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DECENTRALIZED DESIGN AT THE EDGE OF RATIONALITY

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ABSTRACT

The design of complex engineering systems requires interaction among different disciplinary subsystems that affect the entire system. However, this kind of distribution or decentralization of the design decisions leads to designers having to make decisions under various sources of uncertainty and risk. Because of these uncertainties, errors could potentially creep into *rational* decisions made by designers. In this paper, we investigate the rationality of decisions made by engineers in a distributed design framework. For inherently convergent distributed problems, designers, when behaving rationally, converge to Nash Equilibrium solutions that lie at the intersection of their individual Rational Reaction Sets (RRS). However, these solutions are usually not Pareto optimal and due to the dynamics of the designers' interaction in distributed design, it is rarely possible for them to converge to a solution on the Pareto set. However, when error is introduced into individual designer behavior, it is seen that the converged solutions can be an improvement to the Nash solution. Further, inherently divergent distributed problems can even possibly converge when decision error is introduced. This paper studies the effects of the propagation of this error within a distributed design framework and demonstrates that errors made within "rational" decisions could possibly result in favorable solutions.

1. INTRODUCTION

In a recent article on www.msn.com [1], the author advocated that "mistakes are good". The rationale for this comment was a list of products used in our daily lives that are a result of a *mistake*. Chocolate chip cookies, Coca-cola, Post-it notes, Silly Putty and Penicillin are some of the many products that came

about from some sort of mistake. Though the inventors of these products had set out to achieve different goals, an error or unintended consequence resulted in these discoveries that led the author to believe that not all mistakes are bad.

However, for every successful product that is a result of some error or mistake, there exists many that failed due to errors in calculations or improper modeling of system behavior. Examples of the Tacoma Narrows Bridge, the Challenger (51-L), Ford Pinto, Air Canada Flight 143 and the Kansas City Hyatt are some of the popular engineering failures. The failures of these systems have all been attributed to erroneous decisions or mistakes made by designers. Thus, it can be said that there exists conflict in determining the impact of mistakes as they can lead to good or bad results. Mistakes in design decisions that have led to disasters and cataclysmic results have been catalogued and extensively studied. Lessons learned from these mistakes have also been incorporated into decision support tools for effective product design [2, 3]. However, there exists no research in the literature that studies the possibility of achieving innovative designs through mistakes made by the designer. The understanding of this conflict between good and bad "mistakes" is important to product design since errors made in design decisions can either lead to innovative products that are very successful and capture large portions of market share, or to failed products that cause huge losses to the company developing them.

In order to determine if mistakes are good or bad in engineering design, it is important to understand how mistakes are defined and where they occur in the product design process. It is accepted that the design, manufacturing, marketing and sales of modern day products and processes require engineers to make a

large number of decisions. *Decision Based Design* or DBD [4] is the term used for viewing design as a decision making process. The principal phases of DBD are: generate all possible design options and choose the best one [5-7]. Both these phases are individual areas of research and have many methods and tools developed within their realms. For this paper, it is important to note that all the developed tools and methodologies assume the decision maker behaves rationally. That is, all decisions are made based on the solution of some optimization problem, which can be under certainty or uncertainty [8]. Any deviation in the final decision from the supposed optimal solution is termed *irrational* or a *mistake*. This paper investigates the effects of supposed “irrational” behavior in a distributed design framework to conclude if the selection of non optimal designs is indeed *irrational*.

Some of the motivation for this work was drawn from research in economic choice theory where experiments were performed to determine consistencies and rationality of decision maker preferences [9, 10]. As part of this research, 80 decision makers were asked the same 100 pairwise comparison questions where they were required to select one alternative over the other on two separate occasions (with 3-5 days separation). The consistency rates for each person ranged from 60-90%, indicating that the subjects were not answering their questions randomly but rather, their choices had changed and they were not consistent with their answers (answering the questions randomly would have resulted in a 50% consistency rate). In a subsequent study, subjects were given 42 pairwise comparison questions where they had to indicate their choices twice, with the second time coming immediately after the first time. Again, consistencies below 100% were observed.

One explanation for these inconsistencies was that the preferences of subjects changed, that is, the subjects exhibited *stochastic preferences*. Another explanation is that the subjects exhibited some error in their choices (*stochastic choices*). A third explanation was a combination of both *stochastic preferences* and *stochastic choices*. However, it was reasoned that though preferences of the subjects could change over a few days as seen in the first study, preferences typically do not change in a matter of minutes, as seen in the second study. Therefore, it was concluded that subjects behaved rationally by exhibiting deterministic preferences but made errors in their choices [11]. Errors were also observed by the studies in [12] where engineers confirmed that although their choices had changed, their preferences had not and therefore, they had made an incorrect decision. So if informed decision makers make mistakes when faced with very simple choice decisions and complete information, what precedent does that set for engineers making complex technical decisions with incomplete information?

In this paper, inconsistencies in decision maker choices are modeled as error or uncertainty and the effects of propagating this uncertainty within a distributed design process framework are investigated. Uncertainty modeling has been extensively studied in design decision making methodologies. Scott [13] quantified the uncertainties that exist in the Analytical Hierarchy Process [14] to clearly distinguish between the rankings of two design alternatives. Imprecise probabilities

have also been used to model imprecision in the information available for design decision making [15]. For selection decision problems, it has been shown that uncertainties pertaining to insufficient knowledge of all possible alternatives can affect the selected choice especially when using pairwise comparison [16]. The Borda Count pairwise comparison method however, has been shown to not be affected by the addition of new alternatives [17] thus mitigating the effect of these uncertainties. Additionally, the uncertainty in making tradeoffs for multiattribute selection problems has been extensively studied using utility theory (for compensating attributes) [18] and the method of imprecision (for non compensating attributes) [19].

In addition to the modeling of uncertainties and errors, the propagation of errors and uncertainties is also not new to engineering design. Du and Chen [20] identify two sources of uncertainties in Simulation-Based Design – *external uncertainties*, representing variations in input parameters, and *internal uncertainties* associated with inaccuracies in the simulation tools and system models. They then develop methods for the propagation and mitigation of these uncertainties [21, 22]. Possibility-Based Design (PBD) [23] is another method in the literature that is used for problems under uncertainty, where only the possibilities and not even the probabilities of outcomes are known. PBD uses *fuzzy sets* for the quantification and propagation of these uncertainties [24].

In the study of uncertainty modeling and propagation, most of the literature seeks to mitigate the effects of uncertainty by developing *robust* designs. Taguchi’s Robust Design methodology provides tools for reduction of performance variation by reducing performance sensitivity to variation in design variables and design parameters [25, 26]. The Robust Design Simulation (RDS) methodology is another approach that has been developed to quantify uncertainty and mitigate its effects for aerospace systems [27]. Additionally, the propagation of uncertainties associated with precision errors of inputs and bias errors of disciplinary analysis have been studied by investigating the worst case uncertainty. The method of worst case estimation of uncertainty is then integrated with a robust optimization framework to obtain robust designs [28].

In this paper, similar to the aforementioned literature, errors and uncertainties are modeled as probabilities given by normally distributed probability density functions (PDFs). However, these probabilities are not used to model variations in inputs or uncertainties in analyses tools as traditionally used. The modeled errors pertain to mistakes made by designers in the selection of optimal designs. Though it is commonly accepted that deviations from optimal solutions are mistakes and should be avoided, it is shown in this paper that this might not necessarily be true in the context of distributed design. In past research in decentralized complex system design, it has been accepted that in order to achieve a globally optimal solution, individual subsystems will need to intentionally select locally suboptimal design solutions [29], thus incorporating some level of cooperation among the distributed subsystems. However, in this paper, the designers do not extend any form of cooperation to each other and do not intentionally select sub

optimal local design solutions in order to achieve globally optimal designs.

In Section 2, a distributed design framework is introduced and the solution methodology is illustrated using a simple test problem. In Section 3, error in the selection of optimal designs by the designer is introduced into the decentralized design process. The effects on the final solution due to the propagation of this error are also studied in Section 3. Section 4 provides some concluding remarks and lists areas of future work.

2. DECENTRALIZED DESIGN FRAMEWORK

The design of large complex systems requires the input from many distributed design subsystems. For example, designing passenger aircraft require input from various design teams such as fluids, controls and structures to name a few. The distribution of design tasks of a large complex system into individual disciplines or design teams is called *decentralized design* [30-32].

This decentralization of decisions is unavoidable in a large organization where having only one centralized decision maker is usually not applicable [33]. A more effective way is to delegate decision responsibilities to the appropriate person, team or supplier. In fact, decentralization is recommended as a way to speed up product development processes and decrease the computational time and the complexity of the problem [34]. A good example is that of Airbus – the world’s largest civil aircraft manufacturer, which designs and builds its airplanes all across Europe. The first decomposition is made following the main sections of the airplane, and assigned depending on the area of expertise of its subdivisions. For example, the design and manufacturing of the wings is assigned to Airbus UK. However, even a subsystem such as a wing needs to be further decomposed into smaller subsystems since it is a complex system in itself. The decomposition is then made along “Centres of Excellence” and “Centres of Competence”, reflecting the multidisciplinary nature of the system being designed. Decomposition techniques can then be used to determine the allocation of design variables and of resources to these centers, which are further responsible for the interaction with external suppliers [35].

In one approach to decentralized design, one design team solves its optimization problem and passes its solution to the second design team, who then solves its optimization problem before passing its solution to the next design team. The process continues for all design teams (or disciplines) and iterates until all design teams converge to a single solution. Using terminology from game theory, the disciplines or design teams are referred to as *players* and the converged solution is called the *Nash Equilibrium* [36]. In this iterative process, it is assumed that all design teams are making a *rational decision* and the aggregate of these rational decisions is called the *Rational Reaction Set (RRS)* [37, 38]. The schematic of the iterative process is shown in Figure 1 and illustrated using a simple example next.

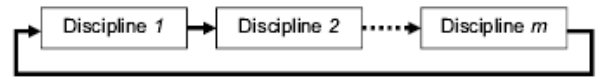


Figure 1. Schematic of Distributed Design Iterative Process

Consider a simple distributed design problem with two players, each minimizing a single objective function. Player 1 optimizes objective function F_1 by changing design variable x while Player 2 optimizes F_2 by altering y . Each designer’s problem formulation is given in Table 1.

Designer 1	Designer 2
$F_1 = x^2 - 3x + xy$	$F_2 = \frac{y^2}{2} - xy$
s.t. $x \geq 0$	s.t. $y \geq 0$

Table 1. Two Designer Distributed Design Problem (Convergent Solution)

Player 1 begins the iterative process by solving its own optimization problem for x selecting a suitable value for y in the first iteration. Player 2 receives the value for x and solves its optimization problem for y keeping x constant. This value for y is then passed back to Player 1 who solves its optimization problem now keeping y constant. The process repeats until the solution converges. The iterative process and converged solution for the problem in Table 1 in design space are shown in Figure 2.

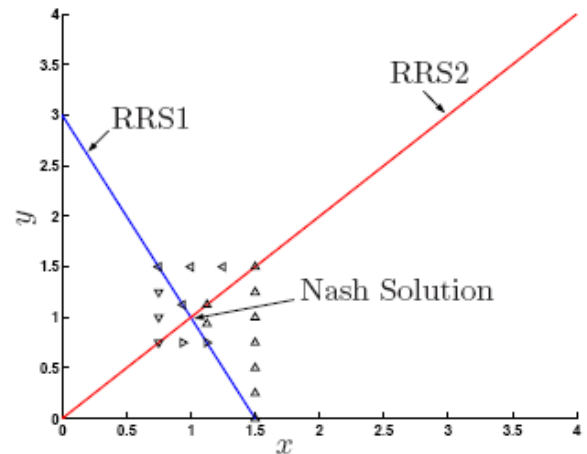


Figure 2. Iterative Solution Process for Two Designer Problem (Convergent Case)

The converged solution for this problem is:

$$(x, y) = (1, 1)$$

$$(F_1, F_2) = (-1, -0.5)$$

As seen in Figure 2, the converged solution lies at the intersection of the RRS’s of the two designers. For the unconstrained objective functions of Table 1, the RRS’s are obtained by simply taking partial derivatives of the objective functions with respect to the locally controlled design variables and setting them equal to zero. For example, designer 1’s RRS is obtained by taking the partial derivative of F_1 with respect to

x . Thus, the RRS for the quadratic objective functions are linear. However, as seen in Figure 3, there are a number of solutions that are better for both designers (shown in green). Note that for multi-objective optimization problems, when the objectives conflict, the optimum is no longer a single design point but an entire set of non dominated design points. This is commonly known as the Pareto set which is composed of Pareto optimal solutions [39, 40]. In simple terms, a Pareto optimal solution is one for which any improvement in one objective must result in the degradation of at least one other objective. Mathematically, a feasible design variable vector, \bar{x}' , is Pareto optimal if and only if there is no feasible design variable vector, \bar{x} , with the characteristics shown in equation (1).

$$\begin{aligned} F_i(\bar{x}) &\leq F_i(\bar{x}') && \text{for all } i, i = 1 \dots n \\ F_i(\bar{x}) &< F_i(\bar{x}') && \text{for at least one } i, 1 \leq i \leq n \end{aligned} \quad (1)$$

where n is the number of objectives and the use of the less than sign indicates an improvement in an objective (minimization). The Pareto set in the design space for the given problem is also shown in Figure 3.

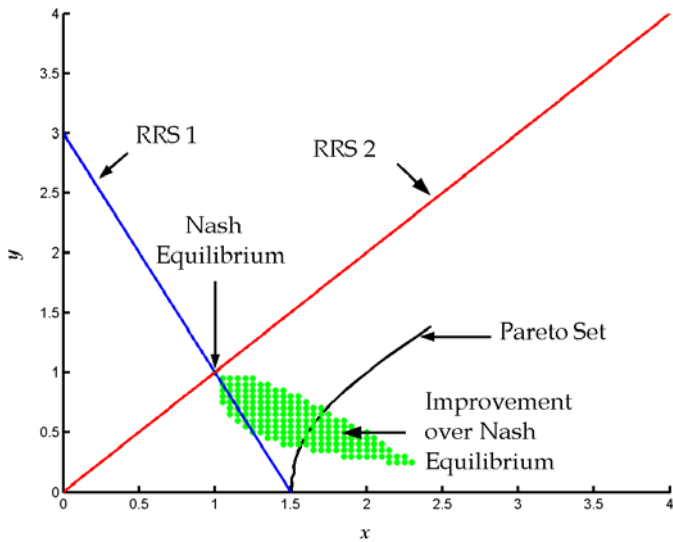


Figure 3. Convergent Problem with Solutions Superior to the Nash Equilibrium

Thus, it is seen that in a distributed design problem, designers converge to the Nash Equilibrium by iteratively solving their respective optimization problems but that there exist many solutions superior to the Nash Equilibrium. However, convergence is not guaranteed for all distributed design problems and there can exist problems where even though the RRS's intersect, the iterative solution process does not converge. For example, consider the two designer problem in Table 2.

Figure 4 shows the RRS and the solution path for the iterative approach in the design space. The solution diverges for all starting points due to the mathematical characteristics of the RRS. This is important because for the problem, though there exists a solution acceptable to both designers (the intersection

of the RRS), due to the dynamics of the problem the solution can never be achieved without some kind of external arbitration or constraining infrastructure.

<i>Designer 1</i>	<i>Designer 2</i>
$F_1 = \frac{x^2}{4} - 1.5x + xy$	$F_2 = \frac{y^2}{2} - xy$
<i>s.t.</i> $x \geq 0$	<i>s.t.</i> $y \geq 0$

Table 2. Two Designer Distributed Design Problem (Divergent Solution)

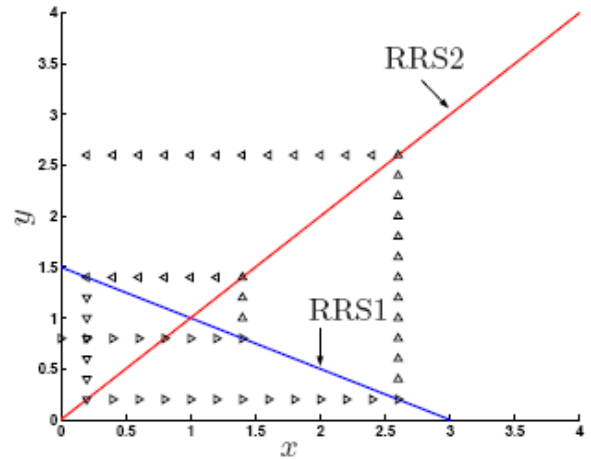


Figure 4. Iterative Solution Process for Two Design Problem (Divergent Case)

Thus, it is shown that when the designers behave rationally, that is, select a design that minimizes their respective objective functions, it is possible that they may either converge to solutions inferior to the Pareto set or diverge, depending on the nature of the problem. In recent work, the dynamics of the distributed designs have been extensively studied and rigorous conditions have been developed based on geometric series, and linear/nonlinear control theory to determine the convergence, stability, and equilibriums of these problems [41-45]. Using these tools, it is now theoretically possible to predict if a distributed design problem will converge and determine the converged solution, namely, the Nash Equilibrium. It is acknowledged that determination of convergence and the Nash Equilibrium can only be obtained by a manager of the system design problem, one who has access to the problem formulation of all the designers. Since this does not align with the formulation of a distributed design problem (where designers do not communicate objective function information), it is said that convergence properties and the resulting equilibrium conditions can only be determined *theoretically*.

However, this previous work is based on the fundamental assumption that the decision maker makes no errors in the selection of the optimal design and always selects a design from the RRS. In the next section, it is assumed that designers make mistakes in stating their rational design selection and the effect of these mistakes on the convergence and final solution is investigated. Errors in the designer's decisions can occur due to

either the uncertainties that exist in the decentralized design of complex engineering systems or mistakes (i.e., stochastic choices) by the designer.

3. DISTRIBUTED DESIGN WITH MISTAKES

In the previous section, it was seen that distributed design problems either converge to a Nash Equilibrium, which is sub-Pareto optimal, or diverge, depending on the nature of the problem. It is also known that for convergent problems, in order to move from the Nash Equilibrium towards Pareto optimal solutions, designers need to cooperate by exchanging more information, such as objective function or gradient formulations [46-48]. However, this rarely occurs in decentralized design problems. Moreover, only the fundamental assumption of individual rationality is a given for such problems and it is assumed that designers always select designs from their respective RRS. In this section, we study the effects on the final solution when the designers cannot precisely state the selected design or make mistakes when selecting the optimal design at each iteration. The convergent and divergent problems from Tables 1 and 2 respectively are used for this study.

In order to model a mistake or error made in the design selection at each iteration, it is assumed that the designer randomly selects a design from a normally distributed random variable with the mean corresponding to the solution given by the RRS and the standard deviation is some set constant. This is analogous to the models that are used for variation in input parameters and other uncertainties in the literature. Equation (2) shows a generalized modified RRS for the j^{th} design team:

$$\bar{x}_{i+1}^j = \bar{x}_{i+1}^j + N(0, \sigma^2) \quad (2)$$

where

\bar{x}_{i+1}^j - Rational solution of local optimization problem for j^{th} design team at iteration i (obtained from the RRS).

$N(0, \sigma^2)$ - Normally distributed random variable with mean 0 and standard deviation σ .

\bar{x}_{i+1}^j - New vector of design variable values for j^{th} design team at iteration $i+1$.

The effects of the modified RRS are studied for the convergent and divergent problems of Tables 1 and 2 next.

Convergent Problem

Based on equation (2), the modified RRS for the problem in Table 1 are given in equation (3a) and (3b).

$$x'_{i+1} = \frac{3 - y_i}{2} + N(0, \sigma^2) \quad (3a)$$

$$y'_{i+1} = x_i + N(0, \sigma^2) \quad (3b)$$

where x'_{i+1} , y'_{i+1} are the modified values for x and y at iteration $i+1$. One particular run of the iterative process for this problem

incorporating error is shown in Figure 5. The value of σ is constant and for Figure 5, $\sigma = 0.8$.

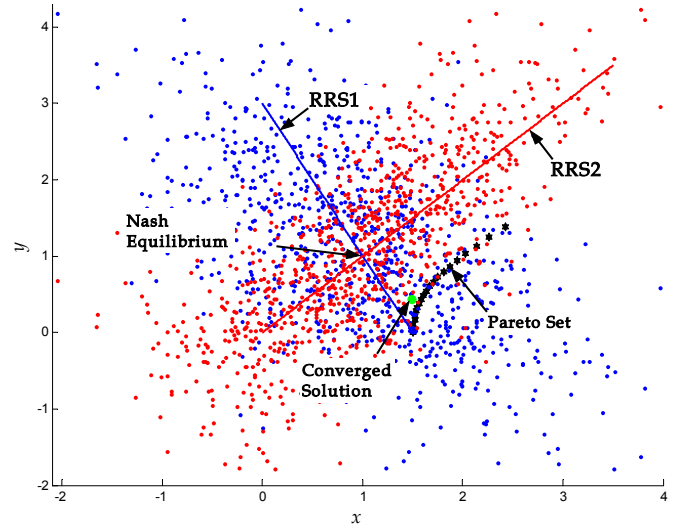


Figure 5. Modified Iterative Solution Process for Convergent Problem

The blue and red data points in Figure 5 represent the solutions by the two players respectively at each iteration. Since designer 1 optimizes its solution first (represented by blue points) followed by designer 2 (represented by red points), the red points are the solutions at the end of each iteration for a single run. The green point is the converged solution. It is seen that the data points are scattered about the RRS, as would be expected from Equations (3a-b). The converged solution and corresponding objective function values are shown in equations (4a) - (4b).

$$(x, y) = (1.493, 0.4378) \quad (4a)$$

$$(F_1, F_2) = (-1.6, -0.6) \quad (4b)$$

Due to the stochastic nature of the problem, the iterative process does not converge to a single solution for every run but rather to different solutions for each run. Figure 5 is one possible solution of the iterative process. Additionally, though the optimization problem requires the design variables to remain positive, it is seen in Figure 5 that the designers visit negative design variable values in the iterative process. This is because the error in the designer's selection decision is introduced after the optimized solution is obtained. The negative points are not a result of the optimization problem and hence cannot be termed as infeasible. The critical observation from Figure 5, however, is that the converged solution is better than the previously obtained Nash Equilibrium. Though the solution is not Pareto optimal, it is an improvement upon the previously obtained solution. Running the distributed design problem multiple times, the final solution was better than the Nash solution approximately 30% of the time.

Another critical point of note for Figure 5 is the value of σ . The value of σ used here is 0.8; however, it is hypothesized that if a larger value of σ is used, the solution will move

further away from the Nash Equilibrium and possibly result in Pareto optimal designs. This would come at the cost of the additional number of iterations for convergence. Further, a large value of σ would also be viewed more like a random search which might not even converge. Therefore, it is important to perform a cost-benefit analysis that studies the benefit of incorporating large tolerances for decision mistakes (that can potentially result in improved designs) against the cost of large number of iterations (and hence large number of function evaluations).

The number of iterations is viewed as a cost for the problems in Table 1 or 2. Though function evaluations for these problems are very cheap in terms of computational time and resources, for real world problems that are larger and more complex, this is a very important factor to consider. This is because function evaluations for large complex products can incorporate computationally intensive simulations and analyses where performing a large number of iterations is rarely possible [49, 50]. The cost benefit analysis for the convergent problem is presented next.

Cost-Benefit Analysis

In this analysis, the cost of obtaining a better solution by incorporating mistakes made by decision makers is compared to the improvement in the converged solution over the Nash Equilibrium for different levels of uncertainty. *Cost* and *Benefit* is defined as:

Cost: Expected number of iterations for convergence.

Benefit: Expected improvement in converged solution over the Nash Equilibrium.

Various simulations are performed to determine the costs and benefits of incorporating decision maker mistakes (modeled as uncertainty) in the decentralized design process. The simulation to determine *expected improvement* from the Nash Equilibrium is averaged over 1000 trials for different, *discrete* levels of σ . Figure 6 shows the plot of the expected improvement in the converged solution over the Nash equilibrium for designer 1's objective function at different error levels.

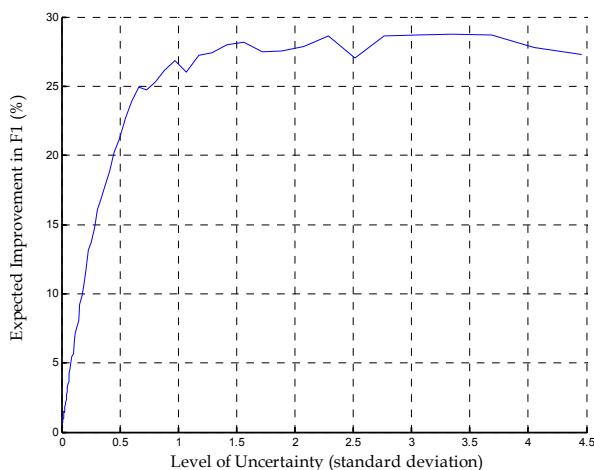


Figure 6. Percentage Expected Improvement in F_1 over Nash Equilibrium for varied σ

As seen in Figure 6, there is a steep increase in the expected improvement for initial increasing error levels. For $\sigma = 1$, there is a 26% expected improvement in F_1 over the Nash Equilibrium solution. However, beyond this level, there is no significant benefit in increasing the accepted error, with a peak expected improvement being around 29%. Figure 7 shows the percentage expected improvement in F_2 . Again, the solution improves by 34% with $\sigma = 1$ beyond which there is no significant expected improvement in the solution.

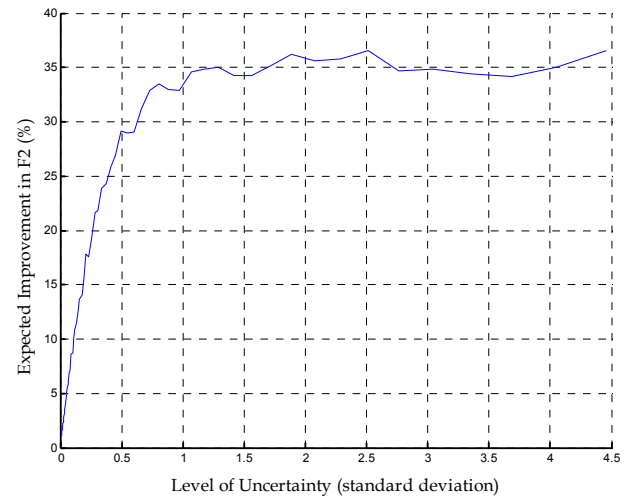


Figure 7. Percentage Expected Improvement in F_2 over Nash Equilibrium for varied σ

However it is important to look at the increase in cost (in terms of number of iterations) as the level of accepted decision error is increased. This is shown in Figure 8.

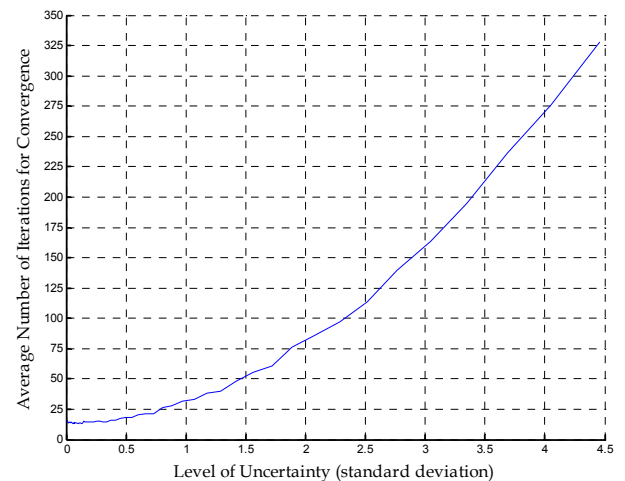


Figure 8. Average Number of Iterations for Convergence vs Error Levels (σ)

Figure 8, as expected, shows that as the standard deviation increases, the number of iterations to convergence increases rapidly. To get approximately 36% improvement in F_1 and 34% improvement in F_2 it requires about 30 iterations. Though this percentage improvement might seem to be small, it is significantly closer to the Pareto set, which is the desired solution set. However, using levels of uncertainty greater than 1

requires a large number of iterations without yielding significant improvement in the objective function values. Figure 9 shows the plot of expected improvement in F_I over the Nash as a function of the number of iterations. As expected, this figure resembles a Pareto set in an objective function space since expected improvement and number of iterations for convergence are conflicting metrics.

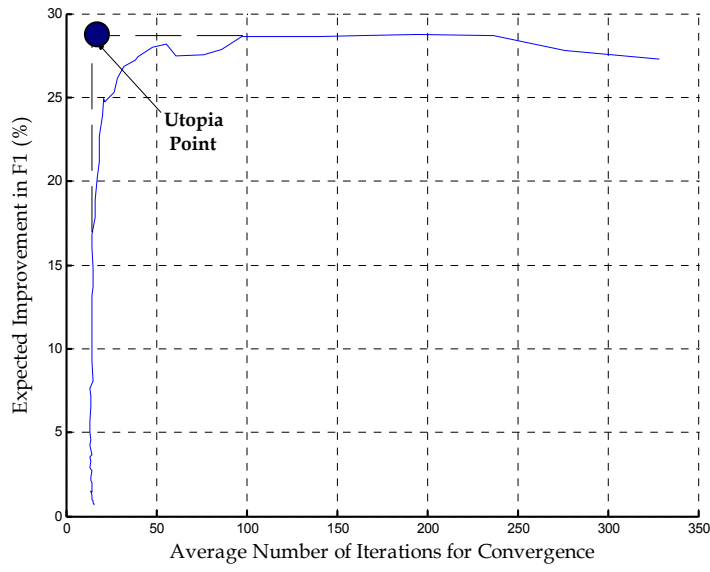


Figure 9. Expected Improvement in F1 vs Average Number of Iterations

For Figure 9, the Utopia point refers to the point corresponding to maximum improvement of the converged solution over the Nash equilibrium and the minimum number of iterations to convergence. This point lies on the upper left corner of Figure 9. As expected for multiobjective optimization problems, this Utopia point cannot be reached. Additionally, the expected improvement does not progress beyond 28.8% for increasing number of iterations.

Therefore, from this cost-benefit analysis, it can be concluded that the considerations of small variations in design decisions can be beneficial without significantly increasing the cost of arriving at a solution. It is acknowledged that these results are for a simple two objective, two design variable, two designer problem and similar results might not be obtained for larger problems. However, as a proof of concept, this example problem validates that error in the selection of the “optimal” choice or deviations from the “optimal” solutions (the RRS) is not irrational behavior as it allows for the possibility of achieving innovative or more desirable design solutions. In the next section, the effect of design decision making errors in decentralized design for the divergent problem from Table 2 is presented.

Divergent Problem

The modified RRS’s for the divergent problem in Table 2 are given in equations (3a) and (3b).

$$x'_{i+1} = 3 - 2y_i + N(0, \sigma^2) \tag{3a}$$

$$y'_{i+1} = x_i + N(0, \sigma^2) \tag{3b}$$

Selection of $\sigma = 0.5$ yields one possible solution as shown in Figure 10.

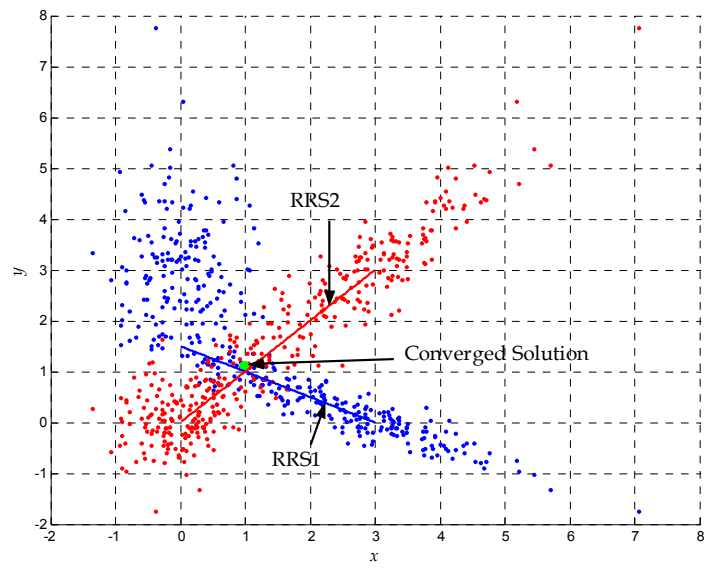


Figure 10. Modified Iterative Solution Process for Divergent Problem

As seen in Figure 10, the iterative solution *converges* when incorporating errors made by decision makers in the selection of an optimal design. As in the case of the convergent problem, the negative design variable points in Figure 10 do not result from the solution of the optimization problem but rather because error in the designers’ selection decision is introduced after the optimization problem. Again, the blue points represent the solution of designer 1 who solves its optimization problem first and the red points represent the solution of designer 2. The red points represent the solution at the end of each iteration and the green point represents the converged solution. However, an important point to note for the solution in Figure 10, the iterative process takes 379 iterations to converge with a standard deviation value of $\sigma=0.5$. Therefore, there is a need to perform a cost-benefit analysis for this problem where the effect of increasing levels of uncertainty on the convergence of the problem is studied. This analysis is presented next.

Cost-Benefit Analysis

The main benefit obtained by incorporating errors made by designers in selecting the optimal design for this problem is that the problem actually converges. Otherwise, the designers without the intervention of some kind of arbitration infrastructure would not converge to a solution acceptable to both parties. However, the number of iterations for convergence will change as the amount of uncertainty changes. Figure 11 shows the expected number of iterations for convergence as a function of different levels of standard deviation.

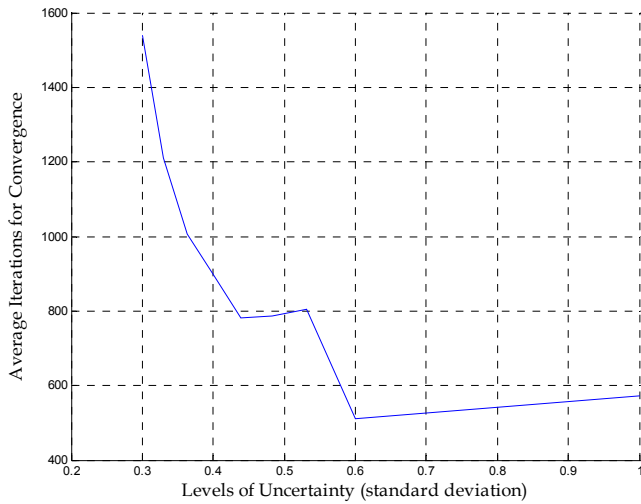


Figure 11. Cost Benefit Analysis for Divergent Problem

As seen in Figure 11, for small values of the standard deviation, the problem takes a large number of iterations to converge. With no uncertainty, the problem would always diverge. However, upon introducing small values of uncertainty into the dynamics of the problem the problem occasionally converges. But other times with small values of uncertainty, the problem still diverges. In this case, the simulation stops after 5000 iterations.

As the uncertainty levels increase, it becomes easier for the solution process to converge to a solution and thus, the average number of iterations for convergence rapidly decreases. Note that for very large levels of uncertainty, the average number of iterations begins to increase. This is also expected, because with large values of uncertainty, the solution process essentially becomes more and more like a random search, increasing the average number of iterations required to converge (and perhaps even leading to divergent behavior). Thus, it is concluded that for a set of uncertainty levels, convergence of the decentralized design process for originally divergent problems can be achieved.

In this section, it is demonstrated that when decision makers make mistakes in the selection of optimal designs, it is possible to obtain desirable solutions that were originally not possible. Additionally, the cost-benefit analysis has shown that with increasing error levels, there is improvement in the solutions of the decentralized design process. This might seem counterintuitive since errors are usually assumed to worsen design solutions. However, in decentralized design, the introduction of error allows for the exploration of regions of the design space that result in improved solutions while preserving the fundamental assumptions of non cooperation among designers. This is similar to the idea of discovering innovative new products by making an error and reaching an unintended but desired consequence.

It is acknowledged that the results presented in this section are for a simple two objective, two designer decentralized design problem. However, similar results can be expected for larger complex problems with more than two designers as well since the designers still operate within a non cooperative framework

and can converge to sub Pareto optimal solutions when working independently. The incorporation of errors in such large problems can also possibly lead to improved solutions but might significantly increase the costs associated with function evaluations and convergence. In the next section, concluding remarks of this research are presented.

4. CONCLUSIONS

In this paper, the assumption that designers always make rational choices is questioned for decentralized design problems. For decentralized design, rationality is defined as the selection of designs that lie on the designer's RRS and any design selected off of the RRS is an irrational choice. However, it has been shown in this paper that selecting designs away from the RRS is an error on part of the designer that can lead to more desirable solutions. The error in the decision maker's behavior can occur due to two factors: the uncertainties that exist in the decentralized design of complex engineering systems or mistakes (stochastic choices) on part of the designer. The significant conclusions and contributions of this work are discussed below:

- Though the results in this paper are for a simple example problem, they indicate that it is important to study errors made by decision makers in the design process, especially since the presence of various kinds of uncertainty is prominent in large-scale systems design.
- The results also indicate that discarding design solutions resulting from designer mistakes by terming them as irrational is not necessarily correct.
- This paper indicates that it is possible to develop innovative new design solutions by propagating solutions resulting from designer selections thought to be erroneous.
- Finally, this paper sets the stage for exploring the effects of errors made by decision makers in different design frameworks and scenarios. The authors hope that the design community would appreciate the central theme of this paper and continue to study the sensitivities of methodologies to uncertainties and possible errors in decision making by rational designers.

As part of future work, different models for designer errors will need to be explored. Additionally, the definition of rationality with regards to design decisions needs to be studied for different design processes and frameworks.

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