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An optimization based approach for structural design considering safety, robustness, and cost

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ABSTRACT

Structural systems are subject to uncertainties due to variability in many hard-to-control *noise factors*, which include external loads, material properties, and construction workmanship. Traditional structural design methodologies, although clearly recognizing the presence of uncertainty, omit robustness against the effects of uncertainty in the design process. First, if the actual uncertainties in the design process are underestimated, the design may fail to satisfy safety requirements. Second, to guarantee safety in the presence of high variability of the system response, the structural designer may be forced to choose an overly conservative, thus inefficient and costly design. When robustness against uncertainty is not treated as one of the design objectives, the trade-off between over-design for safety and under-design for cost-savings is exacerbated. This manuscript demonstrates that safe and cost-effective structural engineering designs maybe achieved by implementing *Robust Design* concepts originally developed in manufacturing engineering to consider robustness against uncertainty. This manuscript presents an optimization-based methodology for the application of Robust Design principles to structural design and demonstrates its application on an academic problem involving design of a reinforced-concrete frame.

1. Introduction

The core of the structural engineer's role is to make rational decisions regarding design parameters in a systematical way. There are countless possible design configurations to choose from with the goal of achieving a constructible, serviceable, safe, and cost-effective design solution for a given problem. These goals have in and of themselves, competing objectives in that the safest design is most likely not the most cost efficient. These competing objectives force designers to make trade-offs to meet all design goals to a satisfactory level. To further complicate the process, these decisions often have to be made under uncertainty [1,2].

The life-cycle of a structural system is plagued by uncertainty, from design through operation. Uncertainty manifests itself in many forms, some of which entail (i) statistical limits, in which designers use discrete samples to predict the behavior of a whole system; (ii) model limits, in which the structural model developed in design and analysis simplifies reality obviating higher level physics in the system; (iii) randomness, in which structural properties are not a single value as assumed, but rather vary spatially; (iv) human error, encompassing mistakes made during the design, fabrication, and construction processes that alter the *true* design or analysis; and (v) time, lack of knowledge of future loading conditions and uncertainty in material deterioration in time [3,4]. The inherent variability in these factors must be accounted for during the design process to ensure the design objectives are met under all circumstances of interest.

Two prominent design approaches have evolved in the structural engineering field to account for variability in design parameters. The first, allowable stress design (ASD), which originated in the 1920s, is based upon a deterministic design approach. Through the ASD approach, instead of quantifying the different sources of uncertainty, designers apply a 'factor of safety' to capture *all* the variability in loads and resistance. The result is usually a conservative and safe design, but one that is likely to be inefficient [5]. The second approach, load and resistance factor design (LRFD), developed in the 1980s, is a form of reliability-based design. Here, uncertainties in the design process are quantified into two categories; load and resistance factors. This separation allows the treatment of uncertain material properties and construction imperfections through resistance factors applied on nominal capacities, and treatment of variable loads through load factors applied on nominal loads [3]. While the LRFD approach can account for variability and incorporates risk assessment, its success hinges on the availability and accuracy of statistical data [6]. In reliability-based designs, if there is an abundance of accurate statistical data,

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and the distributions of each random variable are well established, uncertainties modeled as a random variable or process [7], can be accurately accounted for; otherwise, the random variables themselves may induce uncertainties into the design process [6]. Therefore, safety requirements might be violated due to potentially underestimated variability in the structural behavior. *Explicitly* considering robustness against variability as one of the design objectives can address this concern. This is precisely the aim of the Robust Design concept, which originated in manufacturing and quality engineering.

Robust Design processes, employed in this research, target the robustness of the product output against "hard-to-control" input parameters (called "noise factors"), by adjusting "easy-to-control" input parameters (called "design parameters") [8,9]. Noise factors are factors in the structural design process whose variability cannot be reduced in any practical or feasible way. As such, Robust Design's objective is to eliminate the need for unduly difficult or costly process of reducing the variability in hard-to-control input parameters. Instead, a design that is minimally affected by this variability is sought. The aim of robust design is then to reduce the effects of these noise factors on the response of interest by manipulating the design parameters [10–12].

This study implements principles of robust design through single objective optimization using the Particle Swarm Optimization method; and demonstrates the application and feasibility of *robust structural design* approach on a structural design problem using a concrete frame structure with cross-bracing elements. In this design problem, the column dimensions and stiffness of the bracing elements may be treated as (easy-to-control) design parameters, which can easily be controlled by the designer. The uncertain material properties and forcing functions may be treated as (hard-to-control) noise factors which cannot be controlled by the designer; and the structural responses such as, stresses, strains, and displacements, may be treated as the product of the design process. Robust structural design then aims to find column dimensions and stiffness of the bracing elements that yield the structural response of interest that is robust to uncertain material properties and forcing functions. In doing so, the variability of the structural response is reduced, resulting in not only a safe, but also a cost-effective design [13].

In the remainder of this paper, we will start with an overview of the development of robust design principles, followed by a discussion on the implementation of particle swarm optimization in the proposed robust structural design strategy. Next, the proof of concept application of the proposed design approach is discussed focusing on a reinforced concrete frame. The paper concludes with a discussion of the main findings, along with the limitations and future work for this study.

2. Robust design: overview of the classical approach

Taguchi's approach exploits nonlinear relationships between design parameters and noise factors to identify design parameter values that reduce the effects of noise on the selected performance metric while satisfying the target performance requirement. In doing so, Taguchi prepared separate experimental design for design parameters and noise factors and used the cross-product array to collect the necessary data. The collected data is then analyzed to decipher the interactions between the design parameters and noise factors, to ultimately reduce the variability of the performance metric and to adjust the mean of the performance metric to a target value [11,14].

Taguchi [11] developed a two-step process as demonstrated in Fig. 1. The first step focuses on minimizing variation (Fig. 1a). This step seeks the optimum settings of the design variables by maximizing what Taguchi calls the *signal-to-noise* (S/N) ratio, defined as the ratio of response in the system to the variation in response caused by noise factors. Three different classes of S/N ratios are defined. The first is *nominal-the-best*, where a certain target value is desired. Second is *smaller-the-better*, where the most robust option is a zero value response, and likewise, the third class of S/N ratios, called *larger-the-better*, ideally aims to achieve a target value of infinity.

The second step of Taguchi method focuses on moving the mean to the desired target (Fig. 1b) [15,16]. This can be accomplished through the careful selection of a design parameter(s), which primarily affects the mean of the distribution and exhibits minimal influence on the variation of the distribution, therefore preserving the maximized signal-to-noise ratio achieved in step one. This design parameter(s) is referred to as a scale factor used to *scale* the mean to a desired value and can be calculated according to Eq. (1), where s is the scale factor, τ is the target value, and μ is the mean of the current distribution.

$$S = \frac{\tau}{\mu} \tag{1}$$

Due to its simplicity and proven advantages, the Taguchi method has been widely applied to engineering design problems [17–21]. However, in the adaptation of the principles of Taguchi method, several drawbacks were routinely encountered. One of the major problems has been the inability to locate a scale factor [22–24]. There are many practical design situations where all design parameters affect both the mean and standard deviation making designation of a scale factor rather challenging or even unattainable. In such situations, the maximized signal-to-noise ratio is not upheld in step two, thereby causing an unintentional and coincident shifting of the standard deviation [11,16].

Furthermore, Taguchi method has been criticized for requiring the values of the design parameters and noise factors to be defined a priori, potentially leading to unfruitful calculations at areas of the domain with little relevance from a design standpoint [25]. This aspect combined with the cross-product nature of design of experiments requires unduly high computational efforts to gain insight into interactions between design parameters and noise factors [14,26–29]. Another criticism for the Taguchi method is its inability for systematic treatment of the design constraints [30–34], which are incorporated through a penalty on the defined objective [35].

These drawbacks led to subsequent research, and the development of refined Robust Design methods [10,36–39] including Bayesian [40] and optimization [41–44] based robust design methods. In Bayesian methods [45], the aim is to maximize the posterior predictive probability that the product meets constrains imposed on the responses [46]. In optimization based approaches to robust design, search algorithms are used to find design parameters that satisfy design objectives simultaneously considering the mean and standard deviation of the performance metric. Optimization based approaches, implemented herein, can be said to be of more widespread use compared to Bayesian interpretations of Robust Design, as they can also consider various constraints, such as cost or performance related limitations with ease.

Optimization based approaches can be categorized as single-objective [41] and multi-objective [42–44]. While in single objective optimization, the output is a single optimal solution, in the multi-objective optimization, the vector of conflicting objectives yield a suite of Pareto solutions. In the latter, the evaluation of the trade-offs between conflicting objectives among Pareto solutions and the selection of the final design solution is left to the subjective opinion of the decision maker, introducing uncertainty to the process [47]. Moreover, multi-objective optimization tech-