A Study of Student Design Team Behaviors in Complex System Design

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ABSTRACT

Large-scale engineering systems require design teams to balance complex sets of considerations using a wide range of design and decision-making skills. Formal, computational approaches for optimizing complex systems offer strategies for arriving at optimal solutions in situations where system integration and design optimization are well-formulated. However, observation of design practice suggests engineers may be poorly prepared for this type of design. Four graduate student teams completed a distributed, complex system design task. Analysis of the teams' design histories suggests three categories of suboptimal approaches: global rather than local searches, optimizing individual design parameters separately, and sequential rather than concurrent optimization strategies. Teams focused strongly on individual subsystems rather than system-level optimization, and did not use the provided system gradient indicator to understand how changes in individual subsystems impacted the overall system. This suggests the need for curriculum to teach engineering students how to appropriately integrate systems as a whole.

1 Introduction

The increasing complexity of modern products and systems demands that engineers and designers be equipped with a diverse set of skills and expertise. One of these skills is the ability to address these designs at a systems level that can

effectively integrate disparate subsystems and technologies. The National Academy of Engineering has made the teaching of systems perspectives, including structured methods for integration, a priority of engineering education [1], and in particular, the ability of students to think on a systems level is considered to be a key goal of effective design education [2–4]. Specific examples of such skills include thinking about system dynamics, making estimates, and reasoning with incomplete information [5]. College engineering graduates have been shown to perform particularly poorly in estimation [6].

This study investigates the system-level approaches employed by teams of engineering graduate students with a focus on how they make trade-offs among subsystems to arrive at a "good" overall solution. In engineering practice, the process of designing complex systems by teams remains challenging [7, 8], in part because of the volatile nature of complex system design but also because design teams are populated by humans who can be fallible, err in judgment, or make choices that are inconsistent with each other [9–11]. In practice, good system design is difficult to accomplish even by experienced practitioners under favorable circumstances.

Formal frameworks for system level design, such as Game Theory and Multidisciplinary Design Optimization (MDO), provide strategies for arriving at optimal design solutions that effectively balance trade-offs. In particular, Game Theory hinges on the assumption that subsystem designers consistently make rational choices during the design process in order to arrive at a Nash Equilibrium [12]. In these models, the type of information passed between the sub-system designers helps determine how close to optimal the equilibrium lies. In some models, this information is in the form of a gradient, whose magnitude and direction the designers use to determine how to change the value of a given input parameter.

In this study, student teams are examined in the context of a structure based on a Game Theoretic approach under the belief that any improvements identified will benefit system design overall.

1.1 Research Questions

The broader vision for this research is two-fold: a) to better understand how design teams behave during complex system design in order to create more effective, usable formal tools to support design, and b) to improve our understanding of what skill sets are needed for system design to identify areas for curriculum improvement.

This brief explores the following narrower research questions:

1. In what ways will student decision-making differ from computer simulations?
2. How much will student-generated solutions deviate from optimal solutions?
3. If student-generated solutions do deviate from the optimal, what are the possible causes?

Current formal models define teams using three basic components: communication or team structure, type of information passed between subsystems, and the subsystem decision-making process. By testing different combinations of these three components, these models offer insight into the team design process for a given problem. If a particular combination of team structure, information passing method and decision-making process work "well" together, then that design process can be considered "superior" to other processes tested. This paper investigates communication structure and information passing methods derived from Game Theoretic approaches in a study of student designers.

2 Related Work

The design of complex engineered systems is typically conducted by interdependent, multidisciplinary subsystem design teams. An ongoing challenge in system design is how to distribute limited resources, such as mass, power and budget among a set of subsystems and effectively integrate the subsystem into overall system. This situation is further complicated by the increasing use of distributed teams to design these systems [7] which presents communication and team cohesion problems for collaboration [13]. Formal methods offer some strategies for navigating these challenges but rely heavily on the ability of the designer.

2.1 Structures for system-level design

Large engineering systems are traditionally broken down into functional hierarchies. For example, an aircraft design can be broken down into structures and propulsion subsystems, with overlapping but not identical design parameters [14]. Furthermore, each subsystem can have thousands of input variables. In the classical approach to problems of this type, each subsystem is designed independently by discipline with system-level iterations occurring periodically throughout the process [15]. New systems-level approaches have been developed to increase the speed and effectiveness of the design process [16]. Industry has been quick to adopt systems-level approaches to interdisciplinary design [15–18].

2.2 Design process models for complex systems

A metamodel is one tool used to quickly explore design spaces and converge to an optimal set of solutions. Metamodels either evaluate or approximate subsystem response to design parameter inputs. By generating system-level design outputs by integrating subsystem responses, the models can systematically search the design space and help guide designers towards an optimal design outcome. A limitation stems from the ability of the metamodel to accurately and quickly approximate the subsystem response to design inputs. These tools reflect a balance between local and global knowledge of the system as defined by Papalambros [19]. Designers rely on their expert knowledge of the global design space for validating approximations as they create simplified subsystem models. The numerical algorithms rely on local knowledge at each iteration to make decisions about the "best" direction to search. Simpson, et al. [20] present a wide range of problems that can be addressed through metamodels and associated algorithms. Sobieszczanski-Sobieski and Haftka's survey [21] demonstrates the range of applications in the aerospace industry.

Game Theory [12] is an approach for modeling the multidisciplinary design process and was first proposed by Vincent [22] and further developed by Lewis and others [23, 24]. These traditional game theoretic approaches have further been combined with Decision-Based Design [25] and adopted in a broad range of design research [26–29] to become a prominent framework for the study of multidisciplinary design problems [30]. Game Theoretic design attempts to identify a rational design called Nash Equilibrium [12] given limits to the amount and form of information being passed between designers. The resulting designs may differ depending on the type and quantity of information exchanged. Thus, the resulting designs will be rational given limited information, but will not necessarily result in an optimal design.

2.3 Team structure

Key components common to all of the metamodels are 1) the team structure or roles (i.e. the "direction" and "order" in which information is passed), 2) the form of the information passed between subsystems (such as point design and local sensitivities) and 3) how each subsystem makes decisions and trade-offs. This paper explores the last of these elements. Simulations have allowed researchers to observe the effect of changes, at an abstract level, in team structure, information passed and individual decision-making on performance metrics such as the speed and accuracy of the optimization. Yi, et al. [31] compare seven MDO approaches with different hierarchical team structures. MDO models rely on a system facilitator who will make optimal trade-offs that will benefit the overall system. Honda, et al. [32] compared different team structures, including Game Theoretic and MDO approaches. Lewis and Mistree presented a Game Theoretic approach where each agent is involved in the optimizing task. Agents made decisions using a compromise decision support problem [14]. In doing this type of analysis, researchers have suggested best practices for design processes. Collopy outlines a strategy for reaching an optimal design based on passing of gradient information [33].

2.4 Bounded rationality decision-making in teams

Models such as those presented above often assume designers are homogeneous agents who optimize their objective functions effectively. This assumption uses a definition of objective rationality, where the decision-maker will make the "optimal" or correct choice in every decision [34]. Research in the area of bounded rationality explores the consequences of limited resources found in real-world situations [35]. Models employing bounded rationality assume that since designers may have limited information and problem-solving capabilities they cannot evaluate and therefore cannot optimize their objective functions perfectly [9]. Satisficing and fast and frugal heuristics such as "take the best" or "take the last" algorithms are among the examples of bounded rationality models [36]. Computer experiments such as Gurnani and Lewis' study of collaborative decentralized design can use randomness to simulate this uncertainty [29]. In these situations, bounded rationality is distinct from irrationality, which is defined as making a clearly inferior or sub-optimal choice [34].

2.5 Communication in teams

There is a rich body of literature on factors that affect team performance from organizational behavior, psychology and sociology. Because system design is commonly performed by teams, the most relevant research in this area tests factors which affect team success across an array of interdisciplinary problems.

Communication is a key factor in many of these studies. Nardi and Whittaker [37] emphasize the need for a shared team understanding for social communication. They investigated the importance of face-to-face communication in distributed design situations. Similarly, networking in the physical space of collocated teams has been shown to be an important determinant for design quality [38]. Team communication is also addressed in the area of team cognition. Cooke and Gorman [39] demonstrate several measures using communications as a method for understanding the team decision-making process and its ability to accomplish high-level processing of information and reach an optimal decision.

2.6 Novices and Experts

The novice-expert spectrum has been widely studied in a number of fields [40–42]. Cross' overview covers many of the findings on novices and experts within design research [43]. Kruger and Cross demonstrate that experienced and inexperienced subjects think about and solve ill-defined problems differently [44].

2.7 Research Gap

This study bridges the gap between research on formal strategies for system design and research on team behavior. This paper integrates the lessons from both social science research and formal models for complex system design to understand how well-prepared engineering students are in performing system design given the challenges of making rational decisions. This paper seeks to build on existing work and formal, computational strategies for system level design and human-centered approaches.

In using human subjects to make decisions, the study builds upon complex system design by identifying factors which affect the subsystem decision-making process and their relative importance to the overall system optimization process. This article also draws on previous work in engineering education by addressing the performance of graduate students on system design tasks.

3 Method

In this study, four three-person teams of graduate students from mechanical, aeronautical, and systems engineering performed a design task using communication structure based on a Game Theoretic approach. The approach was modified by relaxing the sequential constraint generally used by Game Theoretic models. All were full-time students, and the subjects had average of 3 years of work experience, ranging from 1 to 10 years. Three of the teams had at least one member who had completed a semester-length graduate engineering course on MDO methods and so had been exposed to formal methods for system design.

4 Procedure

Each team was given a short (10 minute) introduction to the design task. The presentation consisted of an overview of the task, communication tools to be used in the experiment, a walk-through of one iteration of the design cycle, a demonstration of the local sensitivity gradient vector and an explanation of the performance objectives of both the engineering system and of the team. The subjects were then provided informed consent. A custom-built spreadsheet and Skype instant messaging tools were provided to support and capture the team design activity. Team members were then stationed in separate rooms at a computer for the remainder of the experiment in order to: 1) more closely mimic a realistic distributed team scenario and 2) allow the electronic capture of all communication between the subsystems [45]. The subjects were given several minutes to familiarize themselves with the computational and communication software and ask questions regarding the experimental setup. The team had up to one hour to complete the design task. The one hour time limit was determined by testing on a pilot team. The pilot study team felt one hour was more than sufficient to complete the task. At the end of the hour, the team

selected their best iteration and the message logs and design histories were archived.

4.1   Design Task

The *Firesat* satellite example from Wertz and Larson's *Space Mission Analysis and Design* [46] was chosen as the design task because similar problems have been studied in other complex systems optimization research [14, 47, 48]. At the same time, the problem was intentionally presented at a sufficiently high level that no domain expertise beyond an undergraduate engineering degree was required to complete the task. The design problem was broken down into three subsystems: Payload & Orbital, Power, and Propulsion. Figure 1 shows the linked system of input and output variables. The highly coupled nature of the system is manifested by the effect of input variables such as Mass of Payload (M_{pl}), Total Allowable Change in Velocity (ΔV), and Payload Power (P_{pl}) on multiple output variables. An adapted formulation from Honda, et al. [32] was used because its relatively low number of design variables made it tractable within the short time period of the controlled laboratory experiment. The aim of this optimization is to minimize both Ground Resolution (*GR*) and Total System Mass (M_{tot}) by varying M_{pl}, ΔV, and P_{pl}. The quality of a given solution was measured by its closeness to the Pareto Optimal Frontier and its compatability error as defined below. To convert the optimization from a sequential formulation to a concurrent formulation, "slack" variables similar to those used in Linear Programming were introduced. These "slack" variables represent the expected output from subsystems that are required by other subsystems. In this case, the "slack" variables are expected height (h_{exp}) and expected mass of power subsystems($M_{pow,exp}$). Ideally, the expected input values (h_{exp} and $M_{pow,exp}$) must match the calculated values from other subsystems (h_{calc} and $M_{pow,calc}$) at the final design stages.

The compatibility error at a given iteration was defined as the percentage error between either h_{exp} and h_{calc} or $M_{pow,exp}$ and $M_{pow,calc}$, whichever is higher. Compatibility error was calculated using the following equation:

$$\%err = \max\left(\frac{||h_{exp} - h_{calc}||}{(h_{exp} + h_{calc})/2}, \frac{||M_{pow,exp} - M_{pow,calc}||}{(M_{pow,exp} + M_{pow,calc})/2}\right) * 100\% \tag{1}$$

Ideally, the "slack" variables would be equal at the final design state and the compatibility error would be zero. However, an allowable discrepancy of 10% was set for the final iteration to minimize the teams' sense that they had to "polish" their result during the short time frame of the experiment. This compatibility error allows for leeway in the team decision-making process in two ways. First, the compatibility error constraint means that the teams are not forced to act in a completely Game Theoretic manner. For example, one designer could be tasked by the team to act as a systems facilitator to check the compatibility error and as a sub-system designer. The teams could also choose to act in a strict Game Theoretic manner and perform subsystem iterations sequentially and avoid the compatibility error altogether. Teams could also choose to operate somewhere between those two extremes. Second, computer simulation shows that a Modified Game Theoretic approach using slack variables can converge to a Pareto Optimal solution within the desired accuracy in a few iterations [32]. The compatibility allowance for that simulation was set at 0.1%. By allowing a compatibility error of 10%, the number of iterations required to converge to an optimal solution decreases. The error was set at this level to allow for convergence in a realistic number of iterations given the one hour time frame.

4.2 Design Tools

Figure 2 shows the team structure and communication links between team members. In the Modified Game Theoretic approach, the subsystems can communicate freely directly with each other to try to improve system design.

An Excel spreadsheet and an associated Visual Basic subsystem macro, inspired by NASA's Jet Propulsion Laboratory ICEMaker tool [49], was customized to facilitate the exploration of the design space. This spreadsheet allows each subsystem designer to calculate the output parameters for any given input vector. The spreadsheet also alerted the designer by outputting "not a number" in the output parameters if given an infeasible set of input parameters.

4.2.1 Design Guidance

A fundamental challenge of system design is a lack of visibility on how one design decision affects the overall system. The design tool calculated the local sensitivity vectors (gradient) to provide a design indicator to help the designer optimize the objective. The gradient gives the designer information on the local effect of the input variables on each output variable. In this way, the gradient indicates both the desired magnitude and direction of change in the input parameters for minimizing a given output. However, because there are multiple objective outputs, the designer must balance the information provided by the gradient for each objective and decide on a final direction and magnitude. This information is considered essential to finding the optimal solution quickly in this study. Although non-gradient based global search algorithms exist, they generally require thousands of iterations to converge to a solution and are therefore unrealistic in this setting. This information was provided to the subsystem designers to help them focus solely on their decision-making process when balancing competing objectives. The Excel tool automated the calculation of the local sensitivity vector and the design parameter outputs. Communication of this information to the rest of the team was left to the subsystem designer.

4.2.2 Systems-level communication tools

A shared Google Docs spreadsheet was created for communication of these vectors between distributed team members. The Google Docs spreadsheet also combined the gradient information from each subsystem into an overall sensitivity vector for output parameters "Ground Resolution" (GR) and "Total Mass" (M_{tot}) with respect to system input variables. The Google Docs spreadsheet was accessible to multiple team members in near-real-time. The Skype messaging system was used to allow for real-time communication between team members. The team structure was reflected in both the Google Docs spreadsheet and Skype programs with each subsystem able to see and edit all of the group documents. This tool automated several of the key communication requirements. In the Google Docs spreadsheet, there was only one location for design input parameters, so as to prevent errors between subsystems using different inputs on the same iteration. Also automated was the communication of sub-system gradients between different subsystems.

5 Results

The history of design choices of the four teams, referred to as Teams 1 through 4, were analyzed to ascertain the optimality of the final solutions and compared to an optimal baseline of the Pareto Frontier. All teams had at least one

member with MDO experience. The Pareto Frontier was generated via simulated annealing and provides a set of global optima. The teams' self-selected "best" designs are plotted in Figure 3 along with the Pareto Frontier. Beside each "best" design is a percentage value that indicates the error as calculated by the compatibility constraint (Eq. 1). None of the design teams generated a feasible solution that was substantially closer to the Pareto Frontier than the initial design point given to the teams. Only Team 1 was able to keep the compatibility constraint to within 10% (Figure 3). Team 2 appeared to achieve Pareto Optimality, but the compatibility error was unacceptable (25%) causing it to be an infeasible solution. Team 4 also had one iteration within the compatibility constraint but chose an infeasible solution as their final answer.

Figure 4 shows the history of the designs that each team explored over the hour. Teams 1 and 2 generated 8 designs each, Team 3 generated 7 designs and Team 4 generated 3 designs in total. None of teams managed to improve both GR and M_{tot} simultaneously in any iteration.

Figure 5 shows the high variability of compatibility error among the teams at each design iteration. Team 1 had consistently low compatibility error. Team 2's initial design had low compatibility error but this increased as they generated new designs. Compatibility dropped back down after they returned to their initial designs. Team 3 had high compatibility error throughout the hour. Finally, Team 4's initial iterations were within compatability error but then moved to an infeasible solution with an extremely high compatability error.

5.1 Types of decision-making strategies

An analysis of the design histories and the messages passed among team members via Skype showed that all four teams arrived at sub-optimal solutions when compared to computer simulations. The sub-optimal choices can be classified into three types of decision-making errors: 1) performing a global search poorly rather than focusing on executing a local search efficiently, 2) optimizing a single input parameter at a time rather than exploiting coupling information between input parameters represented by the gradient and 3) optimizing the subsystems sequentially instead of concurrently. Table 1 shows the number of Skype messages that each team sent in each category. Since the total number of messages was different for all teams and this tally is only for messages concerning each type of decision, absolute numbers are not significant. Rather, the prevalence of the messages indicates what type of error each team was committing.

In analyzing each team individually, the errors can be broadly labelled as optimizing from a local instead of a system perspective. In essence, the teams preferred a trial-and-error strategy instead of other common optimization techniques used in the computer simulations such as sequential linear programming [50] and sequential conjugate gradient-restoration method [51]. For example, Team 1 optimized a single parameter at a time. Since the subsystems are highly coupled, this method converged to an artificial local optima. In other words, fixing design parameters will provide additional constraints that create local optima that do not exist without these constraints. Thus, optimizing input values independently tends to converge to suboptimal solutions in coupled systems. Team 1 also performed subsystem iterations sequentially instead of concurrently. Given the short time frame of the experiment, concurrent iterations by each subsystem would have allowed for more iterations and possibly a closer-to-optimal solution. However, the sequential iterations avoided compatibility issues as the outputs h_{calc} and $Mpow_{calc}$ were used as the inputs for the next subsystem. This choice of a sequential strategy can be

thought of as an example of bounded rationality. Although the sequential strategy is slower than the concurrent approach and therefore objectively inferior, it could be considered the "best" decision for this team given a limited understanding of how to enforce compatibility between the subsystems. Overall, Team 1 performed the best of the 4 teams in terms of optimality and compatibility error. It must be noted that they chose as their "best" solution an iteration which favored minimizing GR over their final iteration which was actually closer to Pareto Optimality. This may be due to the team's limited information regarding the location of the Pareto Optimal Frontier. Their decision may indicate that the the team was not using gradient information to evaluate how close the solutions were to the Pareto Frontier.

Team 2's message logs show that they also preferred a trial and error strategy. The team searched the design space by doubling or halving input parameters and evaluating the effect on the objective variables. It is possible that this team aimed to look for global minima, rather than local minima. However, this strategy also led the team to arrive at a suboptimal solution. Given a highly-coupled complex system, small local searches are important in order to take advantage of information gained from the current design state. The nonlinear response to input vectors means that a general "downhill" direction can not be established from global searches. The large changes in input parameters also led the team to several infeasible solutions during their exploration of the design space. This strategy also caused large compatibility errors. At two points in their search, the team was close to a Pareto optimal solution, but with large discrepancies between h_{exp} and h_{calc}. At these two times, the team could have used the gradient information to correct the compatibility error. They instead moved the input parameters again and arrived at a final solution very close to the original starting point.

Like Team 1, Team 3 also optimized input variables independently on some iterations, mentioning this a total of 12 times in their message logs. Their searches were more local in nature and they did not explore the breadth of the design space well. Although the team did refer to local sensitivity vectors when discussing design decisions, they did not record the gradient information in their design history. They also had a large compatibility error of over 100%. The team did not mention this large discrepancy or compatibility error in their message logs, even though they had been instructed to keep the compatibility error of at least the final solution to less than 10%. It is not possible from the given message logs and design histories to state whether the team simply focused on other objectives and ignored the compatibility error or did not correctly compute the compatibility error.

Finally, Team 4 also optimized input variables independently. They also had the fewest number of iterations. Although their second design was in the direction of the Pareto Frontier and was within the compatibility error constraint, their final iteration was infeasible and had a compatability error of over $10^{305}\%$. The message logs show the team was using non-local searches on each input variable independently. The team also chose their final iteration as their "best" iteration instead of the second result, which was within all of the constraints. In fact, their second iteration was one of the best designs by all teams, but the teams' lack of experience showed when they chose an infeasible solution over this better design.

Notably, three of the four teams only recorded the gradient information in their design history for several of the iterations. In the message logs, Teams 1 and 3 mentioned the gradient 11 and 8 times respectively, Team 2 only mentioned local sensitivities once. Team 4 recorded gradient information, but only performed three iterations. This coupled with the teams' inability to minimize both objective variables simultaneously in one iteration indicates that teams were using the gradient

information sparingly in their decisions.

6 Discussion

In this study, the three main components of metamodels were implemented in the context of a human design team. The study used a team structure derived from Game Theoretic approach with each subsystem being represented by one designer. Gradient information in the form of a local sensitivity vector was available and freely passed between the subsystems. The individual subsystem decision process was controlled by the human designers. Results showed that the subjects behaved in several unanticipated ways.

6.1 The Use of Subsystem Performance Indicators

Since only the systems-level design histories were archived, it cannot be determined if individual subsystems used the gradient information. However, given the coupled nature of the problem, a systems-level use of the gradient information is more critical. It was therefore expected that teams would look to the local sensitivities vector for guidance in generating their designs, especially since the gradient was provided at minimal extra cost in time or effort. A surprising result is that the Skype logs suggest that teams did not use the gradient. The gradient was mentioned sparingly and the behavior did not indicate that members were working at a systems level.

Because of this, the influence of the type of decision-making strategy became much more important. However, these results show that teams had a difficult time choosing an effective strategy.

Two major components of the decision-making process are the choice of optimization strategy and the convergence criteria. Common optimization techniques utilized by computer simulations are gradient-based strategies such as conjugate gradient techniques and constrained linear programming. These techniques are also widely used by industry due to their step-by-step procedure and ease of implementation. Non-gradient based approaches such as genetic algorithms and simulated annealing are also common optimization techniques in industry. However, these approaches generally require thousands of iterations to converge and are therefore unrealistic for for human design teams to apply [52]. Furthermore, the objective variables can be optimized either simultaneously or sequentially as in the case of constrained linear programming. These techniques contrast with the trial-and-error strategy chosen by the designers in this study. Convergence criteria are not applicable to the results in this study as all of the teams used the full amount of time without converging to a Pareto Optimal solution.

6.2 Team Dynamics

Based on the Skype instant messages exchanged within the teams, team dynamics also played a role in the strategy choice. In accordance with the rational model of group decision-making [53], all of the teams discussed what they should do before they began. However, suboptimal strategic choices were made during this initial stages for all four teams. For example, Team 2 decided to double and halve input parameters to explore the design space in a basic trail-and-error strategy. In the particular case of Team 2, one member suggested the doubling strategy and the other team members may have accepted

it because of pluralistic ignorance. This is likely example of Abilene Paradox [54], in which one team member's suggestion is not refuted because the others perceive that the particular team member has expertise and/or information that they do not possess. The distributed nature of the teams in this study meant individual members did not have information on the relative expertise of other members.

6.3   Designer Skill Level

Optimization skills and systems-level perspectives may be more apparent in design teams with more experience in complex system design. A more experienced design team might be more likely to use gradient information. This case study suggests that complex system design process models could incorporate more information about the human aspects of the decision-making process. In this study, the skill level of the designers with respect to optimization and their inability to think from a systems-level perspective dominated the overall optimization and led to sub-optimal solutions. Also, the teams preferred to not use the gradient information. Since gradient-based optimization approaches are often more efficient, this suggests the need for either alternative methods of presenting the gradient information for effective use, a design protocol which is robust to novice mistakes or more focus on system-level perspective in engineering education.

6.4   Limitations

Limitations to this preliminary study include the size of the population, usability of the software and the distributed nature of the team. First, team trust and cohesion has been shown to be important to team success [13]. Subjects were assigned to teams randomly, but teams who have worked together before or have a stake in working together in the future may have performed differently in this study. The team members were also separated to mimic the work environments of real-life distributed teams, though a related body of research suggests that co-located teams often perform better than virtual teams [16], particularly in the early stages of working together. Secondly, the communication tool was unfamiliar to the subjects and the Excel spreadsheet computation time for each subsystem varied slightly. Slower than real-time communication through the tool could have influenced the number of iterations possible. Finally, although the one hour time limit did not seem to limit the number of iterations used by the teams, it's possible that the time pressure may have affected the choice and execution of the teams' optimization strategies.

7   Conclusions

Results showed that a number of possible human factors dictated the outcome of the decision making process. The student designers preferred utilizing a trial-and- error strategy or drawing on design history rather than using more accurate gradient information that indicated how to best change a design parameter. When individual designers attempted to optimize their subsystems via trial and error, each assumed that his or her subsystem functions were separable with respect to input variables and so optimized each input independently. In reality, the subsystem functions were highly coupled, and this strategy led to suboptimal solutions. It was also found that designers focused on their individual subsystems rather than on the overall system perspective. The students performed poorly when thinking about system dynamics and in understanding

optimization strategies. This brief suggests the need for design protocol that is robust to these types of mistakes. Further focus on these areas is also needed in engineering education.

1. In what ways will student decision-making differ from computer simulations?

   Human design teams differed from computer simulations in their choice of design strategy and in the rationality of their behavior. It was expected that the students would utilize the gradient information provided to guide their choices, but they did not. Without the aid of gradient information, designers relied on various decision-making strategies to generate designs.

2. How much will student-derived solutions deviate from optimal?

   The solutions that resulted from the above strategies deviated substantially from optimal with three of the four teams searching infeasible design spaces.

3. If they do deviate from optimal, what is the cause?

   This study identified several possible causes such as a lack of system-level optimization knowledge or training and team dynamics.

8 Moving forward

The results of this study have implications for how engineering students should be trained and educated. As has been pointed out in Dym [5], current engineering curriculum focuses on analysis of components and subsystems, and less on how to integrate these subsystems into a larger overall system. Most engineering systems, whether simple or complex, require some understanding of how decisions for one subsystem affect those for another subsystem. The factors identified in this case study could be used in future studies refining engineering curricula as well as design process models. In particular, the results of this study suggest that students could benefit from more training in system-level thinking, in particular strategies for making trade-offs and balancing an overall system.

In this brief, several factors were identified as important to team success. Future work will involve studying teams with more experience in designing engineering systems to assess their behavior in this type of system design scenario. This could include both student teams whose members have more system optimization experience as well as teams composed of practitioners. In particular, it would be useful to understand what strategies such designers employ. By varying the experience level of the teams, as well as employing teams with mixed levels of experience, future work could gain insight into how complex system design choices differ along the expert-novice spectrum. Results may also illuminate how team dynamic issues change with differing levels of experience.

Although this thesis was structured around the Modified Game Theoretic model of complex system design, future work could also include testing of team structures such as MDO on human decision-making. Work in this area would be

compelling, as some formal structures were created to mitigate human error. For example, MDO has a systems facilitator role to account for a lack of systems-level perspective in many teams. This type of robustness could be tested using a methodology similar to the one presented in this work.

Achnowledgements

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List of Table Captions

1. Table 1: Errors mentioned in messages between team members

List of Figure Captions

1. Figure 1: Input and output variables for satellite design example

2. Figure 2: Modified Game Theoretic team structure for the design team and task. The three subsystems are allowed to confer and negotiate directly without a mediator.

3. Figure 3: Comparison of 4 "best" design results selected by the teams. The Pareto frontier serves as a baseline. The percentage next to each point is the compatibility error of that solution.

4. Figure 4: Design History for each team. Each path shows the design points explored by individual teams.

5. Figure 5: Compatibility Error between subsystems as function of design iteration

Table 1. Errors mentioned in messages between team members

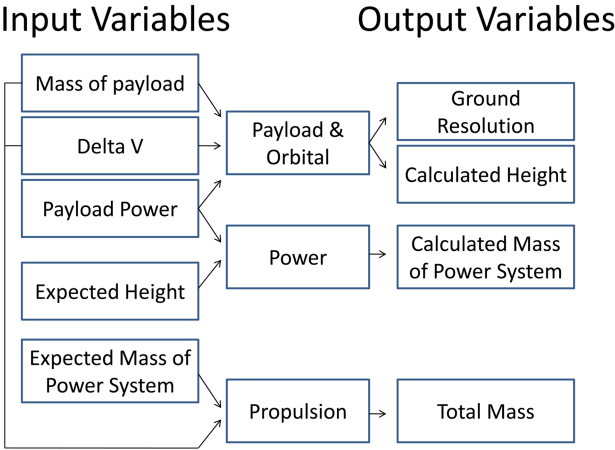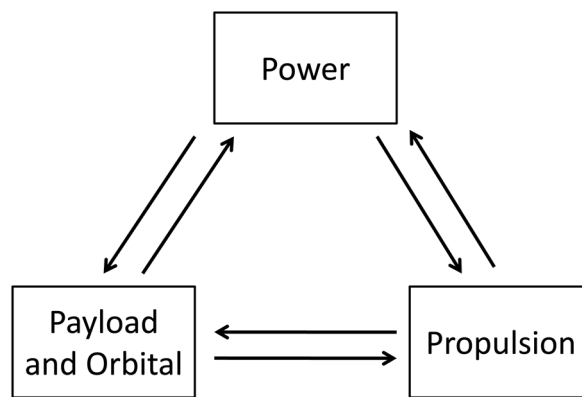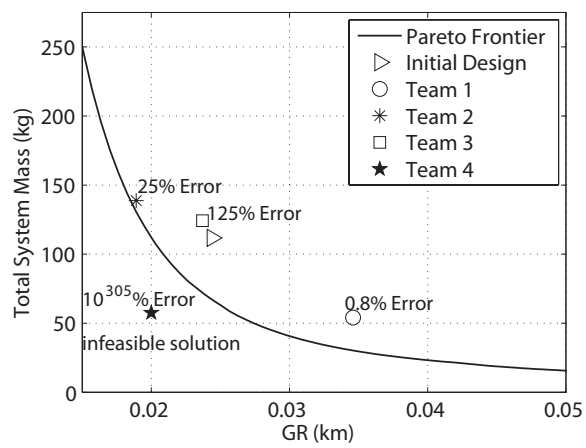| Problem Type	Team 1	Team 2	Team 3	Team 4
Non-local search	2	16	0	10
Optimizing single input	22	9	1	12
Optimizing sequentially	3	4	1	0

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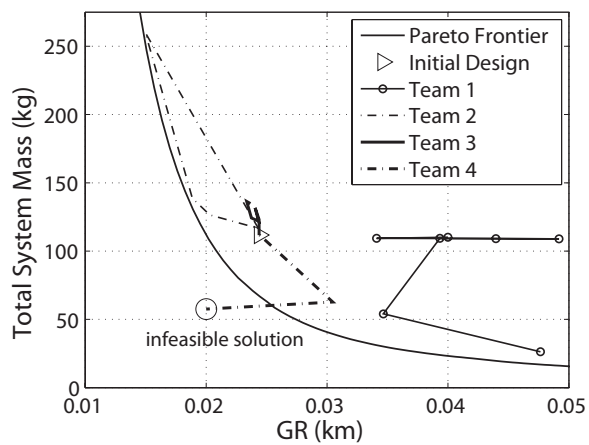
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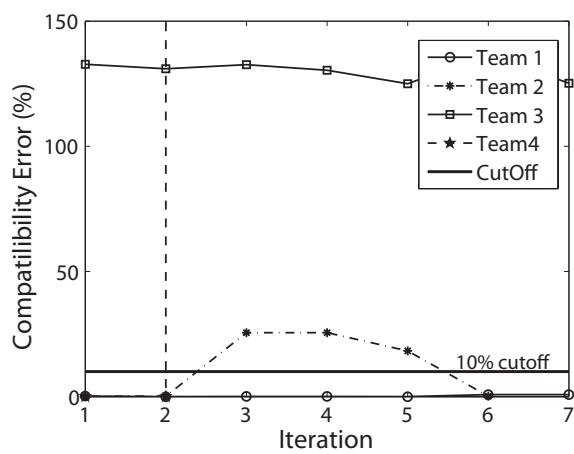
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