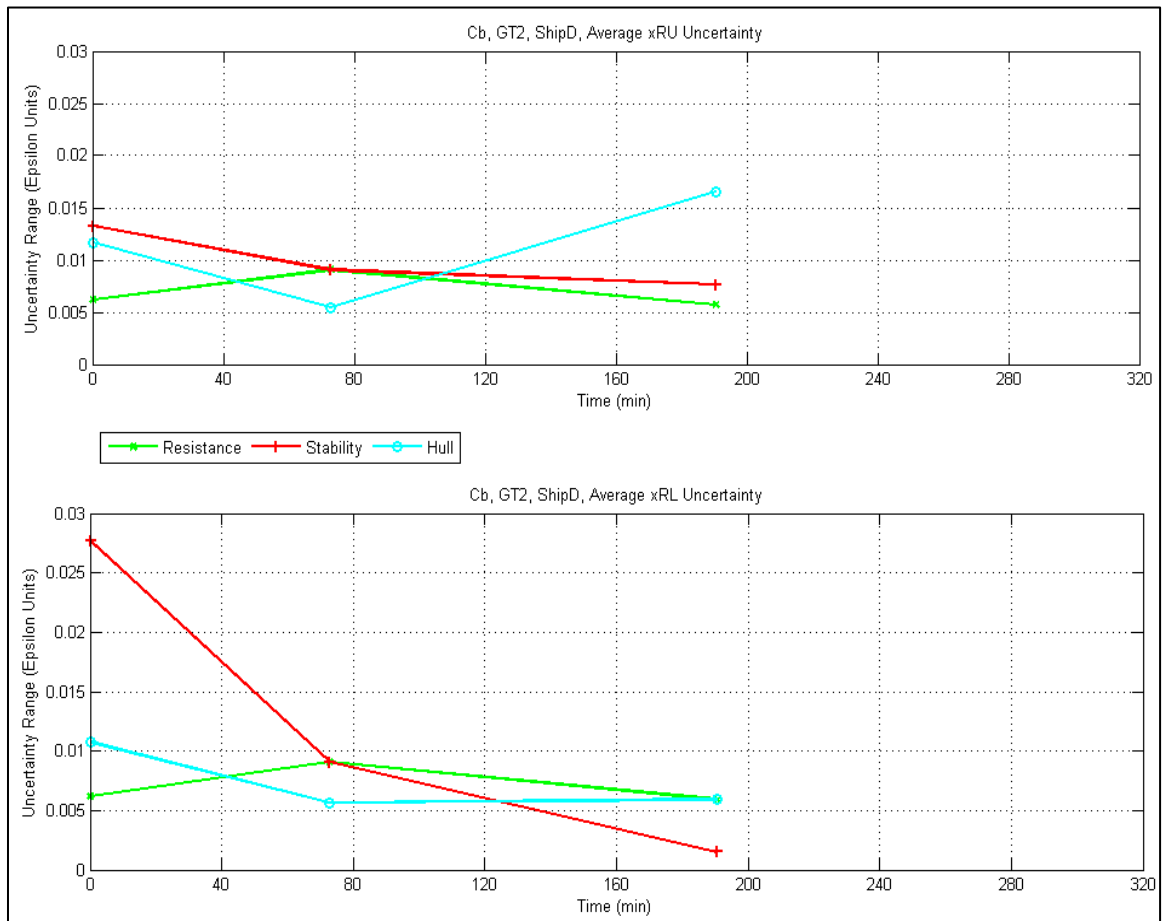
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for *B* vs. Time



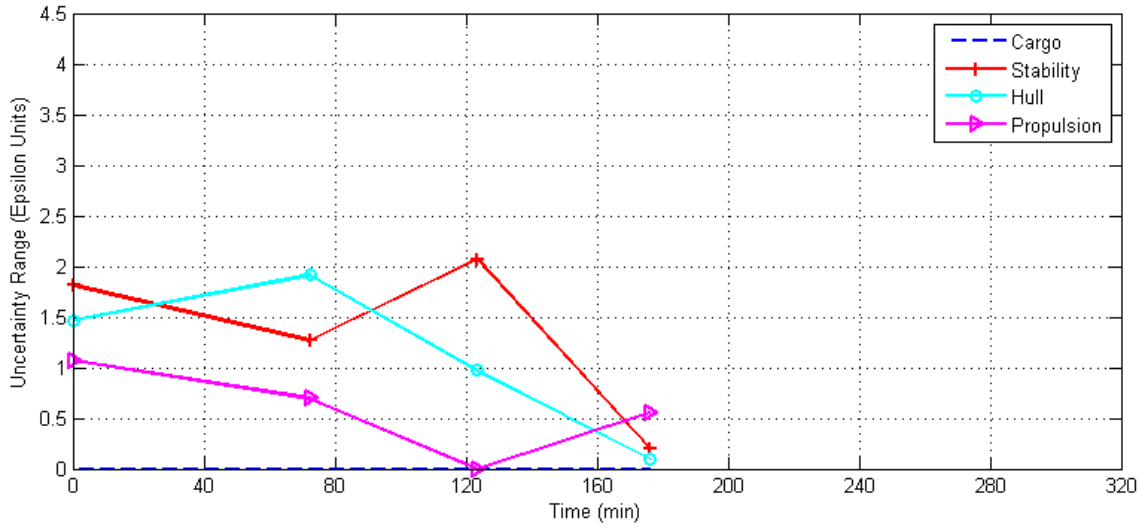
GT2, Ship D, Magnitudes of Uncertainty for *B* vs. Time



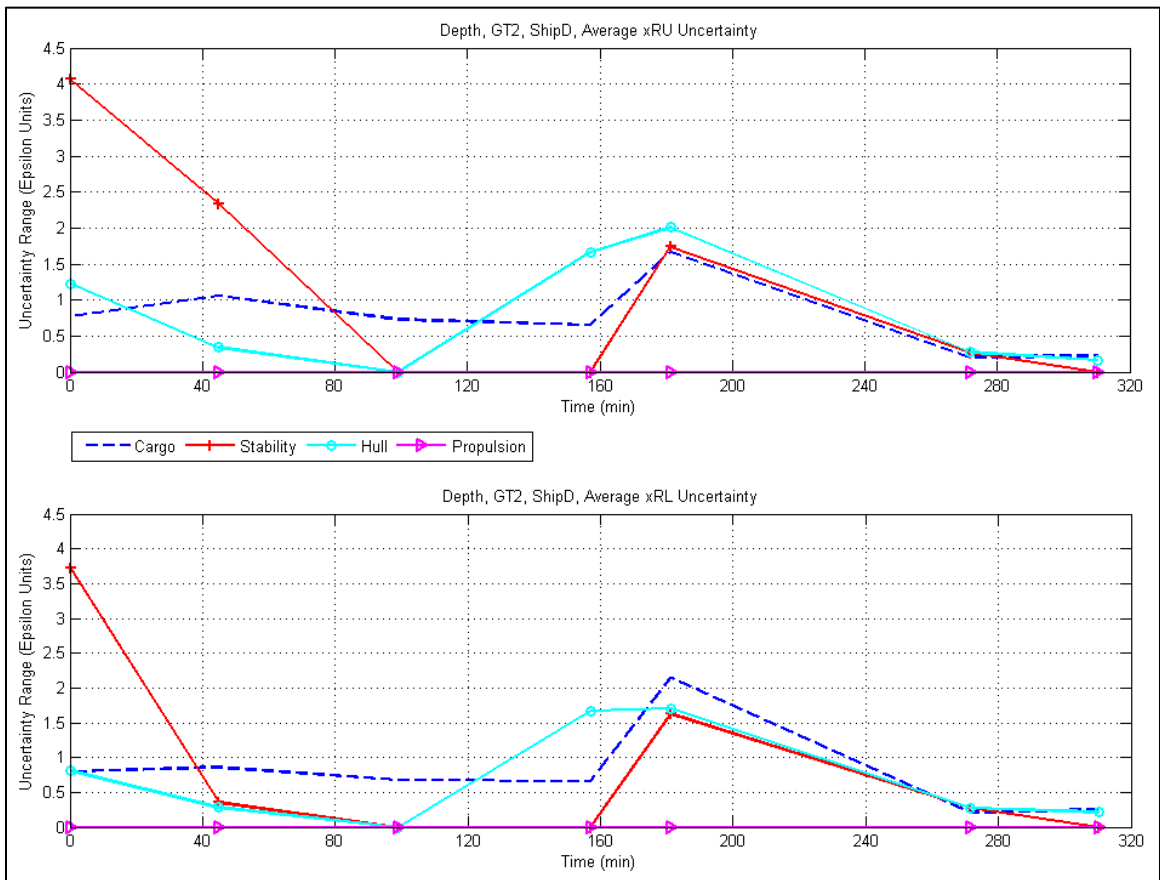
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for C_b vs. Time



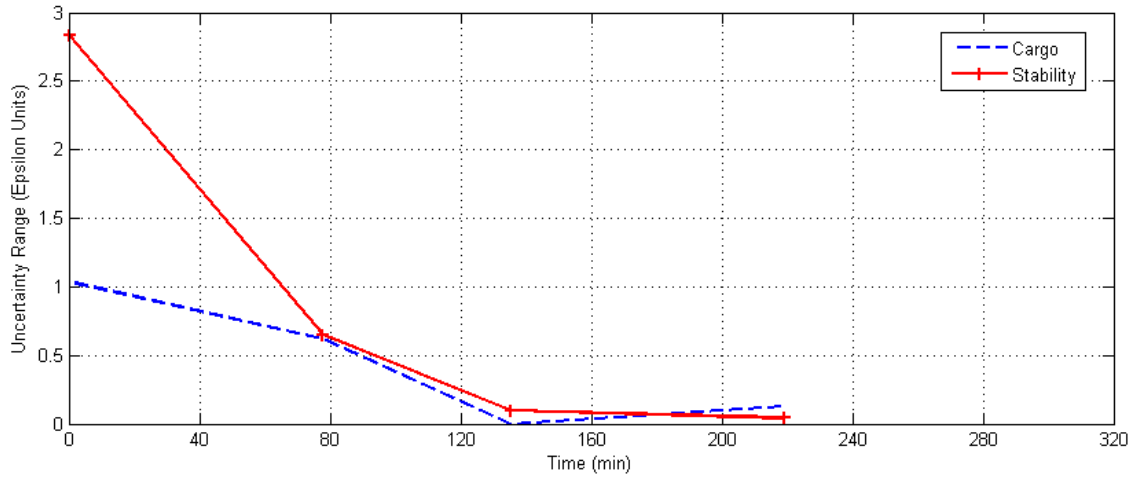
GT2, Ship D, Magnitudes of Uncertainty for C_b vs. Time



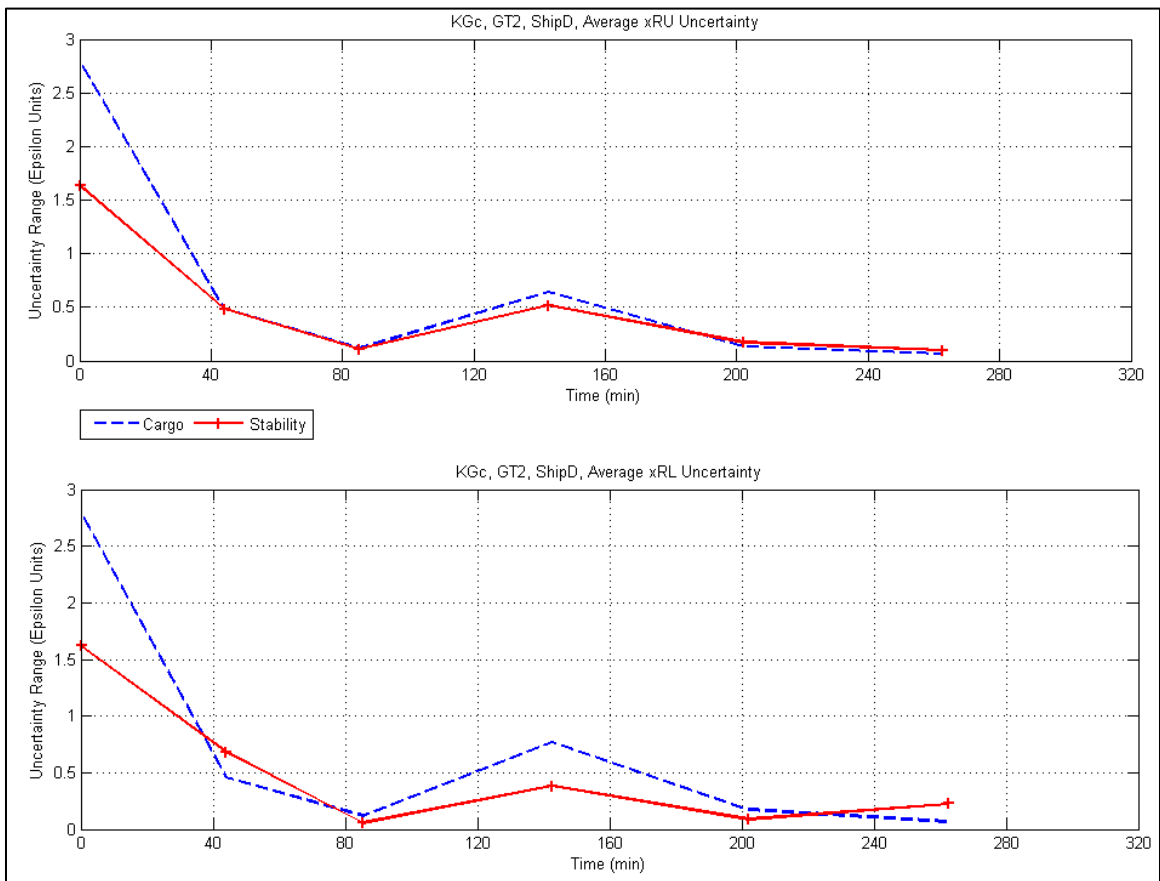
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for D vs. Time



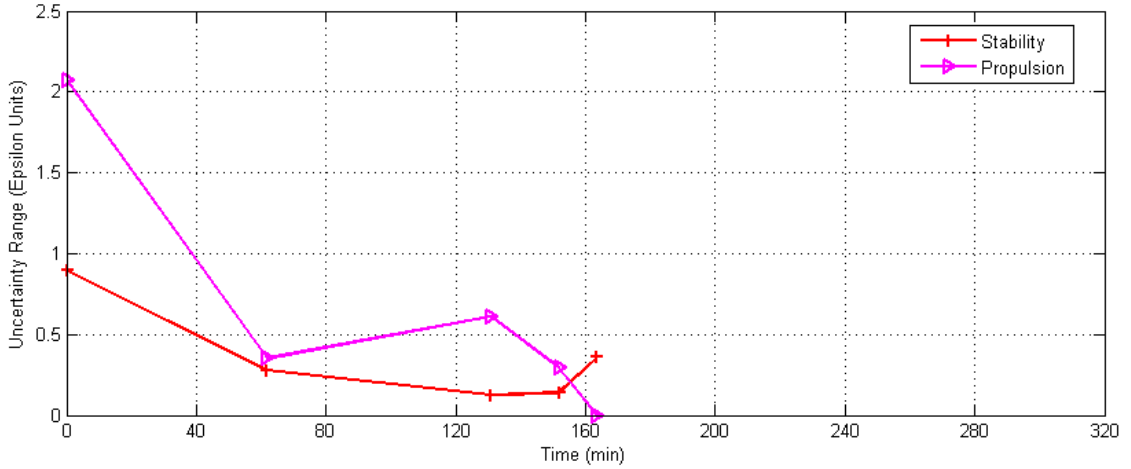
GT2, Ship D, Magnitudes of Uncertainty for D vs. Time



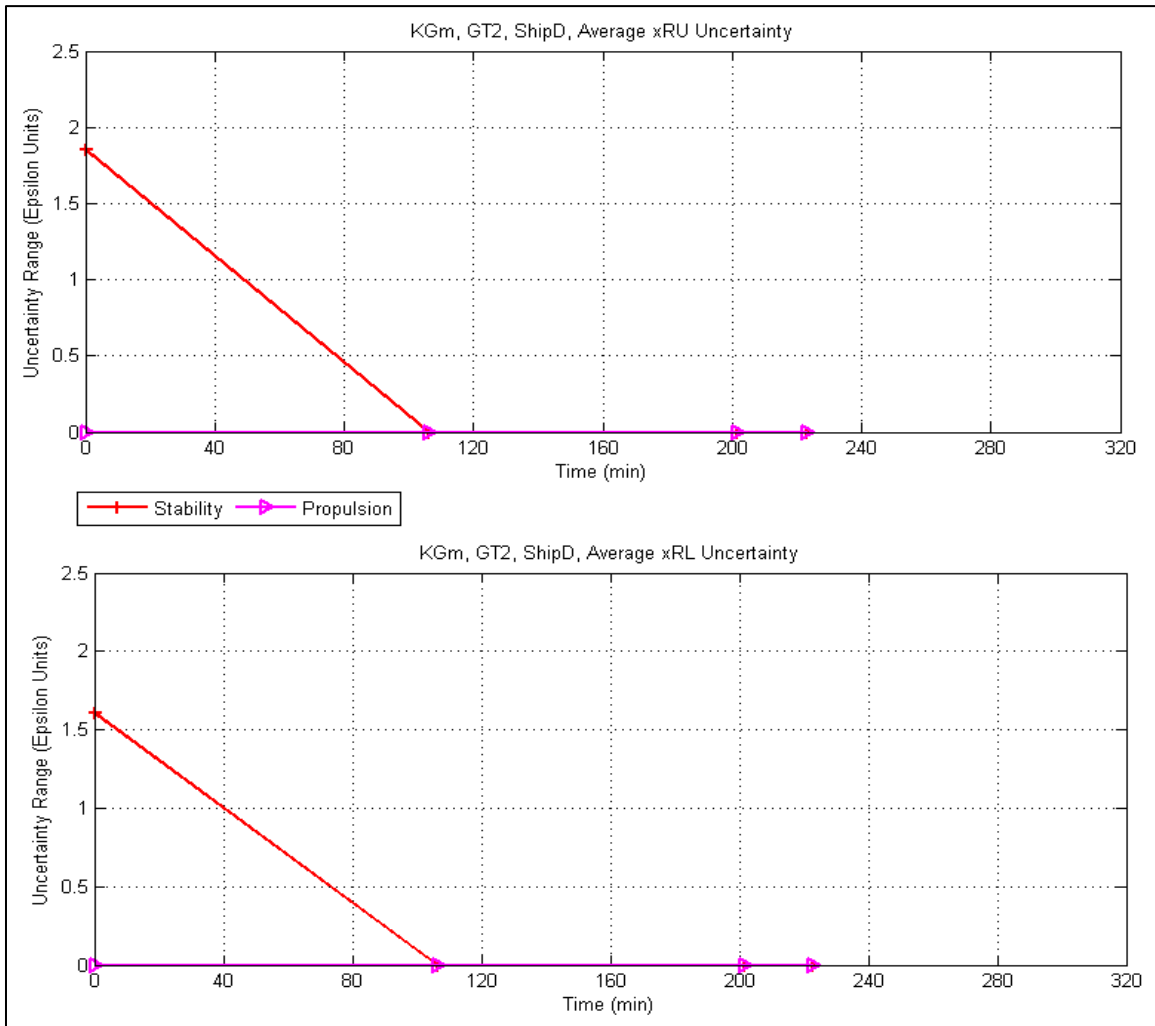
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for *KGc* vs. Time



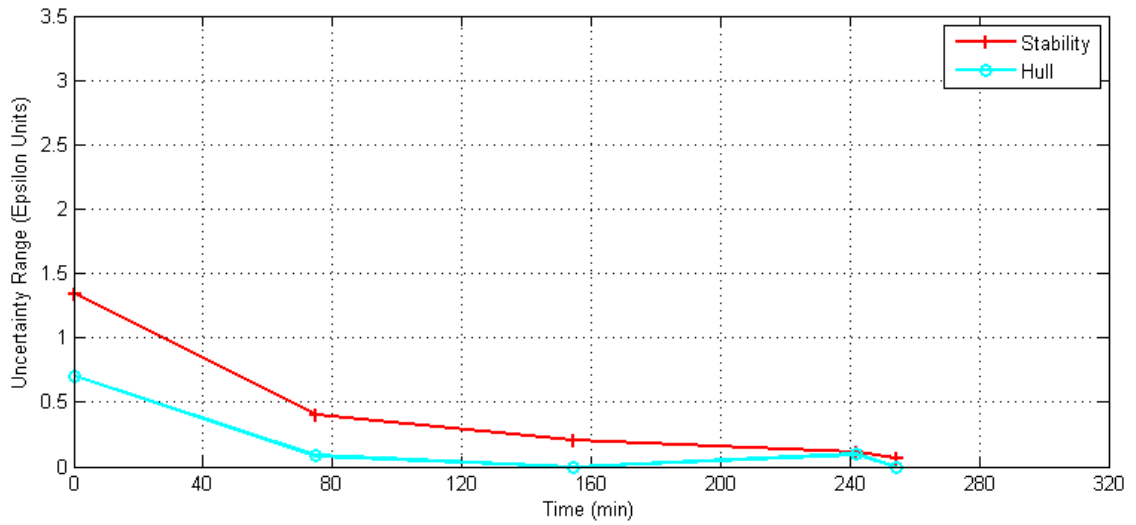
GT2, Ship D, Magnitudes of Uncertainty for *KGc* vs. Time



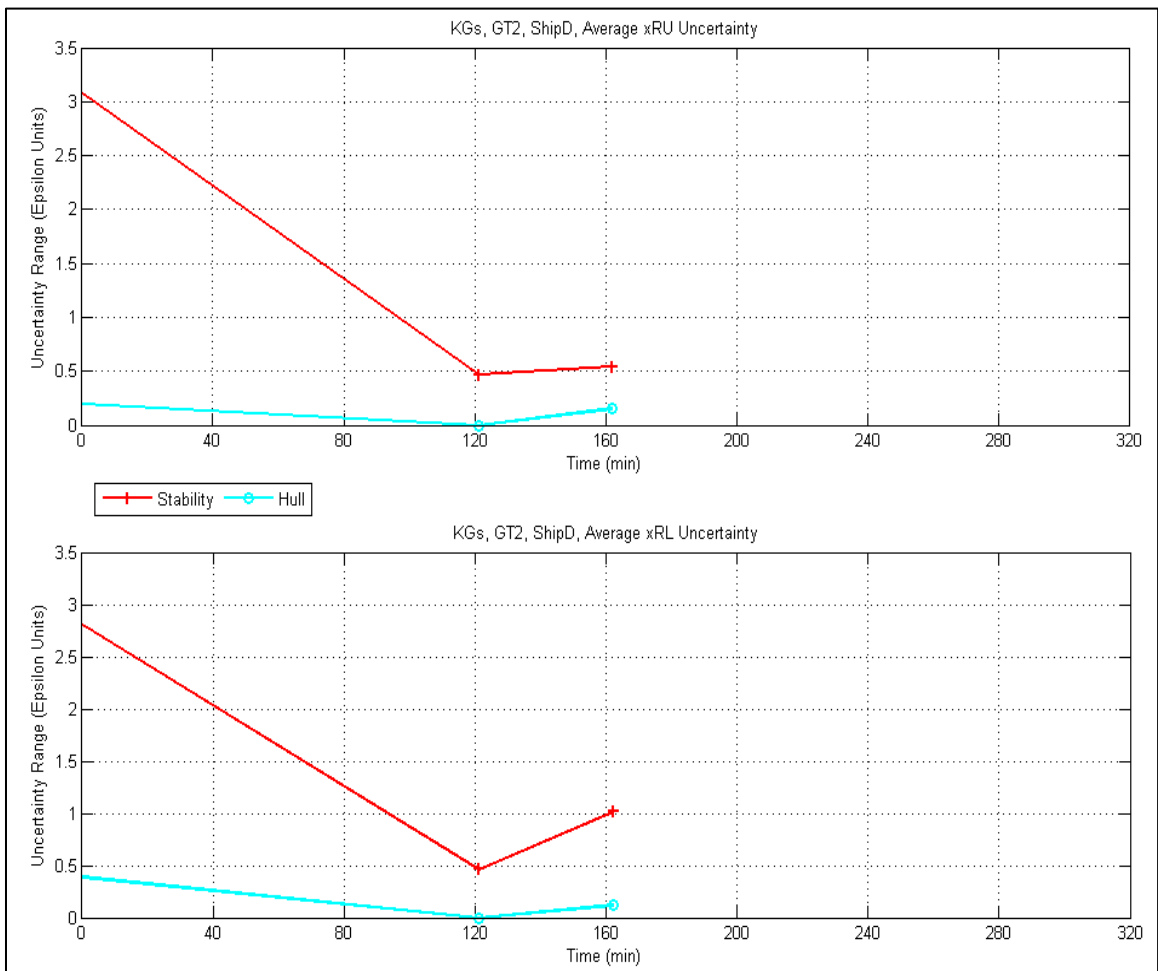
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for *KGm* vs. Time



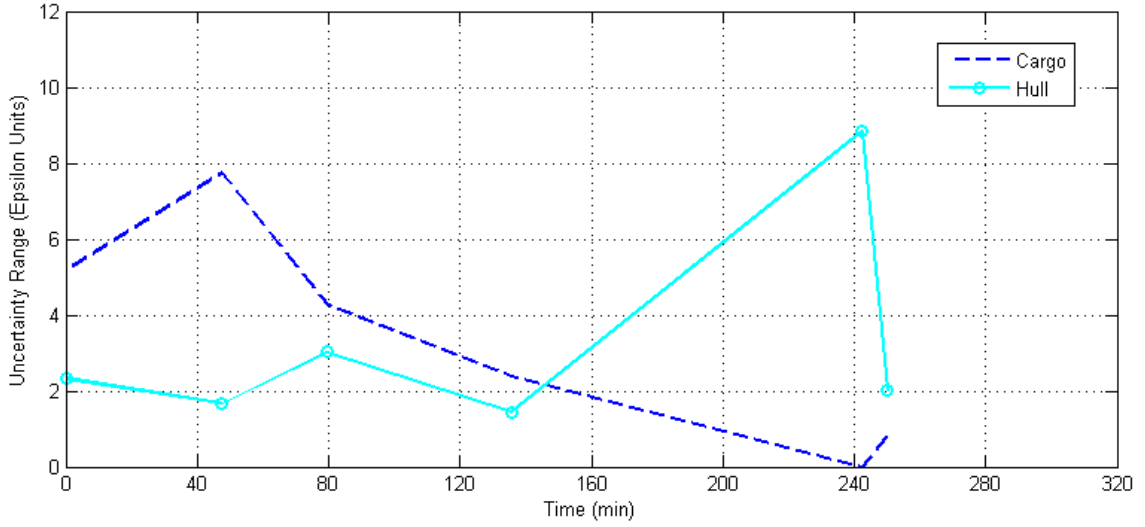
GT2, Ship D, Magnitudes of Uncertainty for *KGm* vs. Time



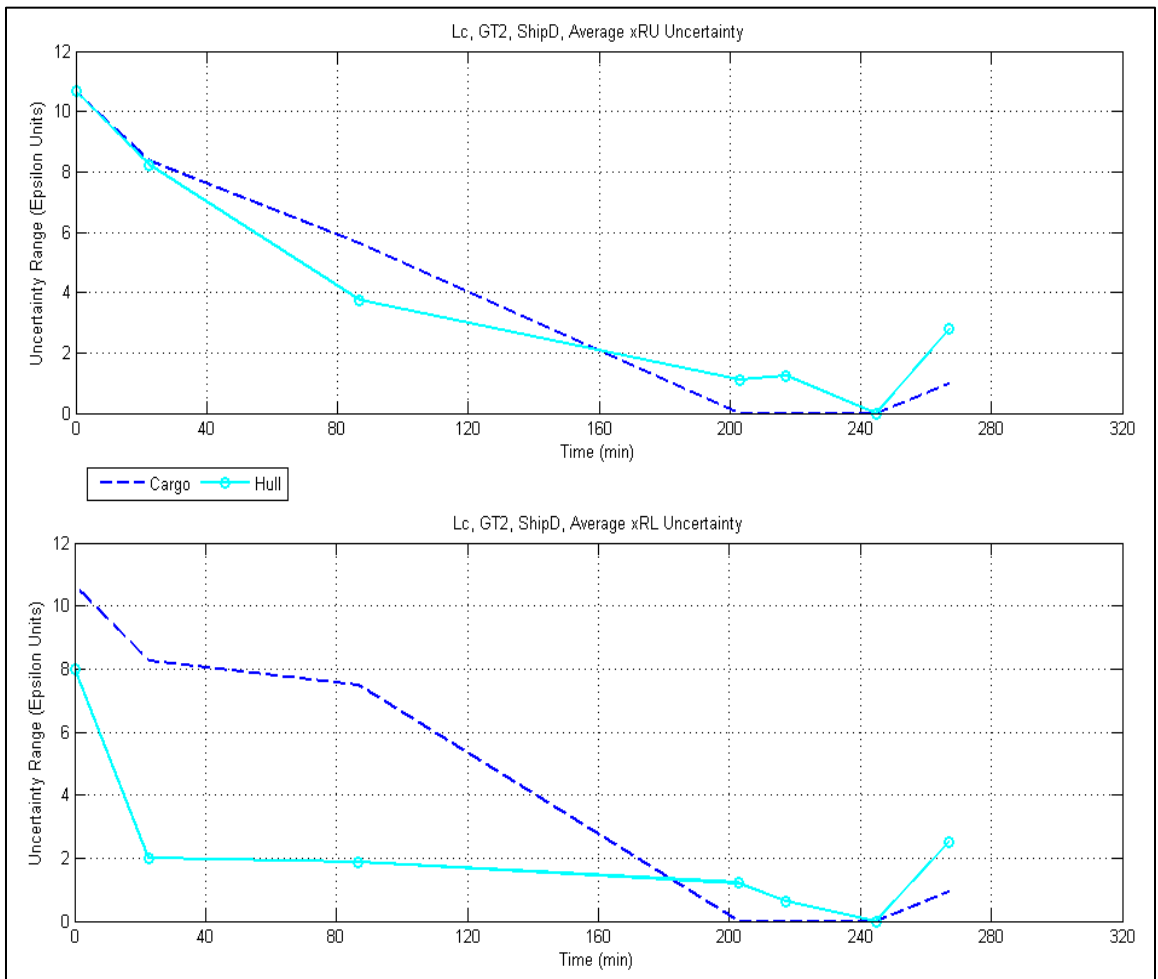
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for KGs vs. Time



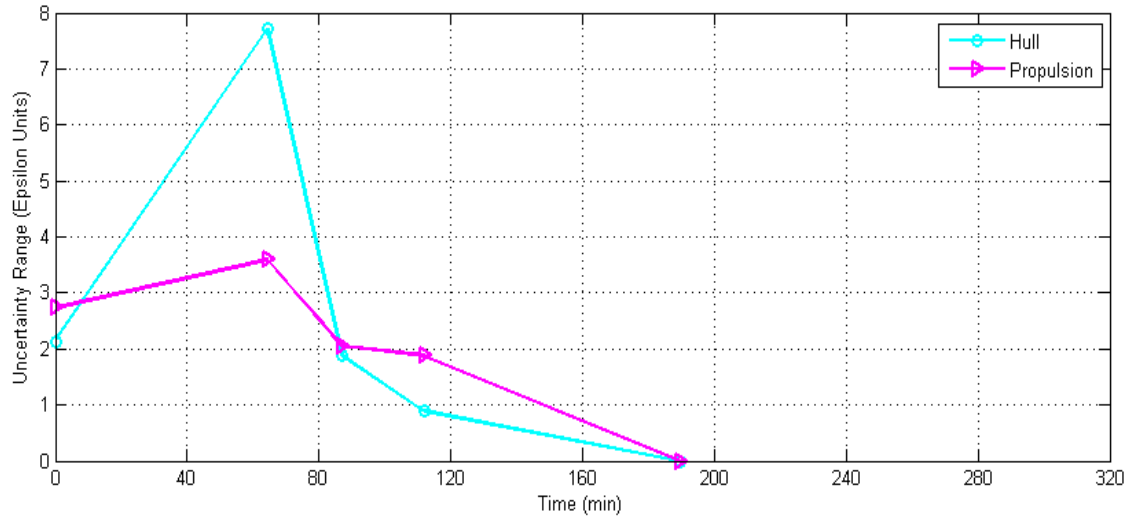
GT2, Ship D, Magnitudes of Uncertainty for KGs vs. Time



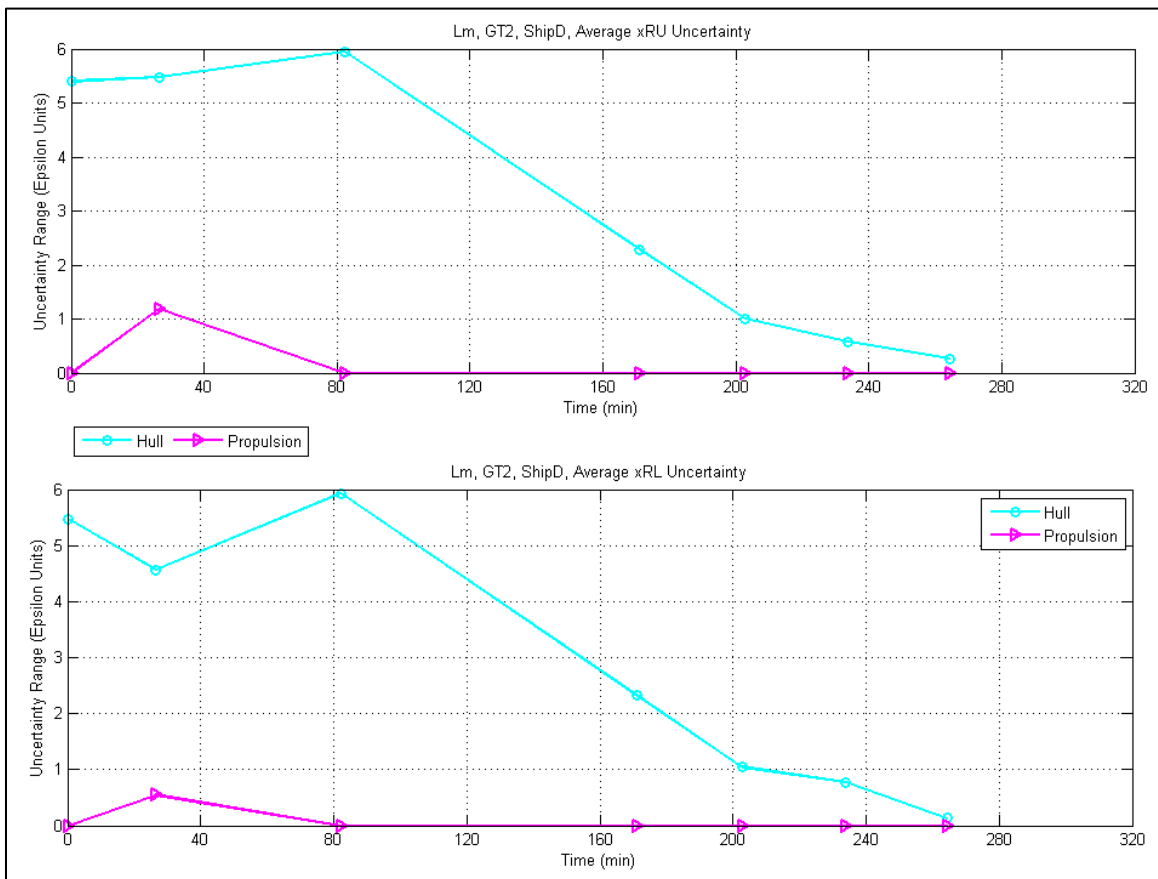
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for L_c vs. Time



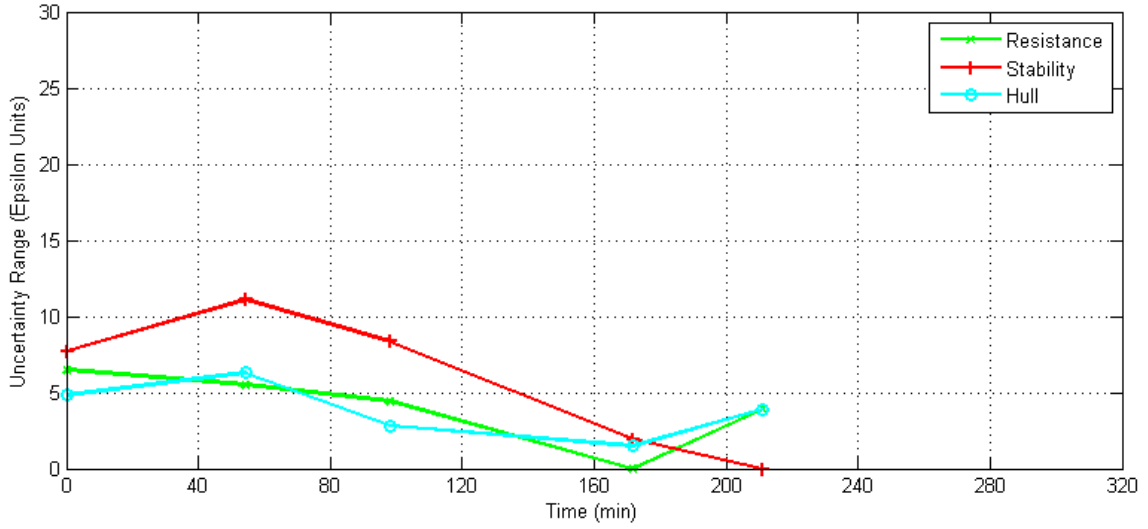
GT2, Ship D, Magnitudes of Uncertainty for L_c vs. Time



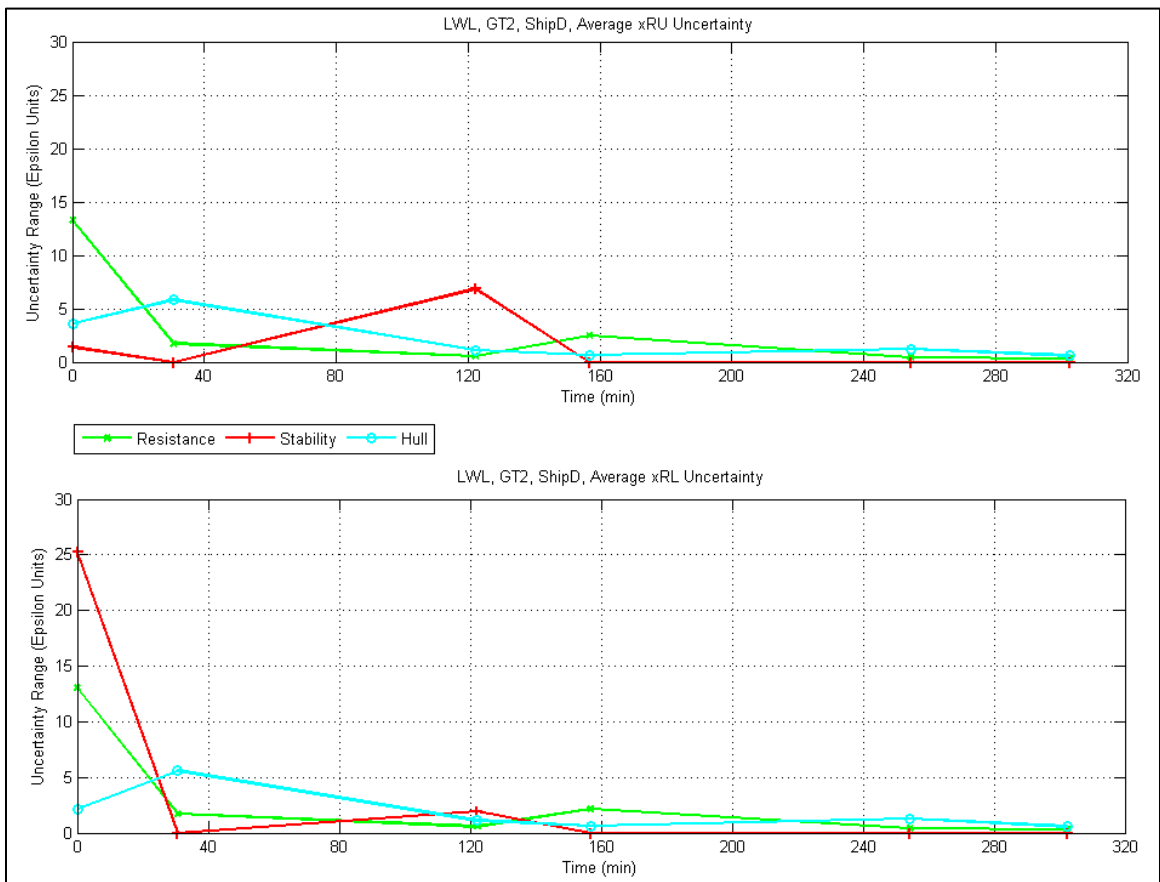
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for L_m vs. Time



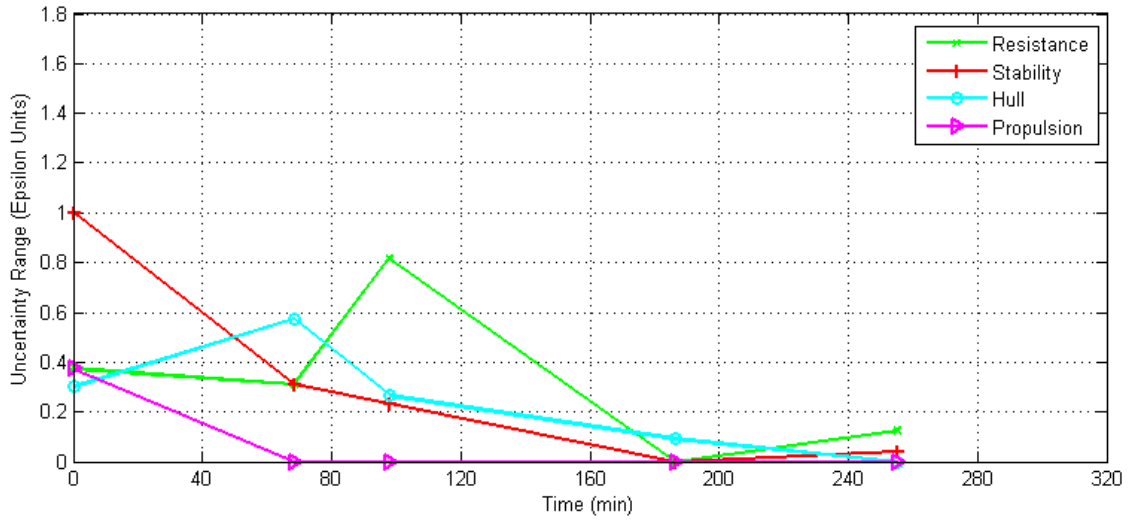
GT2, Ship D, Magnitudes of Uncertainty for L_m vs. Time



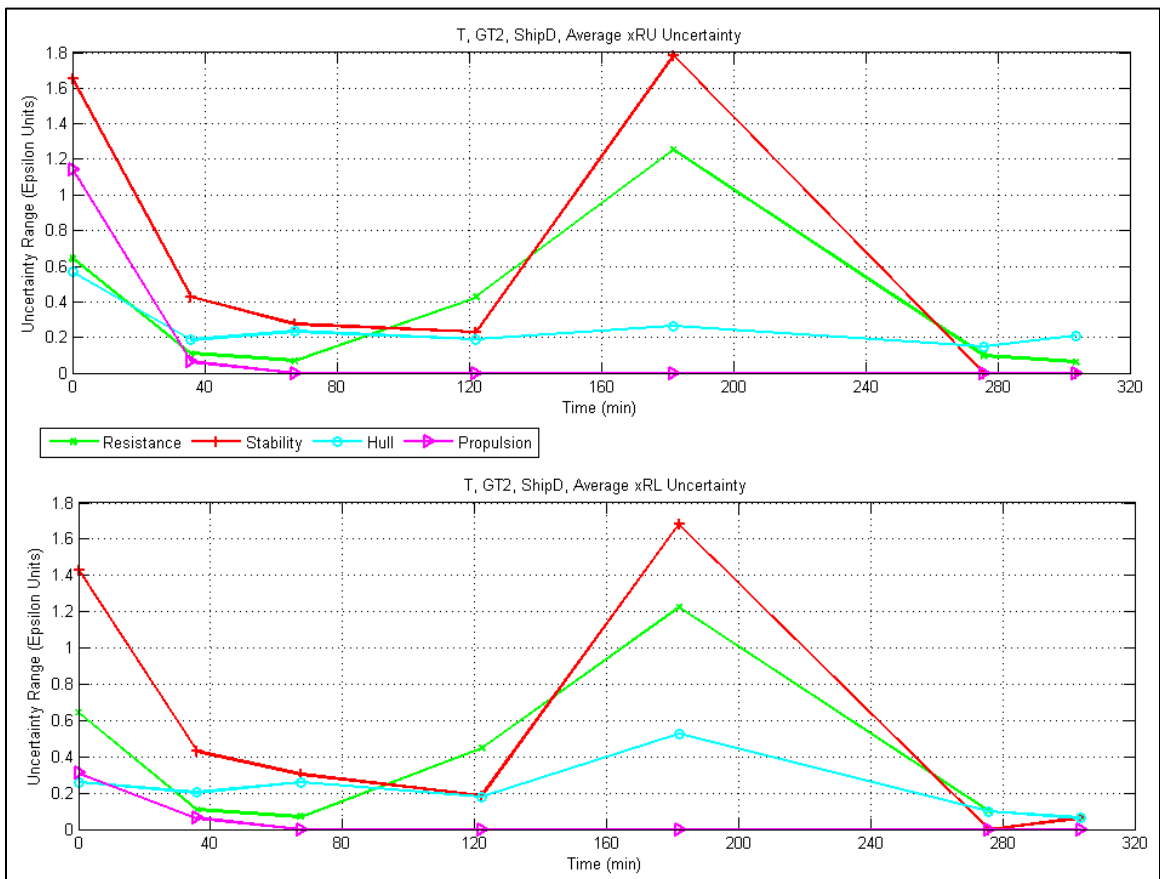
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for *LWL* vs. Time



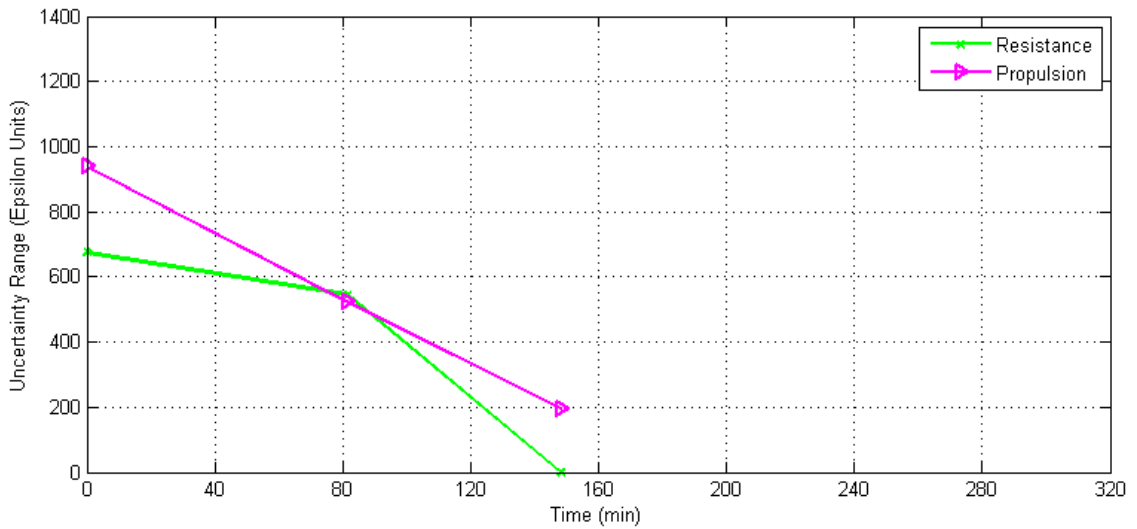
GT2, Ship D, Magnitudes of Uncertainty for *LWL* vs. Time



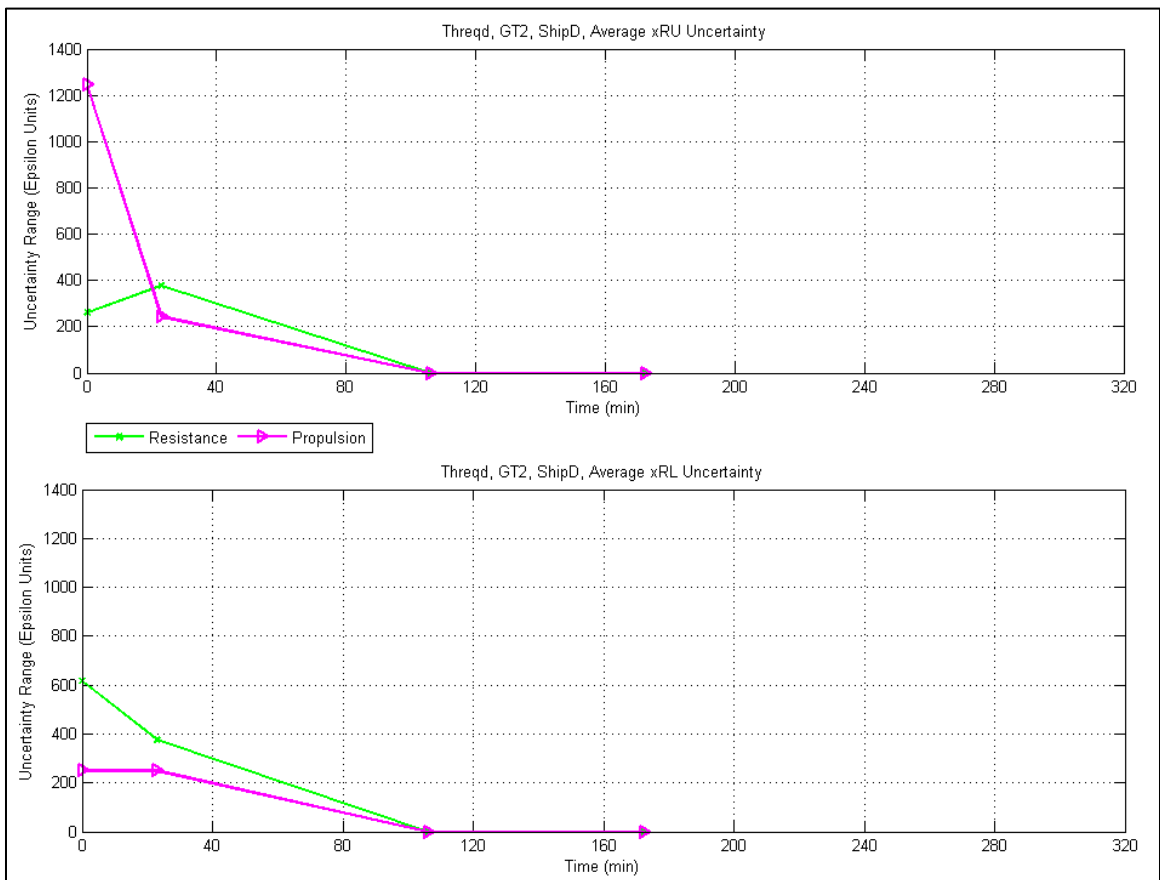
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for T vs. Time



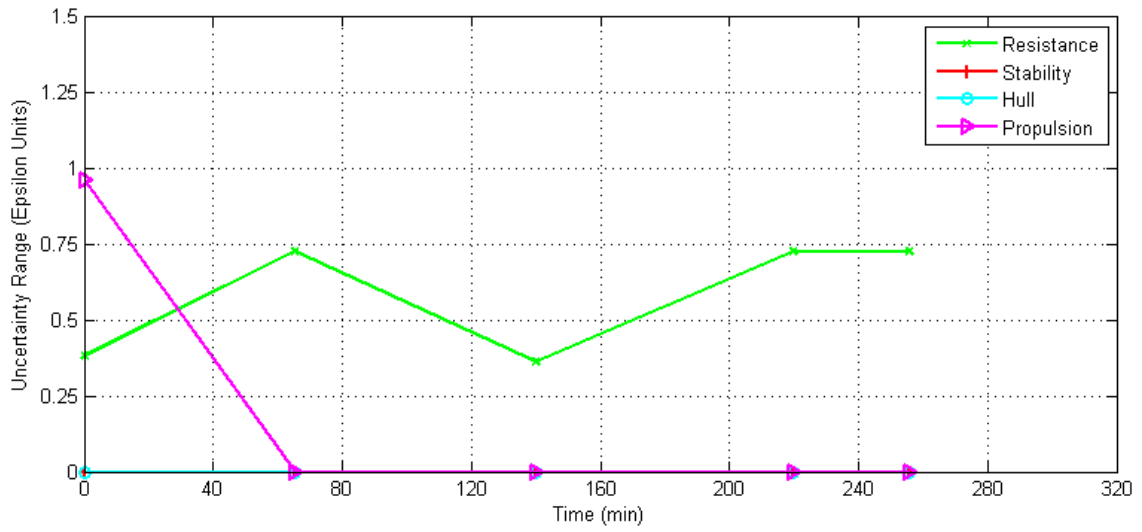
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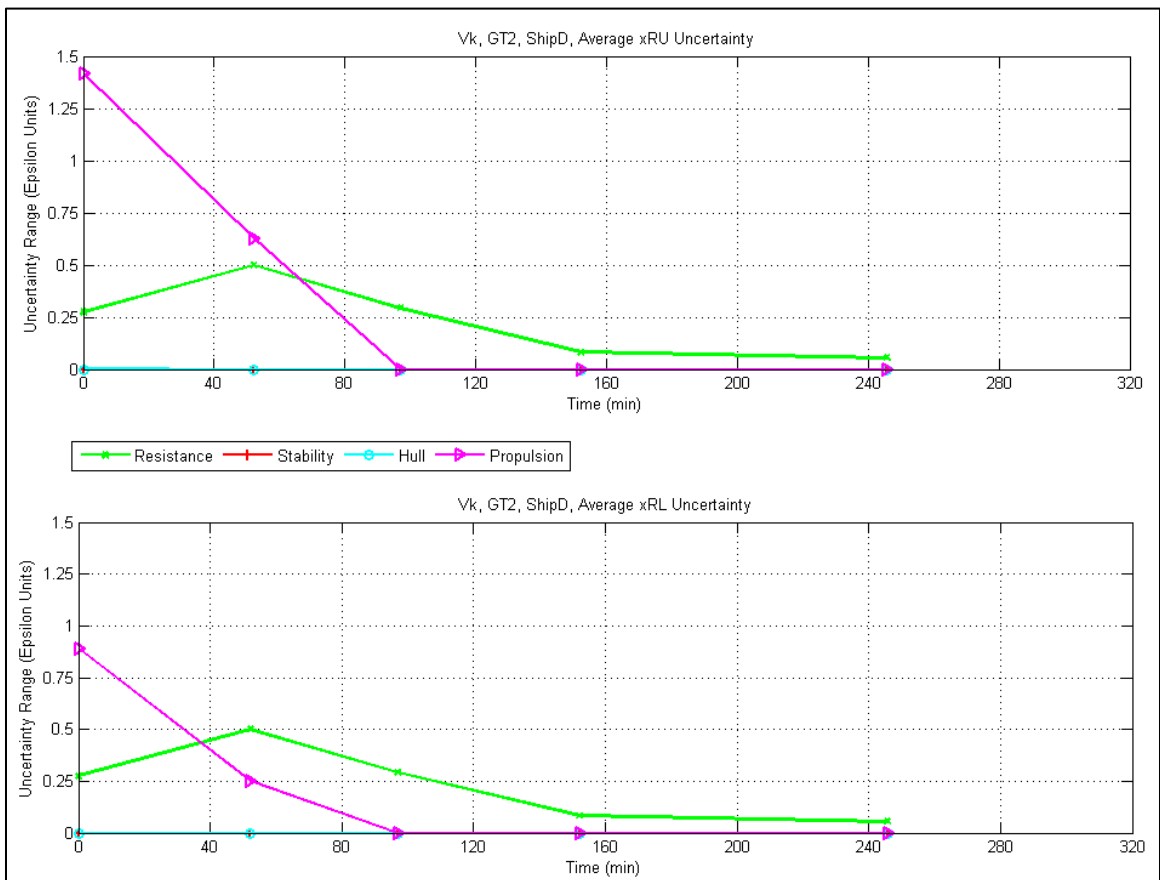
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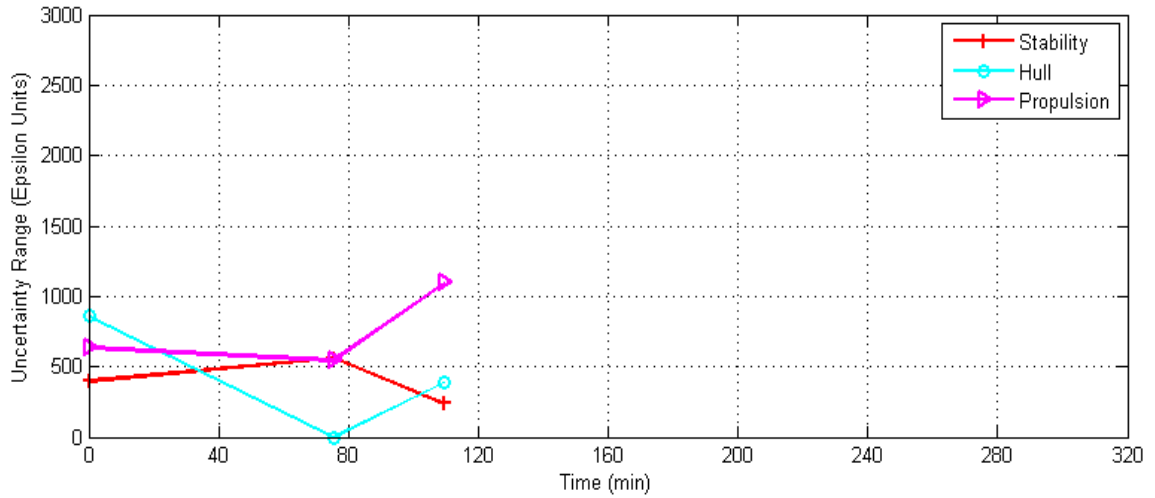
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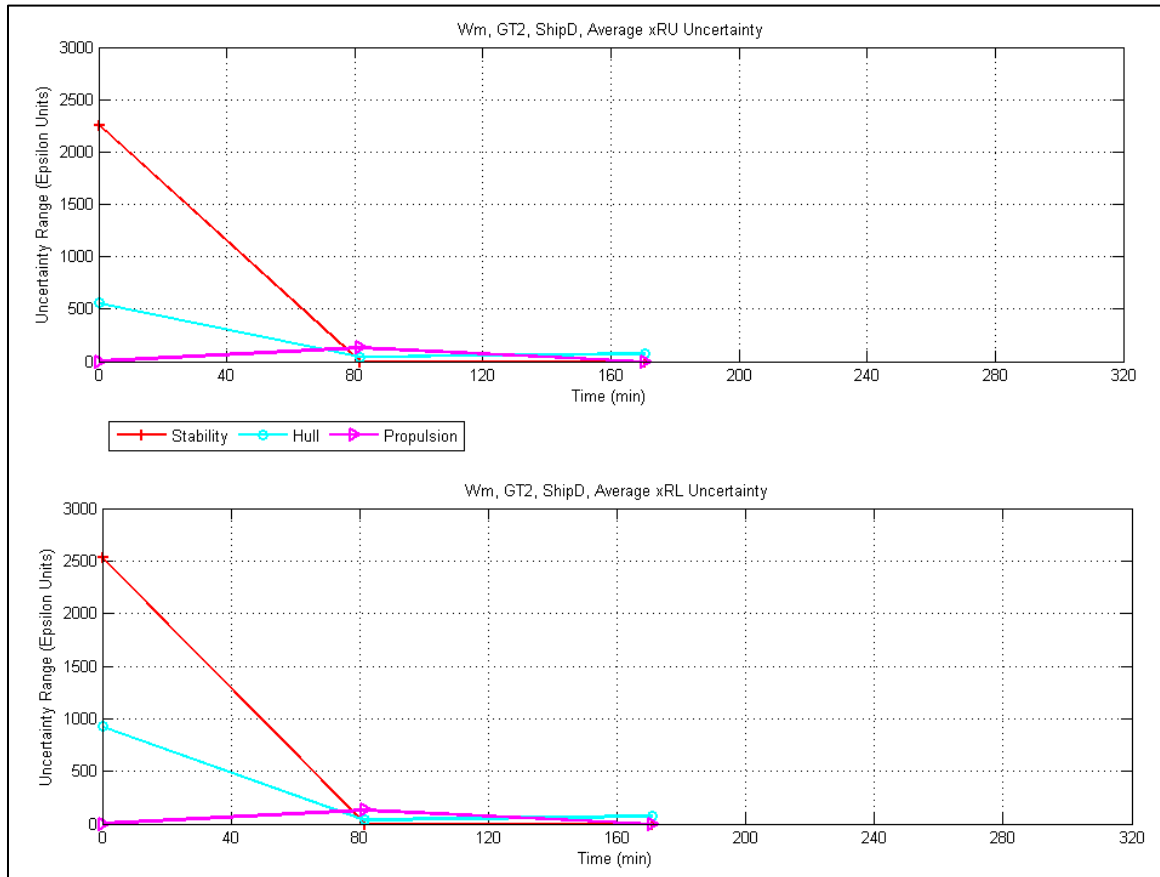
IT2M (Slopes), Ship D, Magnitudes of Uncertainty for V_k vs. Time



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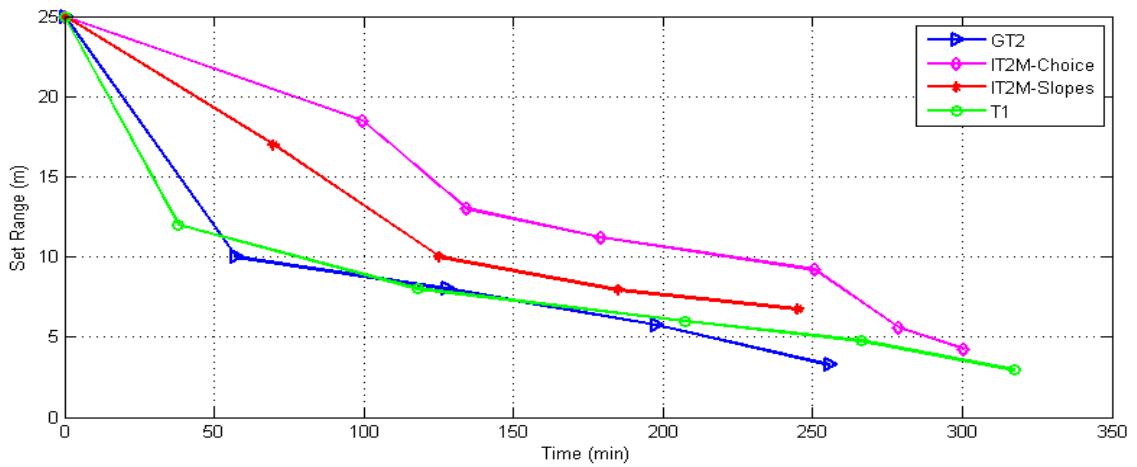


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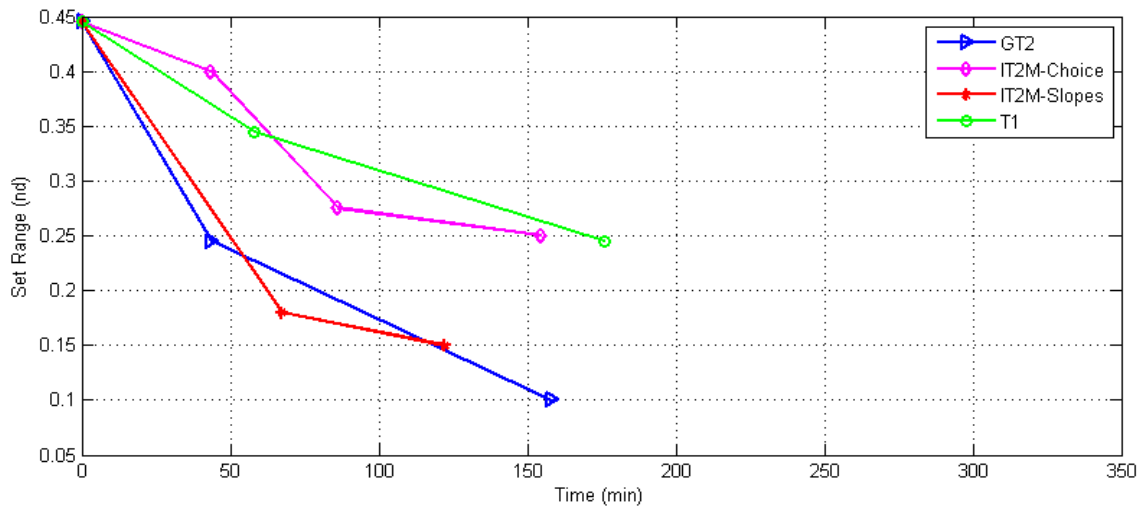


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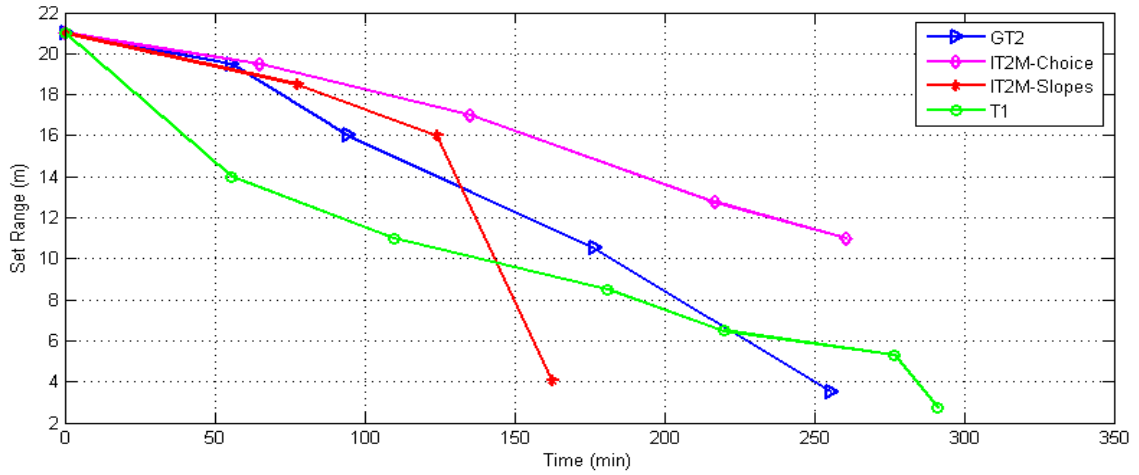
Appendix I
Magnitude of Set-Range vs. Time Plots
for Ship E SBD Experiments



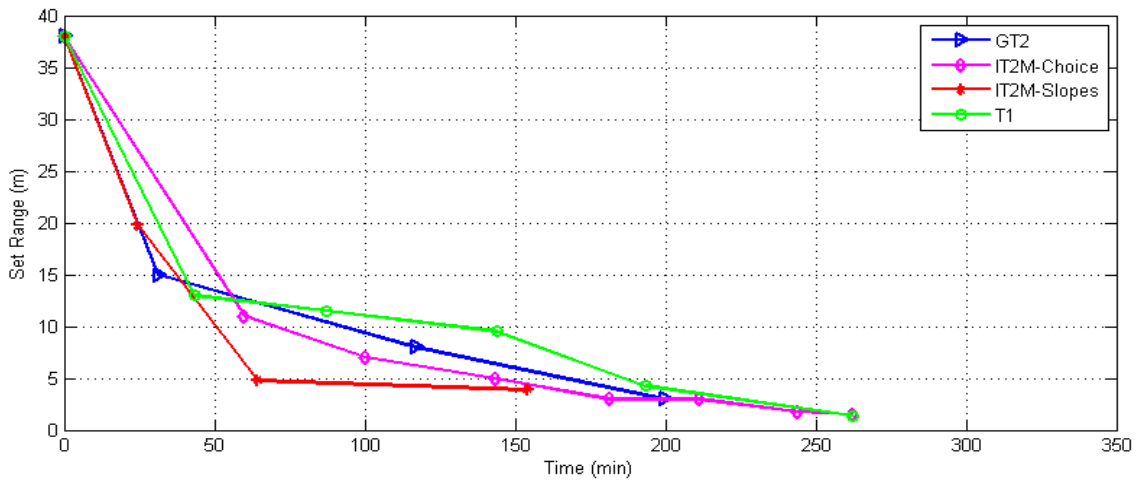
Ship E, Set-Ranges for *B* Negotiation vs. Time



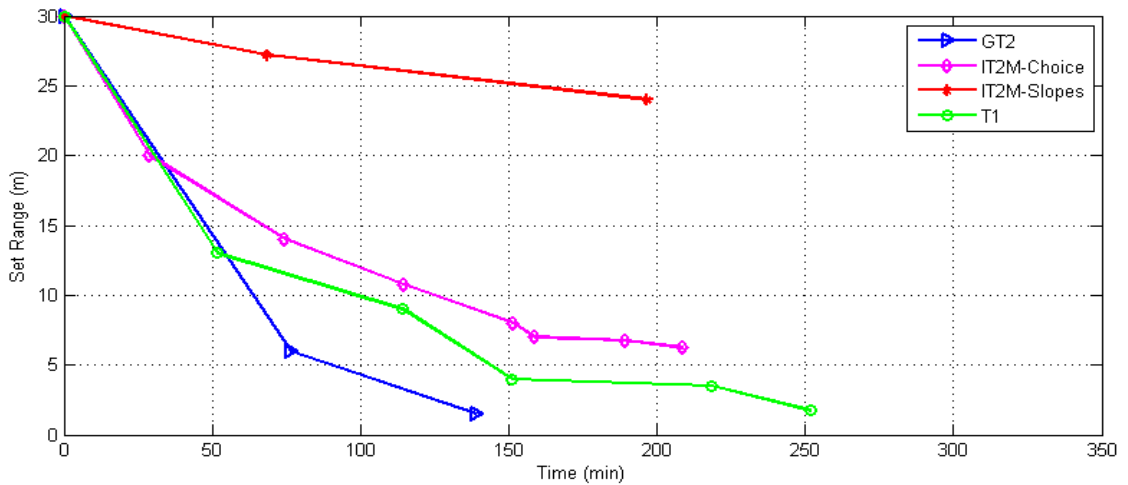
Ship E, Set-Ranges for *C_b* Negotiation vs. Time



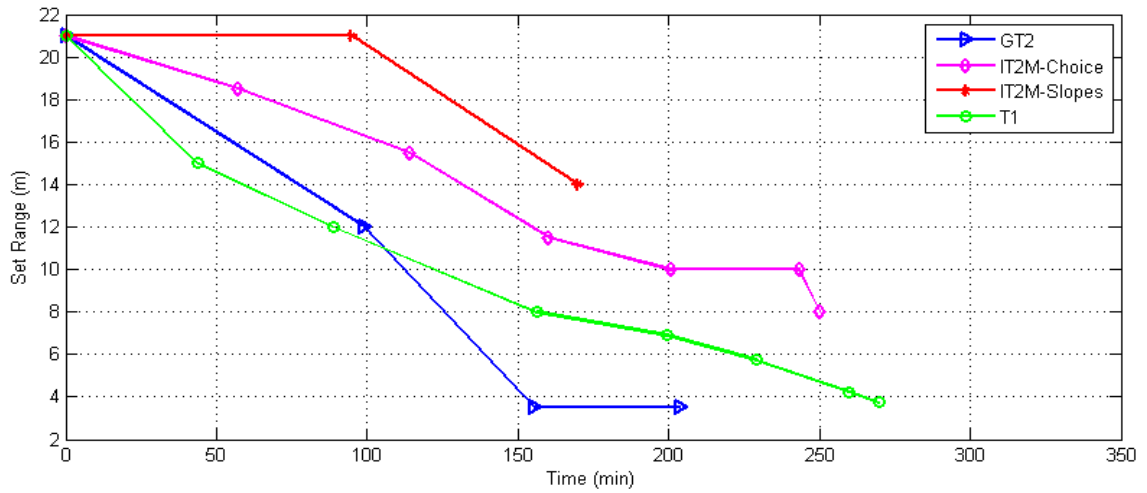
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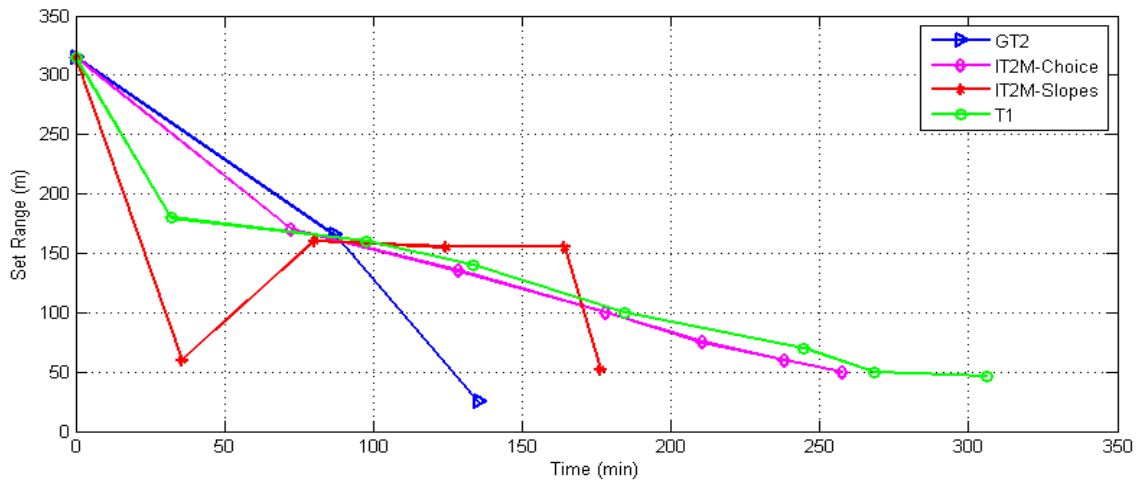
Ship E, Set-Ranges for *KGc* Negotiation vs. Time



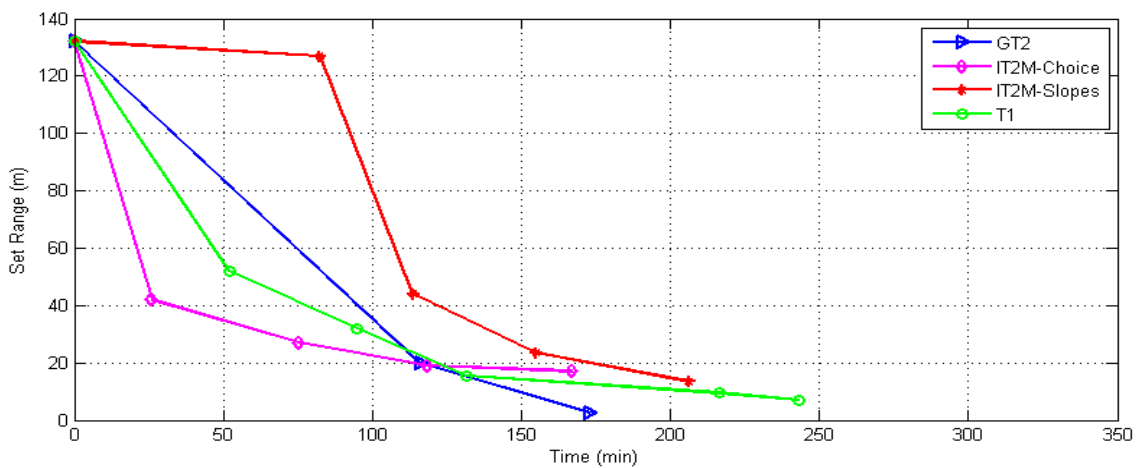
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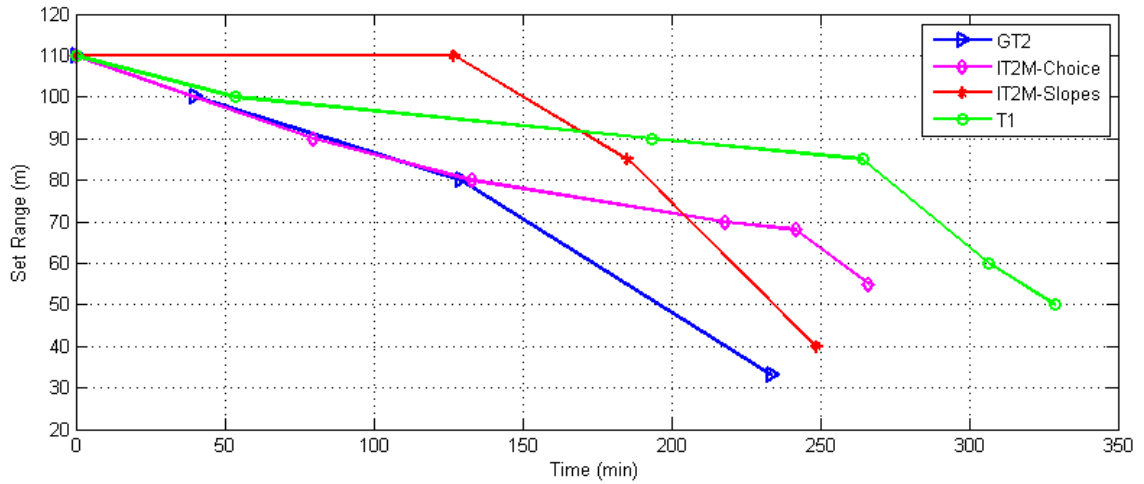
Ship E, Set-Ranges for *KGs* Negotiation vs. Time



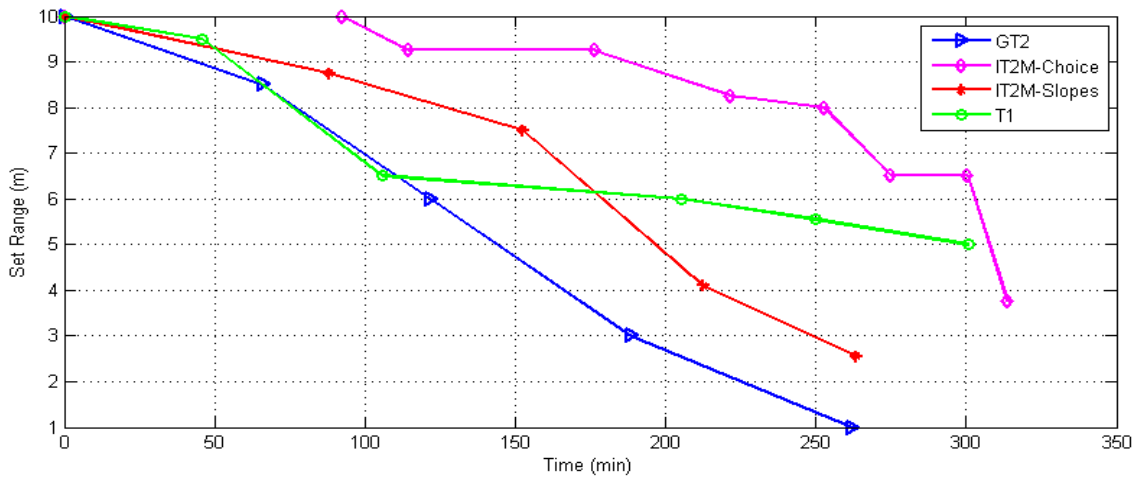
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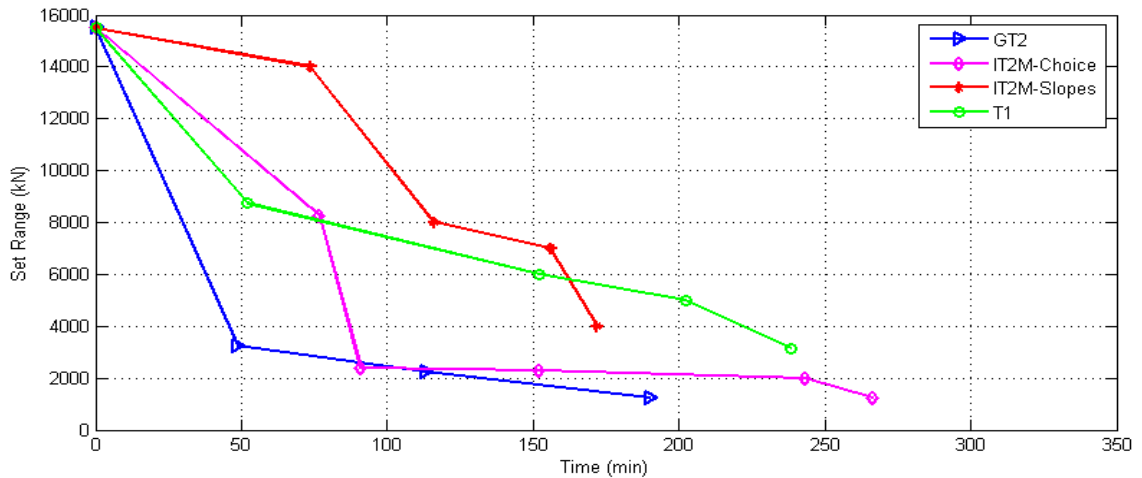
Ship E, Set-Ranges for *Lm* Negotiation vs. Time



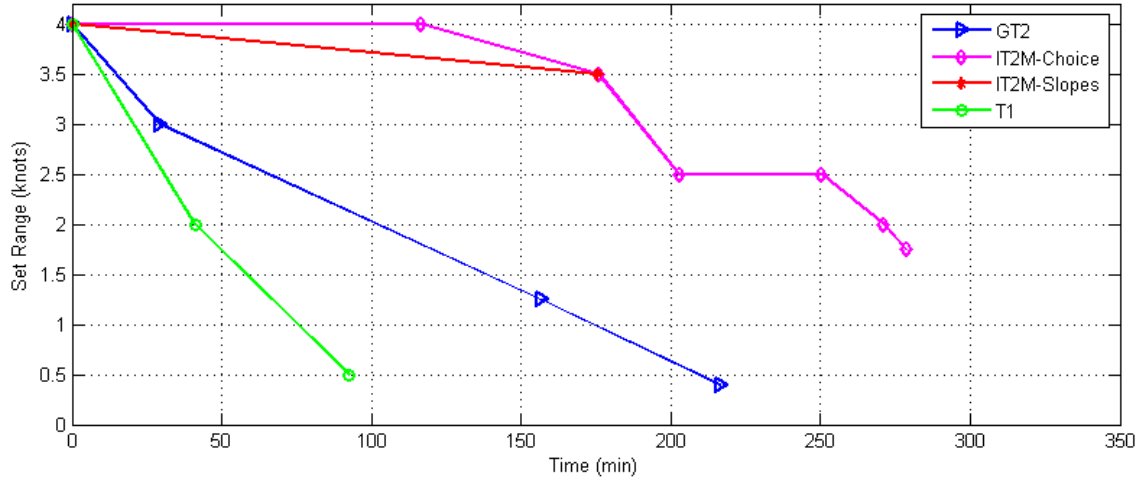
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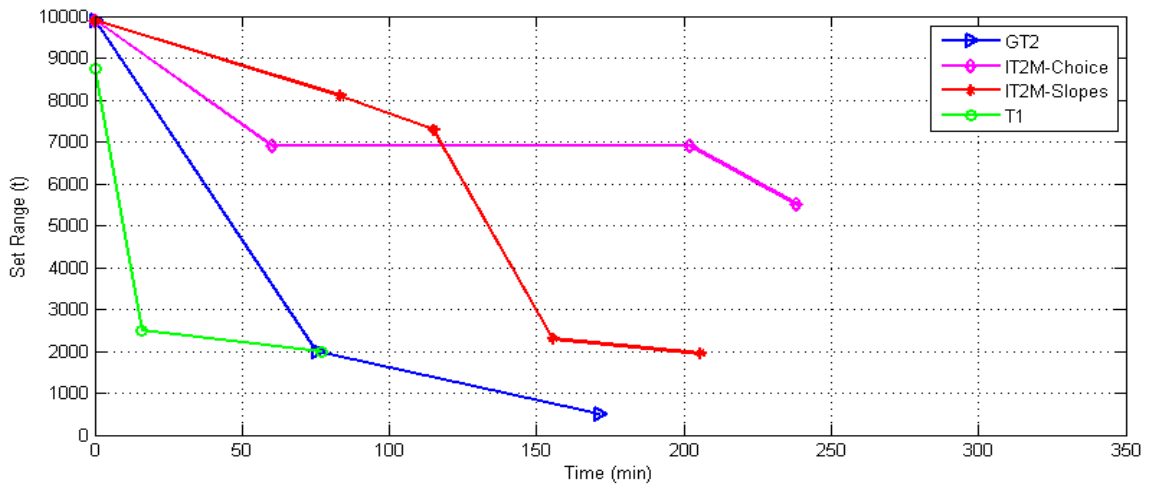
Ship E, Set-Ranges for *T* Negotiation vs. Time



Ship E, Set-Ranges for *Threqd* Negotiation vs. Time

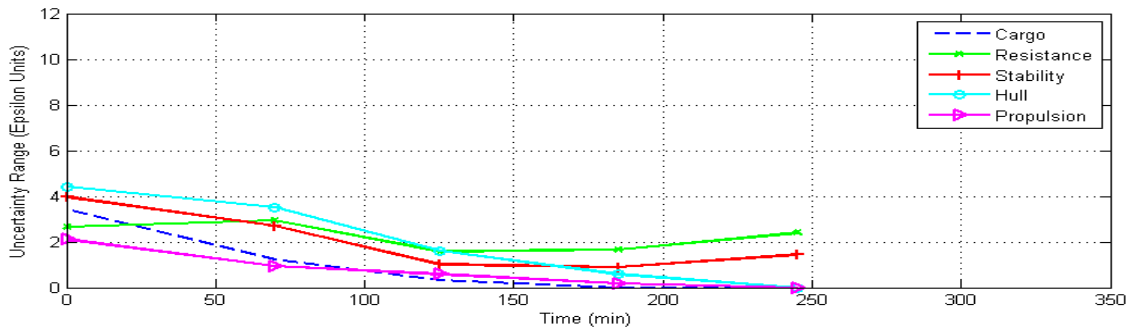


Ship E, Set-Ranges for V_k Negotiation vs. Time

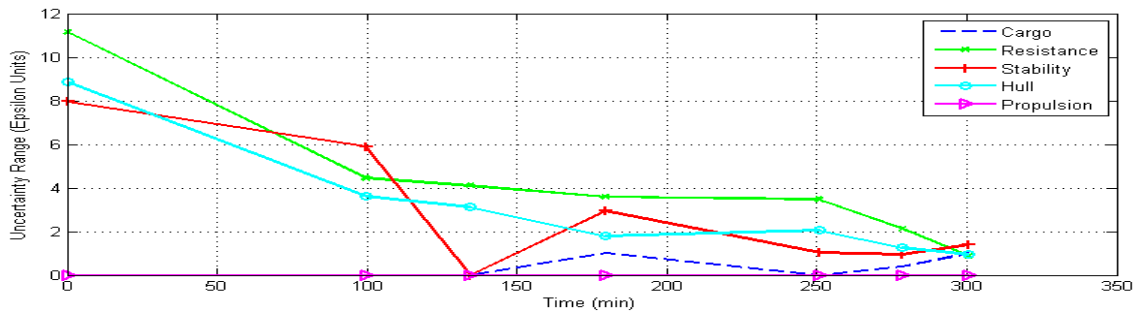


Ship E, Set-Ranges for W_m Negotiation vs. Time

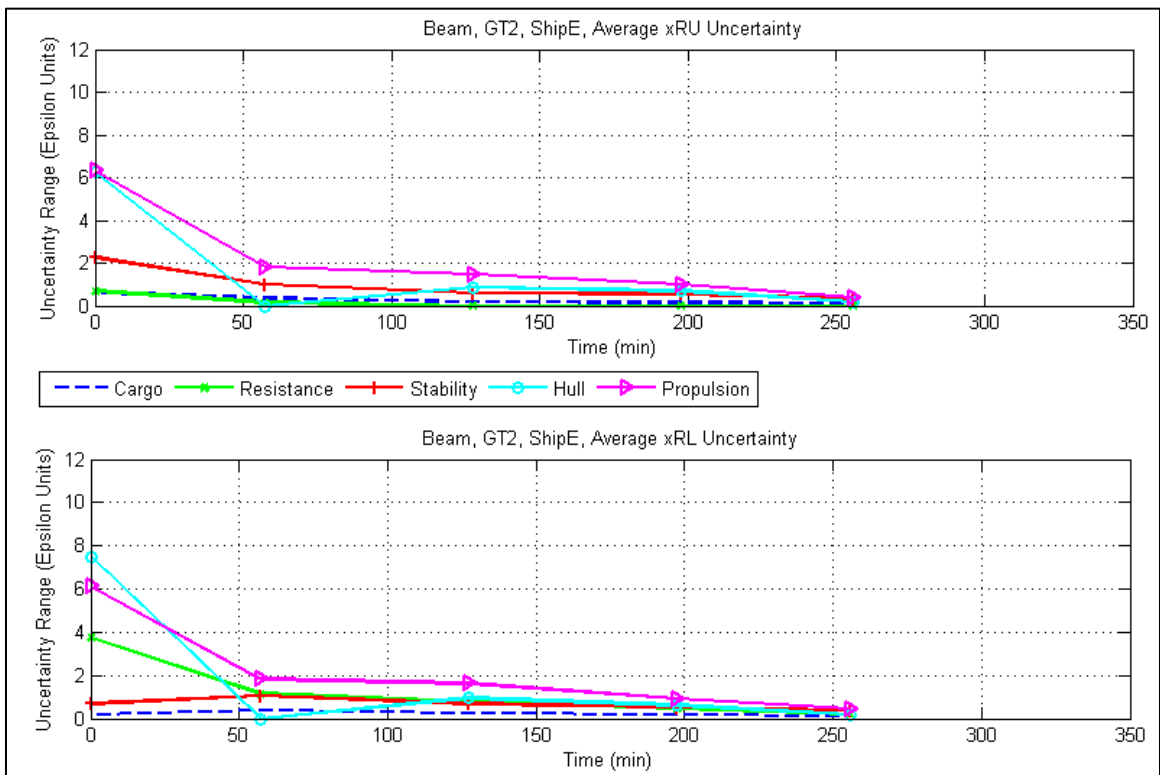
Appendix J
Magnitude of Uncertainty vs. Time Plots
for Ship E SBD Experiments



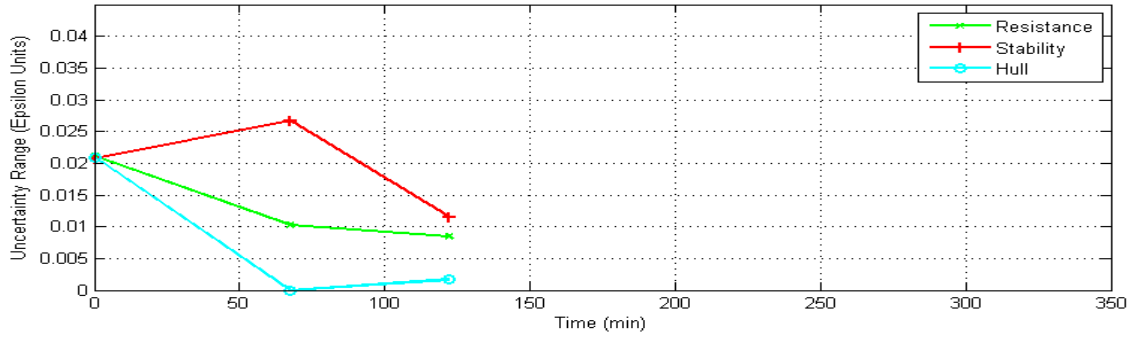
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for B vs. Time



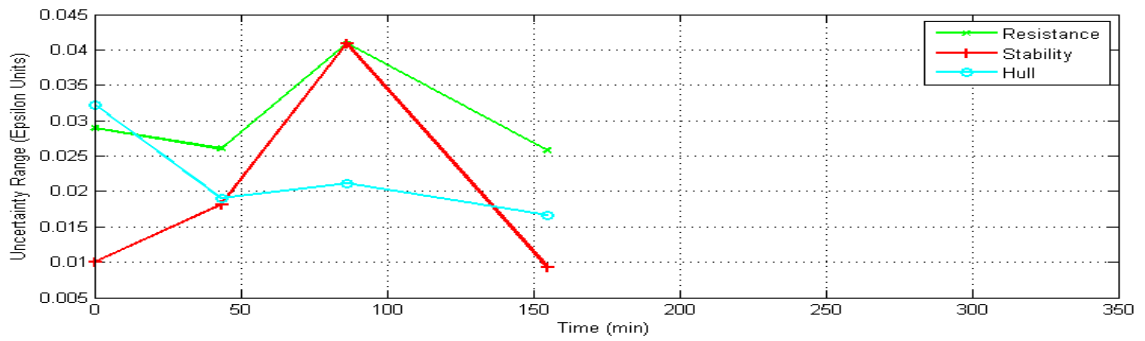
IT2M (Choice), Ship E, Magnitudes of Uncertainty for B vs. Time



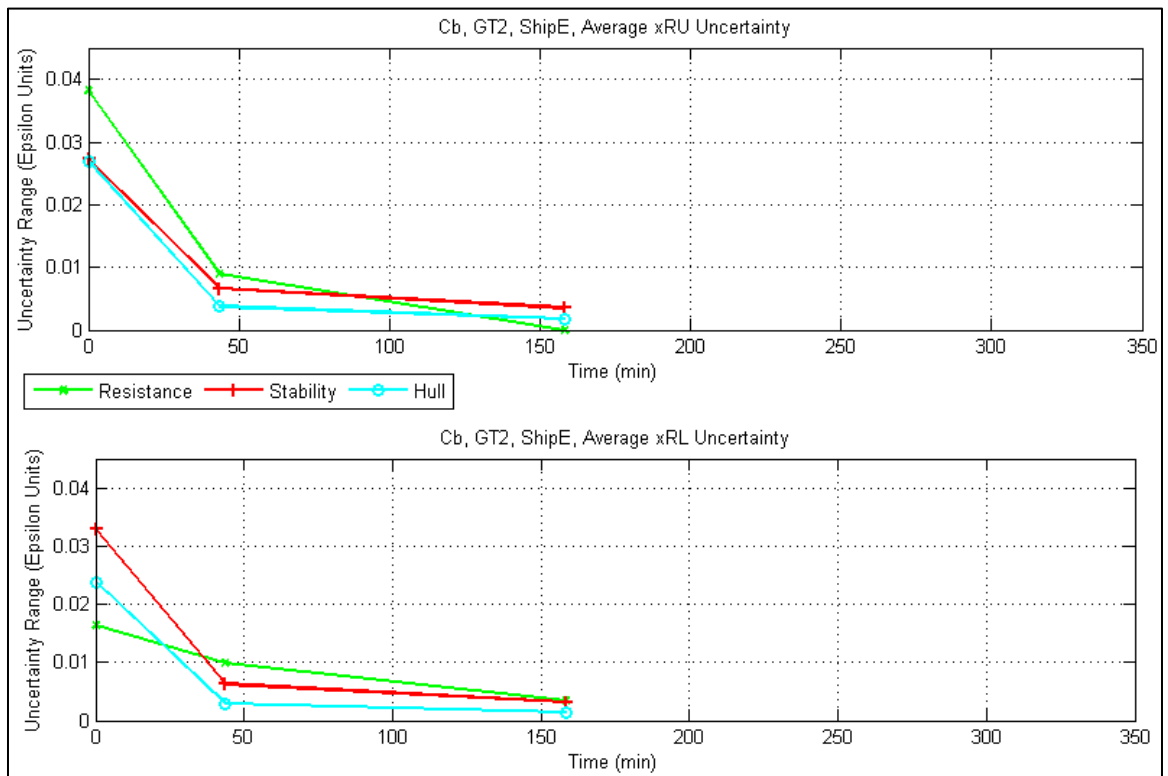
GT2, Ship E, Magnitudes of Uncertainty for B vs. Time



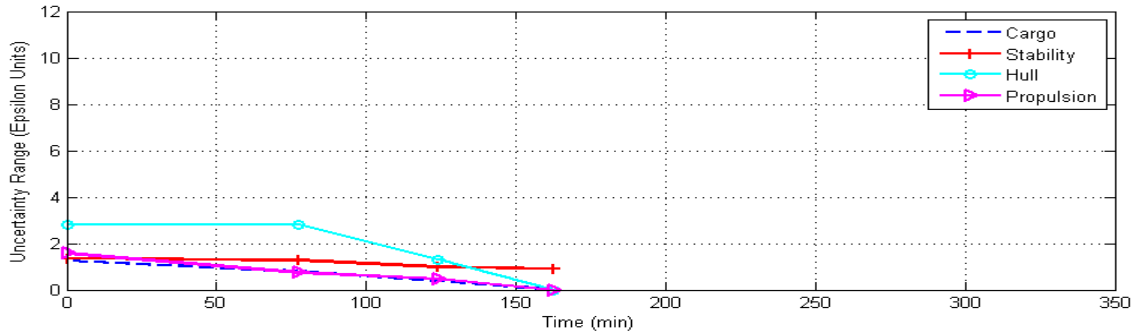
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for C_b vs. Time



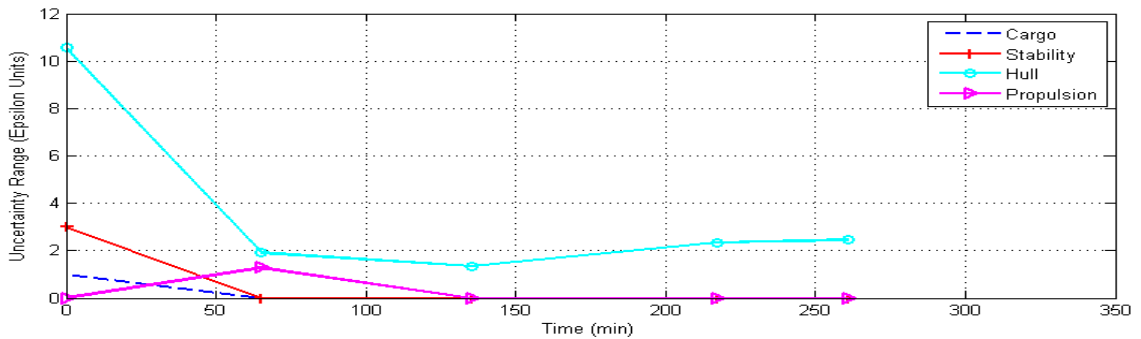
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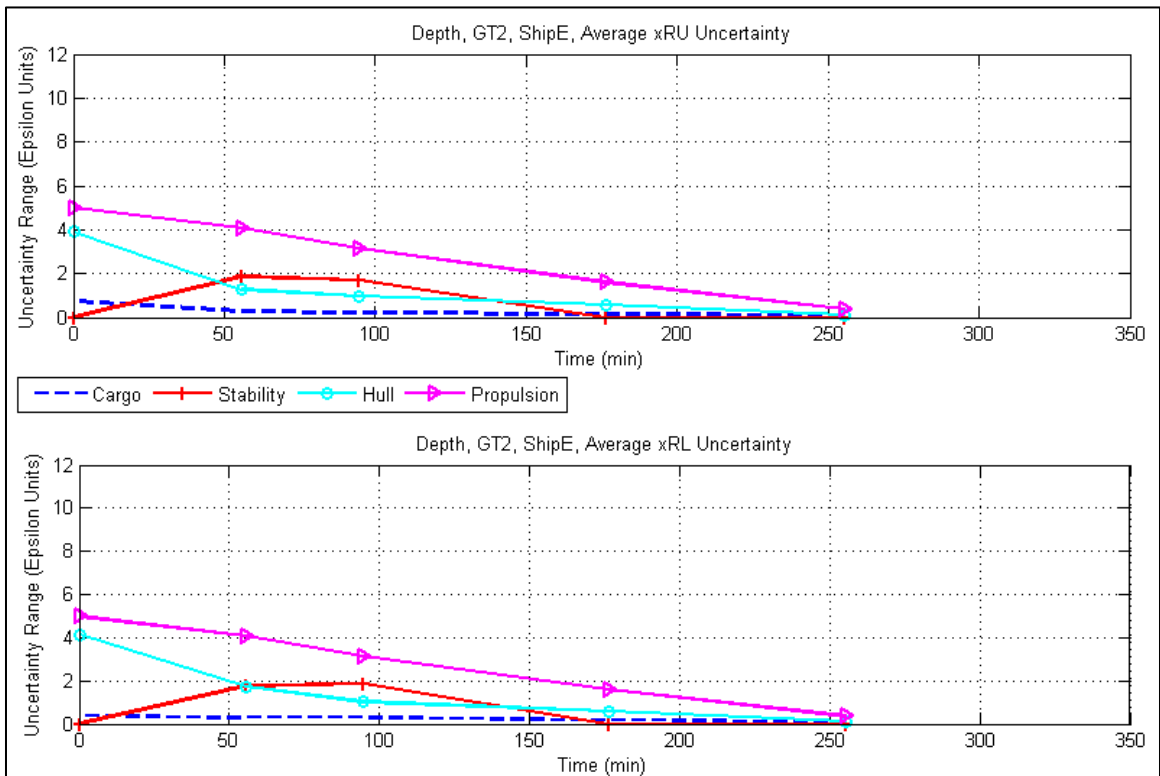
GT2, Ship E, Magnitudes of Uncertainty for C_b vs. Time



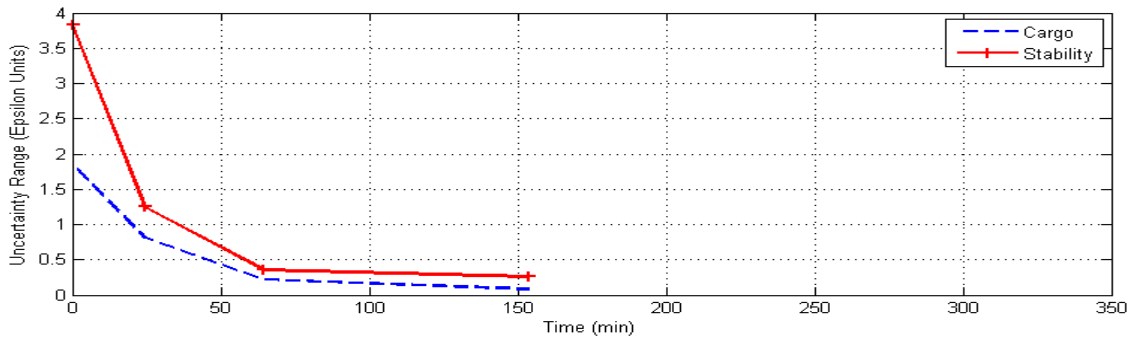
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for D vs. Time



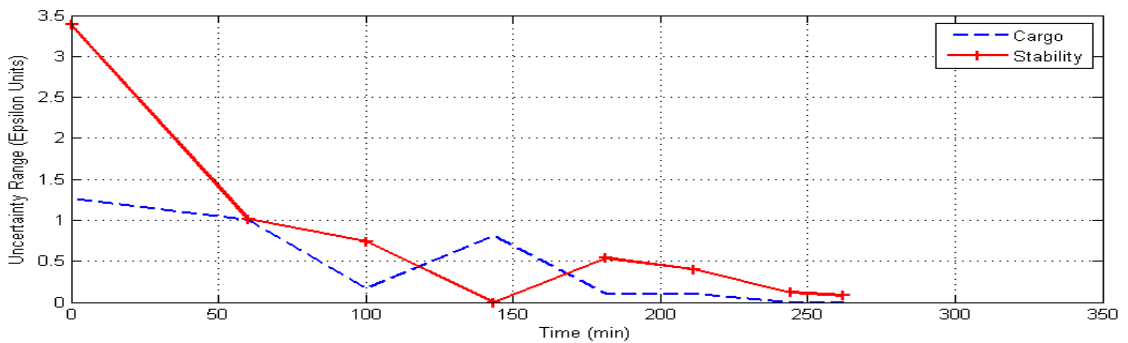
IT2M (Choice), Ship E, Magnitudes of Uncertainty for D vs. Time



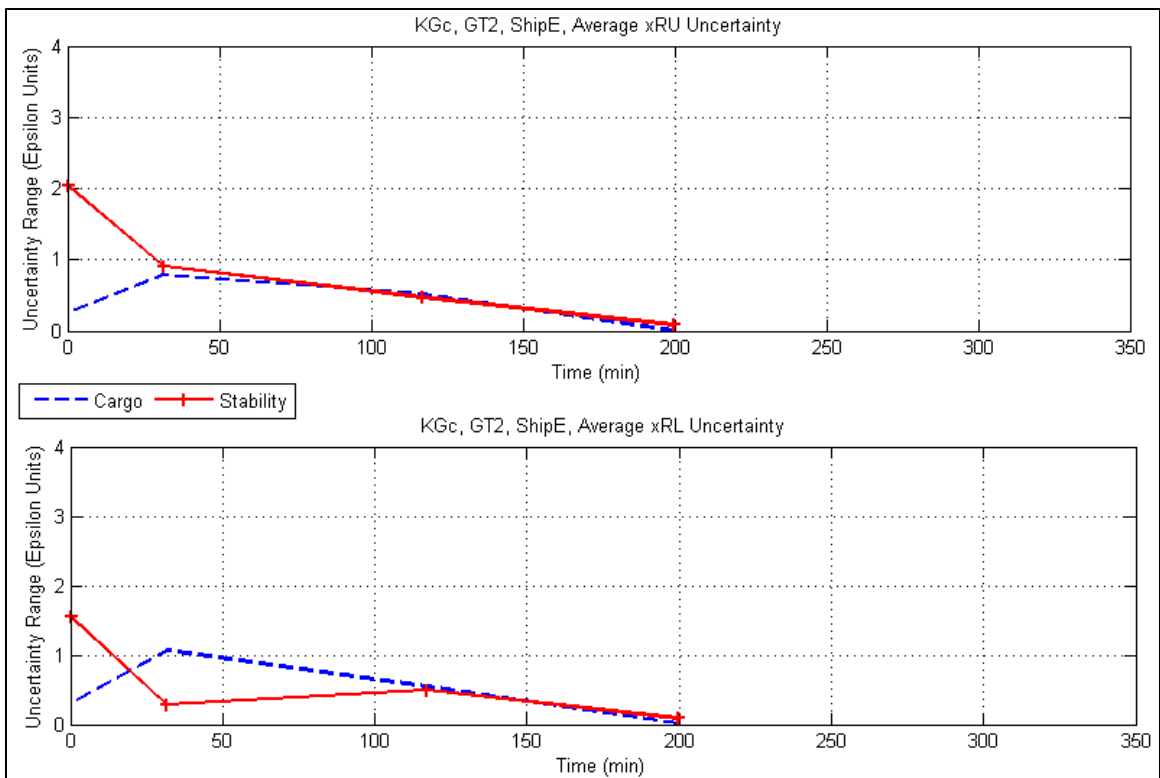
GT2, Ship E, Magnitudes of Uncertainty for D vs. Time



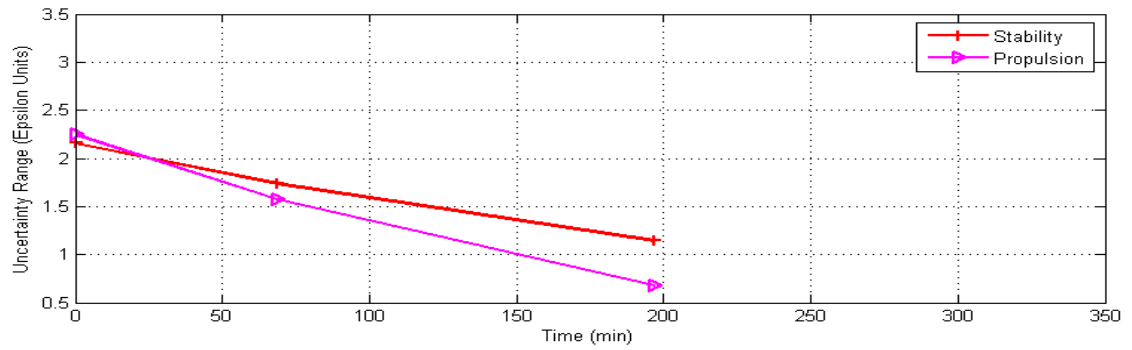
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for KG_c vs. Time



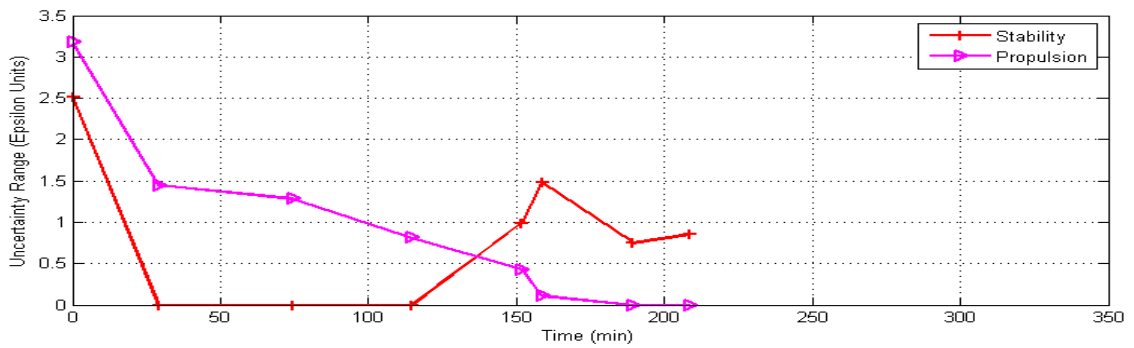
IT2M (Choice), Ship E, Magnitudes of Uncertainty for KG_c vs. Time



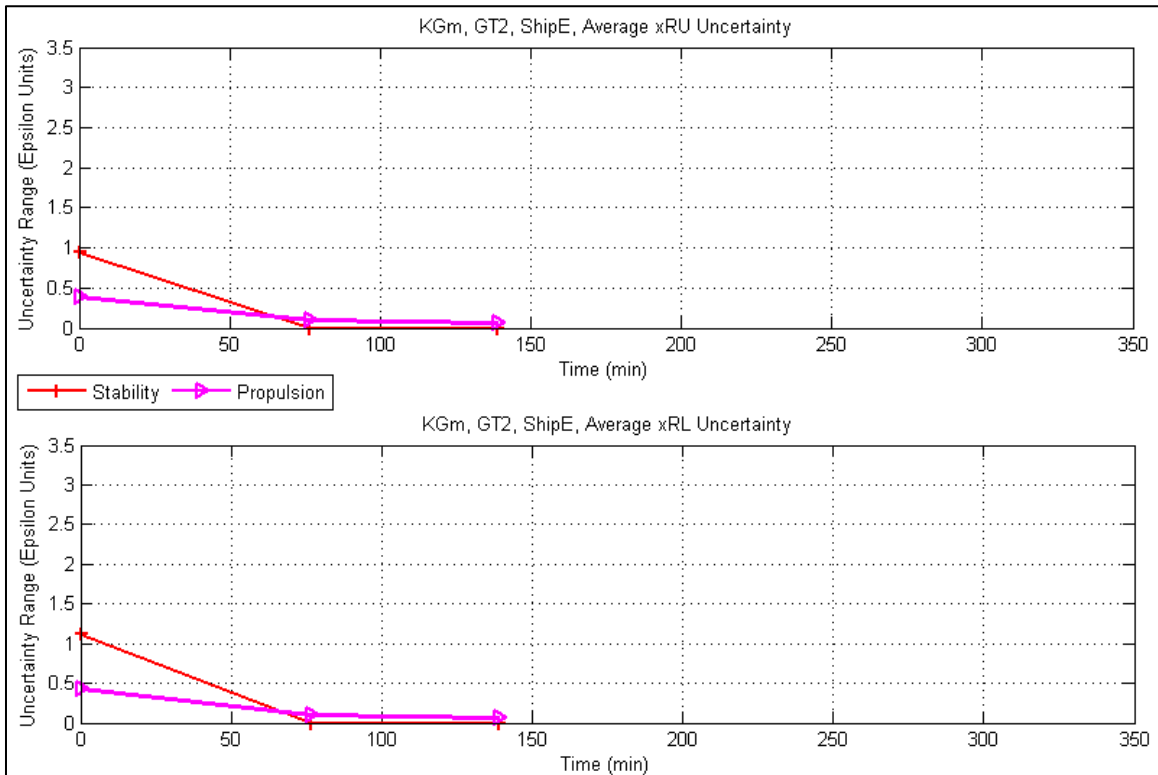
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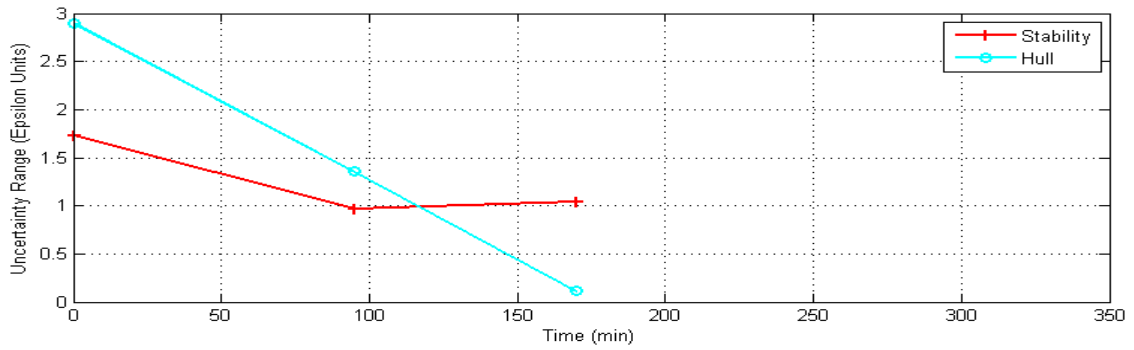
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for *KGm* vs. Time



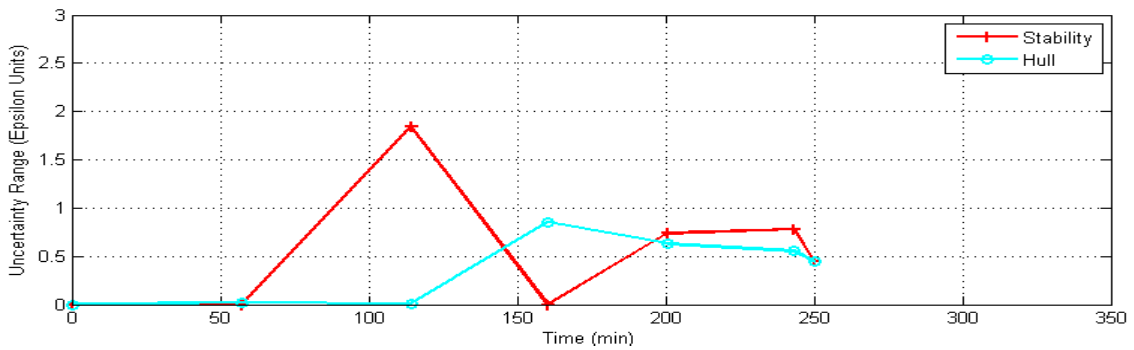
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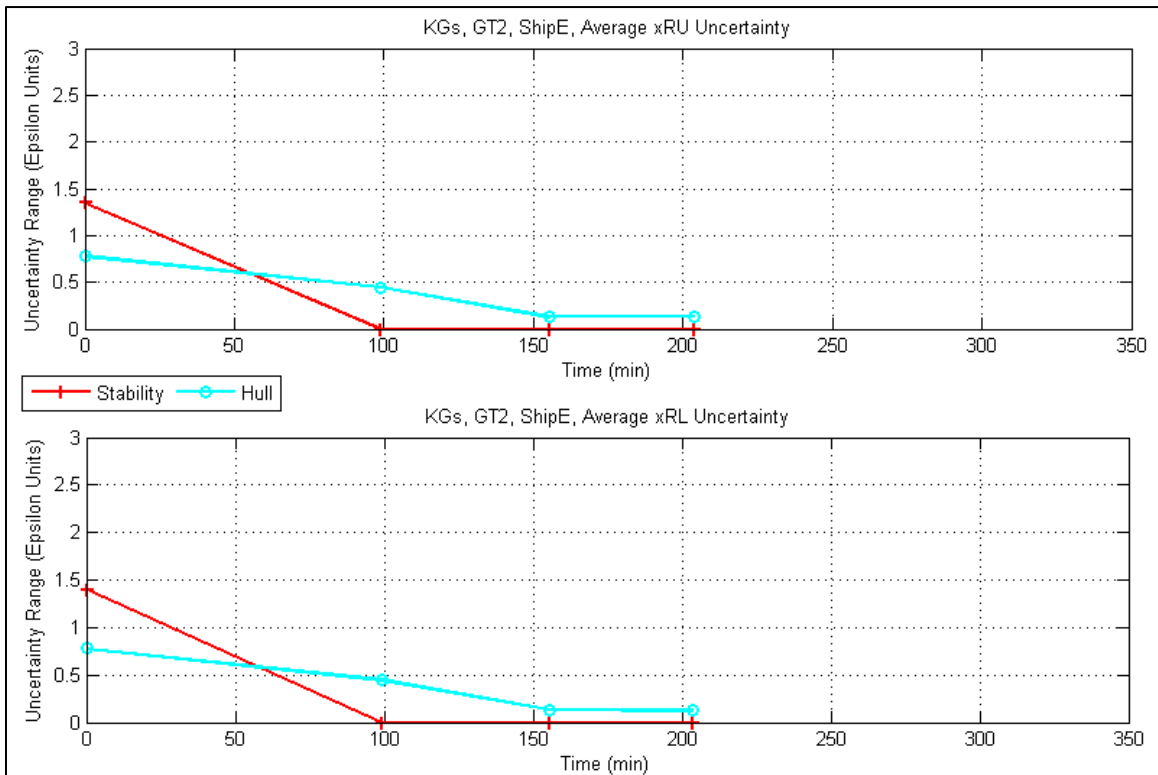
GT2, Ship E, Magnitudes of Uncertainty for *KGm* vs. Time



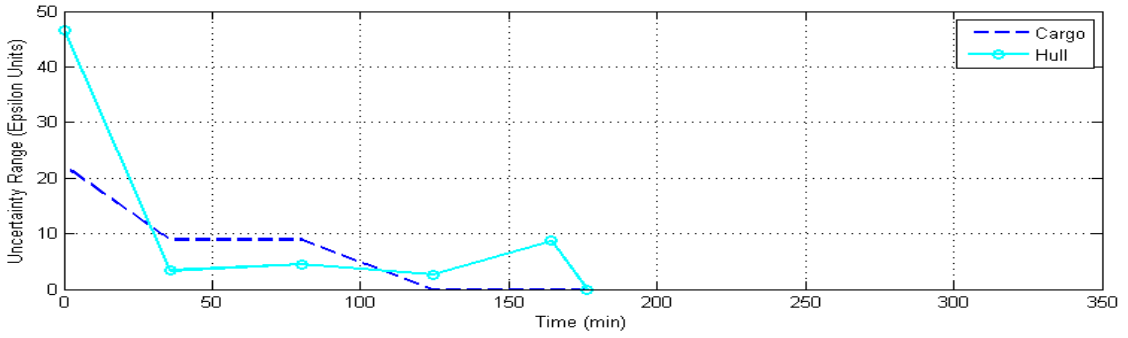
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for KGs vs. Time



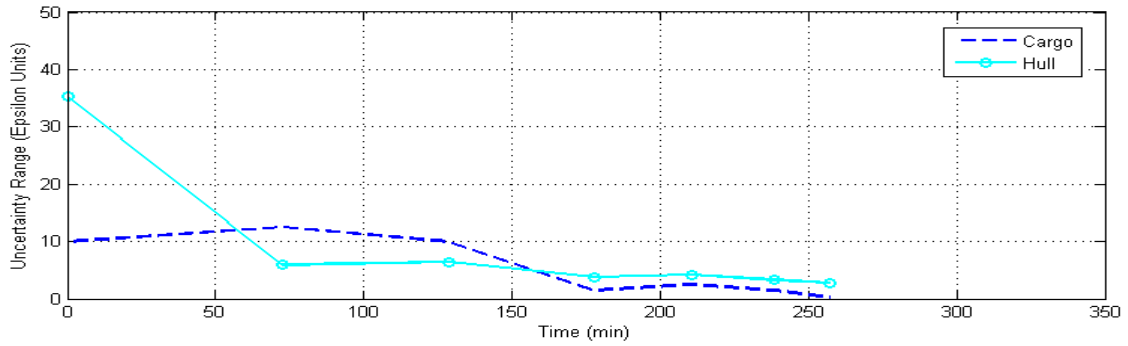
IT2M (Choice), Ship E, Magnitudes of Uncertainty for KGs vs. Time



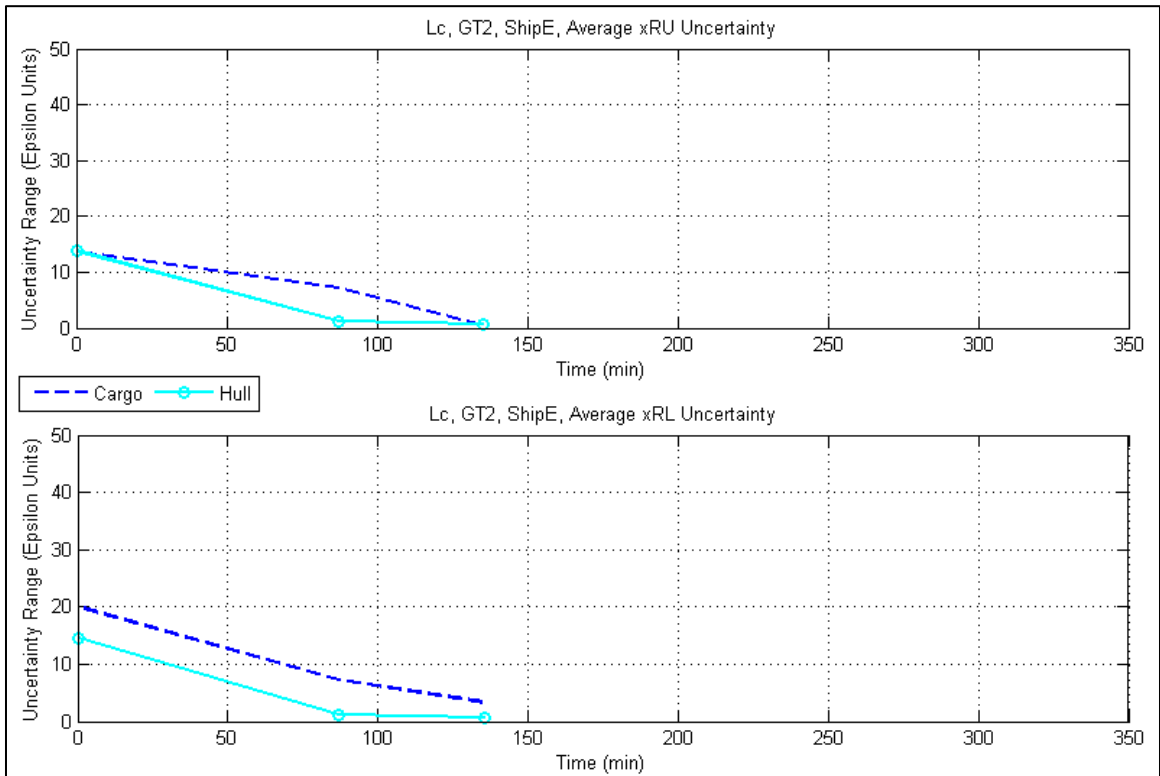
GT2, Ship E, Magnitudes of Uncertainty for KGs vs. Time



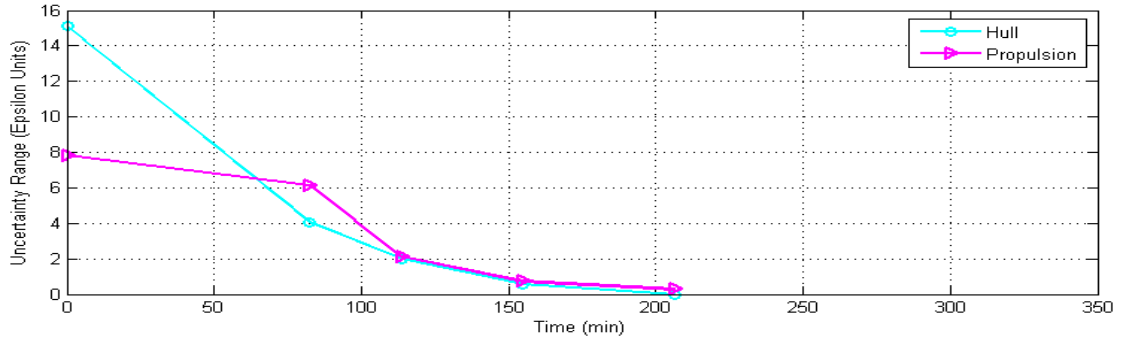
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for L_c vs. Time



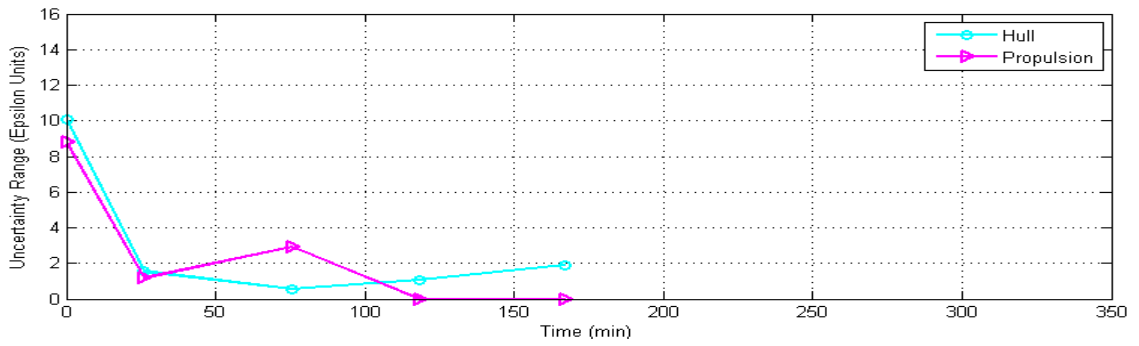
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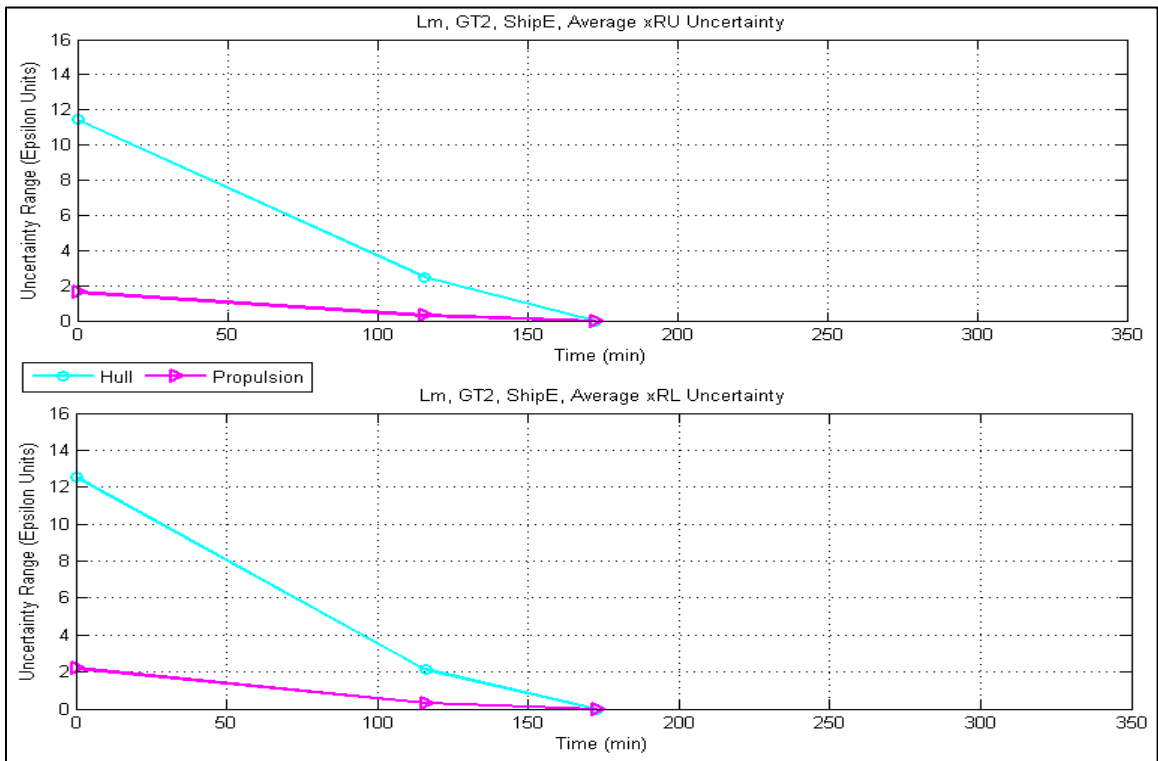
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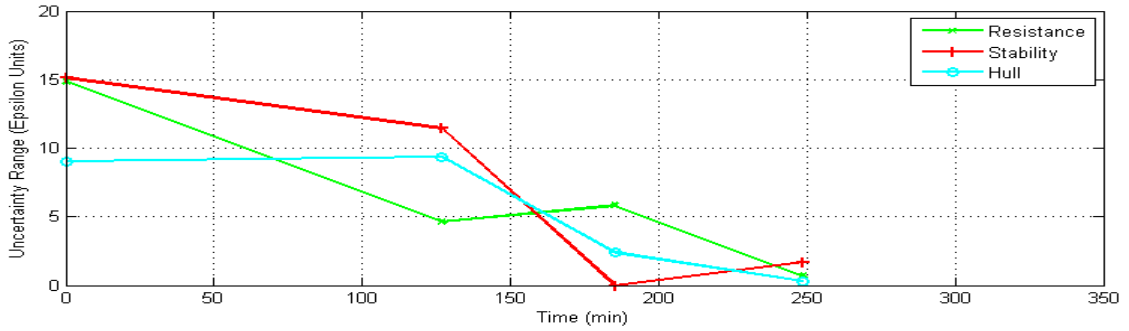
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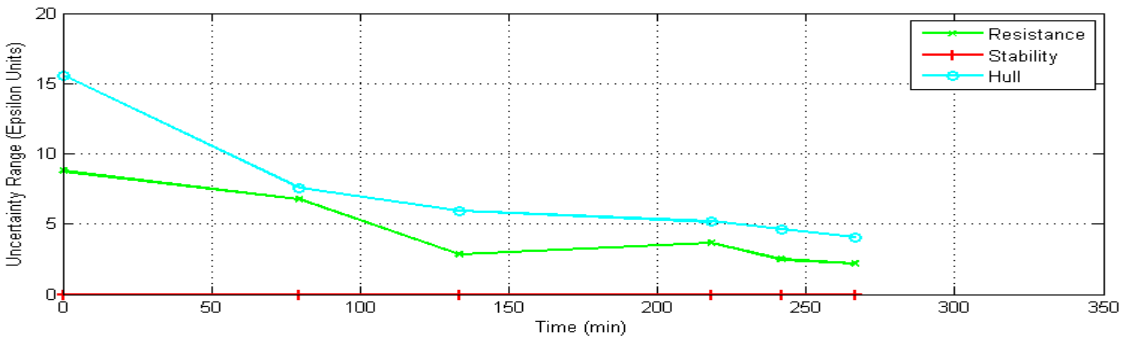
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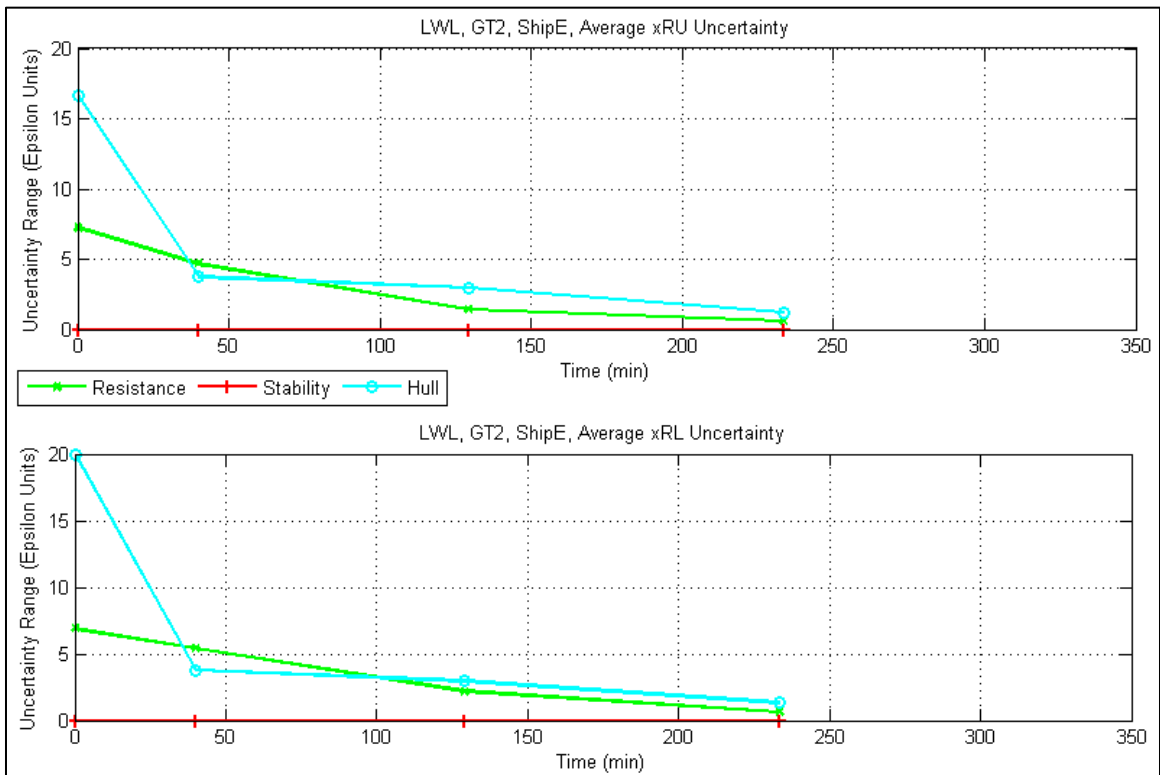
GT2, Ship E, Magnitudes of Uncertainty for L_m vs. Time



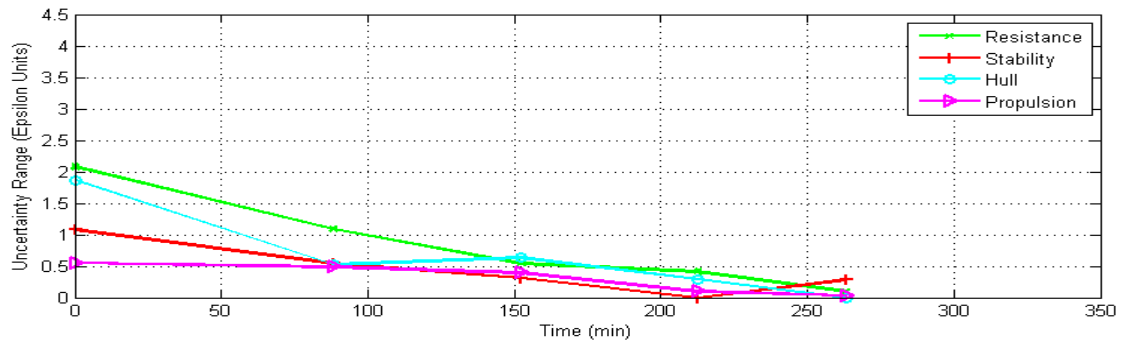
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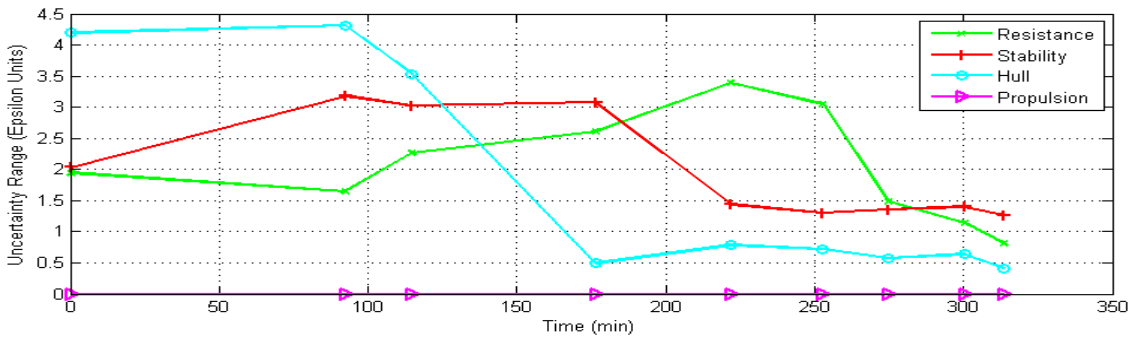
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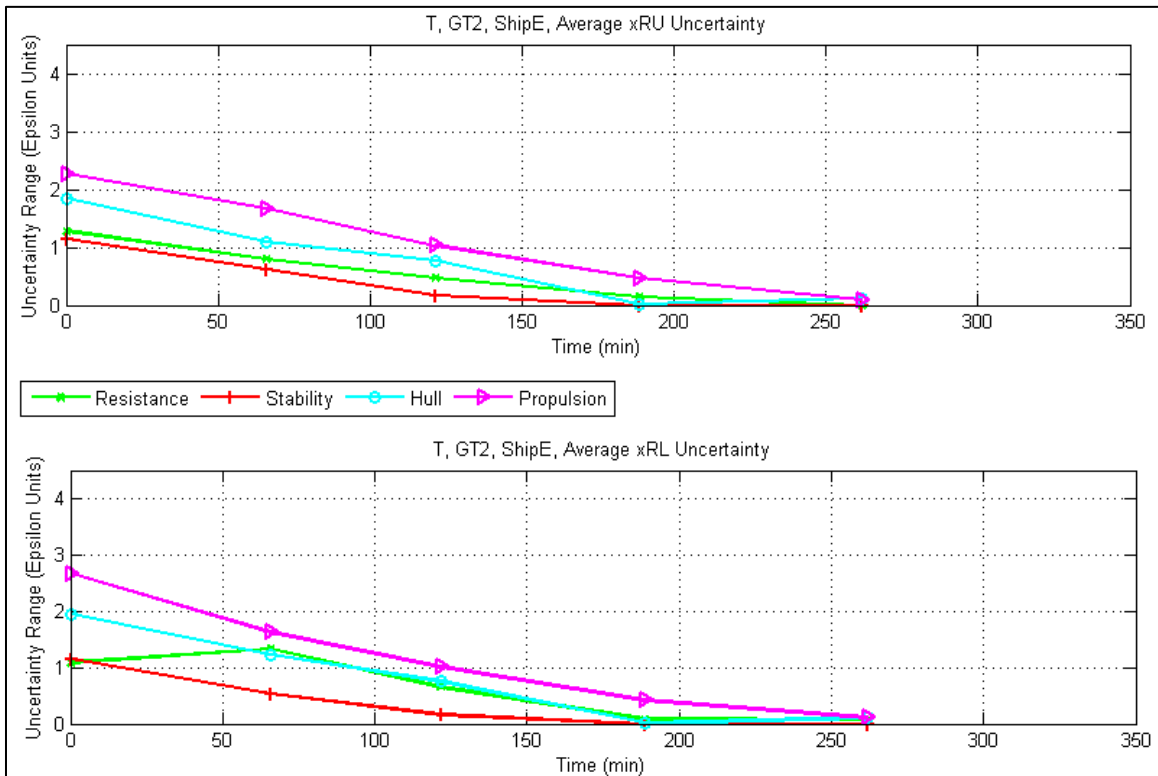
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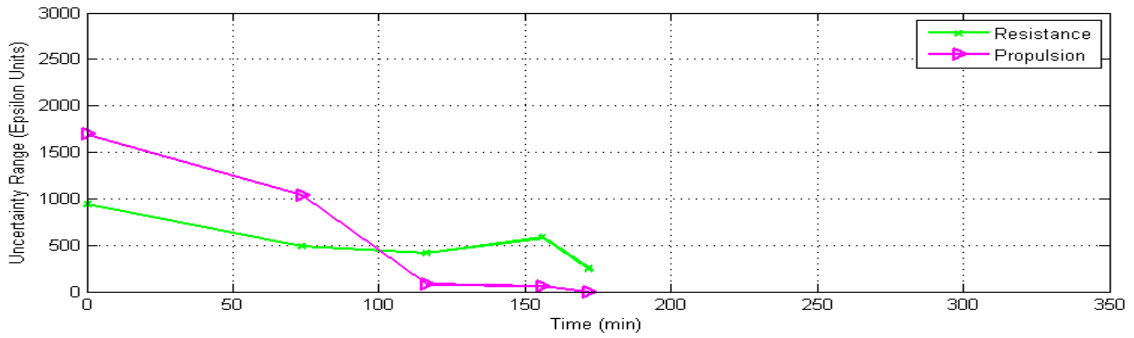
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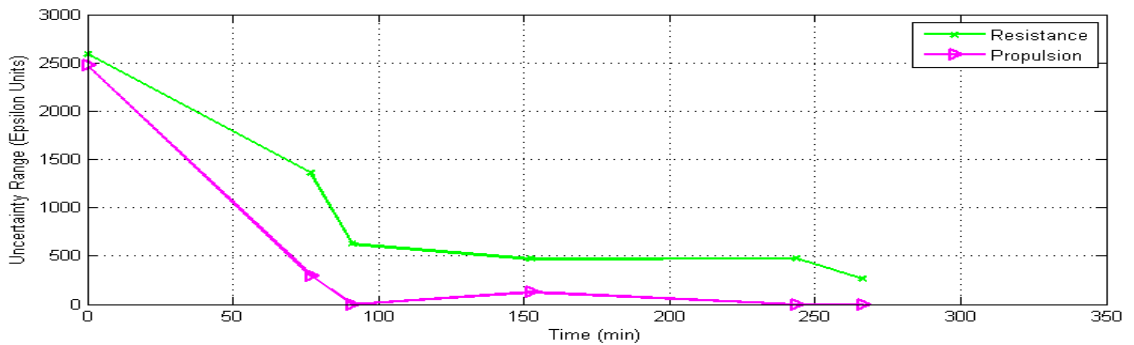
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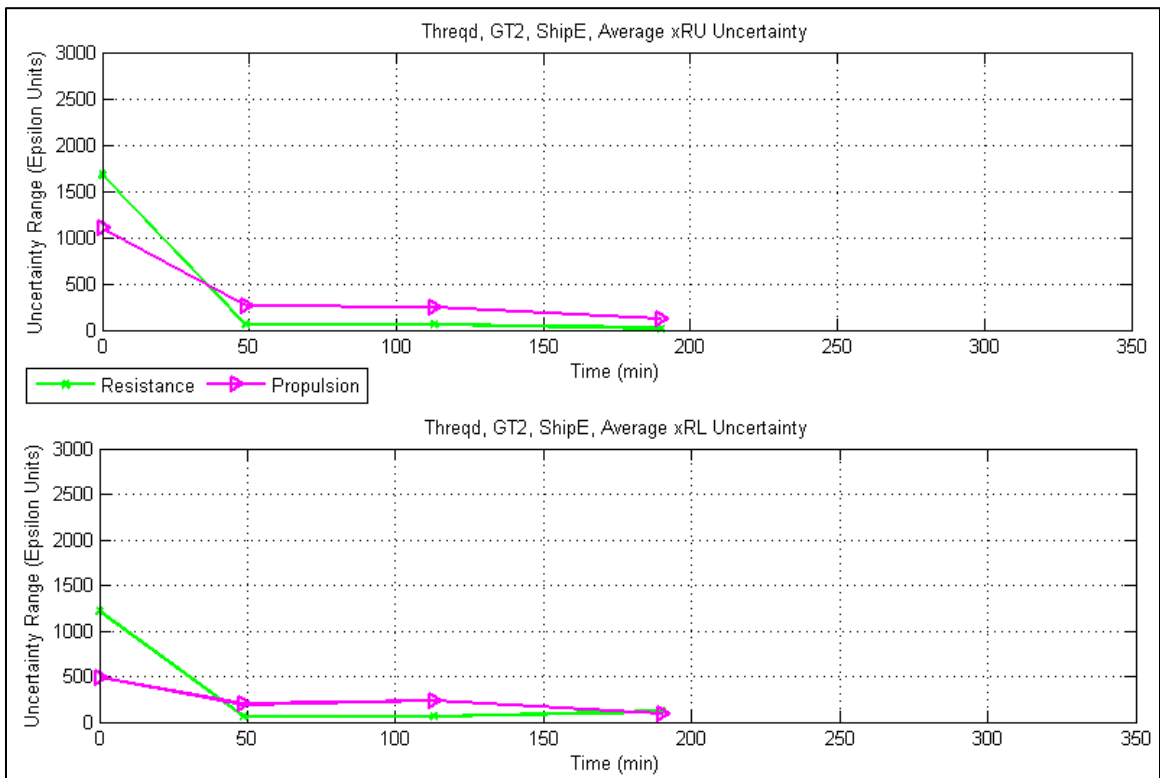
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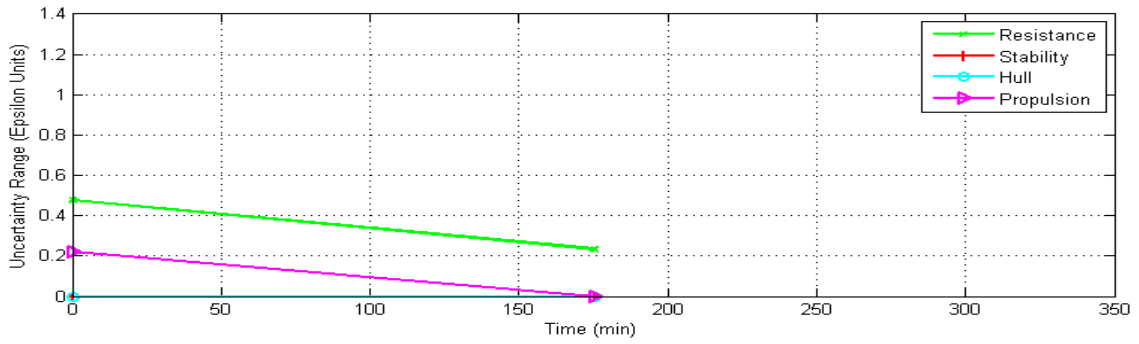
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for *Threqd* vs. Time



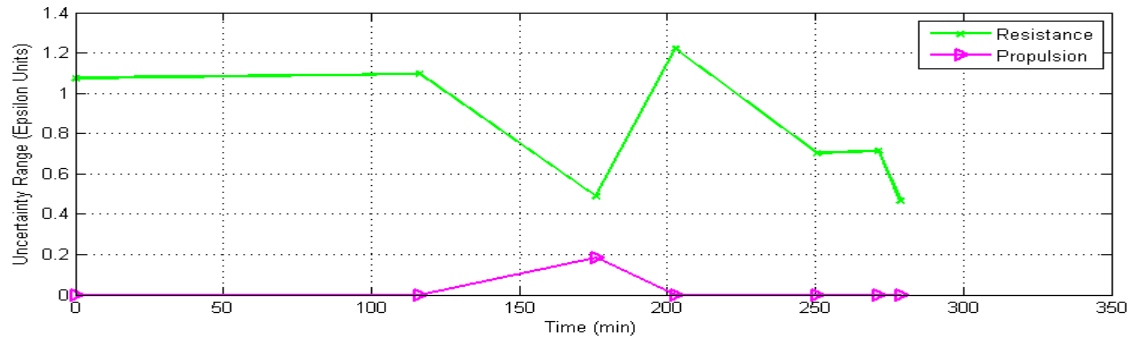
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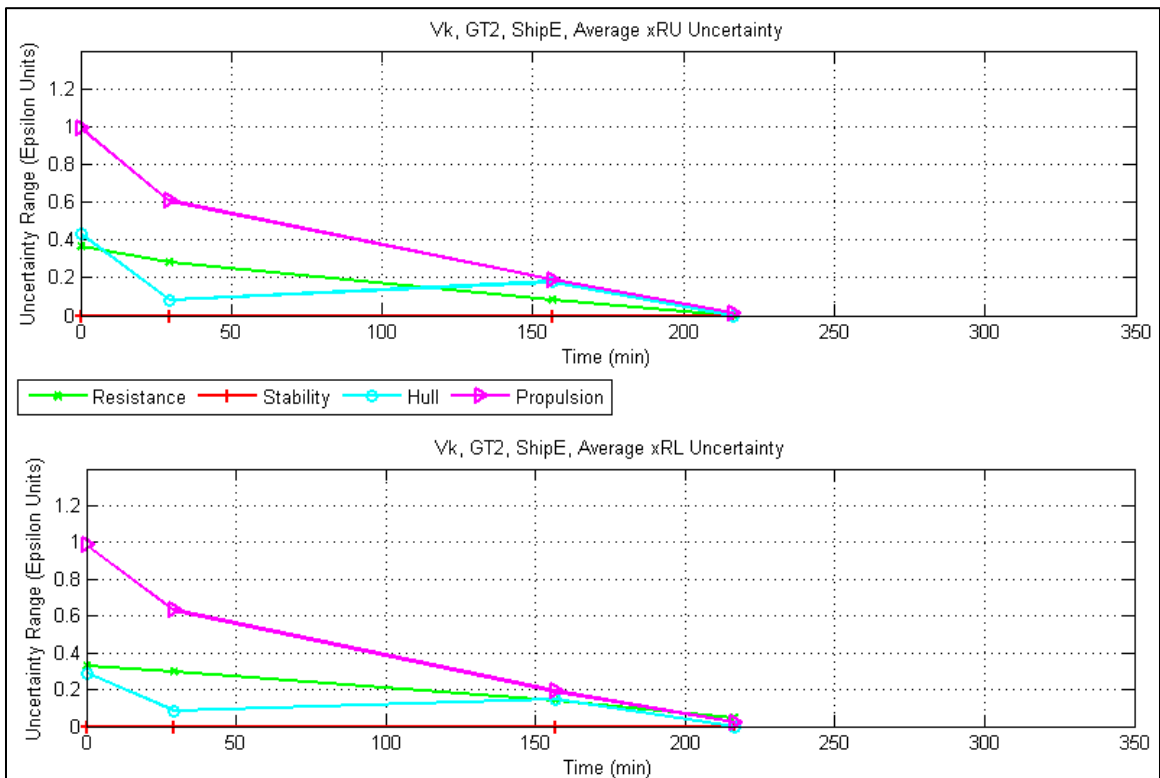
GT2, Ship E, Magnitudes of Uncertainty for *Threqd* vs. Time



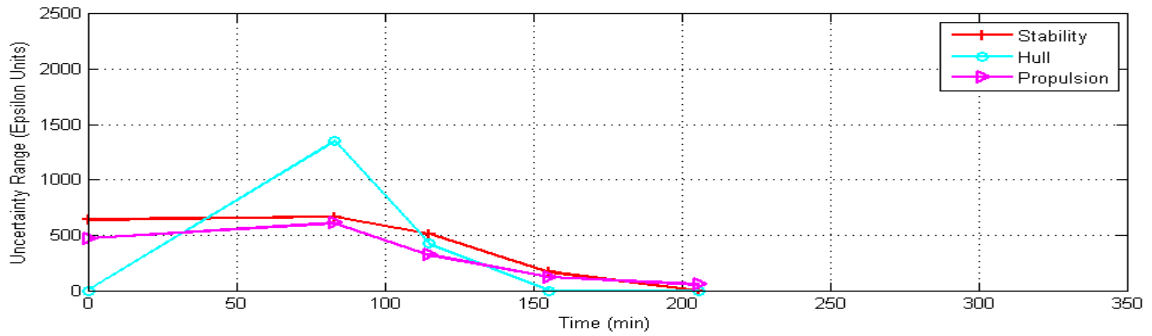
IT2M (Slopes), Ship E, Magnitudes of Uncertainty for V_k vs. Time



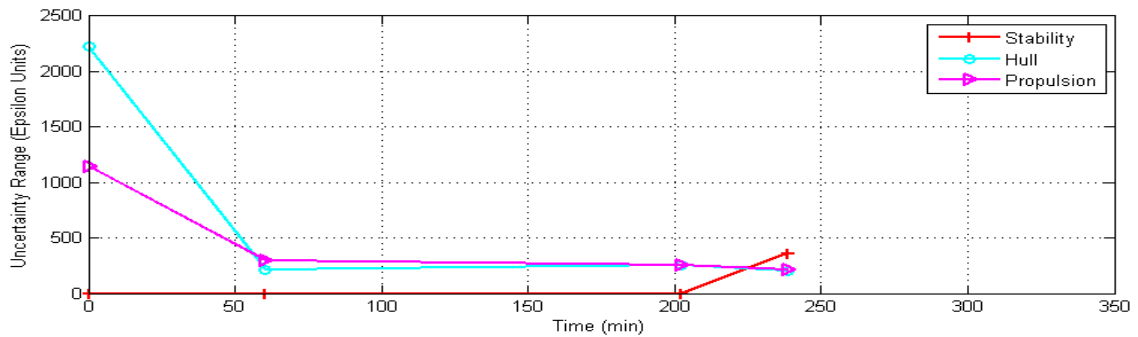
IT2M (Choice), Ship E, Magnitudes of Uncertainty for V_k vs. Time



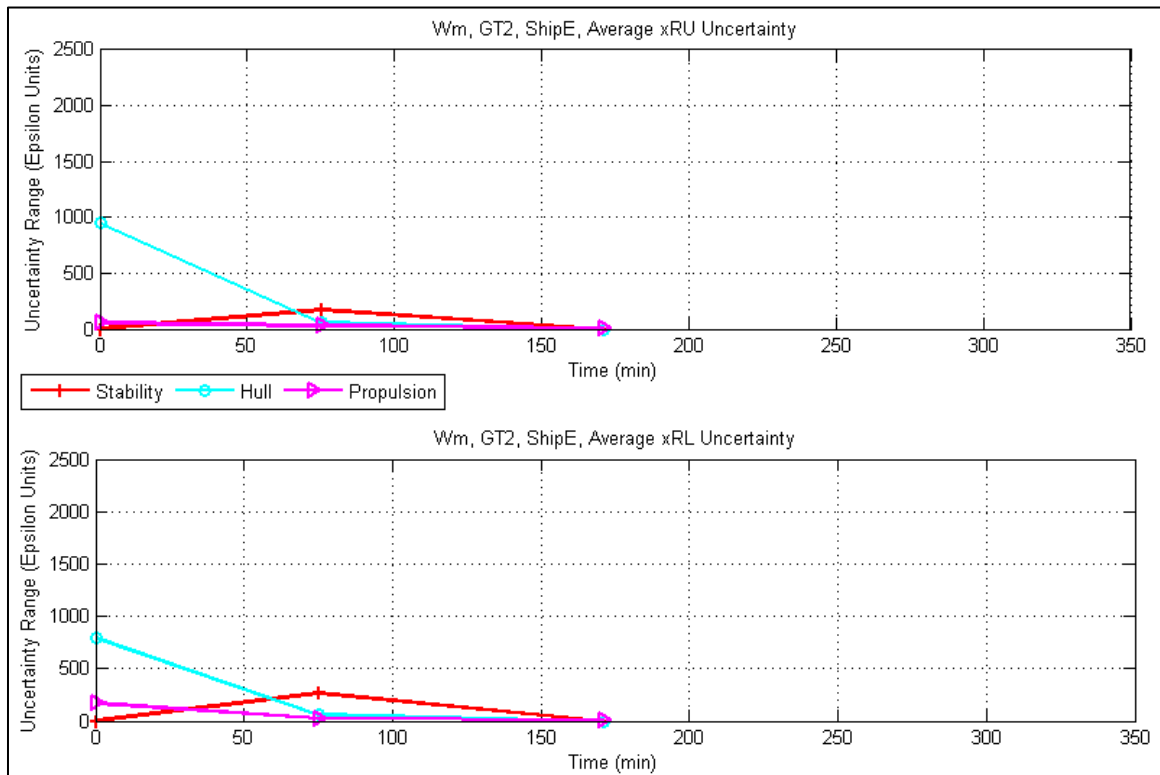
GT2, Ship E, Magnitudes of Uncertainty for V_k vs. Time



IT2M (Slopes), Ship E, Magnitudes of Uncertainty for W_m vs. Time



IT2M (Choice), Ship E, Magnitudes of Uncertainty for W_m vs. Time



GT2, Ship E, Magnitudes of Uncertainty for W_m vs. Time

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