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Reliability-based robust assessment for multiobjective optimization design of improving occupant restraint system performance

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ABSTRACT

Optimal performance of vehicle occupant restraint system (ORS) requires an accurate assessment of occupant injury values including head, neck and chest responses, etc. To provide a feasible framework for incorporating occupant injury characteristics into the ORS design schemes, this paper presents a reliability-based robust approach for the development of the ORS. The uncertainties of design variables are addressed and the general formulations of reliable and robust design are given in the optimization process. The ORS optimization is a highly nonlinear and large scale problem. In order to save the computational cost, an optimal sampling strategy is applied to generate sample points at the stage of design of experiment (DOE). Further, to efficiently obtain a robust approximation, the support vector regression (SVR) is suggested to construct the surrogate model in the vehicle ORS design process. The multiobjective particle swarm optimization (MPSO) algorithm is used for obtaining the Pareto optimal set with emphasis on resolving conflicting requirements from some of the objectives and the Monte Carlo simulation (MCS) method is applied to perform the reliability and robustness analysis. The differences of three different Pareto fronts of the deterministic, reliable and robust multiobjective optimization designs are compared and analyzed in this study. Finally, the reliability-based robust optimization result is verified by using sled system test. The result shows that the proposed reliability-based robust optimization design is efficient in solving ORS design optimization problems.

1. Introduction

Vehicle safety can be assessed by some parameters such as the contact forces and resultant accelerations exerted on occupants during a vehicle crash. An occupant restraint system (ORS) is an important part of vehicle safety systems which can provide supplemental protection to occupants in a crash event. The typical ORS is composed of, but are not limited to, the airbags, seat belts, knee bolsters, and crash sensing systems, etc. Today, the extensive government regulations and consumer information programs make the design and optimization of the vehicle occupant protection into a complex and challenging task. So, researches on ORS performance have become a very important part in both the academe and automotive industry.

To fully evaluate the performance of the ORS and ensure it compliance of product requirement in the automotive industry, the ORS should be tested with multiple crash modes. Use only the physical test to develop the ORS is not only costly but also time consuming. To solve this problem, computer aided engineering (CAE) analysis is widely used to simulate vehicle crashworthiness and ORS in various impact modes [1–3]. For example, Pinfold and Chapman [4] described the design analysis response tool created to investigate the application of knowledge based engineering techniques for the automation of the finite element analysis (FEA) model creation process for such a structure. Vadlamudi et al. [5] demonstrated that it was possible to develop multibody systems-based models of helicopters and simulate appropriate crash scenarios with the use of programs such as MADYMO, and to investigate the effectiveness of occupant protection systems deployed during helicopter crash scenarios. Carter and Neal-Sturgess [6] reconstructed a real-world collision between a vehicle and cyclist using MADYMO. Wang et al. [7] presented a coupled meshfree/FEA method which allows engineers to model the severe deformation area using the meshfree method while keeping the remaining area modeled by the FEA methods. Cheng et al. [8] developed a single model that can be successfully used in computational simulations of full frontal, offset frontal, side, and oblique car-to-car impacts.

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Nevertheless, these above mentioned industrial applications somewhat appeared to rely on engineering experience of designer in an iterative fashion. To attain a satisfactory result, it may be needed to manually alter the design model parameters and then re-evaluate the results, whereas this process is not only time-consuming but also subjective, and this also cannot guarantee a global optimum result. In this sense, the capacity of CAE may have not been fully taken up yet. Therefore, some researchers have begun to work on how to translate CAE from a passive verification tool to a more active design tool in the design process [9–12]. The CAE technology based optimizations signifies a more effective way by seeking for an optimal design systematically and its applications in vehicle safety design have been substantially explored by some researchers [9,13]. For example, a number of researchers have successfully done works using non-dominated sorting genetic algorithm II (NSGA-II) or particle swarm optimization (PSO) algorithm within multiobjective optimization (MOP) frameworks to solve optimum design problems. Among which, PSO has been proven rather effective for solving highly nonlinear design problems. For instance, Ebrahimi et al. [14] carried out a comparison of the proposed algorithm against the original version of PSO, sequential quadratic programming, and method of centers over MOP of the design problem. Venter and Sobieszczanski-Sobieski [15] applied a PSO algorithm within a MOP framework to design a transport aircraft wing. The numerical results obviously demonstrated the PSO algorithm advantages to find optimum points dealing with the noisy and discrete variables compared with gradient based optimization algorithms. Hart and Vlahopoulos [16] utilized a PSO algorithm at the top and discipline levels of a multilevel MOP framework. Furthermore, Yildiz and Solanki [17] presented an improved PSO method for MOP of vehicle crashworthiness.

Although these algorithms are capable of solving the problem of engineering optimization design, the implicit relationship and large scale problem could largely compromise the feasibility and precision in practical applications of prevalent mathematical programming techniques. As an effective alternative, it is common to use surrogate model for approximating the responses. A number of surrogate techniques, such as Kriging (KRG), radial basis function (RBF) and support vector regression (SVR), have been investigated in approximating mathematical test functions. More surrogate techniques to making approximate evaluations of response dispersion data were discussed in several papers. For instance, Fang et al. [18] proposed to apply the RBF and response surface methodology (RSM) for multiobjective crashworthiness design of a full-scale vehicle body in frontal collision. Zhang et al. [19] combined KRG metamodeling technique with multiobjective genetic algorithm for crashworthiness design of foam-filled bitubal structures. Zhu et al. [20] used conservative surrogate models for lightweight design of vehicle parameters under crashworthiness. Pan et al. [21] used SVR for the optimum design of B-pillar using tailor-welded blank structure to minimize the weight under the constraints of vehicle roof crush and side impact. However, SVR achieves more accurate and robust function approximations than RSM, KRG and RBF through many cases validation in the study [22]. Zhu et al. [23] compared the SVR, KG, RBF, and ANN Surrogating techniques and found SVR performs very well in highly nonlinear vehicle crash problems, both on more accuracy and efficiency than the others in the following optimization process. So, SVR surrogate is investigated to approximate the ORS performance in this study, which is one of the most highly nonlinear performances.

Although there has been substantial published works on the optimization for structural crashworthiness design, limited reports have been available to optimize ORS and validate the optimization results via physical tests. MOP for ORS considering the uncertainty also has received limited attention in the literature. Thinking for its significant practical value, it is very important for the ORS development using the multiobjective reliability-based robust optimization design. This paper presents a comprehensive study approach of how nondeterministic optimization schemes are performed in the design of vehicle ORS under a 40% offset crashing scenario based on China New Car Assessment Program (C-NCAP). The multiobjective reliability-based robust optimization design is conducted for minimizing injury parameters of the passenger chest acceleration and chest displacement subjecting to the constraints of key injury criteria, such as HIC_{36} and neck moment, etc. Eight design variables are selected from the airbag, seat and seatbelt parameters which include mass flow rates, vent areas, belt limiter load etc. Based on the design of experimental (DOE), optimization criteria and methods are established for the next step. After validating the SVR surrogate models, the multiobjective particle swarm optimization (MPSO) algorithm is applied to search the optimal solution set. The basic Monte Carlo simulation (MCS) method is applied to perform a reliable and robust analysis. As a result, the three different Pareto sets are generated for deterministic and non-deterministic optimization design, respectively. The reliability-based robust optimal results are validated with physical test data and then will be applied for products design in the future.

2. Theory and methodology

2.1. Design of experiment

A sample of the design variables space as a training data set is generated by design of experiment (DOE). These DOE techniques include full factorial design, optimal Latin hypercube design, uniform design, orthogonal arrays, central composite design, face-centered cubic design, and factorial design.

Full factorial is a classical DOE for studying interactions between variables in Fig. 1(a). It is suited for statistical analysis, since it gives all the information related to the influence of each variable and each interaction. The full factorial algorithm generates every possible combination, and the number of experiments N is given by the product:

$$N = \prod_{i=1}^{k} n_i \tag{1}$$

where n_i is the number of levels for ith variable, and k is the number of variables. The number of levels should be specified for each input variable. The disadvantage of this method is that the number of experiments grows dramatically with the number of variables. A full factorial is practical when less than five or six input variables are analyzed. Too many of design points would increase the computational burden and testing all combinations becomes too hard. One way to solve the problem is the optimal Latin hypercube sampling (OLHS) technique adopted for constructing the surrogate models in the exploratory design space. Unlike the conventional factorial DOE, the OLHS method can capture the higher order of nonlinearity with relatively fewer design points and provide an efficient estimate of the overall mean of the response than the estimated based on random sampling in Fig. 1(b). The number of the OLHS is determined by the total number of factors including control variables and noisy variables in the model.

In this study, $5n$ sample points generated by OLHS are used, where n denotes the total number of design variables. That is, a training data set with forty sample points is generated as there are eight design variables. It is noted that the number of sampling points can vary according to the availability of computing capability.