

# Collaborative, Decentralized Engineering Design at the Edge of Rationality

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*One perspective of a design process in the engineering design community is that it is largely a process marked and defined by a series of decisions. The fundamental assumption in most developed design decision support methodologies is that decision makers make rational choices; that is, choices that maximize the payoff for the predicted outcome. Decisions that do not maximize the predicted payoff are termed as mistakes or irrational choices and discarded. However, research in behavioral economics, psychology, and cognitive science has studied the human mind and suggested the notion of "bounded rationality" to explain decision errors. Bounded rationality refers to the intrinsic inability of human beings to accurately choose "rational" options prescribed by decision models such as expected utility. This paper extends the notion of bounded rationality within engineering design. Specifically, this paper studies the design of complex systems that require interaction among several different subsystems contributing to the overall product design. For convergent decentralized design problems, rational designers converge to equilibrium solutions that lie at the intersection of their individual rational reaction sets. These equilibrium solutions are usually not Pareto optimal and due to the dynamics of the designers' interaction in collaborative design, it is rarely possible for them to converge to Pareto optimal solutions. However, when models for bounded rationality are introduced into individual designer behavior, it is seen that the converged solutions can improve the resulting solution. Bounded rational decisions within decentralized design are modeled, and the effects of propagating such decisions within a design process are studied. [DOI: 10.1115/1.2988479]*

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## 1 Introduction

In a recent article on 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 originated from some sort of mistake. For example, chocolate chip cookies were developed when Ruth Wakefield added chocolate bits to regular cookie dough in an attempt to make chocolate flavored cookies, expecting the chocolate to melt through the cookies as they baked. However, the end result was not chocolate flavored cookies but instead what we currently have as chocolate chip cookies. There are similar stories of inventors who sought to create a particular product but due to an unintended consequence, obtained a different, yet successful product.

However, for every successful product that is a result of a mistake or is an unintended consequence, there exist many that failed due to errors in calculations or improper modeling of system behavior. The Tacoma Narrows Bridge, the Challenger (51-L), Air Canada Flight 143, and the Kansas City Hyatt are examples of some of the popular engineering failures. The failures of these products and systems have all been attributed to erroneous decisions or mistakes made by designers. In addition to these historic failure examples, product design companies regularly encounter

loss in profit and market share. Sometimes, such losses can be attributed to an unsuccessful or failed product design.

For both successful and unsuccessful products, the underlying theme is that the inventor, designer, or engineer involved in the development of the product was unable to exactly predict the outcome of their own efforts. Extending the analogy of these examples to complex decisions made by engineers using large scale and highly technical models, the primary question studied in this paper is "Can engineers' decisions result in unintended outcomes due to their own intrinsic inability to make precisely rational decisions?" More specifically, this paper studies unintended consequences within decentralized design problems modeled using game theoretic protocols. These unintended consequences are hypothesized to arise due to the inability of the designers to accurately model their preferences and make completely rational choices.

In order to develop a better understanding of the outcome of decisions made in engineering design, it is important to understand the *process* of how the decisions are made in the first place. The design, manufacturing, marketing, and sales of modern day products and processes require engineers to make a large number of decisions. *Decision based design* (DBD) [2] reflects a perspective of viewing design as a decision making process. The principal phases of DBD are as follows: generate all possible design options and choose the best one [3–6]. Both these phases are significant areas of research with many effective methods and tools. For this paper, it is important to note that many of the developed tools and methods within DBD assume that the decision maker behaves rationally. That is, all decisions are made based on the solution of some optimization problem where an objective function of some kind was maximized or minimized under certainty or uncertainty. Any deviation in the final decision from the supposed optimal

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solution is termed *irrational* or a *mistake* and therefore less preferred. This paper investigates the effects of supposed “irrational” behavior in a distributed design framework.

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 [7,8]. In 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 day separation). The consistency rates for each person ranged from 60% to 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% but greater than 50% were observed.

One explanation for these inconsistencies was that the preferences of subjects changed; that is, the subjects exhibited stochastic preferences. Another explanation was 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 stochastic choices or errors in their decisions [9]. Within engineering design, errors were also observed by the studies in Ref. [10] 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, the notion of *bounded rationality* is used to better understand decisions made in engineering design processes. The roots of bounded rationality research lie in economics. The concept of demand and supply for a commodity balancing itself and reaching equilibrium through the modification of price and/or quantity supplied is accepted as a norm in economic theory [11]. However, Nobel Laureate economist Herbert A. Simon questioned this accepted norm of economic theory. Simon stated that the entire premise of neoclassical economics is based on the foundation of human beings making decisions with the ability to precisely state optimal choices such as those that maximize expected utility. However, Simon believed that this assumption was not accurate since there were several factors affecting human decision making and hence inhibiting human beings from precisely exhibiting the prescribed rational behavior.

In order to explain empirical results of erroneous choices obtained from experiments on human decision making, Simon coined the term bounded rationality to describe limits on the rational capabilities of humans. He said that an accurate economic theory must rest on empirically valid general theory of human thinking and decision making. That is, this accurate economic theory must be a behavioral theory that incorporates true behavioral patterns where humans use their limited capabilities of rationality to find and choose a reasonable alternative.

For example, a commonly observed behavioral pattern in human beings is selecting an alternative that is “satisficing” as opposed to truly “optimal” [12,13]. Moreover, decision theory posits that decisions are made with procedural rationality implying that rationality exhibited by humans depends on the process they use in making their decisions as opposed to the outcome of the decision reached. Since bounded rationality is rooted in decision theory, bounded rationality is also said to be procedural. The pro-

cess includes how the decision maker perceives the decision making environment, defines his or her goals and methods for attaining these goals, and makes assumptions about the available information. Thus, bounded rationality changes the view of economic behavior as prescribed by neoclassical economics. The causes for “boundedness” in rationality as proposed by Simon are as follows [14]:

- lack of precise decision problem formulation
- deficiency in knowledge of exact decision consequences
- limited ability to adjudicate among multiple goals
- inability to process large amounts of information
- insufficient time or computational resources to make accurate decisions
- inability to make choices with a large number of alternatives

Evidence of the last point, in addition to the work by Simon, is also found in Ref. [15].

Expected utility theory is the most popular normative theory, which is also used in engineering design with rational choices being those that provide the highest utility [16–18]. However, the very bounds on rationality of human decision making also apply to problems in engineering design. The causes for boundedly rational choices are experienced in engineering design decision making as well where engineers make design decisions with limited available information, inputs from several sources, and under the pressures of time.

There have been some past efforts in studying bounded rationality in engineering design decision making. Dym et al. [19,20] referred to bounded rationality as the cause for being unable to generate all possible design options within DBD and also use bounded rationality principles to evaluate developed selection procedures. Additionally, recent behavioral experiments have also concluded that not only are decision makers not completely rational, the form in which irrationality surfaces can be predictable [21]. However, for the most part, the engineering design community, including research on decentralized design, treats the causes of bounded rationality as “uncertainties” in the problem but continue to assume the perfectly rational decision making abilities of the engineer. The literature in engineering design is rich in the study of modeling these sources of uncertainty and their propagation and impact on the design outcome [22–29].

This paper distinguishes bounded rational decisions in engineering from uncertainty by using the analogy of neoclassical economics. Existing research in engineering design decision making is analogous to neoclassical economics where the assumption is that decision makers can make perfectly rational choices. The modeling and handling of uncertainties in engineering design are analogous to the modeling and handling of uncertain conditions affecting market equilibriums in neoclassical economics. However, this paper takes the perspective that despite the consideration of uncertainties in engineering models, engineering decision makers cannot make perfectly rational choices and will make mistakes. These mistakes are purely attributed to their intrinsic inability to make prescribed rational choices.

In this paper, a particular type of engineering problem type, namely, distributed design, a common approach for the design of complex engineering systems, is used to study the impact of bounded rationality decision making models. The designs obtained using completely rational decision making models in this design process are presented and compared to solutions obtained using bounded rationality models. The remainder of this paper is organized as follows. Section 2 provides a background on distributed design where game theory is used as a model for rational decision making and information communication between the different designers. The models for bounded rationality decisions are introduced in Sec. 3. Section 3 also propagates these decisions within a distributed design process to investigate their impact and provides the cost-benefit analysis of incorporating bounded ratio-

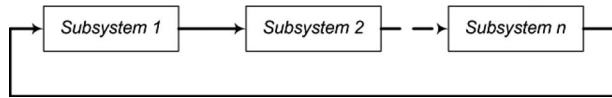


Fig. 1 Schematic of distributed design iterative process

nality based engineering design decisions. Section 4 provides some concluding remarks on the paper and cites areas for future work.

## 2 Collaborative/Decentralized Design

In the previous section, the concept of bounded rationality is introduced to explain erroneous choices in human decision making. Moreover, the possibility of engineers making erroneous choices in design decisions is also introduced. In this section, a particular type of engineering design process, namely, a decentralized design process employed for the design of complex engineering systems, is discussed.

The design of large complex systems requires the input from many distributed design subsystems. For example, designing passenger aircraft requires input from various design teams such as fluids, controls, and structures, among others. The distribution of design tasks of a large complex system into individual disciplines or design teams is called decentralized or collaborative design [30,31]. This decentralization of decisions is unavoidable in a large organization where having only one centralized decision maker is usually not applicable [31].

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 [32]. A good example is that of Airbus, 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 an aircraft 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 [33].

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 [34]. 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) [35,36]. Game theory defines the Nash equilibrium as the intersection of the players’ RRS. Based on the nature of the RRS, a problem can have several Nash equilibriums. For a sequential iterative process, the players may or may not converge as convergence to the Nash equilibrium is problem dependent. Conditions for predicting convergence to these problems have been developed in Ref. [30]. The schematic of the iterative process is shown in Fig. 1 and illustrated using a simple example next.

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

Table 1 Two designer distributed design problem (convergent solution)

Designer 1	Designer 2
$\min F_1 = x^2 - 3x + xy$ such that $x \geq 0$	$\min F_2 = \frac{y^2}{2} - xy$ such that $y \geq 0$

2 optimizes  $F_2$  by altering  $y$ . Each designer’s problem formulation is given in Table 1.

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 Fig. 2.

The converged solution for this problem is

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

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

As seen in Fig. 2, the converged solution lies at the intersection of the RRSs of the two designers. For the unconstrained objective functions of Table 1, the RRSs are obtained by 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 RRSs for the quadratic objective functions of Table 1 are linear. However, as seen in Fig. 3, there are a number of solutions that are better for both designers. 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 nondominated design points. This is commonly known as the Pareto set, which is composed of Pareto optimal solutions [37–39]. 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

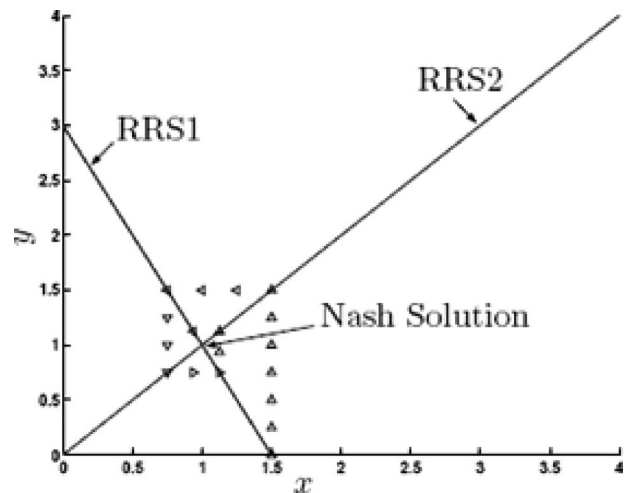


Fig. 2 Iterative solution process for two designer problem (convergent case)

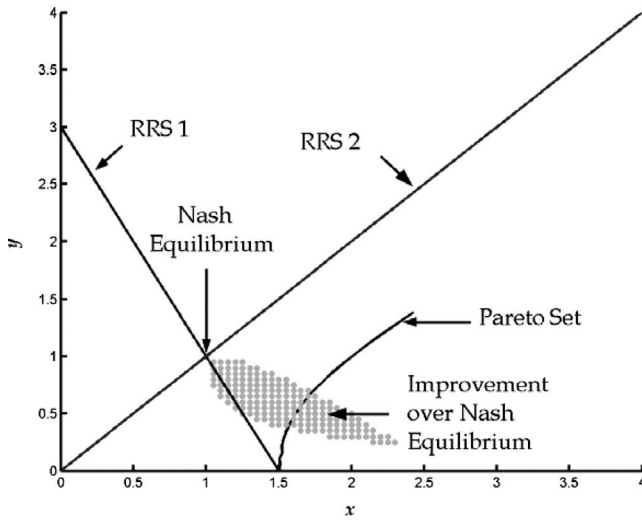


Fig. 3 Convergent problem with solutions superior to the Nash equilibrium

characteristics shown in Eq. (1):

$$F_i(\bar{x}) \leq F_i(\bar{x}') \quad \text{for all } i, \quad i = 1, \dots, n$$

$$F_i(\bar{x}) < F_i(\bar{x}') \quad \text{for at least one } i, \quad 1 \leq i \leq n \quad (1)$$

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 example problem is also shown in Fig. 3. Since this is the design space, the Pareto set does not separate the feasible and infeasible design regions like it does in the performance space where the objective functions are plotted.

Thus, it is seen that in a distributed design problem, designers converge to the Nash equilibrium when behaving rationally 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 RRSs 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 an equilibrium solution acceptable to both designers (the intersection of the RRS), because of the dynamics of the problem, this solution can never be achieved without some kind of external arbitration or constraining infrastructure.

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

Table 2 Two designer distributed design problem (divergent solution)

Designer 1	Designer 2
$\min F_1 = \frac{x^2}{4} - 1.5x + xy$ such that $x \geq 0$	$\min F_2 = \frac{y^2}{2} - xy$ such that $y \geq 0$

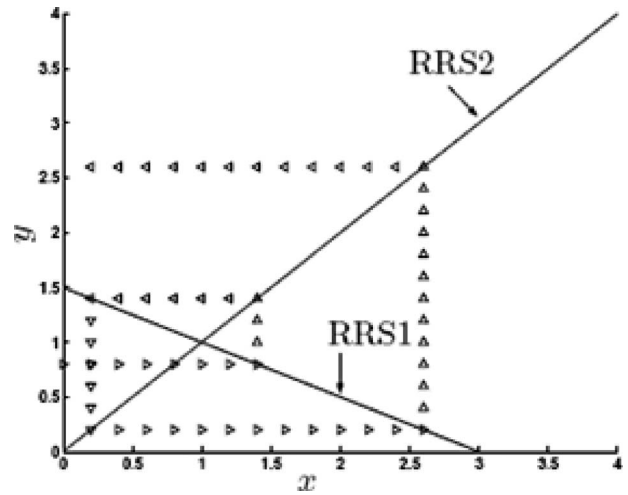


Fig. 4 Iterative solution process for two design problem (divergent case)

these problems [30,40,41]. Using these tools, it is now theoretically possible to predict if a distributed design problem will converge and determine the converged Nash equilibrium solution. It is acknowledged that determination of convergence and the Nash equilibrium can only be obtained by an omniscient outside observer of the system design problem, one who has access to the problem formulations of all the designers. Since this does not align with the formulation of a distributed design problem (where designers do not share objective function information), it is said that convergence properties and the resulting equilibrium conditions can only be determined theoretically.

Moreover, this previous work is based on the fundamental assumption that the decision maker makes perfectly rational decisions in the selection of the optimal design and always selects a design from the RRS. In the next section, a model for bounded rational decisions is introduced in the decentralized design framework. It is assumed that designers make mistakes in stating their rational design selection due to bounded rationality. Moreover, the effect of these mistakes on the convergence and final solution is also investigated through simulations.

### 3 Decentralized Design With Bounded Rationality

In the previous section, the presented distributed design problems either converged to a Nash equilibrium, which was sub-Pareto optimal, or diverged, depending on the problem. In general, as discussed earlier, a convergent distributed design problem results in a Nash equilibrium. The Nash equilibrium solution can either lie on the Pareto frontier or not. If the Nash equilibrium does lie on the Pareto set, it is purely coincidental. This is because if the designers communicate with full cooperation (sharing objectives, constraints, gradients, etc.), the resulting solution is most likely going to lie on the Pareto frontier. However, this paper assumes noncooperation between designers, and the most interesting problems in such scenarios are those that result in sub-Pareto optimal solutions.

In order to move from the Nash equilibrium toward Pareto optimal solutions in such problems, designers need to cooperate by exchanging more information, such as objective function or gradient formulations [42–44]. However, this rarely occurs in decentralized design problems and, in this paper, is not assumed to occur between designers. Moreover, only the fundamental assumption of individual rationality is a given for such problems, and it is assumed that designers, when behaving rationally, always select designs from their respective RRS. In this section, we study the effects on the final solution when the designers make bound-

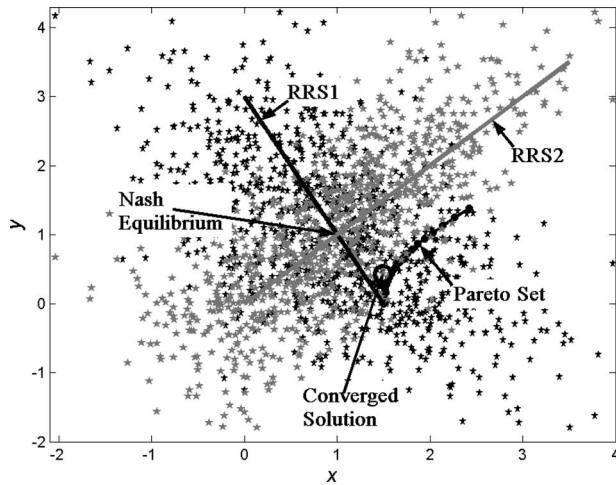


Fig. 5 Modified iterative solution process for convergent problem

edly rational choices in selecting the optimal design during each iteration. The convergent and divergent problems from Tables 1 and 2, respectively, are used for this study.

In order to model bounded rational design choices at each iteration, it is assumed that the designer randomly selects a design from a normally distributed random variable whose mean is the RRS solution at a given iteration with an assumed standard deviation. 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  $\bar{x}_{i+1}^j$  is the rational solution of the local optimization problem for  $j$ th design team at iteration  $i+1$  (obtained from the RRS),  $N(0, \sigma^2)$  is the normally distributed random variable with mean 0 and standard deviation  $\sigma$ , and  $\bar{x}_{i+1}^j$  is the new vector of design variable values for  $j$ th design team at iteration  $i+1$ .

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

**Convergent Problem.** Based on Eq. (2), the modified RRSs for the problem in Table 1 are given in Eqs. (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  $x'_{i+1}$  and  $y'_{i+1}$  are the modified values for  $x$  and  $y$  at iteration  $i+1$ . One particular run of the iterative process for this problem incorporating the stochastic error is shown in Fig. 5. The value of  $\sigma$  is kept constant and for Fig. 5,  $\sigma=0.8$ .

The black and gray data points in Fig. 5 represent the solutions by the two players, respectively, at each iteration. Since Designer 1 optimizes its solution first (represented by black points) followed by Designer 2 (represented by gray points), the gray points are the solutions at the end of each iteration for a single run. The converged solution is also shown in Fig. 5.

The problem is said to have converged if the objective functions for both subsystems do not change within a specified tolerance for two consecutive iterations. More elegant techniques for convergence using the intersections of the subsystems' rational reaction sets have been developed and used in a framework to improve solutions in decentralized design problems [45]. It is seen that the data points are scattered about the RRS given in Eqs. (3a) and (3b). The converged solution and corresponding objective function values are shown in Eqs. (4a) and (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 (introduced within the bounded rational decision models of individual designers), the iterative process does not converge to a single solution for every trial but rather to different solutions for each trial. Figure 5 shows one possible solution of the iterative process. Additionally, though the optimization problem requires the design variables to remain positive, it is seen in Fig. 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 are not considered infeasible.

The critical observation from Fig. 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 simulation multiple times, the final solution was better than the Nash solution approximately 30% of the time, which is a significant result as it demonstrates that there is a potential for improvement over the Nash equilibrium by incorporating a model for bounded rationality.

Another critical point of note for Fig. 5 is the value of  $\sigma$ . The value of  $\sigma$  used here is 0.8; however, it is hypothesized that if a larger value of  $\sigma$  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. Furthermore, for large values of  $\sigma$  the iterative optimization process would behave more like a random search and as a result may not converge. Therefore, it is important to perform a cost-benefit analysis that studies the benefit of incorporating large tolerances for bounded rational decisions (that can potentially result in improved designs) against the cost of a large number of iterations (and hence a large number of function evaluations).

The number of iterations is viewed as a cost for the problems in Table 1 and Table 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 [46,47]. 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 bounded rational decisions in the design process is compared to the improvement in the converged solution over the Nash equilibrium for different levels of the standard deviation. Cost and benefit are defined as follows.

*Cost.* Expected number of iterations for convergence.

*Benefit.* Expected improvement in the converged solution over the Nash equilibrium. This expected improvement is the average improvement over all runs that result in an improvement over the Nash equilibrium.

To determine these costs and benefits in the decentralized design process, 1000 simulations are performed at each value of  $\sigma$ . 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 levels of bounded rationality, as modeled by  $\sigma$ .

As seen in Fig. 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. Beyond this level, there is no significant benefit in increasing the error, with a peak expected improvement being around 29%. Figure 7 shows the percentage expected improve-

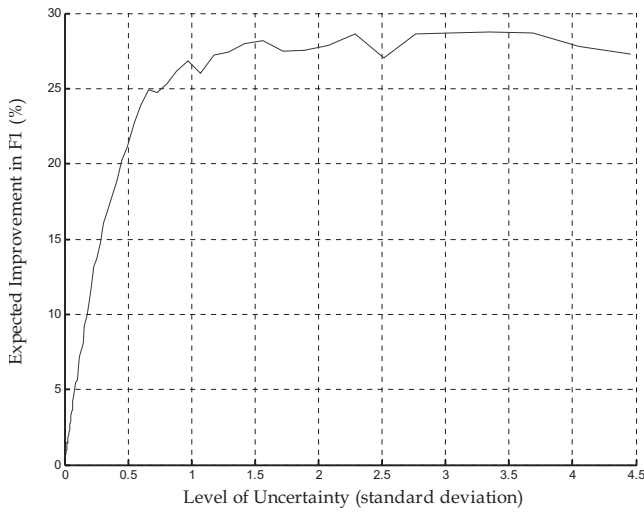


Fig. 6 Percentage expected improvement in  $F_1$  over Nash equilibrium for varied  $\sigma$

ment in  $F_2$ . Again, the solution improves by 34% when  $\sigma=1$  beyond which there is no significant expected improvement in the solution.

However, it is important to look at the increase in cost (in terms of the number of iterations) as the level of the decision error is increased. This is shown in Fig. 8 where it is seen that as the standard deviation increases, the number of iterations to convergence increases rapidly.

In order to achieve approximately 26% improvement in  $F_1$  and 34% improvement in  $F_2$  nearly 30 iterations are required at  $\sigma=1$ . Though this percentage improvement might appear small, it brings the solution very close to the most preferred set of solutions for this problem, namely, the Pareto set. However, standard deviations greater than 1 require a large number of iterations without yielding significant improvement in the objective function values. Figure 9 captures the tradeoff relationship between the expected improvement in  $F_1$  and the required number of iterations. The Utopia point corresponds to the theoretical best combination of maximum expected improvement and minimum number of iterations to converge.

Therefore, from this cost-benefit analysis, it can be concluded

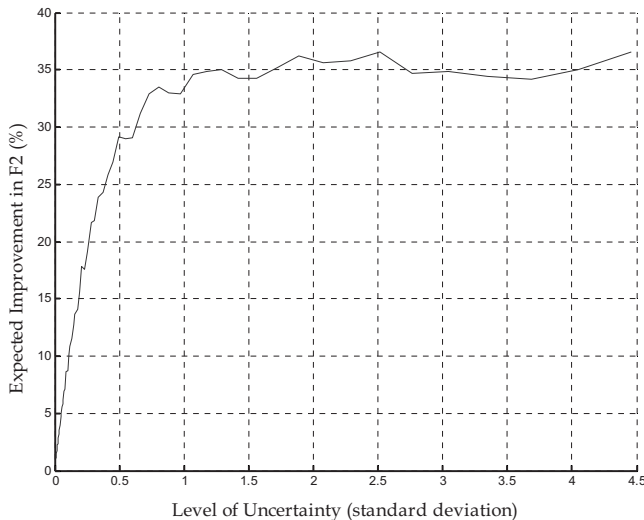


Fig. 7 Percentage expected improvement in  $F_2$  over Nash equilibrium for varied  $\sigma$

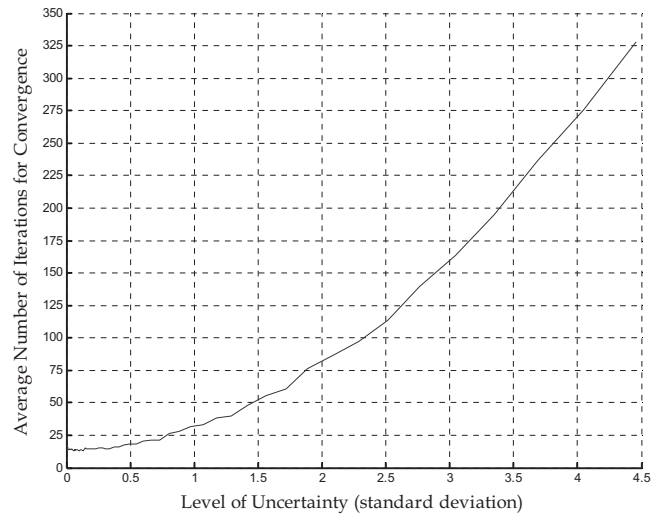


Fig. 8 Average number of iterations for convergence versus error levels ( $\sigma$ )

that the considerations of small variations (as models for bounded rationality) 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 designer problem, and similar results might not be obtained for larger problems. In the next subsection, the effect of bounded rational design decisions in the decentralized design for the divergent problem from Table 2 is presented.

**Divergent Problem.** The modified RRSs for the divergent problem in Table 2 are given in Eqs. (5a) and (5b).

$$x'_{i+1} = 3 - 2y_i + N(0, \sigma^2) \quad (5a)$$

$$y'_{i+1} = x_i + N(0, \sigma^2) \quad (5b)$$

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

As seen in Fig. 10, the iterative solution *converges* when incorporating errors into the optimal design chosen by the decision makers. As in the case of the convergent problem, the negative design variable points in Fig. 10 do not result from the solution of the optimization problem but rather because bounded rationality

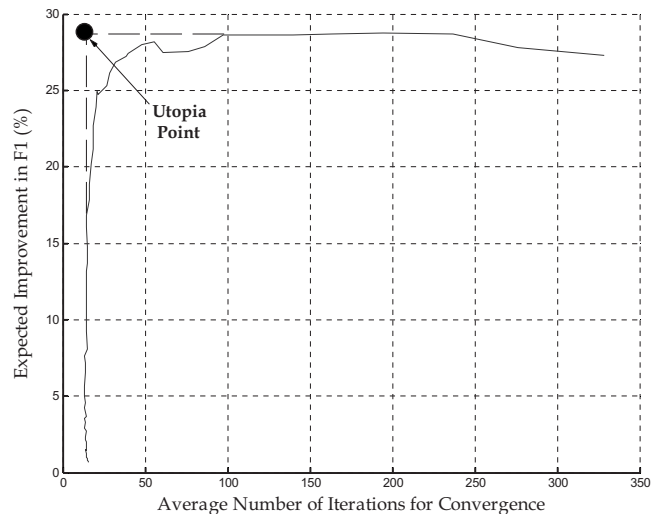
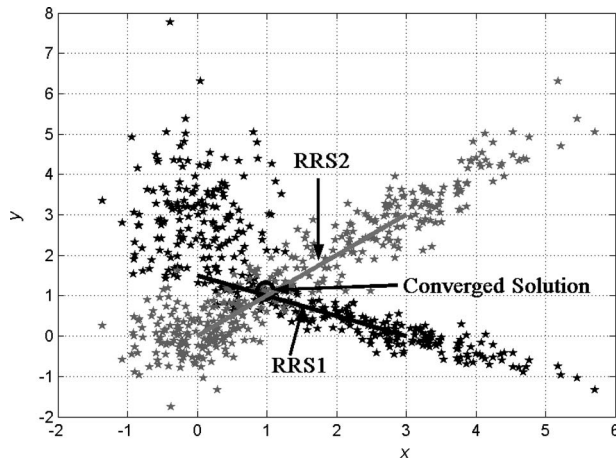


Fig. 9 Expected improvement in  $F_1$  versus average number of iterations

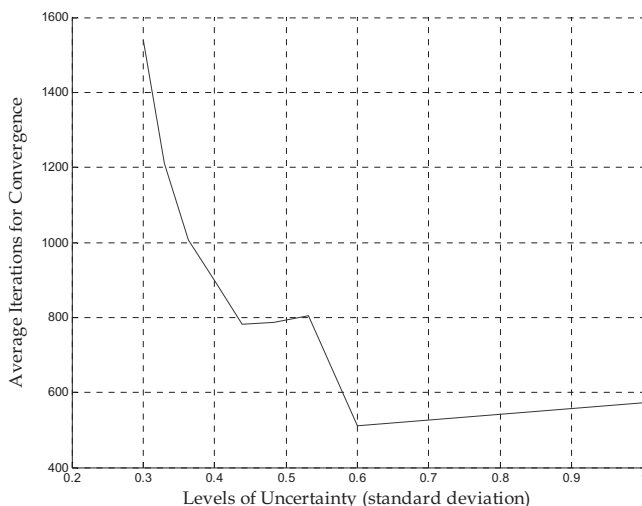


**Fig. 10 Modified iterative solution process for divergent problem**

in the designers' selection is introduced after the optimization problem is solved. Again, the black points represent the solution of Designer 1 who solves its optimization problem first and the gray points represent the solution of Designer 2. The gray points represent the solution at the end of each iteration, and the converged solution is shown in a bold black circle close to the intersection of the RRS. However, an important point to note for the solution in Fig. 10 is that 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 may converge. 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 standard deviation changes. Figure 11 shows the expected number of iterations for convergence as a function of different levels of standard deviation.

In Fig. 11, the standard deviation varies between 0.3 and 1.0. For a standard deviation value of 0.3, the problem occasionally converges but almost always diverges. When the process diverges,



**Fig. 11 Cost benefit analysis for divergent problem**

the simulation stops after the maximum number of iterations (5000) which is also the value used in the average number of iterations calculation. Therefore, the curve in Fig. 11 is asymptotic for values of standard deviation 0.3, indicating largely divergent behavior. For values of  $\sigma$  less than 0.3, the problem never converges.

As the standard deviation increases, Fig. 11 shows a steep decline in the average number of iterations required for convergence. This indicates that as the error model allows for more variation, some of the divergent instances of the problem start to converge. However, this behavior is only exhibited for the standard deviation range between 0.45 and 0.7. Beyond a standard deviation value of 0.7, the problem solution process becomes similar to a random search and therefore requires a large number of iterations to converge, if it even converges at all. This explains the increase in iterations for standard deviations of 0.7 and higher. Thus, for a range of standard deviation values, convergence of a decentralized design process for originally divergent problems can be achieved.

In this section, it is demonstrated that when decision makers make bounded rational decisions 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 values of standard deviations, 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 noncooperation among designers. This is similar to the idea of discovering innovative new products by making an error and reaching an unintended but desired outcome.

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 noncooperative framework and can converge to suboptimal solutions when working independently [36,48]. The incorporation of errors in such large problems can not only potentially 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, and a model for bounded rationality to better explain errors in human decision making is introduced. For decentralized design problems, 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 by incorporating bounded rationality through selection of designs off of the RRS can lead to more desirable solutions. The significant conclusions and contributions of this work are discussed below.

- This paper uses game theory as a modeling tool for decentralized design problems and studies the assumption of perfect rationality in individual subsystems within these game theoretic models. The motivation for examining individual subsystem rationality when making design decisions is derived from *bounded rationality*, which is defined as the inability for human decision makers to exercise perfect rationality in decision making.
- This paper models bounded rational decisions within game theoretic frameworks as decisions that deviate from a subsystem's rational reaction set. These bounded rational decisions are then propagated through the decentralized design

process, and the impact on the overall solution process is studied.

- Though the results in this paper are for a simple example problem, it is observed that by relaxing the assumption of perfect rationality and implementing a bounded rationality assumption within these game theoretic models, the final solution can result in an improvement over the previously obtained solutions. While an improved solution is not always guaranteed when incorporating bounded rationality, the possibility that an improved solution can be obtained is a significant step toward improving the game theoretic models for decentralized design.
- Finally, going back to the original question posed in the Introduction section of this paper, we can conclude that at least for decentralized design problems modeled using game theory, engineers' decisions can result in unintended outcomes due to their intrinsic inability to make perfectly rational decisions. The solutions superior to the Nash equilibrium are the unintended outcomes that are obtained only when the decision maker makes decisions with imprecise rationality. With perfect rationality, the decision maker's intended outcome is to obtain the very best for its own objective. This in turn would lead to the Nash equilibrium, making it the intended outcome, which is not desired.

This paper also sets the stage for exploring the effects of bounded rationality in decisions made by engineers in different design frameworks and scenarios. In the next section, current and future research challenges in this area are discussed.

## 5 Future Work

In Ref. [45], the preliminary understanding of bounded rationality in engineering decisions has been further studied in decentralized design frameworks. The modified approximation-based decentralized design (MADD) framework develops models for boundedly rational decisions for various subsystems that are part of the decentralized design process. The MADD framework combines the bounded rationality based decision models within a novel regression scheme to steer each subsystem's rational reaction set to converge close to the Pareto optimal. The MADD framework is currently being further developed for large scale multidisciplinary design optimization (MDO) problems, which will expand the research presented in this paper from a "proof of concept" stage to real world decentralized engineering design problems [49].

In addition to the research presented in this paper, there has been significant interest recently in studying irrationality and bounded rationality in decision making [21,50,51]. All these publications attest to the fact that while the presented work is preliminary, research on this topic is extremely critical. While the referenced articles do not examine engineering design decision making, they do provide some foundation for future research in this area. Some of the key areas identified for future research are as follows.

- Expanding the understanding of bounded rational behavior among engineers and designers. This would require studying various design decision making tools and mechanisms to identify the decisions made by engineers, the possible impacts of boundedly rational decision making, and the nature of the impact.
- Developing accurate models for bounded rational behavior as exhibited in the studied engineering design scenarios.
- Finally, incorporating the developed models for bounded rationality within existing engineering decision making tools and methodologies. This is critical as we move forward in developing effective engineering design processes.

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