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Crashworthiness optimization with uncertainty from surrogate model and numerical error

Na Qiu[a,b], Yunkai Gao[c,*], Jianguang Fang[d,e], Guangyong Sun[e], Qing Li[e], Nam H. Kim[b,*]

[a] Mechanical and Electrical Engineering College, Hainan University, Haikou 570228, China
[b] Dept. of Mechanical & Aerospace Engineering, University of Florida, Gainesville, FL 32611, USA
[c] School of Automotive Studies, Tongji University, Shanghai 201804, China
[d] Centre for Built Infrastructure Research, School of Civil and Environmental Engineering, University of Technology Sydney, Sydney, NSW 2007, Australia
[e] School of Aerospace, Mechanical and Mechatronic Engineering, The University of Sydney, Sydney, NSW 2006, Australia

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ABSTRACT

Due to the expensive cost of full-scale tests, more and more designs rely on simulation. For highly nonlinear crash simulation, numerical uncertainty is an inherent by-product, which refers to the oscillation of results when the simulation is repeated at the same design or the design variables are slightly changed. This oscillation directly influences the quality and reliability of the optimal design. This paper shows how these issues can be addressed by proposing a simple uncertainty quantification method for numerical uncertainty (noise) and surrogate model uncertainty (error) in the optimization process. Three engineering problems, a tube crush example, an automotive front-rail crush example and a multi-cell structure crush example, are used to illustrate this method. Firstly, the level of numerical uncertainty is quantified in terms of noise frequency and amplitude, and the convergence study of these two criteria is employed to determine an appropriate data size to describe numerical noise. Secondly, an estimation method considering both numerical noise and surrogate model error is proposed based on the prediction variance of the polynomial response surface. Finally, the tube and front rail structures are optimized according to the proposed uncertainty quantification method. It was found that by considering the two sources of uncertainty, the optimal designs are more reliable than the deterministic solutions.

1. Introduction

Vehicle crashworthiness has drawn increasing attention because it is associated with public safety and socioeconomic benefits. One possible way to enhance crashworthiness is to optimize the energy absorption capability of key automotive components, thereby reducing severe injuries and fatalities when a collision occurs. With the increase of speed and power of computers in recent years, the ability to simulate complex systems has been improved [1], which facilitates crashworthiness optimization in aerospace and automotive engineering fields. Despite the wide use of finite element analysis in crashworthiness optimization, the presence of numerical uncertainty (noise) requires more attention.

Here, numerical uncertainty (noise) represents the oscillations with small wavelengths when the same simulation model is calculated several times or the design variables are slightly changed. Many researchers [2–4] pointed out that the crash simulations are not repeatable and have obvious numerical uncertainty due to the instability of structures (such as buckling) [2], contact bifurcations, numerical rounding errors and parallel computing errors [5]. Thole and Mei [6] revealed that the unstable behavior or large numerical noise in crash simulations is due to bifurcations, which in turn are caused by parallel computing algorithms, contact search problems, buckling, and levers. Will and Bucher [7] revealed the existence of numerical noise in front-crash load case for a passenger vehicle and proposed a method to identify and quantify the numerical noise. Duddeck [3] claimed that the level of noise in the crash simulation varies from 1% to 10%, which depends on the FE model, configuration, and load cases. They also assumed that frontal impact load case is much more sensitive to bifurcations than the lateral load case. Therefore, in this paper, we will use the tube and front rail models as examples to quantify the numerical noise and to take into account it in the crashworthiness optimization process.

Many existing studies are limited to deterministic optimization. However, there are a number of uncertainties which must be compensated during the optimization process. For uncertainty-based optimization, most researchers [8–16] mainly considered the parametric

* Corresponding authors.
E-mail addresses: gaoyunkai@tongji.edu.cn (Y. Gao), nkim@ufl.edu (N.H. Kim).

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uncertainty in sheet thickness, geometry size and mechanical properties of materials due to manufacturing imperfection and/or other factors. However, surrogate model uncertainty may have a large effect on the reliability and robustness of the optimum and should be taken into account in the optimization process [17,18]. In this regard, Picheny et al. [19] developed a conservative surrogate method by adding a safety margin to consider the surrogate model uncertainty. Viana et al. [20] investigated the conservative modeling technique to consider the model form error by using cross validation method. Zhang et al. [17] proposed a new robust design method based on the prediction variance of kriging model to take into account both surrogate model uncertainty and parametric uncertainty. Kim and Choi [21] discussed a reliability-based design optimization method including the effect of response surface error. However, the previous studies on crashworthiness optimization often focus on input randomness and surrogate model error and fail to consider the effect of numerical uncertainty. For constrained optimization problems, the optimum solution tends to be pushed on the constraint boundary, which leaves a little room to tolerate the prediction error of surrogate model and numerical uncertainty. Therefore, the numerical uncertainty and surrogate model uncertainty need to be considered to ensure reliable optimal design.

Even if we know the presence of numerical uncertainty in crashworthiness simulation, it is unclear how to quantify its level, how to determine the suitable data size to quantify it, and how to obtain reliable optimums. All of these are the difficulties that need to be solved when considering numerical uncertainty in engineering applications. This paper aims to address these issues by following the flowchart as shown in Fig. 1. The paper is structured as follows: Section 2 reveals the presence of numerical uncertainty in crashworthiness simulations and quantifies the level of numerical noise according to the frequency and amplitude of noise. Based on these two criteria, the sample size is determined from the convergence study. The estimation method for both numerical and surrogate model uncertainties is discussed in detail in Section 3. Section 4 aims to develop an uncertainty-based optimization methodology by considering both numerical uncertainty and surrogate model uncertainty, followed by conclusions in Section 5.

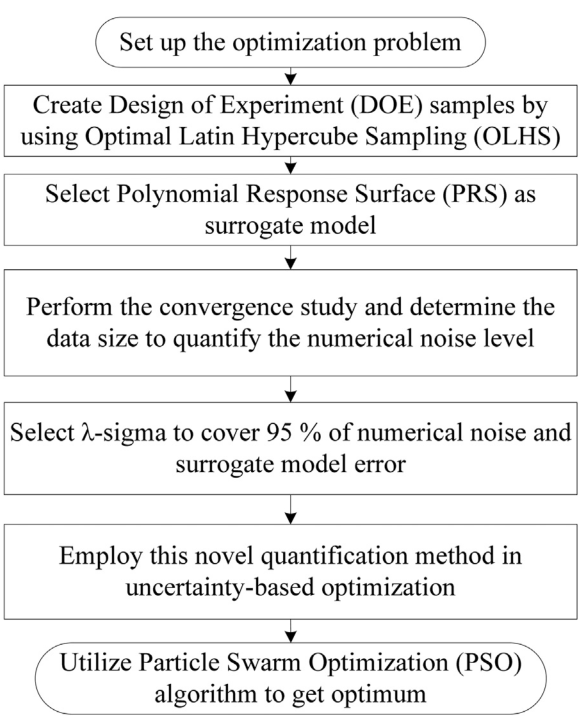

Fig. 1. The flowchart of dealing with numerical noise in uncertainty-based crashworthiness optimization.

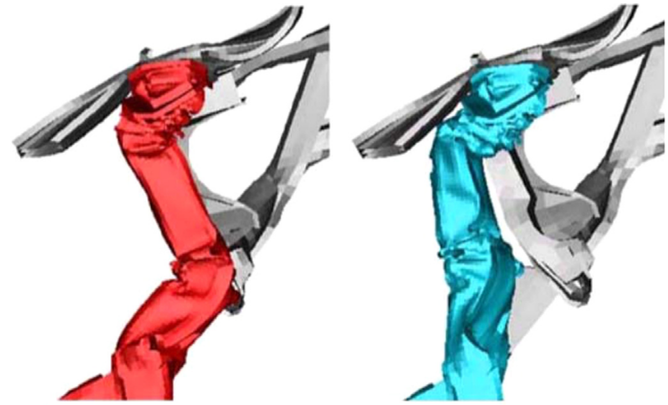

Fig. 2. Example of a frontal crash simulation with the same FE model and hardware shows two different reaction patterns because of bifurcation [22].

2. Determination of data size to quantify numerical noise

Because of the expensive cost of full-scale tests, most of crashworthiness optimizations are conducted based on computer simulations. However, most commercial programs for simulating crashworthiness use an explicit time integration scheme, a penalty-based contact/impact formulation, and distributed memory parallelization. For the highly nonlinear nature of crashworthiness simulation, the objective functions are often non-convex, with a number of extrema and discontinuities [5]. For these reasons, the simulation results are subjected to significant numerical error and noise, which is considered as the main difficulty in crashworthiness optimization and largely affects the reliability and robustness of optimum designs. Numerical uncertainty means that different runs at different times or machines yield different results. Even with the same FE model and hardware, the simulation results can be different [3,22], as shown in Fig. 2. Therefore, the response of a design cannot be represented by the value from one simulation, but a confidence interval considering numerical uncertainty, which can yield more robust and reliable optimums for crashworthiness optimization.

2.1. Problem description

In this study, specific energy absorption (*SEA*) is considered as an objective function to quantitatively evaluate the crash performances. *SEA* is a key indicator to take into account the energy absorption capability and the mass factor, and can be calculated from the following formula:

$$SEA = \frac{EA}{M} = \frac{\int_0^d F(s)\mathrm{d}s}{M} \tag{1}$$

where F is the impact force at the crash distance s and d is the total crash displacement concerned. *EA* is the energy absorption at the displacement d. The crash performance of the front rail performs better when it can absorb more energy so that less energy is transferred to passengers in the event of a crash. At the same time, light weight is preferable for the lightweight requirement. In this study, d is set to 120 mm for tube and multi-cell structure and 150 mm for front rail examples, respectively.

2.1.1. Tube crash example

In this paper, a square tube under axial compressive loading (see Fig. 3) is used as an example to study how to deal with the numerical error and noise in crashworthiness. Since the energy absorber in the front rail is a tube-like structure, some researchers [13,23–29] have previously investigated the tube structure in order to improve the crashworthiness performance of the front rail. As an important energy