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CHANGING SUBSYSTEM INFORMATION STRATEGIES USING WEIGHTED OBJECTIVES: INCREASING ROBUSTNESS TO BIASED INFORMATION PASSING

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ABSTRACT

Complex system design requires managing competing objectives between many subsystems. Previous field research has demonstrated that subsystem designers may use biased information passing as a negotiation tactic and thereby reach sub-optimal system-level results due to local optimization behavior. One strategy to combat the focus on local optimization is an incentive structure that promotes system-level optimization. This paper presents a new subsystem incentive structure based on Multi-disciplinary Optimization (MDO) techniques for improving robustness of the design process to such biased information passing strategies. Results from simulations of different utility functions for a test suite of multi-objective problems quantify the system robustness to biased information passing strategies. Results show that incentivizing subsystems with this new weighted structure may decrease the error resulting from biased information passing.

1 Introduction

A constant challenge in large engineering organizations is to design and develop complex systems that successfully balance competing subsystem trade-offs. A number of powerful structured design approaches have been formulated to model and optimize these trade-offs. In real-world practice, however, these approaches cannot always be applied. In fact, teams must make choices based on time and budget, and may opt for satisficing decision-making [1], and often must address poorly defined problems [2].

A rich body of literature exists to help complex system designers reach more optimal solutions. Formal conflict resolution processes and associated design support tools, such as the NASA Jet Propulsion Lab's Icemaker [3] and market-based allocation algorithms [4], have also been developed to facilitate communication and decision-making between subsystems. Mathematical simulations are also used to simulate the optimization of complex systems. Simpson, et al. review the multitude of problems that can be addressed through these types of algorithms [5]. Sobieszczanski-Sobieski and Haftka [6] demonstrate the range of aerospace applications.

Previous field study interviews by the authors with designers of complex systems has demonstrated two key findings about complex system design decision-making within a large aerospace organization. First, the informal system of negotiation between subsystems resolved the vast majority of design parameter conflicts. System integrators and subsystem designers estimated that the formal conflict resolution process resolved between 5 to 10% of all conflicts. Second, biased information passing was a negotiation strategy used by many of the subsystems throughout the design process. This strategy consists of reporting overly-conservative estimates of design parameters to other subsystems in order to reserve excess capacity as a negotiation chip in future negotiations [7]. In other words subsystems tended to optimize around their own needs, rather than the needs of the overall system. This second observation was formally modeled, and experiments showed that biased information passing could have a negative impact on the speed and feasibility of reaching a design solution. Reflection on the above two findings suggested one possible strategy to combat biased information passing, which is to formulate an incentive structure to bring subsystems into alignment with the goals of the overall system.

This paper presents results from simulations of biased information passing that build on [7] by examining the role of subsystem incentives. In the new proposed incentive structure, at the end of every iteration each subsystem is evaluated not only on its own performance but also partially on the performance of the other subsystems. This may incentivize subsystem designers to consider solutions that benefit both subsystems instead of just their own. The simulations use Multi-Disciplinary Optimization (MDO) techniques to investigate the possible effects of changing incentive structures for subsystems.

This study seeks to answer the following questions:

1. What is the effect of biased information passing on system-level optimality in a complex system with the proposed weighted incentive structure?
2. What impact might these strategies have on the speed and quality of system optimization?

Speed and optimality are important indicators for comparing optimization algorithms and can lead us to a better understanding of the impact of the proposed incentive structure. Is it feasible for such a system to achieve more optimal results if subsystems are incentivized to consider the performance of other subsystems? If so, is this structure more robust to biased information passing than a normal system?

2 Related Work

This paper draws on previous work in both formal mathematical models of the design process, negotiation within complex system design as well as decision-making literature from a variety of fields. Perspectives from these sources are used to gain insight into the design of proposed incentive structure and its effect.

2.1 Complex System Design Process Models

A substantial literature exists on modeling complex system design. One approach, Game Theoretic design, attempts to identify a rational design given limits to the amount and form of information being passed between designers. The use of Game Theory as an approach for modeling complex system design has been developed by Vincent [9], Lewis [10], and Whitfield, et al [11]. Traditional Game Theoretic approaches combined with Decision-Based Design [12] have been used in a broad range of design research [13–16], becoming a leading framework for the study of multidisciplinary design problems [17].

The complex system design process can also be viewed as a multi-objective optimization problem. Multidisciplinary Optimization techniques utilize this philosophy [18]. MDO models often rely on a system facilitator to make optimal trade-offs between subsystems to benefit the larger system. Design researchers draw from this literature to appropriately model their particular instance of complex system design.

2.2 Design Process Simulations

Simulations based on these formal models have allowed researchers to observe the effect of changes on a number of factors. Researchers have compared team structures [18–20], information passing strategies [7,21,22] and decision-making [23]. In doing this analysis, researchers have also suggested best practices for design processes.

Collopy proposed gradient-based information passing strategy for reaching optimal solutions [24]. Research areas such as robust design have explored the use of uncertainty models to support the decision-making process [25]. This study relies on this work to inform the design and analysis of the process simulations.

2.3 Negotiation in Complex System Design

The design of large-scale complex systems often relies upon negotiation between subsystems to determine the values of engineering parameters. Due to its importance to design outcomes, this type of negotiation has been studied in a variety of fields including design research, management science, economics and psychology. One area of research examines current practice within complex system design teams. Yassine, et al. described the phenomena of information hiding in complex system design [26]. The effect of the team or network structure on subsystem negotiations has also been studied [27]. Di Marco, et al. investigated the effect of individual team member culture on the negotiation process [28].

Another branch of research uses these insights to create prescriptive strategies for improving design outcomes. Ledyard et al. propose a market-based mechanism from economics for optimizing the allocation of resources in the design of shuttle payloads [4]. Smith and Eppinger utilized Work Transformation Matrices to help design teams identify controlling features of a physical design and which subsystems that will require more iterations than others [29] . Yassine and Braha developed a method to help subsystems represent complex task relationships better when negotiating through the use of an information exchange model [30] . This paper draws on these sources to help model the negotiation between subsystems and serve as a guide for the development of the proposed incentive structure.

2.4 Margin Use in Complex System Design

Uncertainty and its propagation through complex systems is a well-studied area in design research. Takamatsu defined the concept of formal design margins for use in risk management throughout the complex system design process [33]. Based on this work, formal design margins are often defined as probabilistic estimates of design parameter uncertainty relative to either worst-case estimates or performance objectives. These margins may be used as a replacement for heuristic margins and intuition previously used by design teams. Thunnissen proposed methods for determining these margins and using them to manage risk tolerances [34]. Eckert et al. describe the multiple definitions of and use cases for margins in current practice. They then proposed clear definitions for margin use in complex system design [35]. Other researchers have demonstrated the range of applications of these concepts in supporting complex system design [36, 37].

2.5 Incentive Structures

Incentives and rewards can drastically influence individual's behaviors, and aligning subsystem incentives with the strategic interest at the system level is one of the most important factors in the success of organization design [45]. Nadler and Tushman summarized that incentives must be clearly linked to performance, and also relate directly to the performance at each level of the organization [46]. Organizations also need create proper incentives structures to avoid errors and accidents. Paté-Cornell reported cases in off-shore oil platform design where insufficient incentives to take safety measures lead to unsafe decisions [47]. Previous studies suggest incentive structures is a possible way to mitigate the effect of biased information sharing between subsystems.

2.6 Design Support Tools

A wide range of design support tools have been developed based on insights from complex system design research. NASA Jet Propulsion Laboratory's ICEmaker is a spreadsheet-based tool for enabling communication of design parameters and constraints across subsystems [3]. Wang et al. review the use of metamodels to help designers approximate computationally-intensive complex system design tasks [38]. Intelligent decision-making support in Computer-aided Design tools allows subsystems to collaboratively work on solid models with embedded constraints [39, 40]. Other fields such as requirements engineering [41], architecture [42] and structural design [43] have also developed tools to help manage trade-offs in complex systems.

2.7 Problem Selection

The selection of test problems is a key issue in the validation of design process simulations. Coello, et al. [31]

provide a framework for multi-objective optimization test problems and guidelines for selecting a test suite. This work is part of a larger area of research addressing the development of appropriate test suites [32]. Although test suites can be useful for comparing and evaluating optimization algorithms, they may not be representative of algorithm performance on "real-world" problems. Both Coello, et al. and Deb, et al. recommend test suites comprised of a variety of types of problems in order to gain the most insight about performance differences. This paper draws from several sources to incorporate as many different types of test problems as possible.

2.8 Research Gap

This paper focuses on the interactions between subsystems in complex system design. Current complex system design support tools focus on formal interactions between subsystems through the use of committees, system integrators, contracts, auctions or other mechanisms. Since informal negotiations between subsystems may dominate formal interactions, this paper seeks to adapt the insights and techniques from the formal interactions to improve the behavior in the informal interactions. In particular, this study hopes to both improve the effectiveness of complex system design simulations by more realistically modeling the social component of human behavior and to improve design outcomes by suggesting a roadmap for developing a process which is robust to biased information passing.

3 Method

The work presented in this study consists of MDO simulations of different biased information passing behavior under a proposed incentive structure. The simulations aim to quantify the effect of a change in incentive structure on system behavior when subsystems bias information passing. A two-player system was simulated as this is a common situation in the studied organization and also simplified initial calculations.

3.1 Previous System Model

Previous work by the authors suggested that design teams may utilize a design optimization architecture which is sequential [7], such as fixed-point iteration [44]. The simulation structure is designed to emulate this behavior. The two-player system model consists of two subsystems and their respective associated objective functions. Optimization is performed sequentially. First one subsystem optimizes its design parameters and then point design information is passed to the second subsystem. The second subsystem then uses the passed information to minimize its design parameters. Point design information is then passed back to the first subsystem, completing a single system iteration.

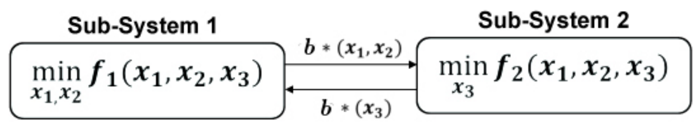

Figure 1. System schematic for one iteration

The previous study defined the concept of biases in the passing of point design information between subsystems and demonstrated their effect on system performance. The same model is used in this simulation structure. The biased information model consists of multiplying each passed design point by a bias factor b. Three models were defined: no bias with $b = 1$, static bias $b = 1.3$, and decreasing bias where b was initially 1.3 and then decreased by .1 at each system iteration. These values for the bias were based on interviews of subsystem designers which found that subsystems followed each of these patterns, with the decreasing case being most common. This study builds on the previous simulations by changing the objective functions of the subsystems to reflect the proposed incentive structure. This is presented in Figure 1.

3.2 Proposed Incentive Structure

The proposed incentive structure is based on weighted-sum approaches from MDO [31]. In weighted-sum approaches, a single utility function is created consisting of a weighted sum of the objective functions.

$$U = \sum_{i=1}^{n} w_i f_i \tag{1}$$

where U is the utility function, i is the index of the objective function, w_i is a weighting coefficient between 0 and

1 with $\Sigma w_i = 1$, and f_i is an individual subsystem objective function. The weighting coefficient is used to determine the relative importance of each objective function. For a given set of w_i the utility function can be optimized and give an optimal solution to the system.

In the previously studied organization, subsystem performance is evaluated on the subsystem level. Each subsystem is given goals by system integrators and meeting or exceeding the goals determines the performance of the subsystem. In the proposed incentive structure, subsystem performance would be evaluated at each system iteration as a weighted sum of the performance of all subsystems. By evaluating a subsystem using a utility function as the performance of the subsystem, it is hypothesized that subsystems may choose locally sub-optimal results that achieve more optimal system-level results.

3.3 Simulation of Impact of Incentive Structure

The proposed incentive structure could impact subsystem designer behavior and thereby system performance in a variety of ways. Subsystem designers could change the information passed, their decision-making process, their team structure, or their negotiation strategy. For example, subsystem designers could choose to reduce the amount of bias in the information passed. The simulations presented in this paper assume that subsystems will use the proposed utility function directly as their objective function. In addition, these simulations assume that the subsystem designers will not make any change to their negotiation strategy, that is they will continue to bias the information passed. In a real system, this would involve greater effort on the subsystem designer's part to determine the response of the other subsystem to the design inputs. In practice, this could be achieved through communication between the subsystem designers in their negotiation process. A subsystem designer might ask for information about the other subsystem's response to proposed inputs. These simulations test the situation in which subsystem designers have perfect information about both subsystem responses but are continuing to bias the information passed to the other subsystem.

In summary, the simulations consist of the optimization of two subsystems whose objective functions are utility functions. The utility functions are defined as the weighted sum of the subsystem objective functions from the test problem.

$$U_1 = w_1 f_1 + w_2 f_2 \tag{2}$$

$$U_2 = w_2 f_1 + w_1 f_2 \tag{3}$$

For example, a system consisting of the utility functions $U_1 = .9f_1 + .1f_2$ and $U_2 = .1f_1 + .9f_2$ would model a system where 10% of each subsystem's performance was based on the other subsystem's performance. During each system iteration, the passed point design information was multiplied by a bias factor b. This is presented in Figure 2.

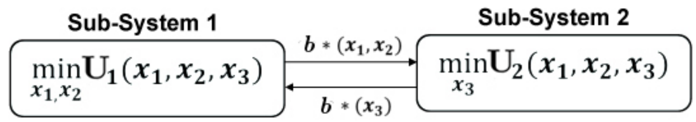

Figure 2. System schematic for one iteration

In this study, the weighting coefficients were varied to see the effect on system performance. A system without the incentive structure is represented by $w_1 = 1$, while the extreme case of each subsystem equally considering the performance of both subsystems is represented by $w_1 = w_2 = 0.5$. The weighting coefficient was varied by 5% between 0.5 and 1 in order to get an overview of the incentive space. Thus, the weighting coefficients were defined as $w1 = 0.5 + 0.05n$ for $n = 0, 1, \ldots 10$. This work also tested the three bias conditions presented in the previous study.

These test conditions were simulated on a test suite of two-objective problems drawn from Multi-objective Evolutionary Algorithms by Coello, et al. [31] and from a test suite proposed by Deb, et al. [32] as described in section 2.7.

The final system performance was defined as the Euclidean distance of the final system design from the Pareto Frontier after satisfying the stopping condition. This can be considered the system-level optimality. This distance was normalized by the Euclidean distance between the Pareto maximum and minimum [1]. A value of zero for this normalized distance, d_{PF}, would indicate a solution directly on the Pareto Frontier and a value of 100% would indicate a solution at the normalizing distance. The stopping condition was defined as either convergence for both subsystems $f_1(i) = f_1(i-1); f_2(i) = f_2(i-1)$ or reaching a Nash Equilibrium [8] $f_1(i) = f_1(i-2); f_2(i) = f_2(i-2)$. The Pareto Frontier for these test problems was often given as an analytical solution in the test suite. If not available, the Pareto Frontier was calculated using the MATLAB Genetic Algorithm function GAmultiobj. The minimization of each subsystem was performed using the MATLAB optimization function f_min_con with the interior-point algorithm.

Several parameters were varied at each condition. Each condition and test problem was solved starting at 100 randomly selected points to check for robustness to initial conditions. The order of sequential optimization was also varied for each testing condition. This checked whether having the first or second subsystem optimize first in each system iteration changed the behavior of the system.

The system optimization behavior was then analyzed to determine what the effect of each testing condition was on the performance metrics. The behavior was also compared to the specific problem characteristics such as types of constraints and objective functions. This analysis is presented in the results and discussion sections.

4 Results

Simulation results are shown in Figures 3 and 4. System performance under the test conditions was measured in terms of optimality and speed. Optimality was defined as the mode of the normalized Euclidean distance to the Pareto Frontier, d_{PF} [7]. Two characteristics of the optimization setup were varied at each bias condition: the subsystem sequential optimization order and the initial starting points. The sequential optimization order had a negligible effect on the final system performance. In a small minority of test problems, changing the sequential order added a few extra solutions to the set of final system results from the 100 random starting points. However, the use of linear utility function did change the sensitivity of system performance to the initial conditions. This was seen in the impact on the number of runs resulting in the modal optimality. Weighted-sum methods have been shown to have problems realizing Pareto Frontiers for problems whose true Pareto Frontier is concave [31]. This was also true in these simulations. For the test problems with concave Pareto Frontiers, the average number of runs resulting in the mode was reduced from 77 to 42 with the introduction of utility functions. Additionally, only results from the static bias test condition are shown. This because the previous study demonstrated the decreasing bias and no bias case resulted in optimal solutions. Thus, adding a utility function to these strategies did not improve on the performance. Also, adding a utility function increased the number of iteration necessary in both the no bias and decreasing bias conditions.

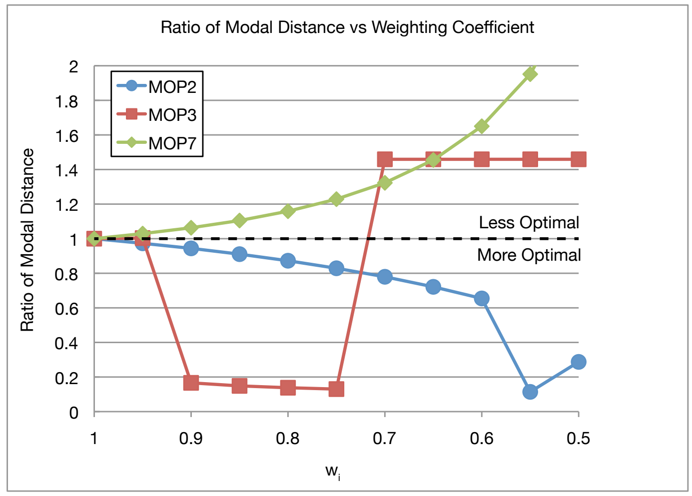

Figure 3. Ratio of the Modal Distance vs. Weighting Coefficient: graph presents the ratio of the mode of the normalized Euclidean distance to the Pareto Frontier for the tested weighting coefficient to the mode of the normalized Euclidean distance to the Pareto Frontier in the unweighted case $\frac{d_{PF,w_i}}{d_{PF,w_i=1}}$.

Figure 3 shows the ratio of the d_{PF} for the tested weighting coefficient to d_{PF} for the unweighted case $w_1 = 1$ for several example test problems under the static bias condition $b = 1.3$. This ratio can be used to demonstrate whether there is an advantage to using the utility function. If this distance ratio is less than 1, or beneath the red dashed line, the system reached a more optimal solution in the weighted case. Lower values correspond with more optimal solutions compared to the unweighted case. Values above 1, or above the red dashed line, show the system performed less optimally at that weighting coefficient. Multi-Objective Problems 2, 3, and 7 from Coello, et al.'s test suite (MOP2, MOP3, and MOP7) were chosen as representative problems as they illustrate the different types of

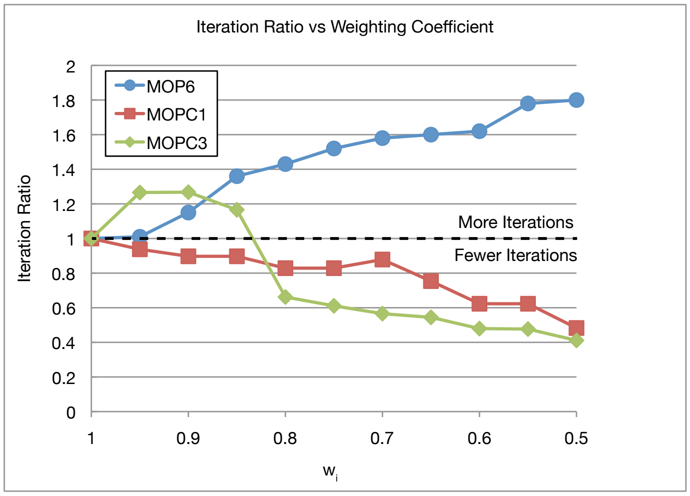

Figure 4. Iteration Ratio vs. Weighting Coefficient: graph presents the ratio of the average number of iterations for the tested weighting coefficient to the average number of iterations in the unweighted case $\frac{iter_{w_i}}{iter_{w_i=1}}$

behavior exhibited by the test problems. When designers had increasing shared incentives (x-axis of Figure 3), three different behaviors were observed: decrease in optimality (MOP7), both decrease and increase in optimality (MOP3), and increase in optimality (MOP2).

As seen in Figure 3, MOP2 reaches a more optimal solution for every tested weighting coefficient. It reaches the most optimal solution for the weighting coefficients $w_1 = 0.55, w_2 = 0.45$. Seven of the 15 test problems behaved this way. MOP7 always performs worse with weighting coefficients than in the unweighted case. In fact the edge case, $w_1 = w_2 = 0.5$ is off the chart in the less optimal direction. Four of the test problems behaved this way. MOP3 is an interesting result in that the system performs better for weighting coefficients between $w_1 = 0.95$ and $w_1 = 0.7$, and worse for $w_1 < 0.7$ Three problems behaved this way. In one of the test problems (DTLZ6) the system optimality was unaffected by changes in the weighting coefficient.

Figure 4 shows the ratio of the number of iterations until the stopping condition for the tested weighting coefficient to the number of iterations for the unweighted objective function. Similarly, a value above 1, or above the red dashed line, indicates worse performance, and below 1 or the line indicates improved performance. Three different behaviors were observed: decrease in iterations (MOPC1), both decrease and increase in iterations (MOPC3), and increase in iterations (MOP6).

For example, MOP6 always takes more iterations when using a utility function. Seven of the test problems were in this group. MOPC1 always takes fewer iterations to converge for all weighting coefficients. Only two of the test problems exhibited this behavior. MOPC3 takes more iterations for weighting coefficients in between $w_1 = 0.95$ and $w_1 = 0.85$ and then fewer iterations for the rest of the tested utility functions. MOP3 was the only other test problem to take longer on average for some weighting coefficients and then improve for others. In four cases the speed is unaffected by weighting coefficients.

5 Discussion

The results presented here demonstrate that using utility functions as the subsystem objective function does have an effect on system behavior given biased information passing. In 10 of the 15 test problems, overall system performance improved when the subsystems consider the performance of the other subsystem. This suggests that further study of this incentive structure on real-world problems with human designers would be worthwhile. A key question is how to determine the best weighting for a given problem. The simulations suggest that there is not a generalizable direction for choosing a weighting as the optimal weighting is sensitive to the test problem characteristics and this would be especially true for real-world problems. Literature has suggested tools for finding regions of greatest attraction when estimating other subsystem behavior [25]. The results from this study suggests that a similar approach may be beneficial for mitigating the effects of biased information passing. For example, system integrators could choose the weighting dynamically based on past system performance, as in the adaptive weighted-sum approach from MDO [48].

The results from this study highlight an interesting tradeoff between additional system-level information and sequential optimization. Giving the subsystems information in their objective function about the overall system often improved system optimality. However, given that the subsystems only minimized along their design parameters, the system performance was negatively effected in several of the test problems as they got stuck in local minima when considering both subsystems at each subsystem iteration.

Another notable result is that using utility functions also increased system sensitivity to initial conditions. In many of the test problems, the unweighted case converged to a single solution regardless of the starting point. In the weighted cases, a larger set of the system solutions was found. This may be due to the interaction between the weighting and sequential optimization. This is further evidence that determining the correct set of weighting coefficients is crucial to system performance in this incentive structure.

The number of iterations was either unaffected or increased with the introduction of weighted utility functions in the majority of test problems. This was likely due to several factors. First, the additional information may make the problems more difficult to solve resulting in more iterations. Subsystems which compromise but are unable to control all design variables are likely to take smaller steps in the optimal direction. Finally, in real-world tasks, a multidisciplinary team would require additional engineering resources at the subsystem level to understand additional information from outside of the subsystem's expertise. This would likely increase the time needed for each iteration as well as the overall time to project completion.

Several limitations exist for this study. First, the incentive structure may affect subsystem behavior in several ways. One way is to consider the other subsystem performance when making design decisions. This is modeled in this study by the utility functions. However, this assumes that subsystems can accurately access information about the other subsystem and have the necessary knowledge to process this information. The degree to which this assumption is accurate depends on the skills within the subsystems and the connection between the subsystems. If the subsystems have previously worked closely together on projects this may be a good assumption. Subsystems may change their behavior in other ways, such as reducing the bias in their information, perhaps switching to other negotiation tactics. Although this is not modeled in this simulation, this would be a desirable outcome as the biased information passing strategy has been shown to be sub-optimal. Secondly, these simulations were performed on well-formulated test problems. These do not necessarily reflect the behavior of real-world problems. The subsystem models, or objective functions, also do not change with time as they would in real-world problems. Additionally, using the mode of the final system results to define system behavior may introduce errors in the test problems with concave Pareto Frontiers. Literature has shown that linear utility functions may not realize or converge to the Pareto Frontier in these cases [31]. This was shown in the greater sensitivity to initial conditions of the results for test problems with concave Pareto Frontiers. Finally, this study presents results from a two-player case. Real systems have many more subsystems and the negotiations would be between multiple subsystems. Results from this study suggest that it is worthwhile to explore this incentive structure for larger systems.

6 Conclusions and Future Work

Previous work in subsystem decision-making has demonstrated that subsystem designers in some organizations use biased information passing as a negotiation tactic. This tactic can lead to sub-optimal results. Previous research also found that this negotiation happens at an informal level between subsystem designers and is not affected by the formal conflict resolution processes in place. This study proposes an incentive structure based on weighted-sum approaches from MDO which evaluates subsystem performance based on a weighted sum of all subsystems. Results from simulations of biased information passing within this structure were used to answer the following research questions.

1. What is the effect of biased information passing on system-level optimality in a complex system with a weighted incentive structure?

   Simulations suggest that the optimality of systems whose subsystems are using a biased information passing strategy but are considering the other subsystems performance can be improved depending on the weighting coefficients. However, this is problem specific and several test problems converged to less optimal solutions. Also, the sensitivity to inital conditions was increased which may lead to sub-optimal results in real-world problems.

2. What impact might these strategies have on the speed of system optimization?

   The number of iterations used in the simulations was negatively affected by the introduction of utility functions in most of the test problems. Additionally, in a real-world task, considering the performance of the other subsystem would use up engineering resources and would likely increase the time needed for each iteration as well as the overall time to project completion.

6.1 Future Work

This study paints a road map for influencing informal negotiations in complex system design teams. Although results from simulations suggest the proposed incentive structure may be more robust to biased information passing, further study is needed to determine what effects new incentive structure will have an real design teams. Future work will include simulations of larger teams and experiments with human design teams. It will also include modeling different incentive structures, such as implementing mandatory formal conflict resolution processes randomly throughout the larger team hierarchy.

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