VEHICLE OCCUPANT RESTRAINT SYSTEM DESIGN UNDER UNCERTAINTY BY USING MULTI-OBJECTIVE ROBUST DESIGN OPTIMIZATION

HIROSUKE HORII
Department of Mechatronics, University of Yamanashi, Japan.

ABSTRACT

This research reports a vehicle occupant restraint system design that takes account of uncertainties of crash conditions and situations by using a multi-objective robust design optimization method called MORDO. The vehicle occupant restraint system is composed of restraint equipment, such as an airbag, a seatbelt and a knee bolster. The optimization aims to improve the safety performance of the system and its robustness simultaneously. The safety of the system is evaluated by some indexes based on some safety regulations, which are calculated by response surface model of an occupant at a crash. In addition, its robustness is evaluated by the mean value and the standard deviation of objective functions, which are calculated by using Monte Carlo simulation based on a certain probabilistic distribution in space of design variables around each design candidate. Some helpful information for designing the restraint systems, such as trade-off information of safety performance and its robustness, are provided by visualizing and analysing the Pareto optimal solutions.
Keywords: evolutionary algorithm, machine learning, multi-objective optimization, occupant safety, robust optimization

1 INTRODUCTION

Performance of a vehicle occupant restraint system is affected by interaction among occupant restraint equipment, such as an airbag and a seat belt. Furthermore, situations of crashes, such as speed at the crash and posture of occupants, are various. Therefore, performance of the system requires robustness under the interactions and the uncertainties of the design, the condition and the situation. In automotive engineering field, summation of the mean value and the standard deviation is used as the objective function at the robust design optimization of the performance and the stability so far (e.g. Fu and Abramoski [1]).

On the other hand, in the aerospace and aeronautics field, some multi-objective robust design approaches have been proposed, such as the multi-objective robust design optimization, MORDO by Padovan *et al*. [2] and Parussini *et al*. [3], and the design for multi-objective six sigma, DFMOSS by Shimoyama *et al*. [4] The features of those methods are (1) the performance and the stability under uncertainty are set as independent objective functions, and then (2) trade-off information of the performance and the stability are obtained in one time optimization.

The author has been working on improving the vehicle occupant restraint system design so far. Firstly, evaluation time of the safety performance of the design was reduced by using response surface models of the injury criteria by Horii [5]. The response surface models were constructed by using some machine learning methods whose training data set was CAE sampling results of an occupant behaviour simulation. The simulation model was constructed by using a multi-body dynamics simulation. Then significant reduction of the evaluation time in multi-objective optimization by using evolutionary algorithm was derived by applying the response surface models by Horii [6].

In this research, with incorporating the above outcomes, the MORDO is employed for the vehicle occupant restraint system design. This design system evaluates some injury criteria

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and their stabilities under uncertain conditions, and then trade-off information of the performances and the stabilities are provided to users. Subject of the design is an occupant restraint system at a frontal crash of a vehicle.

2 MULTI-OBJECTIVE ROBUST DESIGN OPTIMZATION, MORDO

2.1 Robustness in engineering design

In engineering design, robustness against perturbation is necessary. The perturbation includes tolerance in manufacturing, uncertainty of operating condition, error at operation and so on. On the other hand, usual optimization seeks the best point of an objective function. A conceptual diagram of the above idea is shown in Fig. 1. The point A is the optimal point and the point B is the suboptimal point, but the response of the point A is steeper than that of the point B. If the design has fine precision, the point A may be the best solution. But if the design includes a perturbation, the performance of the point A may be unstable and it may not be suitable. So the engineering design requires taking account of the perturbation and the precision of the design variables, and their effect to the objective function.

2.2 Robustness evaluation with MORDO

In MORDO, each design variable is set any probabilistic distribution of perturbation. Robustness of a design candidate is evaluated by mean value and standard deviation of objective functions, which are calculated by using Monte Carlo simulation based on the above probabilistic distribution in space of design variables around each candidate. A conceptual diagram of the above idea is shown in Fig. 2. Each design variable x_i is set a certain normal distribution. Then the mean

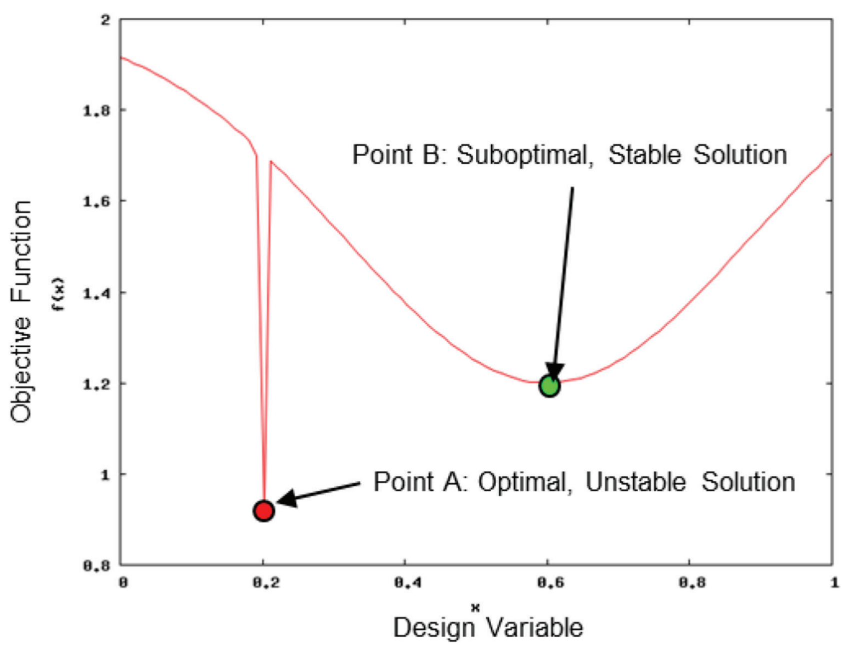

Figure 1: Conceptual diagram of stability of design (at minimization).

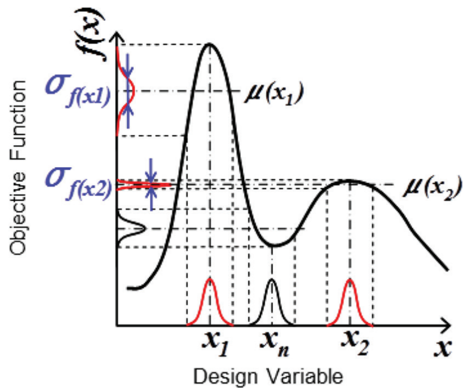

Figure 2: Conceptual diagram of robustness evaluation at MORDO.

value $\mu(x_i)$ and the standard deviation $\sigma_{f(x_i)}$ of the objective function are calculated. Those mean value and standard deviation are also set as another objective function in MORDO. Decision maker of a design is able to understand the balance of performance and robustness of many design candidates all at once after the optimization.

3 OCCUPANT RESTRAINT SYSTEM DESIGN BY USING MORDO

3.1 Response surface model of vehicle occupant restraint system

In this research, since huge number of function evaluation is required for optimization and robustness evaluation, it is impossible to employ direct simulation. Firstly, response surface models are constructed by using limited samplings of direct simulation. Then, the response surface models are employed for optimization and robustness evaluation.

Injury criteria of an occupant at a frontal crash are estimated by using a machine learning method, Gaussian Process. The Gaussian process is a Bayesian approach, based upon the expression of knowledge in terms of probabilistic distribution (Rasmussen and Williams [7]). This method is a powerful regression model specified by parameterized mean and covariance functions and suitable for estimating non-polynomial responses.

An occupant's behaviour model of a full-frontal crash testing shown in Fig. 3 is constructed by using a multi-body dynamics tool, MADYMO. The model is composed of a

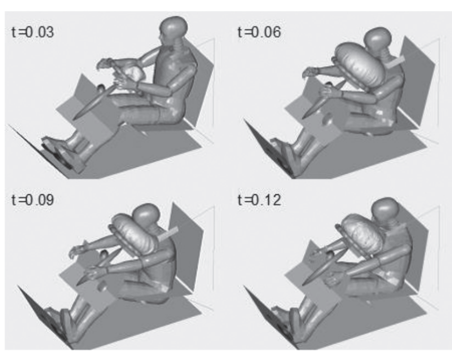

Figure 3: Occupant behaviour model at frontal crash.

Table 1: Definition of design variables.

	Variable	Range and name
Airbag:	Time to fire (sec.)	0.015≦AB_TTF≦0.035
	Mass flow rate	0.5≦AB_MFR≦2.0
	Vent hole factor	0.5≦AB_VHF≦2.0
Seatbelt:	Time to fire (sec.)	0.01≦Belt_Preten_TTF≦0.03
	Load limit (N)	2000≦Belt_Preten_LL≦6000
Knee bolster:	Stiffness factor	0.5≦SF_KB≦2.0

Hybrid-III dummy, surrounding equipment such as a seat and a steering wheel, and restraint equipment such as an airbag, a seatbelt and a knee bolster. The model simulates the occupant's behaviour at the crash for 0.12 sec.

Input variables for controlling the behaviour of the model, consists of six design variables regarding the restraint equipment, which strongly affect safety indexes, an airbag, a seatbelt and a knee bolster. Definition of the design variables are shown in Table 1.

Output variables are three safety indexes based on the Japan NCAP, head injury criterion, thoracic resultant acceleration in 3 msec. and femur load. The head injury criterion, HIC is an index of head injury risk. The thoracic resultant acceleration in 3 msec., T3MS is measured by an accelerometer mounted on centre of mass of a crash dummy's chest. The femur load, FL is measured by load cells mounted on the dummy's left and right femurs. FL_L is the left femur's value, and FL_R is the right femur's value.

After good agreement of actual simulation and response surface models were confirmed by Horii [5], the response surface models, which are constructed by 500 of the number of sampling of the training data set, are employed for following optimization.

3.2 Implementation of MORDO for vehicle occupant restraint system design

Here, the above four response surface models of HIC, T3MS, FL_L and FL_R are employed for optimization of the vehicle occupant restraint system. The optimization problem is defined as four-objective minimization problem. The objective functions are the mean value and the standard deviation of the HIC and the T3MS. The FL_L and the FL_R are set as constraints. Summary of the objective functions and the constraints are shown in Table 2.

Table 2: Summary of the objective functions and constraints.

	Name
Minimize:	Mean of HIC, $\mu(HIC)$
	Mean of T3MS, $\mu(T3MS)$
	Std. Dev. of HIC, $\sigma(HIC)$
	Std. Dev. of T3MS, $\sigma(T3MS)$
Subject to:	$\mu(HIC)+3\sigma(HIC)\le 1000$
(Regal regulation)	$\mu(T3MS)+3\sigma(T3MS)\le 588$
	FL_L ≤ 1000
	FL_R ≤ 1000

An evolutionary multi-objective optimization algorithm, the Adaptive Range Multi-Objective Genetic Algorithm, ARMOGA by Sasaki and Obayashi [8] is employed as an optimizer. The flowchart of the ARMOGA is shown in Fig. 4. In order to taking account of perturbation of detecting time of a crash, AB_TTF and Belt_Preten_TTF are selected as robust parameter. The AB_TTF and the Belt_Preten_TTF are the parameters that define the operation timing of the airbag and the seatbelt pretensioner. Normal distribution is selected as the probabilistic distribution for Monte Carlo simulation. At each evaluation point, 100 samplings are generated under the above distribution for assessing the robustness. Summary of the MORDO setting is shown in Table 3.

3.3 Optimization result

All design candidates, which were explored and evaluated by the MORDO, are shown in Fig. 5. Pareto optimal solutions, which were extracted from the above all design candidates,

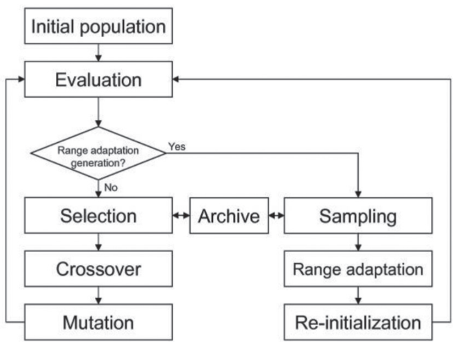

Figure 4: Flowchart of ARMOGA.

Table 3: Summary of the MORDO setting.

Optimizer setting	
Optimizer	ARMOGA
Population size	40
Generation	50
Crossover method	BLX-0.5
Crossover rate	1
Mutation rate	0.1
Range adaptive operation:	
Starting generation	20
AR interval	5
Robust setting	
Robust Parameter	AB_TTF Belt_Preten_TTF
Probabilistic distribution	Normal distribution
Std. Dev. of perturbation	$\sigma = 5.0\times10^{-4}\,sec.$
Number of sampling	100

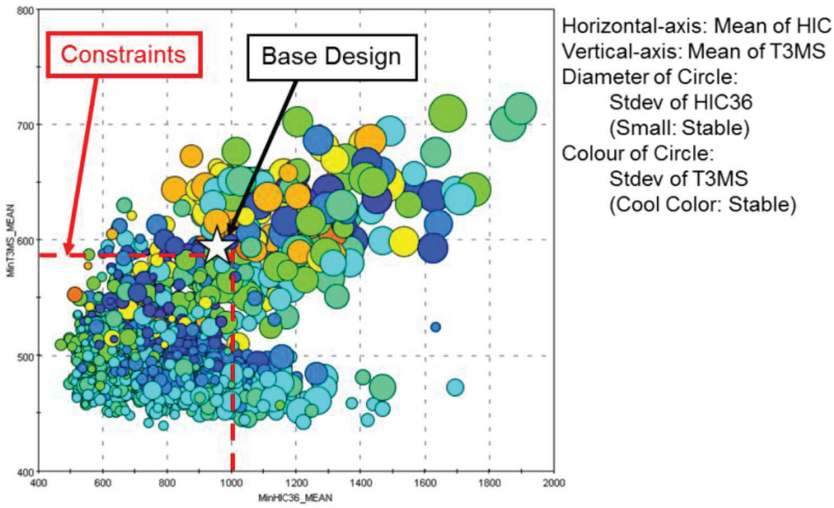

Figure 5: All design candidates that were explored and evaluated by the MORDO.

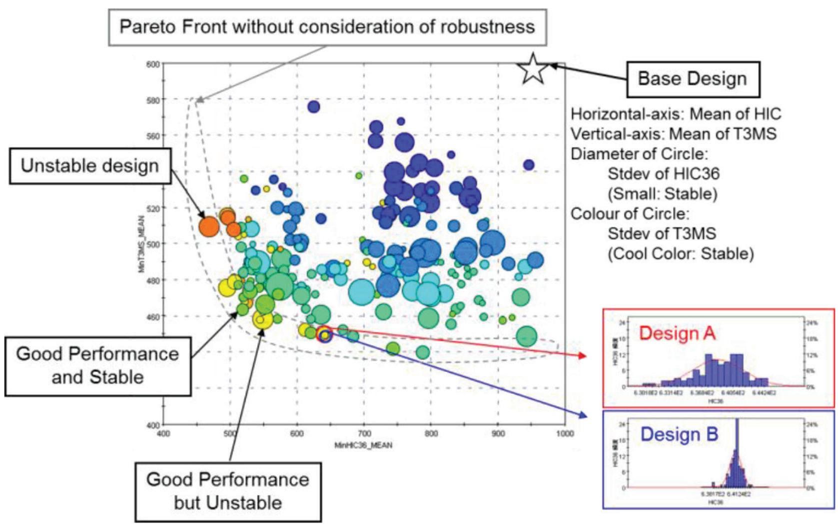

Figure 6: Pareto optimal solutions that were extracted from all design candidates.

are shown in Fig. 6. The horizontal axis represents the mean of the HIC. The vertical axis represents the mean of the T3MS. The diameter of each circle represents the standard deviation of the HIC. The small circle means stable and large circle means unstable. The colour of each circle indicates the standard deviation of the T3MS. Cool colour means stable and warm colour means unstable. These charts help the decision maker to understand the trade-off balance of injury risks between head and thoraces, and stability of each design candidate simultaneously.

As an example of showing an effectiveness of the MORDO, here we focus on two similar design candidates, the design A and the design B in Fig. 6. The frequency distribution charts

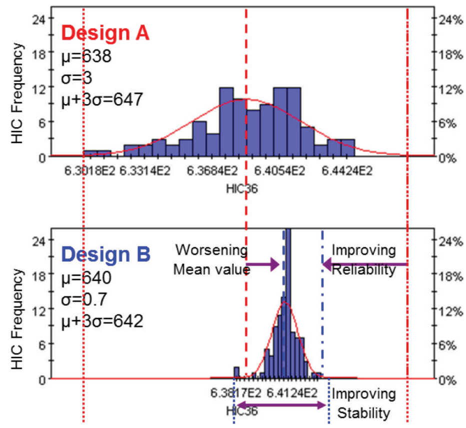

Figure 7: Frequency distribution of Monte Carlo sampling of HIC.

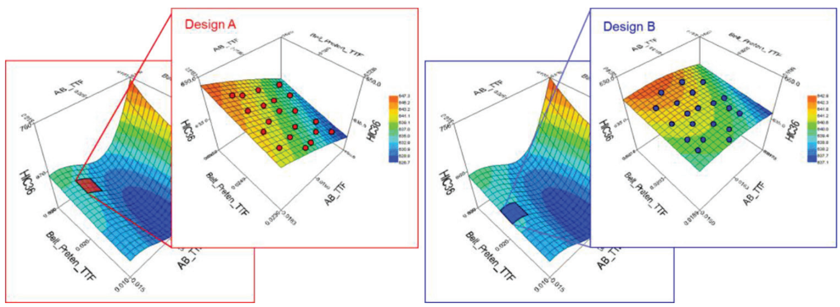

Figure 8: Response surface of HIC

of Monte Carlo sampling of the HIC of the two design candidates are shown in Fig. 7. The response surface of the HIC for two robust parameters, AB_TTF and Belt_Preten_TTF are shown in Fig. 8.

Figure 7 shows that though the mean value of the HIC of the design A is slight superior to that of the design B, the standard deviation of the HIC of the design A is larger than that of the design B. Therefore, the design A is unstable and the statistical worst case, that is, $\mu(HIC)+3\sigma(HIC)$ is inferior to the design B. Figure 8 also shows that the design A is on the slope of the response surface and it seems unstable. On the other hand, the design B is on a relatively flat surface and it seems more stable. Accordingly, if a slight worsening of the mean value is accepted, a robust design candidate can be obtained.

In this way, the MORDO provides a design environment, which is able to decide a final design with taking account of robustness at a vehicle occupant restraint system design.

4 CONCLUDING SUMMARY

In this research, a multi-objective robust design optimization method, the MORDO was applied for a vehicle occupant restraint system design. The MORDO provided a design environment, which was able to decide a final design with taking account of robustness. The effectiveness of MORDO was shown by visualizing and analysing with some results, such as scatter plot, frequency distribution of Monte Carlo sampling designs and shape of response surface of an objective function.

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