Proceedings of IDETC/CIE 2005
ASME 2005 International Design Engineering Technical Conferences
& Computers and Information in Engineering Conference
September 24-28, 2005, Long Beach, California USA

DETC2005-84965

VEHICLE CRASHWORTHINESS DESIGN VIA A SURROGATE MODEL ENSEMBLE AND A CO-EVOLUTIONARY GENETIC ALGORITHM

Karim Hamza and **Kazuhiro Saitou**[§]
Department of Mechanical Engineering
University of Michigan
Ann Arbor, Michigan, USA
{khamza, kazu}@umich.edu

ABSTRACT

This paper presents a new method for designing vehicle structures for crashworthiness using surrogate models and a genetic algorithm. Inspired by the classifier ensemble approaches in pattern recognition, the method estimates the crash performance of a candidate design based on an ensemble of surrogate models constructed from the different sets of samples of finite element analyses. Multiple sub-populations of candidate designs are evolved, in a co-evolutionary fashion, to minimize the different aggregates of the outputs of the surrogate models in the ensemble, as well as the raw output of each surrogate. With the same sample size of finite element analyses, it is expected the method can provide wider ranges potentially high-performance designs than the conventional methods that employ a single surrogate model, by effectively compensating the errors associated with individual surrogate models. Two case studies on simplified and full vehicle models subject to full-overlap frontal crash conditions are presented for demonstration.

1. INTRODUCTION

Vehicle crashworthiness is an important design attribute which designers strive to improve. However, design for structural crashworthiness is a difficult task, which often involves non-obvious decisions beyond simply designing stiffer structures. A vehicle structure has to be strong in some parts to help minimizing the intrusion of the passenger compartment, yet compliant in other parts to absorb the impact energy. Moreover, performance criteria such as deformation, acceleration, and the risks of passenger injury are usually related to the design variables (*e.g.*, length and thickness of structural members) via complex nonlinear functions that have no known closed form solutions.

While actual testing is a more direct measure of vehicle crash performance, the computational crash simulations using finite element (FE) analyses are widely used in industry during design iterations, due to the no need of building physical prototypes. The main drawback of FE crash simulation is the requirement of massive computational resources, which makes them prohibitively difficult to be used within optimization. It is practical, therefore, is to construct a surrogate model from the results of the FE simulations of a small number of sample designs, and use the surrogate model with an automated optimization algorithm. While the DOE/Surrogates is a dominant approach in practice [1], its major problem is the difficulty in constructing a high fidelity surrogate over a large design space with a number of samples practical for running time-consuming FE crash simulations [2,3].

To achieve high fidelity with a limited number of samples, this paper presents a new method that utilizes an ensemble of surrogate models, rather than a single surrogate model, to estimate the crash performance of a candidate structure during optimization. It is inspired by the classifier ensemble approaches in pattern recognition [4-8], where the different aggregates, such as the weighted average, best, and majority votes, of multiple pattern classifiers trained from the different sets of training data, are used for improved performances over the single classifiers. Based on multi-objective genetic algorithms [9,10], the proposed method, which we shall refer to as Multi-Scenario Co-Evolutionary Genetic Algorithm (MSCGA), evolves multiple sub-populations of candidate designs in a co-evolutionary fashion [11], that minimize the different aggregates of the outputs of the surrogate models in the ensemble as well as the raw output of each surrogate. With the same sample size of finite element analyses, it is expected the method can provide wider ranges potentially high-performance designs than the conventional methods that

[§] Corresponding Author

employ a single surrogate model, by effectively compensating the errors associated with each surrogate models in the ensemble.

This paper started with a motivation that leads to introducing the proposed approach. The following sections provide a review of relevant literature, followed by the details of the proposed algorithm. A simple numerical study is presented, and then the proposed approach is applied to two case studies involving a simplified vehicle model, as well as a full vehicle subjected to full-overlap frontal crash conditions. The paper concludes with a general discussion.

2. RELATED WORK

2.1. Surrogate Models in Crashworthiness Design

Meta-models or surrogate models have been widely used to assist design optimization when computer models for estimating design performances are too computationally expensive. A review of the applications of and the challenges using meta-models is presented in [1]. For crashworthiness optimization, typically, the surrogate models based on Polynomial Regression [12,13], Neural Networks [14,15], Radial Basis Networks [15, 16] and Kriging [17,18], which are constructed from the sample designs obtained by Design of Experiments (DOE) methods such as the orthogonal arrays [19-21] and Latin hypercube [22], are used with the optimization algorithms such as multi-start Sequential Quadratic Programming (SQP) [15] and Genetic Algorithms (GA) [23]. Examples of crashworthiness design are presented, for example, in [24-27]. There have been studies that compared the performance of meta-modeling techniques for engineering applications [2,3,28-30]. In most of these studies, Kriging seems to prevail. However, Yang *et al.* [2,3] suggested that none of the techniques can be decisively judged as the best for small sample sizes.

To obtain the best possible surrogate out of a given set of sample simulations, Yang *et al* [25] reported a "multi-resolution" surrogate modeling, where the "fine resolution" models are constructed with the samples within a narrower region of the design space in the vicinity of the optimal design obtained with the "coarse resolution" model. While this approach was reported to improve the accuracy of the resulting estimations by surrogates, the problem remains since the region for finer sampling are affected by the accuracy of the coarse resolution model, which is constructed from a limited number of samples.

2.2. Ensemble Classifiers in Pattern Recognition

Classifiers in the context of pattern recognition refers to a function that takes as an input a set of data (pattern) and returns its classification in a predefined category, sometimes with a confidence level of the classification [31]. Classifiers are often constructed through *supervised learning*, where initialized classifiers are "trained" by being presented a set of the pairs of an input pattern and its correct classification (called teaching data) – a process analogous to the construction of surrogate models from sampled simulation data. In fact, modern classifiers are often implemented as feed-forward Artificial Neural Networks, which are also popular as surrogate models for design optimization.

Ensemble classifier approaches are a class of methods to utilize a set (ensemble) of classifiers, instead of a single classifier, to classify input patterns by taking the aggregates (such as average, best confidence, and majority votes) of the outputs of the multiple classifiers in the ensemble [4-8]. A comprehensive review the area can be found in [6]. It has been shown that the ensembles of classifiers, when property constructed, are often much more accurate than the individual classifiers that make them up. The necessary and sufficient conditions for an ensemble of classifiers to be more accurate than any of its individual members are if the classifiers are accurate and diverse [4]. An accurate classifier is the one that has an error better than random guessing on unseen input patterns. Two classifiers are diverse if they make different errors on unseen input patterns.

The proposed method adopts the ensemble approach to surrogate-based design optimization, by integrating it within a co-evolutionary genetic algorithm as described in detail in the next section.

3. MULTI-SCENARIO CO-EVOLUTIONARY GENETIC ALGORITHM (MSCGA)

3.1. Rationale

The proposed method assumes an ensemble of surrogate models constructed from the different sets of the sampled data of FE crash simulations. Each surrogate model takes as an input a vector of design variables and outputs a vector of crash performances. Examples of design variables are the lengths and thicknesses of structural members, and examples of the crash performances (to be minimized) are the mass of the structure and the amounts of the violation of design targets such as cabin acceleration and intrusion.

Considering that each surrogate model contains errors associated with its estimation of the outputs of the FE crash simulations, the methods provides a designer with the following potentially high-quality designs, some or all of which can be chosen for further examinations with FE analyses:

- Designs predicted as Pareto optimal by each surrogate.
- Designs predicted as Pareto optimal by the ensemble, where the outputs of the ensemble are defined as 1) the weighted average and 2) the most conservative, of the outputs of all surrogate models.
- Designs that show a balanced compromise among the outputs of all surrogate models in the ensemble, *i.e.*, Pareto optimal with respect to the non-aggregated (raw) outputs of the ensemble.

More precisely, the method provides approximate solutions of the following $r + 3$ multi-objective optimization problems:

$$\begin{aligned}&\text{minimize} \quad \boldsymbol{\Phi}_i(\boldsymbol{x});\ \ i = 1, 2, ..., r \\ &\text{subject to} \quad \boldsymbol{x} \in D\end{aligned} \tag{1}$$

$$\begin{aligned}&\text{minimize} \quad \boldsymbol{f}_i(\boldsymbol{x});\ \ i \in \{w, c, s\} \\ &\text{subject to} \quad \boldsymbol{x} \in D\end{aligned} \tag{2}$$

where, $\boldsymbol{x}$ is the design variable, D is the domain of the design variable, r is the number of surrogate models in the ensemble, $\boldsymbol{\Phi}_i$: $D \rightarrow \mathbf{R}^m$ is the i-th surrogate model in the ensemble, m is the number of crash performances in the output vector, and $\boldsymbol{f}_i$: $D \rightarrow \mathbf{R}^m$ is the outputs of the ensemble defined as:

$$\boldsymbol{f}_w(\boldsymbol{x}) = w_1\boldsymbol{\Phi}_1(\boldsymbol{x}) + w_2\boldsymbol{\Phi}_2(\boldsymbol{x}) + \cdots + w_r\boldsymbol{\Phi}_r(\boldsymbol{x})\,; \tag{3}$$

$$\boldsymbol{f}_c(\boldsymbol{x}) = \left(\max_{i\in\{1,\ldots,r\}} \Phi_i(\boldsymbol{x})_1, \ldots, \max_{i\in\{1,\ldots,r\}} \Phi_i(\boldsymbol{x})_m \right)^{\mathrm{T}} \tag{4}$$

$$\boldsymbol{f}_s(\boldsymbol{x}) = \left(\Phi_1(\boldsymbol{x})_1, \ldots, \Phi_1(\boldsymbol{x})_m, \ldots, \Phi_r(\boldsymbol{x})_1, \ldots, \Phi_r(\boldsymbol{x})_m\right)^{\mathrm{T}} \tag{5}$$

In Equations (1) and (2), the constraints are treated as one of the objectives to be minimized. Equations (3) and (4) represent the weighted average with weights w_i (assumed to sum up to unity) and the most conservative (*i.e.*, the largest values) of the outputs of all surrogate models, respectively. Equation (5) is the vector of (raw) outputs of all surrogate models in the ensemble. Note that the vector functions $\boldsymbol{f}_w$ and $\boldsymbol{f}_c$ have m elements, whereas $\boldsymbol{f}_s$ has $r \times m$ elements.

The $r + 3$ multi-objective optimization problems as defined in Equations (1)-(5) are *simultaneously* solved by using the Multi-Scenario Co-Evolutionary Genetic Algorithm (MSGA), whose details are provided in the next section. In essence, MSCGA is a co-evolutionary genetic algorithm, which evolves r sub-populations P_1, P_2, … P_r, where each sub-population evolves for minimizing two indices: the internal dominance count λ_{ij} and the external dominance count μ_{ij} where:

- λ_{ij} is the number of members ("chromosomes") in the i^{th} subpopulation P_i that dominate[1] the j^{th} member with respect to the output of i-th surrogate model $\boldsymbol{\Phi}_i$ in the ensemble.
- μ_{ij} is the number of members ("chromosomes") in all the sub-populations P_1, P_2, … P_r, other than P_i that dominate the j^{th} member with respect to the outputs of the corresponding surrogate models $\boldsymbol{\Phi}_1$, $\boldsymbol{\Phi}_2$, … $\boldsymbol{\Phi}_r$.

During the evolution of sub-populations P_1, P_2, … P_r, a copy of high-quality members with respect to λ_{ij} and μ_{ij} are passed onto the next generations. Upon the termination of the algorithm, un-dominated (Pareto optimal) members with respect to the outputs of $\boldsymbol{\Phi}_1$, $\boldsymbol{\Phi}_2$, … $\boldsymbol{\Phi}_r$ (the solutions of the problems (1)), $\boldsymbol{f}_w$, $\boldsymbol{f}_c$, and $\boldsymbol{f}_s$ (the solutions of the problems (2)) are collected from all sub-populations and stored in the $r + 3$ solution sets L_1, L_2, … L_r, L_w and L_c, and L_s, respectively, which are presented to a designer as the outputs of the algorithm for further examinations with FE analyses. While it is possible to individually solve the optimization problems (1) and (2), an advantage of MSGA is that it can provide the solutions with a single optimization run.

3.2. Algorithm

MSCGA is a class of co-evolutionary genetic algorithm where each sub-population is evolved in a manner similar to NSGA-II [NSGA-II]. The following description is kept brief by assuming the basic understanding of NSGA-II algorithm. Interested readers should refer to [9] for details.

Algorithm MSCGA:

1. Randomly initialize multiple sub-populations P_1, P_2, … P_r of n_p chromosomes. Initialize the generation counter.
2. Compute $\boldsymbol{f}_1 = \boldsymbol{\Phi}_1(\boldsymbol{x})$, …, $\boldsymbol{f}_r = \boldsymbol{\Phi}_r(\boldsymbol{x})$, and $\boldsymbol{f}_w(\boldsymbol{x})$ and $\boldsymbol{f}_c(\boldsymbol{x})$
3. Update L_w and L_c, so they contain only the un-dominated members with respects to $\boldsymbol{f}_w$ and $\boldsymbol{f}_c$, respectively.
4. For all members in all sub-populations P_1, P_2, … P_r, compute λ_{ij} and μ_{ij}, and then ρ_{ij}, the Pareto-based dominance rank [9] with respect to (λ_{ij}, μ_{ij}).
5. For each sub-population P_i, create the new sub-population Q_i of size n_p, which contains 1) member j with $\lambda_{ij} = 0$, 2) member j with $\rho_{ij} = 1$, and 3) new members created by selection (with respect to ρ_{ij}), crossover, and mutation. Replace Q_i with P_i.
6. Increment the generation counter. If the number of generation reached the pre-specified limit, proceed. Otherwise, go to step 2.
7. For each sub-population P_i, create L_i so it contains member j with $\lambda_{ij} = 0$.
8. Create L_s so it contains member j with $\mu_{ij} = 0$ in all subpopulations P_1, P_2, … P_r
9. Return L_1, L_2, … L_r, L_w, L_c, and L_s

The implementation used in the following examples adopts tournament selection, arithmetic and heuristic crossover, and uniform random mutation [32]. While the algorithm does not dictate any particular type of surrogate model, polynomial regression [12,13] is used for the following examples.

4. PRELIMINARY EXAMPLE

Consider a two-variable, two-objective problem:

$$\begin{aligned}&\text{minimize} \quad f_1 = (x_1+5)^2 + (x_2+5)^2 \\ &\text{minimize} \quad f_1 = (x_2-5)^2 + (x_2-5)^2 \\ &\text{subject to} \quad -10 \le x_1, x_2 \le 10\end{aligned} \tag{6}$$

[1] One member x dominates another member y if and only if x out-performs y with respect to both indices λ and μ.

The Pareto optimal solutions of this problem are all points on the line segment between the points (-5, -5) and (5, 5) shown in Fig. 1. Fig. 2 shows the Pareto plot, the values of the objective function of these Pareto optimal solutions in the f_1-f_2 space.

To demonstrate the proposed approach, a uniform random noise of maximum magnitude ± 20.0 is introduced on the values of f_1 and f_2, then 24 random samples are drawn out. A half the samples are used to fit the surrogate $\boldsymbol{\Phi}_1$, the other half is used to fit the surrogate Φ_2, and all the samples are used to fit the surrogate $\boldsymbol{\Phi}_3$. All surrogates were the second order polynomial regression of the corresponding samples, fitted via the least squares error. The weights in Equation (3) were chosen as $(w_1, w_2, w_3) = (0.3, 0.3, 0.4)$.

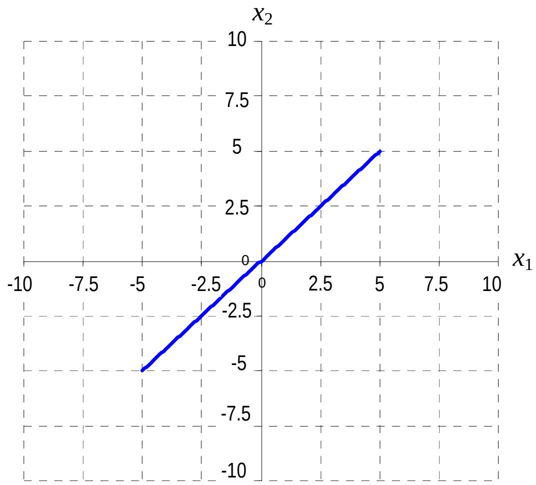

Fig. 1. Pareto optimal solutions of the problem (6).

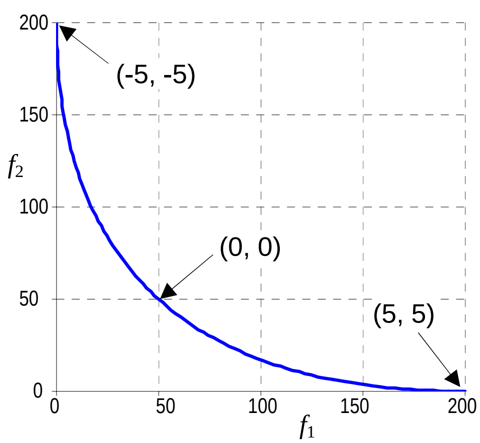

Fig. 2. Pareto plot of the problem (6).

For this simple problem, it is fairly easy to obtain the “exact” Pareto optimal solutions without running optimization, based on the polynomial coefficients of each surrogate. The Pareto plots for each surrogate fit with a set of 24 random samples are shown in Fig. 3, together with the ones for the ensemble (weighted average and most conservative).

For the three surrogate models $\boldsymbol{\Phi}_1$, $\boldsymbol{\Phi}_2$ and $\boldsymbol{\Phi}_3$, MSCGA is run with the sub-population size of 80, the number of maximum generations of 200, the crossover probability 90%, and the mutation probability 5%. Figs. 4 and 5 show the results, where the solid lines represent the “exact” Pareto-plot in Fig 3, while the scattered points are those generated by MSCGA. It is clear that for this example, MSCGA was successful in reaching a wide range of designs on the “exact” Pareto plots.

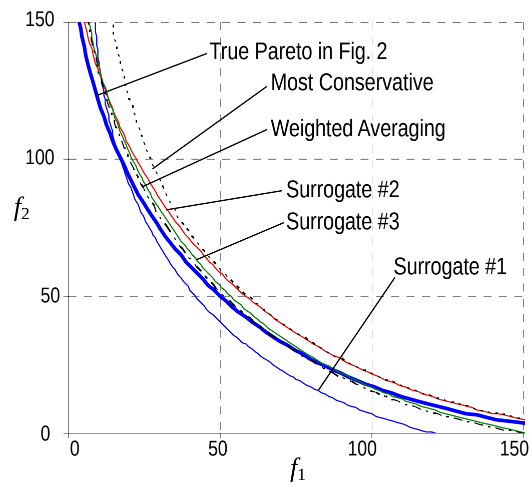

Fig. 3. The “exact” Pareto plot of surrogates 1-3, and the ensemble (weighted average and most conservative).

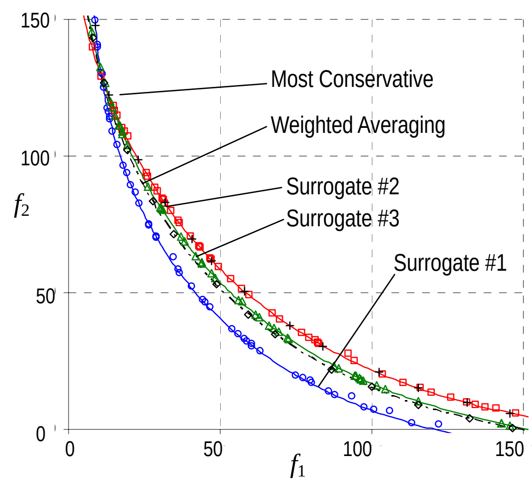

Fig. 4. Results by MSCGA: the objective function values of the solutions in L_1, L_2, L_3, L_w, and L_c, plotted with the “exact” Pareto plots in Fig. 3.

In order to better access the performance of the algorithm, ten runs of MSCGA were conducted for the surrogate models constructed from the ten independent sets of 24 samples. The quality of the resulting solutions are measured as the average Euclidean distances between the solutions in L_1, L_2, L_3, L_w, L_c, and L_s obtained at each run, and the closest points on the true

Pareto-optimal set (the line segment between (-5, -5) and (5, 5)). The results are listed in Table 1.

It is observed that the solutions in L_w often show better accuracy than the ones by a single surrogate in L_1, L_2, and L_3 and in L_c and L_s. They also seem to have good consistency in the accuracy of predictions, indicated by the small standard deviations. While the solutions in L_c and L_s seem overly conservative causing them not to be very accurate, they rarely score the worst performance in any of the ten runs (unlike a single surrogate), and both scenarios seem to have good consistency in their accuracy of predictions. While this example is too simple to draw any general conclusions, the results suggest none of the solution sets is predominantly superior to the rest. In other words, for effective design, it is advisable to examine all solutions in L_1, L_2,, … L_r, L_w, L_c, and L_s.

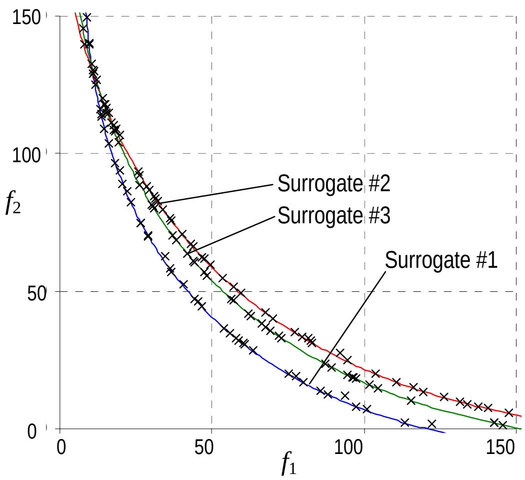

Fig. 5. Results by MSCGA: the objective function values of the solutions in L_s, plotted with the "exact" Pareto plots in Fig. 3.

Table 1. Average Euclidean distances between the MSCGA solutions and the true Pareto-set. The grayed cells indicate the best of each run.

Run #	L_1,	L_2	L_3	L_w	L_c	L_s
1	7.93	6.53	5.61	6.22	7.59	7.35
2	7.02	6.34	7.03	5.97	6.04	6.79
3	7.05	5.70	6.94	6.58	7.12	7.00
4	6.32	5.78	6.53	6.22	7.31	6.78
5	7.67	6.71	6.11	7.09	7.37	7.13
6	6.10	7.37	6.21	6.76	6.80	6.94
7	7.70	5.86	5.78	5.95	6.74	6.53
8	6.91	5.46	7.09	5.96	6.69	6.86
9	6.56	7.06	7.20	7.03	6.98	6.91
10	6.02	6.12	7.25	5.98	6.31	6.54
Avg	**6.93**	**6.29**	**6.58**	**6.38**	**6.90**	**6.88**
StdDev	**0.68**	**0.62**	**0.61**	**0.45**	**0.48**	**0.25**

5. CASE STUDIES

This section describes the application of the proposed approach to crashworthiness design. It is assumed that the references for the "true" crash performances, based on which the surrogate models are constructed, are provided by the FE crash simulations rather than the results of the physical tests. The reader should keep in mind, therefore, that all stated "true" performance values in this section come from FE simulations, which have not been verified by actual crash testing.

Similar to the preliminary example in the previous section, three surrogate models, $\boldsymbol{\Phi}_1$, $\boldsymbol{\Phi}_2$ and $\boldsymbol{\Phi}_3$, are constructed from the data obtained from the DOE sampling of the design space using the FE crash simulations: one from a half of the data, another from the rest of the data, and yet another from all data.

5.1. Vehicle Front Half-Body Subject to Full-Overlap Frontal Crash

This case study considers a FE model representing the main structural members of a vehicle subjected to full-overlap frontal crash conditions (Fig. 6). It has 18 design variables, 4 of which are continuous representing the height and width of upper and lower members, while 14 of the variables are discrete representing the sheet metal thickness in 14 different zones. The design objectives for this test condition are the intrusion into the passenger compartment and the peak acceleration at the passenger point:

$$\text{minimize } f_1 = \text{Passenger Compartment Intrusion [mm]} \quad (7)$$
$$\text{minimize } f_2 = \text{Max. Passenger Point Acceleration [G]} \quad (8)$$

The best design in our previous publication [33] (shown in the second column of Table 2) is used as the baseline design around which the samplings are conducted. The sample domain is restricted to ±10 mm for the heights and widths of the cross sections of the structural members, and ± one step (0.2 mm) in the sheet metal thicknesses. The L_{54} array [20] is employed that gives a three-level fractional factorial DOE requiring 54 samples, where the sample levels are set as: level 1 = lower bound; level 2 = value of the baseline design; and level 3 = upper bound.

The sampling was performed by randomly assigning the design variables to the columns of the L_{54} array. Two sets of 54 samples are collected using two independently randomized variable-column assignments, and used to construct the surrogate models $\boldsymbol{\Phi}_1$ and $\boldsymbol{\Phi}_2$ with quadratic polynomials. In addition, all the 108 samples are used to construct the surrogate model $\boldsymbol{\Phi}_3$. The Pareto plot all the samples are shown in Fig. 7. It is noted that some of the samples fall within a special region of interest (f_1 < 100 mm and f_2 < 30 G), and dominate the rest of the samples, including the baseline design. The design variables and objective values for these samples are listed in the Table 2.

Fig. 7 shows the Pareto plot of the results by MSCGA[2]. Among many suggested solutions twenty representative designs are chosen for the verification with FE analyses, whose results are shown in Fig. 8. It is observed that the results of the FE simulation gave lower performances than the ones estimated by the surrogate models. However, the scatter of the designs is shifted nearer to the best known Pareto-optimal ones, and one of the designs suggested by MSCGA (a solution in L_2) is actually dominates all DOE samples, resulting in the discovery of a new Pareto optimal design. Details of the newly found design are reported in Table 2.

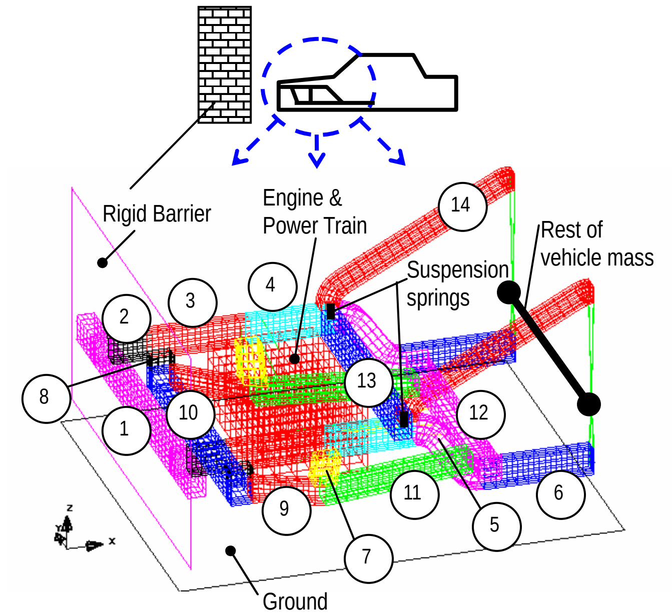

Fig. 6. FE model of front half body of a vehicle subjected to full-lap frontal crash [41].

5.2. Full Vehicle Subjected to Full-Overlap Frontal Crash

This case study considers an accurate half-million-element FE model of a full vehicle subjected to a full-overlap frontal crash condition (Fig. 9). It has 12 design variables, each governing the sheet metal thicknesses of the 49 important components in the vehicle structure, which can vary among five to six discrete choices. The same objective functions as in the previous case study (Eqs. 7 and 8) are used.

Two sets of DOE samplings with the randomized L_{27} array [20] are performed around the baseline design, shown in the first column of Table 3. Due to proprietary issues, the detailed definitions and the actual values of the design variables and objective functions cannot be disclosed. Instead, Table 3 shows the values of the design variables in a dimensionless form, scaled with respect to the baseline design, and the values of the objective functions also in a dimensionless form, scaled with respect to the values of a region of interest. The Pareto plot all the samples are shown in Fig. 10. The values of design variables and objective functions (in dimensionless forms) of four un-dominated samples are listed in Table 3.

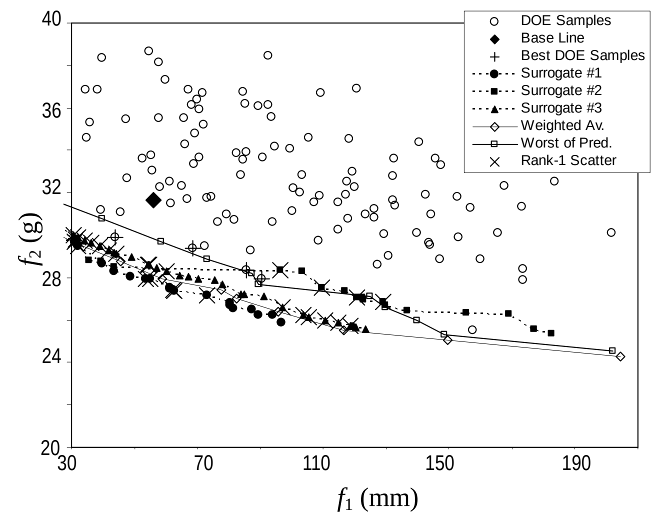

Fig. 7. Pareto plot of the baseline design, DOE samples, and the results by MSCGA.

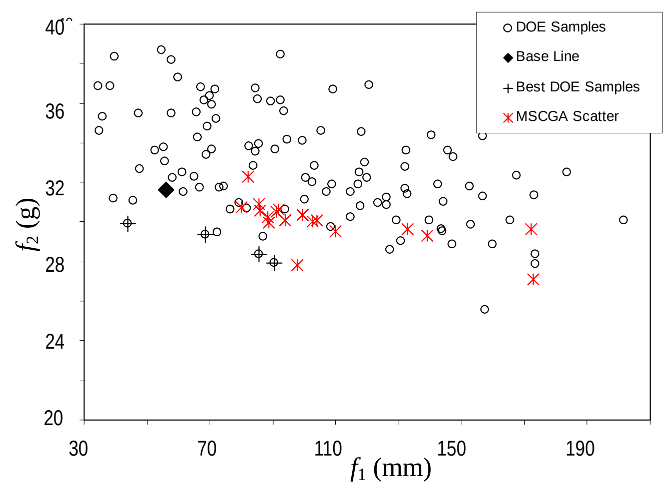

Fig. 8. Pareto plot of the results of FE re-testing of some designs suggested by MSCGA

Fig. 10 shows the Pareto plot of the results by MSCGA3. Among many suggested solutions seven representative designs are chosen for the verification with FE analyses, whose results are shown in Fig. 11. Similar to the first case study, the results of the FE simulation gave lower performances than the ones

[2] In Fig. 7, "Worst of Pred." and "Rank-1 Scatter" represents the solutions in L_c and L_s, respectively.

[3] In Fig. 10, "Worst of Pred." and "Rank-1 Scatter" represents the solutions in L_c and L_s, respectively.

estimated by the surrogate models. However, two designs suggested by MSCGA (solutions in L_s and L_1) dominates all DOE samples (and one of them dominates the other), resulting in the discovery of a new Pareto optimal design (a solution in L_1). Details of the newly found design are reported in Table 3.

Table 2. details of some designs

	Base-line	Best of DOE Samples				Found by MSCGA
		#35	#16	#22	#66	
x_1 (mm)	120.0	130.0	120.0	130.0	110.0	110.3
x_2 (mm)	60.0	70.0	60.0	50.0	60.0	56.0
x_3 (mm)	70.0	80.0	80.0	70.0	70.0	78.3
x_4 (mm)	60.0	60.0	70.0	70.0	70.0	50.0
x_5 (mm)	2.6	2.4	2.6	2.8	2.8	2.8
x_6 (mm)	2.6	2.4	2.4	2.6	2.6	2.8
x_7 (mm)	2.2	2.0	2.0	2.0	2.0	2.0
x_8 (mm)	2.4	2.4	2.2	2.2	2.4	2.2
x_9 (mm)	3.6	3.4	3.6	3.4	3.8	3.8
x_{10} (mm)	3.2	3.4	3.2	3.4	3.2	3.2
x_{11} (mm)	2.8	3.0	3.0	2.8	3.0	2.8
x_{12} (mm)	2.0	2.2	2.2	2.2	1.8	2.2
x_{13} (mm)	1.8	1.6	2.0	1.8	2.0	1.6
x_{14} (mm)	3.6	3.4	3.6	3.6	3.4	3.6
x_{15} (mm)	2.8	2.8	3.0	3.0	2.6	2.8
x_{16} (mm)	2.0	1.8	2.0	1.6	2.6	2.2
x_{17} (mm)	2.8	3.0	2.6	2.8	3.0	3.0
x_{18} (mm)	2.0	2.2	2.0	2.2	2.4	2.4
f_1 (mm)	56.0	43.9	68.6	85.6	90.5	97.8
f_2 (g)	31.6	29.9	29.4	28.4	27.9	27.8

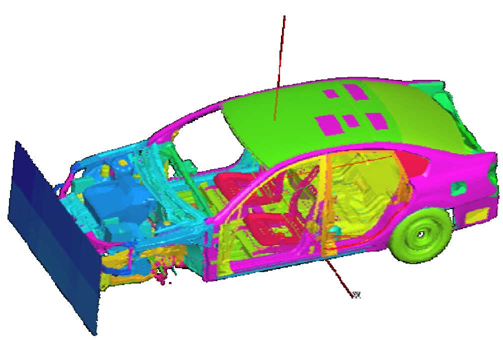

Fig. 9. A detailed FE model of a vehicle subjected to full-overlap frontal crash

6. CONCLUDING REMARKS

This paper presented a new method for designing vehicle structures for crashworthiness using an ensemble of surrogate models and a co-evolutionary, multi-objective genetic algorithm. Multiple sub-populations of candidate designs are evolved, in a co-evolutionary fashion, to minimize the different aggregates of the outputs of the surrogate models in the ensemble as well as the raw output of each surrogate. Two case studies on simplified and full vehicle models subject to full-overlap frontal crash conditions successfully demonstrated that the method is effective in providing a designer with wide ranges potentially high-performance designs.

In the case studies, it was observed that the estimation error of the surrogate models was quite significant. This is most likely due to the relatively low accuracy of polynomial regression, and a simple scheme to split samples for constructing an ensemble. Accordingly, future work could explore different meta-modeling techniques, such as Kriging and Radial Basis Neural Networks, as well as different sampling techniques for ensemble construction, such as Bagging and AdaBoost [6].

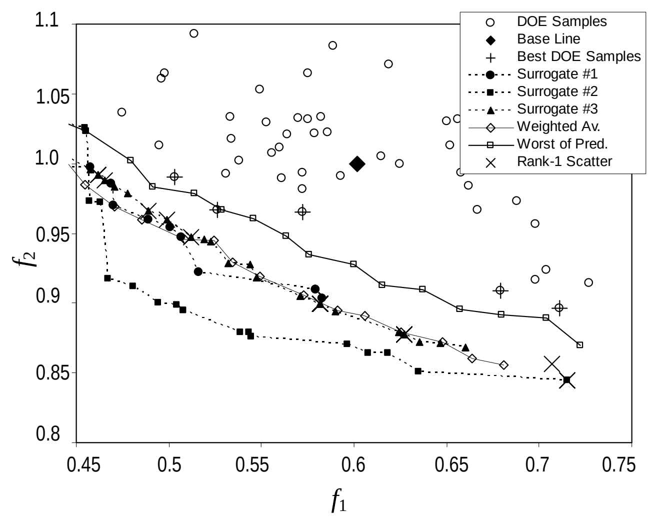

Fig. 10. Pareto plot of the baseline design, DOE samples, and the results by MSCGA.

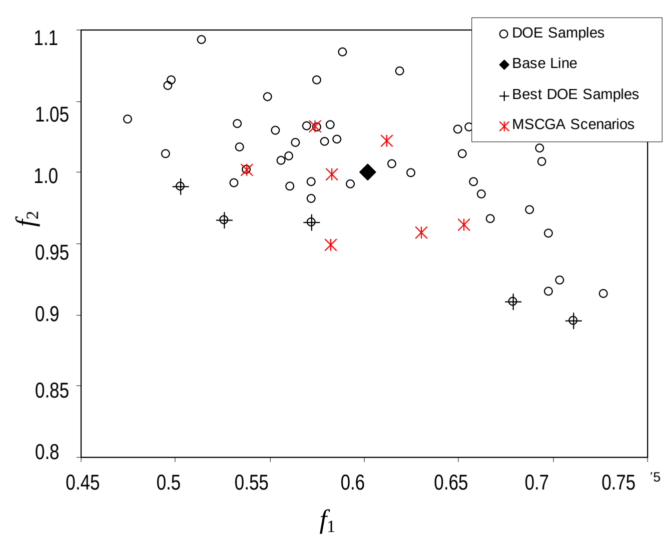

Fig. 11. Pareto plot of the results of FE re-testing of some designs suggested by MSCGA

Table 3. details of some designs

	Base-line	Best of DOE Samples				Found by MSCGA
		#17	#12	#14	#44	
x_1	1.000	1.000	1.000	1.167	1.167	1.056
x_2	1.000	1.167	0.889	1.000	0.889	1.056
x_3	1.000	0.900	1.100	1.100	1.000	1.000
x_4	1.000	1.000	1.063	0.875	0.875	1.000
x_5	1.000	1.000	0.933	0.933	1.000	0.967
x_6	1.000	1.000	1.100	1.000	0.900	0.900
x_7	1.000	0.800	1.000	0.800	1.200	1.133
x_8	1.000	0.889	1.000	1.167	1.167	1.111
x_9	1.000	1.100	1.000	1.000	0.900	1.050
x_{10}	1.000	1.167	0.889	1.167	1.167	0.889
x_{11}	1.000	0.875	0.875	1.000	1.000	1.063
x_{12}	1.000	1.167	1.167	0.750	1.000	0.75
f_1	0.602	0.503	0.526	0.679	0.711	0.583
f_2	1.000	0.990	0.966	0.909	0.896	0.949

ACKNOWLEDGMENTS

This research is sponsored by Nissan Technical Center North America, Inc. (NTCNA). The Pam Crash software used for this research is provided by ESI North America, Inc., through the university discount program. The authors acknowledge the support, discussions, and suggestions offered by Mr.'s Ken Jimbo and Akira Toyama at NTCNA, and Mr.'s Etienne Gai, Brain O'Keefe and Ramesh Dwarampudi at ESI North America.

REFERENCES

[1] Simpson, T., Booker, A., Ghosh, D., Giunta, A., Koch, P. and Yang, R., 2004, "Approximation Methods in Multidisciplinary Analysis and Optimization: A Panel Discussion," *Structural and Multidisciplinary Optimization*, **27**, pp. 302-313.

[2] Yang, R. J., Gu, L., Liaw, L., Gearhart, C., Tho, C. H., Liu, X. and Wang, B. P., 2000, "Approximations for Safety Optimization of Large Systems," Proceedings of *ASME DETC*, September 10-13, Baltimore, Maryland, DETC2000-DAC14245.

[3] Yang, R. J., Wang, N., Tho, C. H., Bobineau, J. P. and Wang, B. P., 2001, "Metamodeling Development for Vehicle Frontal Impact Simulation," Proceedings of *ASME DETC*, September 9-12, Pittsburgh, PA, DETC2001-DAC 21012.

[4] Hansen, L. and Salamon, P., 1990, "Neural Network Ensembles," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **12**(10), pp. 993-1001.

[5] Sharkey, A., 1999, "Multi-Net Systems," *Combining Artificial Neural Nets: Ensemble and Modular, Multi-Net Systems*, pp. 1–30. Springer-Verlag.

[6] Dietterich, T. G., 2000, "Ensemble methods in machine learning," Proceedings of *First International Workshop on Multiple Classifier Systems (MCS 2000)*, pp. 1–15.

[7] Kuncheva, L. I. and Jain, L. C., 2000, "Designing Classifier Fusion Systems by Genetic Algorithms," *IEEE Transactions on Evolutionary Computation*, **4**(4), pp. 327-336.

[8] Jin, Y., and Sendho, B., 2004, "Reducing Fitness Evaluations Using Clustering Techniques and Neural Network Ensembles," Proceedings of *GECCO 04: Genetic and Evolutionary Computation Conference*, Seattle, Washington, July 26-30.

[9] Deb, K., Argawal, S., Pratab, A. and Meyarivan, T., 2000, "A Fast Elitist Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization: NSGA-II," Proceedings of *Parallel Problem Solving from Nature VI*, Paris, France, pp. 849-858.

[10] Coello, C., Van Veldhuizen, D. and Lamont, G., 2002, *Evolutionary Algorithms for Solving Multi-Objective Problems*, Kluwer Academic/Plenum Publishers, New York.

[11] Werfel, J., Mitchell, M. and Crutchfield, J., 2000, "Resource Sharing and Coevolution in Evolving Cellular Automata," IEEE *Transactions on Evolutionary Computation*, **4**(4), pp. 388-393.

[12] Box, G., Hunter, W. and Hunter, J., 1978, *Statistics for Experimenters*, John Wiley & Sons, NY.

[13] Myers, R. and Montgomery, D., 1995, *Response Surface Methodology: Process and Product Optimization using Designed Experiments*, Wiley & Sons NY.

[14] Rumelhart, D., Hinton, G. and Williams, R., 1986, "Learning Internal Representations by Error Propagation," *Parallel Distributed Processing: Explorations in the Microstructures of Cognition, 1: Foundations*, MIT Press, Cambridge, MA, pp. 318-362.

[15] MathWorks, 2001, *MatLab 6 Documentation*, MathWorks Inc., Natick, MA.

[16] Dyn, N., Levin, D. and Rippa, S., 1986, "Numerical Procedures for Surface Fitting of Scattered Data by Radial Basis Functions," *SIAM Journal of Scientific and Statistical Computing*, **7**(2), pp. 639-659.

[17] Krige, D., 1951, *A Statistical Approach to some Mine Evaluations and Allied Problems at the Witwatersrand*, M.Sc. Thesis, University of Witwatersrand, Germany.

[18] Sasena, M., Papalambros, P and Goovaerts, 2002, "Exploration of Metamodeling Sampling Criteria for Constrained Global Optimization," *Engineering Optimization*, **34**(3), pp. 263-278.

[19] Taguchi, G., 1993, *Taguchi on Robust Technology Development: Bringing Quality Engineering Upstream*, ASME Press, NY.

[20] Phadke, M., 1989, *Quality Engineering using Robust Design*, Prentice Hall PTR, Englewood Cliffs, NJ

[21] Owen, A., 1992, "Orthogonal Arrays for Computer Experiments, Integration and Visualization," *Statistica Sinica*, **2**, pp. 439-452.
[22] Stein, M., 1987, "Large Sample Properties of Simulations using Latin Hypercube Sampling," *Technometrics*, **29**, pp. 143-151.
[23] Goldberg, D., 1989, *Genetic Algorithms in Search, Optimization and Machine Learning*, Addison-Wesley.
[24] Chen, S., 2001, "An Approach for Impact Structure Optimization using the Robust Genetic Algorithm," *Finite Elements in Analysis and Design*, **37**, pp. 431-446.
[25] Yang, R. J., Gu, L., Tho, C. H. and Sobieski, J., 2001, "Multidisciplinary Optimization of a Full Vehicle with High Performance Computing," Proceedings of *American Institute of Aeronautics and Astronautics 2001 Conference,* pp. 688-698, AIAA Paper Number: AIAA-2001-1273.
[26] Andersson, J. and Redhe, M., 2003, "Response Surface Methods for Pareto Optimization in Crashworthiness Design," Proceedings of *ASME DETC*, September 2-6, Chicago, IL, DETC2003-DAC48752.
[27] Gu, L., Tyan, T. and Yang, R. J., 2004, "Vehicle Structure Optimization for Crash Pulse," Proceedings of *ASME DETC*, September 28 – October 2, Salt Lake City, Utah, DETC2004-57479.
[28] Jin, R., Du, X., and Chen, W., 2001, "The Use of Metamodeling Techniques for Optimization Under Uncertainty," Proceedings of *ASME DETC*, September 9-12, Pittsburgh, PA, DETC2001-DAC 21039.
[29] Srivastava, A., Hacker, K., Lewis, K. and Simpson T., 2004, "A Method for Using Legacy Data for Metamodel-Based Design of Large-Scale Systems," *Structural and Multidisciplinary Optimization*, **28**, pp. 146-155.
[30] Martin, J., and Simpson, T., 2004, "On the use of Kriging Models to Approximate Deterministic Computer Models," Proceedings of *ASME DETC*, September 28 – October 2, Salt Lake City, Utah, DETC2004-57300.
[31] Winston, P. H., 1992, *Artificial Intelligence*, 3rd edition, Addison Wesley.
[32] Michalewicz, Z., 1996, *Genetic Algorithms + Data Structures = Evolution Programs*, 3rd edition, Springer-Verlag, Berlin-Heidelberg.
[33] Hamza, K. and Saitou, K., 2004, "Design for Crashworthiness of Vehicle Structures via Equivalent Mechanisms and Crash Mode Matching," Proceedings of *ASME IMECE*, November 13-20, Anaheim, CA, IMECE2004-62226.