

SURVEY OF ROBUST DESIGN WITH APPLICATIONS TO MULTIDISCIPLINARY AND MULTISCALE SYSTEMS

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ABSTRACT

The intent in robust design is to improve the quality of products and processes by reducing their sensitivity to variations, thereby reducing the effects of variability without removing its sources. Robust design is especially useful for integrating information from designers working at multiple length and time scales. Inevitably this involves the integration of uncertain information. This uncertainty is derived from many sources and robust design may be classified based on these sources – uncertainty in noise or environmental and other noise factors (Type I); uncertainty in design variables or control factors (Type II); and uncertainty introduced by modeling methods (Type III). Each of these types of uncertainty can be mitigated by robust design. Of particular interest are the challenges associated with the design of multidisciplinary and multiscale systems; these challenges and opportunities are examined in the context of materials design.

Keywords: robust design, quality, multiscale design

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1. An Introduction to Robust Design

In engineering design, the concept of robustness is used to mitigate the consequences of information that is uncertain or difficult to model or compute. In robust design, the objective is to make the system response insensitive to variations without removing the underlying sources of those variations [1, 2]. This anticipated variability often represents information from other parts of the product realization process, beyond the boundaries of the system to be modeled and designed. For example, a system may be designed for performance (response) that is relatively insensitive to design variations caused by the manufacturing process.

Conceptually, it is useful to identify different types of robust design based on the source of the variation. In the robust design literature, there are three categories of information: control factors, noise factors, and responses, as shown in Fig. 1. Control factors, also known as design variables, are parameters which a designer adjusts to reach a desired product. Noise factors are exogenous parameters that affect the performance of a product or process but are not under a designer's control. Responses are performance measures for the product or process.

<Figure 1 goes about here>

Historically, two types of robust design have been investigated [3]:

- *Type I Robust Design* is used to identify control factor (design variable) values that satisfy a set of performance requirement targets despite variations in noise factors.
- *Type II Robust Design* is used to identify control factor (design variable) values that satisfy a set of performance requirement targets despite variation in control factors themselves. For example, in the early stages of design, it is clear that design variable values will change as the design evolves; therefore, it is preferable to identify starting values which, if they change, have the least

possible effect on the system performance and thus require minimal iteration as the design process proceeds.

Type I robust design is most commonly encountered in practice. Type II robust design has been documented in the literature [4], but its use is not as prevalent in practice as Type I. A third type of robust design is emerging to address variability embodied in the model that describes the system [5].

- *Type III Robust Design* is used to identify adjustable ranges for control factors (design variables), that satisfy a set of performance requirement targets and are insensitive to variability within the system model. For example, a model may incorporate simplifying assumptions or random factors (e.g., random realizations of a microstructure in materials design) that affect the accuracy and precision of its predictions. Methods exist in embryonic form for studying this type of robust design [5]; preliminary results look promising.

With these types of robust design, a designer can accommodate uncertainty in input parameters and simulation models themselves. In this paper, we review the foundations of each type of robust design. Then, we discuss opportunities and challenges for using robust design to relate two or more distinct perspectives or aspects of a system, thus forming the basis for an approach to both multidisciplinary and multiscale design in which uncertainty is propagated through a chain of processes.

The foundations of robust design, anchored in the work of Genichi Taguchi, are presented in Section 2, followed by criticisms of the Taguchi approach and alternative methods for robust design in Section 3. In Section 4, we discuss the applications of robustness in the early stages of design, primarily by implementing Type II robustness. We expand the discussion in Section 4 to introduce Type III robust design – robust design against variations in models. In Section 5 we discuss the challenges for robust design in the study of multidisciplinary systems and in Section 6 we expand the discussion to the challenges of robust design in multiscale systems.

2. ROBUST DESIGN – THE BACKGROUND

Robust design is a method for improving the quality of products and processes by reducing their sensitivity to variation, thereby reducing the effects of variability without removing its sources [6, 7]. A robust design is a product or process that can be exposed to variations—in the manufacturing process and environment, in customer operating and usage conditions, or in the design specifications themselves—without suffering unacceptable performance degradation.

The collection of design principles and methods known as robust design is founded on the philosophy of a Japanese industrial consultant, Genichi Taguchi, who proposed that product design is a more cost-conscious and effective way to realize robust, high-quality products than by tightly controlling manufacturing processes. Taguchi noticed that there are two ways a product may prove to be unsatisfactory – the product may not meet target performance specifications or the variability in the product’s performance may be unacceptably large. From Taguchi’s perspective, tolerance design—which involves tightening tolerances on product or process parameters—is expensive and should be utilized only when robustness cannot be ‘designed in’ by selecting parameter levels that are least sensitive to variations. Robust design occurs during the parameter design stage that precedes tolerance design but follows the system design in which a preliminary layout is specified for the product or process. Taguchi notes that too many tolerance-driven engineers skip directly from system design to tolerance design and ignore the critically important parameter design stage.

Instead of measuring quality by means of tolerance ranges, Taguchi proposed a Quality Loss Function in which the quality loss, L , is proportional to the square of the deviation of performance, y , from a target value, T , as illustrated in Fig. 2. If Y represents the actual process response and t is the target value, then

$$L = k(y - T)^2 \quad (1)$$

As shown in Fig. 2, any deviation from target performance results in a quality loss as does an increase of variability in product performance. The Quality Loss Function

represents Taguchi's philosophy of striving to deliver on-target products and processes rather than those that barely satisfy a corporate limit or tolerance level.

<Figure 2 goes about here>

Taguchi's robust design approach for parameter design involves clearly separating *control factors*—design parameters that can be controlled easily—from *noise factors*—design parameters that are difficult or impossible to control. Designed experiments, based on orthogonal arrays, are conducted in control and noise factors to evaluate the effect of control factors on nominal response values and sensitivity of responses to variations in noise factors. The intent is to minimize performance deviations from target values while simultaneously bringing mean performance on target, as shown in Fig. 2. In Taguchi's approach, the overall quality of alternative designs is compared via signal-to-noise ratios that combine measures of the mean response and the standard deviation. Product or process designs, characterized by specific levels of control factors, are selected that maximize the signal to noise ratio. Note that for all types of robust design, robust solutions may not be 'optimal;' conversely, optimal decisions are rarely robust.

In robust design, it is important to take advantage of interactions and nonlinear relationships between control and noise factors to dampen the effect of noise factors and thus reduce variation in the response(s). This approach is termed Type I robust design. In Type I robust design, design variable values are identified to satisfy a set of performance requirement targets regardless of noise factors. Noise factors are not under a designer's control and include such things as environmental factors and operating factors.

In Type II robust design, the control factors – or design variables - themselves vary. Design variable values are determined that satisfy a set of performance requirement targets regardless of anticipated variations in those design variables. Variation in the design variables typically occurs during the evolution of the design; thus Type II robust design is useful in the early stages of design.

Taguchi initiated a paradigm shift in engineering design towards considering quality, robustness and variability earlier in the design process rather than exclusively in the final, detailed stages of design when manufacturing tolerances are specified. As a result of Taguchi's influence, systematic statistical methods are commonly used in the design process to consider the non-deterministic nature of many factors and assumptions.

3. METHODS FOR ROBUST DESIGN

Taguchi provided the initial insight into robust design, however many improvements have been proposed to his methods.

3.1 Limitations to the Taguchi Approach to Robust Design

Although Taguchi's robust design principles are advocated widely in industrial and academic settings, his statistical techniques, including orthogonal arrays and the signal-to-noise ratio, have been criticized extensively, and improving the statistical methodology robust design has been an active area of research [1, 2, 4, 8]. In the panel discussion reported by Nair [1], practitioners and researchers discuss Taguchi's robust design methodology, the underlying engineering principles and philosophy, and alternative statistical techniques for implementing it. For example, many alternative experimental designs have been proposed [9-12], and a significant point of debate and scholarly research has been dedicated to the comparative advantages of Taguchi's cross arrays (in which control factors and noise factors are varied according to separate plans) versus combined arrays (in which control and noise factors are varied jointly according to a single plan). A key advantage of the combined array approach is that it provides flexibility for the designer to rule out certain effects *a priori* and thereby accomplish computational savings. Welch and colleagues [13] were the first to propose the combined array which was later expanded upon by Shoemaker and coauthors [14], Borror and Montgomery [15], and others. Today, with many alternative combined array

designs available, a systematic approach to selection became necessary and has been provided by Wu and Zhu [16]. Despite the convincing theoretical case for combined arrays, empirical studies suggest that cross arrays provide superior outcomes under a wide range of conditions [17, 18]. Shoemaker and coworkers [14] note that combined arrays are successful to the extent that the model fits well.

It has been demonstrated that using the signal-to-noise ratio as the objective in robust design can hide information about noise interactions [14, 19]. Nair [1] also reports that a panel of statisticians suggest independently modeling the mean response and variability directly or via statistical data transformations [2, 19, 20], rather than modeling the signal to noise ratio—a practice that discards useful information about the response (particularly by confounding mean response with variance information). In the engineering literature, many authors separate out the objectives of mean-on-target (signal) and variability (noise); Mourelatos and Liang [21] show a Pareto frontier for the trade-offs among these objectives. Chen and coauthors [3] also construct an approximate function—labeled quality utility—for the Pareto efficient frontier to facilitate exploration of alternative robust design solutions for bi-objective problems involving bringing the mean on target and minimizing variation.

Murphy and coauthors [22] review mathematically rigorous methods for considering multiple responses. Chen and coauthors [3] and Bras and Mistree [23] formulate a robust design problem as a multiobjective decision using the compromise Decision Support Problem (DSP). Both control and noise factors are considered as potential sources of variation, and constraints are modeled in a worst-case formulation to ensure feasibility robustness. Separate goals of bringing the mean on target and minimizing variation (for each design objective) are included in a goal programming formulation of the objective function. This provides flexibility for achieving compromises among multiple performance objectives as well as individual or collective compromises among mean values and variations for all objectives. In more recent work, Chen and coauthors have extended the approach to include alternative formulations of the objective function, such as compromise programming [24] and physical programming [25].

Researchers have also developed alternative analysis procedures including “response modeling” [13], dual response approaches [20], and rejection of pre-decided criteria in favor of graphical analysis and discovery [19]. Leon and coauthors proposed the performance measure independent of adjustment (PerMIA) for use in robust design optimization. An important alternative to conventional analysis of robustness measures is known as “operating window methods”; the operating window is the set of conditions under which the system operates without failure [26, 27]. Robust design methods have been developed based on operating windows to increase the window by applying severe restrictions on the design early in technology development.

Type III robustness also encompasses problems with variation in the objectives for design. In most problems, these are drawn from the design specifications or requirements and are assumed to be invariant, however, when uncertainty is present, it is possible to design systems which are robust to that type of uncertainty. A particularly interesting situation is one in which a designer is uncertain about the degree of robustness required in a particular problem. As discussed in Sections I and II, robustness implies a balance between a situation in which the mean is on target and one in which variability is minimized. Gunawan and Azarm [28] and Muourelatos [21] investigate this further and present Pareto frontiers of designs with a balance between these objectives. They and Gurnani and coauthors [29] develop methods of selecting among this set of concepts or alternatives using multiple, potentially conflicting criteria.

3.2 Solving Robust Design Problems

Taguchi’s robust design principles have also been extended by applying them to simulation-based design. With increasing pressure to cut development costs and reduce development times, robust design is increasingly conducted by evaluating the relationship between input factors and responses using computer simulations rather than prototypes and physical experiments. Given that computer experiments lack pure error, different experimental design and analysis strategies are recommended [30]. In response

to this need, the field of Design and Analysis of Computer Experiments has grown rapidly in recent decades providing a variety of useful techniques [10].

A number of researchers advocate nonlinear programming approaches for robust design. Ramakrishnan and Rao [31] formulate a robust design problem based on Taguchi's quality loss function, using statistical concepts and nonlinear programming. They consider variations in both control and noise factors. Cagan and Williams [32] establish first-order necessary conditions for robust optimality based on measures of the flatness and curvature of the objective relative to local variations in design variables. Michelena and Agogino [33] introduce an approach based on monotonicity analysis for solving robust design problems in which nominal performance values are preferred. Sundaresan and coauthors [34] introduce a sensitivity index for formulating a nonlinear objective function for robust design.

Since constraints are typically an important aspect of a nonlinear programming problem, several authors have investigated the formulation of constraints for robust design applications. Parkinson and coauthors [35] coined the term 'feasibility robustness' for designs that continue to satisfy constraints and remain within a feasible design space despite variations in control or noise factors. They proposed worst case, Taylor series-based and linear statistical analysis approaches for calculating the magnitude of variation that is transmitted from control and noise factors to constraints. Yu and Ishii [36] propose a manufacturing variation pattern approach for adjusting constraints to account for correlated, manufacturing-induced variations. Otto and Antonsson [37] adopt a constrained optimization approach for robust design using a modified version of Taguchi's signal-to-noise ratio as the objective function.

Once a robust design problem has been formulated, it must be solved. The computational burden can be significant, particularly for design problems in which a broad design space must be explored. Solution of a robust design problem is distinguished by the need to evaluate not only a nominal value for each response but

also the variation of each response due to control or noise factor variation. If, as shown in Fig. 1, a response, y , is a function of control factors, \mathbf{x} , and noise factors, \mathbf{z} , then

$$y = f(\mathbf{x}, \mathbf{z}) \quad (2)$$

where the function, f , can be a detailed simulation model, a surrogate model, or a physical system, the challenge is to estimate the expected value, μ_y , and variance, σ_y^2 of the response. There are many techniques for transmitting or propagating variation from input factors to responses, and each technique has strengths and limitations. Monte Carlo analysis is a simulation-based approach that requires a very large number of experiments [38]. It is typically very accurate for approximating the distribution of a response, provided that probability distributions are available for the input factors. On the other hand, it is very computationally expensive, especially if there are large numbers of variables or if expensive simulations are needed to evaluate each experimental data point. Du and Chen [39] review several approaches for maintaining feasibility robustness and introduce a most probable point (MPP) based approach that offers accuracy similar to Monte Carlo based approaches with fewer computations. If only a moderate number of experimental points are affordable, a variety of space-filling experimental designs are available [40, 41], and experimental designs such as fractional factorials or orthogonal arrays can be used [4, 9]. These experimental designs provide adequate estimates of the range of the response rather than its distribution, and they require fewer experimental points. All of these experimental techniques can be used in two ways: (1) to provide estimates of the variation or distribution in responses at a particular design point or (2) to construct surrogate models of the response that can then be used in place of a computationally expensive simulation model for evaluating mean responses and variations [3, 13, 42]. All of these methods suffer from the problem of size identified by Koch and coauthors [43] in which the number of experiments becomes prohibitively large (given the computational expense of most engineering simulations) as the number of input factors or design variables increases.

An alternative method for propagating variation is by Taylor series expansions [44]. A first order Taylor series expansion, for example, can be used to relate variation in response, Δy , to variation in a noise factor, Δz , or a control factor, Δx , as follows:

$$\Delta y = \sum_{i=1}^k \left| \frac{\partial f}{\partial x_i} \Delta x_i \right| + \sum_{i=1}^m \left| \frac{\partial f}{\partial z_i} \Delta z_i \right| \quad (3)$$

where the variation may represent a tolerance range or may be a multiple of the standard deviation. Higher order Taylor series expansions can be formulated to provide a better approximation of the variation in response, but higher order expansions also require higher order partial derivatives of the response function with respect to control and noise factors. Taylor series expansions are relatively accurate for small degrees of variation in control or noise factors but lose their accuracy for larger variations or highly nonlinear functions. A Taylor series expansion requires evaluation of the partial derivative or sensitivity of the response function with respect to changes in control or noise factors. If analytical expressions are available for the sensitivities, this can be a computationally attractive and relatively accurate approach even for large numbers of control and noise factors [45]. Alternative approaches include, estimating sensitivities using finite differencing techniques, automatic differentiation (a feature built into some computer programming languages), and other techniques such as perturbation analysis and likelihood ratio methods [46], however these techniques can diminish the computational attractiveness and accuracy. Sensitivity-based approaches have been proposed for modeling both constraints [30, 33, 44] and objectives [47-48] in robust design.

With the techniques described in this section, the feasibility of solving robust design problems increases, and it becomes possible to formulate and solve more complex problems in the early stages of design.

4. ROBUSTNESS IN THE EARLY STAGES OF DESIGN

Much of the work on robust design has focused on the detailed design stages. It is usually assumed that a preliminary design—with concrete layout and preliminary design specifications—has already been determined, but exploration of a broad design space and significant adaptations or variations in a system are typically not undertaken or

facilitated. However, some authors have focused on infusing robust design techniques in the earlier stages of design when decisions are made that profoundly impact product performance and quality. Primarily, this has been achieved by Type II robust design which enhances the robustness of design decisions with respect to subsequent variations in designs themselves. Although we do not intend to catalog all of the applications of robustness in the early stages of design, we mention a few interesting design applications here.

Chen and coauthors [3, 49] formulate the Robust Concept Exploration Method (RCEM)—a domain-independent, systematic robust design approach for the early stages of design—by integrating statistical experimentation and approximate models, robust design techniques, multidisciplinary analyses, and multiobjective decisions. The computing infrastructure of the RCEM is diagramed in Fig. 3. The RCEM has been employed successfully for a simple structural problem and the design of a solar powered irrigation system [50], a High Speed Civil Transport [49], and a General Aviation Aircraft [51]. In addition, RCEM has been extended to facilitate the design of complex, hierarchical systems [52] and product platforms [53].

<Figure 3 goes about here>

There are some cases in the early stages of design when requirements themselves are uncertain and most appropriately expressed as a range rather than a target value, as shown in Fig. 4. In these cases, it is not appropriate to bring the mean on target and minimize variation. Instead, it may be necessary to measure the extent to which a range or distribution of design performance satisfies a ranged set of design requirements. Design capability indices are a set of metrics designed especially for assessing the capability of a ranged set of design specifications for satisfying a ranged set of design requirements. These design capability indices are incorporated as goals in the compromise DSP within the RCEM framework. The details are described by Chen and coauthors [54]. In further work, Chen and Yuan [55] introduced a design preference index that allows a designer to specify varying degrees of desirability for ranged sets of performance, rather than specifying precise target values or limits for a range of requirements beyond which designs are considered worthless.

<Figure 4 goes about here>

In addition to facilitating the generation of robust, flexible, ranged sets of design specifications, the RCEM framework also facilitates exploration of a broad design space. Response surface and kriging approaches for metamodeling have been considered within the RCEM framework [41, 56] has used artificial neural networks.

Parkinson [35] notes that robust design has the ability to “control or absorb variability”, therefore robust design is useful for problems in which a controlled degree of variability is valuable, such as in the design of product families. Simpson [51] extended the use of robust design principles into a formal methodology to optimize scalable product platforms for families of products, demonstrating its use to design families of electric motors [53], general aviation aircraft [57, 58], and absorption chillers [59]. Robust design is also valuable for the design of flexible systems – “systems designed to maintain a high level of performance ... when operating conditions or requirements change in a predictable or unpredictable way” [60]; for example, aircraft which can reconfigure their wings in flight are flexible systems as are robots which adapt to changing environments or tasks.

In the methods and applications discussed so far, a fundamental assumption is that the topology or layout of the design is known before robust design methods are applied. However, Seepersad and colleagues [61, 62] have developed a technique for robust topology design in which the topology of the product is adjustable along with parameters which describe that topology. For example, Seepersad designs heat sinks for combustor liners from linear cellular or honeycomb materials that contain a series of channels to facilitate heat flow while maintaining structural integrity. In the robust topology design of these channels, the design variables include the shape of the channels (triangular, rectangular, etc.), the layout and the specific dimensions. The robust topology design method is useful not only for minimizing the impact of fabrication-related imperfections but also for minimizing the impact of subsequent topological or

dimensional adjustments that, in later stages of design, may be required for meeting additional, multifunctional requirements.

As we move to the earlier stages of design, however, the analysis models used are usually approximations of the exact models used in the later stages of design. Accordingly, a third type of robust design is especially important for design – Type III robust design which is used to identify adjustable ranges of control factors (design variables), that satisfy a set of performance requirement targets and are insensitive to variability within the system model.

The focus in Type III robust design is on obtaining design solutions that are insensitive to variability or uncertainty embedded within the system model. This capability is particularly important in the early stages of design when approximate models are used to explore a design space. This embedded uncertainty differs from uncertainty in noise and control factors because the variability or uncertainty lies in the parameters of models, metamodels, and equations, or in assumptions made in developing those models. When model uncertainty results in variability or symmetric bounds around a predicted response value, it can be used directly within the squared error loss function discussed in Section 1; however, this is seldom the case. Usually the assumptions made in the modeling process result in biased and/or asymmetric models. The problem of model uncertainty has been studied extensively across many disciplines, especially, but not limited to, computational fluid dynamics and controls. In this review, we emphasize approaches that have the potential for obtaining solutions that are robust to unknown variations in the model.

Choi and coauthors [5] study Type III robust design in the context of the Robust Concept Exploration Method with Error Margin Indices (RCEM-EMI). An error margin index is a mathematical construct indicating the location of mean system performance and the spread of the performance considering both variability in design variables and system models. These are then used in a robust formulation of the compromise Decision Support Problem. Choi's approach fosters computational concurrency and limits the amount of re-

calculation necessary if the problem is modified as further information becomes available. Choi's approach also accommodates unparameterizable variability associated with factors such as random realizations of microstructure in materials design, caused by stochastic material processing.

Du and Chen [63] investigate both parameter and model uncertainty by deriving a range of system output based on extreme conditions. Data sampling within the range of extreme conditions yields a probabilistic distribution of output. This is then incorporated into a multidisciplinary design optimization (MDO) framework with robust design objectives [64]. This approach is relatively computationally expensive.

5. ROBUST DESIGN FOR MULTIDISCIPLINARY SYSTEMS

Types I, II and III robust design provide the building blocks for designing more complex robust systems. As discussed in Section 1, robust design has served to interface distinct disciplines in the design process, specifically design and manufacture. The potential of robust design for integrating multiple disciplines or teams is beginning to be recognized. In what follows, we use the term multidisciplinary for a design project that incorporates information from multiple disciplines, such as structural and thermal engineering. Multiscale design problems require input from multiple length or time scales; for example, for some designs it may be necessary to consider variables for material microstructures through overall system configuration. Multiscale problems are multidisciplinary, but multidisciplinary problems are not necessarily multiscale.

<Figure 5 goes about here>

If we assume that a robust design problem is an inter-dependent part of a more expansive robust design process, one must assume that some of an individual designer's noise factors, control factors, and responses are independent and some are shared as shown in Fig. 5. There are several ways in which factors or responses could be shared between distributed designers and their robust design process modules:

(1) *Shared control factors.* For example, designers A and B in Fig. 5 may share dimensions as control factors.

(2) *Interdependent Responses and Control Factors.* For example, a materials designer working at the continuum level (A) determines material constitutive properties that become control factors for a product-level designer (C).

(3) *Interdependent Responses and Noise factors.* For example, a macroscale material designer (B) determines the cellular topology of an aircraft skin material to adjust its temperature profile while an aircraft structural designer (D) considers the resulting thermal boundary conditions as noise factors for designing the aircraft frame.

In case (1), the objective of Designer A should be to identify the broadest possible range of control factor values that satisfy target values for responses despite any noise in the system. Broad control factor values serve as ranged sets of specifications that can be passed to the other Designer B, providing him/her with design freedom that is not available from point solutions. In cases 2 and 3, the objective of Designer A or B should be to maintain a desirable *range of performance* that can be achieved, despite noise in the system, by adjusting control factors. This ranged set of performance/response values is then passed to Designers C or D, providing him/her with design freedom. In each case, the point is to preserve, maintain, or create ranges of values for control factors and/or responses rather than simply dealing with uncontrollable noise in control and/or noise factors as in Type I or II robust design.

To clarify the way that this information is used in multiscale design, a diagram of a generic two-scale, multiobjective design process is shown in Fig. 6. In this figure, Design A and Design B are on the upper level – or system level - and C and D are on a lower level. Designer A passes a ranged set of control factors (design variables) to Designer B who then passes on both ranged sets of control factors (design variables) and goal bounds to the lower level Designers C and D. Multiscale design is clearly the most complex of the types of design we consider in this paper. Before discussing multiscale design in Section 6, we review the opportunities for applying robust design methodology to multidisciplinary problems.

<Figure 6 goes about here>

To reduce the computational cost of multidisciplinary design and to leverage distributed designer expertise and computing resources, multidisciplinary design activities may be decomposed and distributed among multiple designers or design teams, each of whom bring discipline-specific expertise to the design process. However, the effects of interactions between multiple disciplines (or designers) on system-level performance must be considered. Comprehensive reviews of deterministic multidisciplinary design optimization are available in the literature [65, 66]; here, we focus on applying robust design methodology to multidisciplinary problems.

In general, two categories of methods have been developed for handling the uncertainty that is an integral part of robust design of multidisciplinary systems. One method is single disciplinary or all-in-one integrated analysis and the other is multidisciplinary uncertainty analysis. An all-in-one approach analyzes the effect of uncertainty in input random variables (x_1 and x_2) on the final performance (z). The system boundary of this approach is large since multiple subsystems are treated as one system. On the other hand, in the multidisciplinary approach the propagation of uncertainty through each subsystem in the system must be considered.

Many studies have been directed toward improving the accuracy of the all-in-one approach when limited amounts of data are available. The available methods include Monte Carlo simulation, first-order and second-moment analysis, and the stochastic response surface method [67]. However, all-in-one approaches have a critical drawback because it is necessary to implement all-in-one automated simulation or experimental models across subsystem boundaries. If the decomposed subsystems are controlled by multiple teams or reside in a distributed environment, interfacing the subsystems for large numbers of all-in-one simulations is costly, even if computational frameworks for system integration are available.

Multidisciplinary uncertainty analysis and robust design methods can overcome these difficulties by distributing the application of robust design methodology along with design and analysis activities. For example, Gu and coauthors [68] propose worst case propagated uncertainty analysis and robust optimization. With their approach, first order sensitivity analysis is performed on each subsystem. A final system response deviation is estimated by propagating the result of individual subsystem uncertainty analysis. Du and Chen [61, 62] propose efficient analysis methods to accommodate a generic probabilistic approach instead of using worst case sensitivity analysis to estimate the amount of uncertainty more accurately. Also, the methodology of analytical target cascading (ATC) for hierarchical system design optimization is extended to account for uncertainties [69]. Random quantities are represented by their expected values which must match among sub-problems to ensure design consistency. The probabilistic formulation is also augmented to allow introduction and matching of additional probabilistic characteristics. Applying robust design principles, a probabilistic analytic target cascading (PATC) formulation is proposed in which design consistency is achieved by matching the first two moments of interrelated responses and linking variables. Although these methods reduce the computational cost of multidisciplinary design, all of them require a great deal of information to be passed across boundaries between subsystems to estimate final performance variation.

In most of the existing methods, the processes of uncertainty analysis and design exploration are tightly coupled. Whenever an uncertainty analysis is requested from a design exploration algorithm, the subsystem analyses must be executed sequentially, and the mean and variance of the final performance sent back to the design exploration algorithm in real time. In CSSUA (Concurrent SubSystem Uncertainty Analysis) method, Du and Chen [64] propose parallelizing the associated subsystem analyses to identify the mean of linking variables. However, because the robust optimization process is sequential and the uncertainty analysis computed during the optimization, this method cannot be fully parallelized. These sequential repeated uncertainty analyses consume a great deal of computing power. Furthermore, if one of the subsystems' models in the series is changed, then the entire process needs to be repeated to estimate

propagated uncertainty. Thus, sequential propagation of uncertainty becomes more problematic in a distributed environment.

To overcome these limitations, Choi and coauthors [70] propose an Inductive Design Exploration Method (IDEM) to facilitate distributed robust design. The strategy in the solution procedure is to find sets of design specifications that define a feasible solution space and communicate these sets in a top-down manner, maintaining “*design freedom*” as much as possible. Design freedom is defined here as the ratio between the feasible range and the entire design space. If upstream variables are coupled with downstream design activities, design variable ranges are chosen to maximize design freedom. Once a mutually feasible design space is identified, the best solution is identified by maximizing its degree of robustness against predicted levels of cumulative uncertainty.

In a different approach to the design of multidisciplinary systems, Chen and Lewis [71] couple robust design methods with game theory protocols for modeling interactions and enhancing flexibility in multidisciplinary design processes involving multiple designers. In a Stackelberg game theoretic protocol, two designers are designated as a leader and a follower. In this work, a rational reaction set (RRS) is formulated to serve as a prediction of the follower’s behavior in response to the leader’s decision. Specifically, the RRS is a response surface model of the values of the follower’s shared variables (i.e., variables controlled by the follower but also required by the leader) as a function of possible values for the leader’s shared variables. The leader solves his/her design problem using the RRS and his/her own analysis models and generates robust design solutions that include ranged sets of values for the shared variables. Finally, the follower selects values of the shared variables from within the ranges specified by the leader and solves his/her design problem. In a notable extension of this work, Xiao [72] uses design capability indices and game theory protocols to facilitate flexible, robust, interactive decision-making among multiple, distributed designers. Kalsi and coauthors [73] treat shared variables as noise factors in complex, multidisciplinary systems design performed by multiple designers. Each designer searches for solutions that are robust to changes in shared variables by other designers. A lead designer solves his/her

disciplinary design problem for solutions that are robust with respect to the coupled noise factors. This preliminary solution is communicated to a secondary designer who solves his/her design problem and selects specific values of the coupled or shared variables within the specified ranges. Both Kalsi and coauthors and Chen and Lewis demonstrate that the robust design methods improve the follower's design performance in exchange for relatively small sacrifices in the leader's design performance. The approach of Kalsi and coauthors can accommodate two-way interactions between designers and does not require RRS's, that can be computationally expensive to develop and may not be very accurate. On the other hand, their approach relies on identifying mutually satisfactory ranges for coupled or shared variables *a priori*—a task that may require some iterative communication among designers.

In similar work, some researchers have applied Type I and II robust design techniques to limit the effects of coupling by treating coupled design variables as noise [71]. For example, Chang and Ward [74, 75] facilitate simultaneous, distributed design by encouraging designers to make conceptually robust decisions that are relatively insensitive to variations in the decisions of other designers who share coupled parameters. Chang and Ward model these shared parameters as noise factors.

A significant barrier to the application of robust design methods to multidisciplinary design problems has been the required computational expense. Utilization of fast metamodels allows integration of multidisciplinary analyses across disciplines, thereby facilitating multidisciplinary design. In addition to the metamodeling methods used within the RCEM, Section 4, several authors have investigated metamodeling applications in robust design, e.g., [42, 76] to replace discipline-specific, computationally intense analysis tools. Simpson and coauthors provide an extensive review of metamodeling applications in robust design in the 1990s [30]. However, the cost associated with constructing a high-fidelity surrogate model over a broad design space can be prohibitive, especially when a large numbers of variables must be considered. Furthermore, many of the existing methods for robust design of multiscale

systems require that each subsystem must be modeled with differentiable mathematical models, thus eliminating the possibility of obtaining information from experimentation or simulation models, however Azarm and his students [63, 77-79] present methods which may be used for robust optimization in multiobjective problems which have discontinuous objective and constraint functions.

6. RESEARCH CHALLENGES IN ROBUST DESIGN OF MULTISCALE SYSTEMS AND MATERIALS

As reviewed in the preceding sections, important progress has been made in advancing the state-of-the-art in robust design, but many research challenges remain. In this section, we highlight some of those pending challenges for applications of robust design to multiscale systems and materials. Multiscale design is defined as the design of systems that span physical scales, with variables and underlying phenomena that interact across multiple spatiotemporal scales from full scale products to continuum levels and possibly even atomic levels. An example is materials design—the simultaneous design of a product and the material from which it is made.

Multiscale materials design is an inherently hierarchical, multifunctional activity. For example, multiscale design of an aircraft, as illustrated in Fig. 7, may include the design of not only its macro-scale physical system, subassemblies, and parts but also its constituent materials whose properties and performance characteristics often depend on phenomena that operate at different length and time scales, spanning from angstroms to meters and from picoseconds to years. Whereas the materials play a significant role in bounding the physical characteristics (e.g., dimensions) and operating ranges of the macroscale system, the system places multiple functional requirements on the materials—such as structural load bearing, thermal transport, cost, and long-term stability requirements—that cannot be defined in isolation from overall system operating conditions and requirements.

<Figure 7 goes about here>

Accordingly, multiscale design requires collaboration across disparate spatiotemporal and functional domains. In many ways, multiscale design problems are similar to multidisciplinary design problems because both require decomposition, distribution, and integration of a complex systems design problem. By definition, however, multiscale design is not synonymous with multidisciplinary design, because the multiscale design problem explicitly spans a range of spatiotemporal scales—a characteristic not necessarily exhibited by multidisciplinary design problems. This feature introduces and amplifies a host of new challenges for robust design that have not been managed in many multidisciplinary or hierarchical design applications to date. In this section, we highlight three of those challenges:

- To generate robust designs for multiscale systems, uncertainty must be bounded and managed as it emanates from many sources, including (1) modeling simplifications, approximations, and assumptions; and (2) sparse data from different sources with varying degrees of precision. Furthermore, uncertainty propagates through linked models on multiple scales and functional domains, intensifying its impact on the level of confidence in the final design.
- On submacro scales, robust design is essential to account for the inherent variability in the processing and fabrication of multiscale systems and particularly materials. This variability is often difficult to parameterize, manifesting itself as stochastic variations in morphology from specimen to specimen.
- Finally, robust design methods are needed for facilitating collaboration across spatiotemporal and functional domains. The complexity of many multiscale phenomena prohibits formulation of single models that unify all of the constituent length scales and motivates distribution of analysis and design with active involvement by dedicated experts. In this context, robust design methods are needed for making local design decisions that are flexible enough to accommodate changes in the coupled variables shared with designers operating at different scales and functional domains.

In the remainder of this section, we explore these challenges in greater depth.

6.1 Model Uncertainty and Propagation of Uncertainty

There are significant and varied sources of uncertainty in multiscale design. In addition to the conventional sources of uncertainty associated with noise and control factors, there is the issue of uncertainty in modeling. In most cases, multiscale models themselves yield imprecise estimates of properties of interest, and this uncertainty is often amplified as data is propagated through a series of models.

As a representative example, consider the design of a reactive particle metal mixture (RPPM) based on shock simulations of the thermal and mechanical conditions that initiate exothermic reactions [70]. The analysis is conducted by generating a physically realistic microstructure comprised of aluminum and iron oxide particles, epoxy binder, and interspersed voids; performing a shock simulation; and then analyzing the results. In this case, model-related uncertainty arises from the pseudo-random generation and arrangement of particles, based on fixed input parameters (e.g., mixture composition, particle size), as illustrated in Fig. 6—with resulting morphology that is physically realistic, considering the randomness inherent in material processing. This randomness causes large variation in response that is difficult to quantify due to the computational expense of individual simulations. Furthermore, the shock simulation model itself is based on a number of simplifying assumptions, such as that of plane strain and two-dimensional loading. These and other assumptions cause the model to deviate from experimental results.

<Figure 8 goes about here>

Efficient methods are needed to calibrate and characterize the accuracy of models when data is sparse and physical experimentation is expensive. Furthermore, the models must be qualified in terms of the fundamental assumptions and the context in which they are based and the bounds within which they are predictive and valid. Error bands or confidence intervals on the predictions are also needed, and they may be different for surrogate models and physical models. The issue of bounding and managing uncertainty in these models is a crucial aspect of any multiscale or materials design

effort. Methods for managing uncertainty are needed as well as robust design methods that yield solutions that are robust or relatively insensitive to model-related uncertainty and are accompanied by quantified confidence intervals.

It is also important to consider the propagation of uncertainty across multiple scales when designing products, the materials from which they are made, and the design and fabrication processes by which they are realized. Design process uncertainty emanates from: (a) changes in design specifications as a result of downstream or concurrent decisions and design activities or (b) the propagation and potential amplification of uncertainty due to the combined effect of analysis tasks performed in series or in parallel. Both sources of design process uncertainty are common and important for multiscale, multi-physics materials design, with a plethora of shared or coupled variables and analyses performed on multiple length and time scales.

Consider, for example, the broader context of the shock simulations discussed previously in this section. The role of the shock simulations in a broader multiscale design process for macroscale, energetic projectiles is outlined in Fig. 7. As shown, the results of the shock simulations serve as input for continuum models of reaction initiation, and several additional hierarchical steps in the design process are required before projectile-level simulations of systems-level performance can be completed. Uncertainty propagates and builds throughout this multiscale chain of design and analysis, potentially causing amplified errors in the simulation of the systems-level performance.

< **Figure 9 goes about here** >

Robust design methods are needed to address these issues of propagation and accumulation of uncertainty throughout a multiscale and multifunctional design process. Techniques are needed for characterizing and bounding uncertainty as it propagates from level to level. Robust design methods are needed for reducing the sensitivity of system-level solutions to this uncertainty and for ensuring that solutions remain feasible and satisfactory.

6.2 Robust Design on Sub-macro Scales

By definition, multiscale materials design problems involve designing on spatiotemporal scales smaller and shorter than that of a large-scale product. Particular challenges are associated with designing at smaller scales. For example, when selecting materials for a new product, designers require reliable databases of the properties of a new material, along with estimates of likely variation in properties from sample to sample. Therefore, a materials designer's task is to provide accurate estimates of this variation and to minimize it when designing or customizing a new material. In many ways, this task is more difficult on material spatiotemporal scales than on the larger macroscopic scale of an overall product. For example, material morphology from specimen to specimen inevitably deviates from its intended form, because of stochastic processing conditions and operating environments. In many cases, the parametric variations are much larger, relative to intended parameter values, than those experienced on larger scales. In other cases, the uncertainty is not parametric but topological or combinatorial in nature, associated with stochastic arrangements or distributions of material phases, defects, and other features.

<Figure 10 goes about here>

As an example, consider the design and fabrication of prismatic cellular or honeycomb materials. As shown in Fig. 10, possible imperfections introduced during the fabrication process include tolerances or dimensional variation, curved or wrinkled cell walls, cracked or missing cell walls or joints, and variations in porosity and other properties of the cell wall material. Whereas the tolerances are examples of parametric imperfections (i.e., parametric shifts in dimensions), the missing cell walls and joints are examples of topological imperfections (i.e., changes in the topology of the material) [80]—the effects of which must be analyzed with sets of experiments in possible combinations of defects, with potential combinatorial explosions in the number of possibilities. Analogies can be found in the arrangement of phases, grains, defects, and other features in microstructural design contexts, such as the reactive particle mixture discussed in the previous section. The impact of these imperfections and variations can be profound; for example, reductions in effective elastic stiffness and strength by fifty percent or more

are not uncommon in metallic prismatic cellular materials subjected to defect rates of five percent [81]. Furthermore, in many cases, the expected values and distributions of material properties also vary with time as a function of usage and processing conditions. Materials designers face the challenge of identifying and characterizing the many types of variation for a particular material and the added challenge of developing efficient robust design methods for assessing and minimizing the impact of that variation on properties of interest, especially when the variation assumes a topological or spatial form.

6.3 Distribution and Collaboration in Materials Design

In materials design, a hierarchy of models is developed and applied to specific length and time scales. Each model is used to inform the formulation of other models on higher length scales that capture the collective behavior of lower length scale subsystems, but it is very difficult to formulate a single model for macroscopic material properties that unifies all of the length scales. For example, first principles models, based on theoretical and solid-state physics, can be used on atomistic and molecular levels to predict structure and properties of ideal designs, but they are too computationally expensive to model real materials with highly heterogeneous structures that strongly influence their macroscopic properties. On the other hand, continuum-based models, based on classical continuum theory, are useful for describing properties at a macroscopic scale relevant to many engineering applications, but they are inappropriate for smaller scale phenomena that require atomistic resolution. While it is extremely challenging to develop physics-based models that embody relevant process-structure-property relations on different scales for diverse functions, the complexity and restricted domain of application of these models limit their explicit integration across the length and time scales illustrated in Fig. 7. Multiscale materials design involves a number of scale- and discipline-specific models that are coupled but cannot be combined into a single unified model.

Consider, for example, the mesoscale design of cellular materials for use as combustor liners in gas turbine engines [61], as illustrated in Fig. 7. The design of the cell

morphology depends on both the continuum-level properties of the bulk material in the cell walls and on the boundary conditions (e.g., space allocations, flowrates of air, etc.) supplied by designers of the combustion chamber itself. In turn, the combustion chamber designer relies on estimates from the cellular material designer, such as maximum combustion-side temperature and pressure capabilities of the cellular liner, to complete the design of the combustion chamber. Also, system-level performance objectives, such as thrust and efficiency, depend on complex interactions between the combustion chamber and other components in the engine such as the compressor and turbine. Design activities are strongly coupled. Furthermore, each scale and component is complex enough to warrant dedicated experts for simulation and design. It is difficult to automate the generation and refinement of alternative solutions without participation by domain-specific experts in terms of model refinement, validation, and other roles.

To facilitate such a distributed, multiscale design process, analysis and synthesis activities must be distributed and simultaneously linked in a manner that facilitates exploration of the systems-level design space by a collaborative team of experts. These requirements are similar to those of multidisciplinary systems, but the multiscale context introduces some additional challenges that are not fully addressed by the multidisciplinary robust design approaches reviewed in Section 5.

For example, in most multiscale design applications, neither analysis nor design is fully automated. Designers with scale- and/or domain-specific expertise must be kept in the loop. These expert designers are needed for monitoring and verifying the results of materials models that, in many cases, are not mature enough to execute automatically. Also, they must direct the search for solutions that may be non-local in a non-parametric design space (e.g., introduction of an alloying element). Some multidisciplinary design approaches (e.g., concurrent subspace optimization or collaborative optimization) accommodate a degree of distributed *design* as well as distributed *analysis* activities, but they often require extremely large numbers of system-level iterations. Such frequent systems-level iterations are clearly undesirable when each iteration relies on the efforts

of multiple designers or design teams, working independently with computationally expensive analyses.

The need to reduce systems-level iterations often conflicts with the need to manage interdependencies between distributed design teams who address different scales and functional domains. Accordingly, another fundamental role of each domain-specific expert or team is to make decisions that rely on information and solutions generated by other decision-makers at other levels of the hierarchy. Furthermore, these decisions involve synthesizing and identifying solution alternatives to achieve desirable tradeoffs between sets of conflicting material property goals. Again, traditional single and multi-disciplinary optimization approaches are limited in this context because their emphasis is on sharing single point solutions. Such solutions offer no freedom for modification by collaborating designers and inevitably prompt a series of iterative exchanges, simply to identify mutually *feasible* solutions.

We believe that effective resolution of these challenge requires a transition from the point-based iterative methods underlying MDO to interval- or range-based methods in which mutually feasible design spaces are identified and gradually narrowed. There is an important role for robust design methods in generating flexible local solutions that can be adapted easily to accommodate couplings with other scales and disciplines and to pursue systems-level objectives. As noted in Section 5, progress has been made in developing flexible, collaborative, robust design methods, but much more work remains to be done. For example, collaborative robust design methods must be scaled to accommodate complex multiscale design processes such as the one illustrated in Fig. 9. Also, methods are needed for effectively representing, communicating, and archiving interval- or range-based solutions. Robust design methods are needed for integrating data from multiple sources (e.g., multiple computational models and experimental databases) with different levels of precision and for evaluating and managing the impact of this imprecision on the systems-level design. To support distributed robust design, improved techniques are required for enhancing parallelism in computational uncertainty analysis and for quantifying uncertainty in coupled problems in

computationally tractable ways. We believe that robust design and robust decision-making have major roles to play in addressing many of the challenges of multiscale design. By addressing these challenges, we have an opportunity to significantly improve our ability to design not only multiscale systems but also many other products, processes, and systems with similar challenges.

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Figure 1. A P-diagram showing the information input and response in a design product or process. Robust design is classified based on the source of variability.

Figure 2. The quality loss function and performance target for three manufactured products whose performance varies through different ranges and whose values of mean performance may or may not coincide with the desired performance.

Figure 3 – Computing Infrastructure for the Robust Concept Exploration Method (modified from Chen, [49])

Figure 4. Comparing two Designs with Respect to a Range of Requirements

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