Paper

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An Approach for Impact Structure Optimization Using the Robust Genetic Algorithm

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Abstract

A practical approach for impact structure and crashworthiness optimization is introduced. This approach takes advantage of the global-searching ability of GA, yet also considers the instability of explicit finite element analysis. A numerical example was solved and the result was compared with the result obtained by traditional NLP. The result showed that global searching can not be ignored at least in the current example. The approach shows promise in implementing impact structure optimization.

1. Introduction

The numerical methods for simulation of crashworthiness and impact analysis have been developed for about twenty years. Many commercial packages, like DYNA3D and its variants, are available today and have been used for industrial product analysis. These packages use explicit finite element analysis, which requires very small integration time steps. Therefore its computational time is relatively expensive when compared with other finite element analysis, for example, linear or nonlinear static analysis.

However, the design optimization of impact structure has been a difficult issue due to the nature of numerical crashworthiness analysis. Researchers have been noticing the instability and uncertainty of impact analysis [1]. From experience usually the simulation process has to go through several iterations before one satisfactory result can be obtained. This kind of instability prevents integrating the analysis

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process with the optimization program. Also, the computational expense of explicit finite element analysis makes the fully integrated optimization process unfeasible.

For this reason researchers have been trying to develop some simplified mathematical or physical models for replacing some exact analysis cycles during crashworthiness analysis. Knap and Holnicki-Szulc [2] used VMD based dynamic analysis and two-level design concepts for optimization of adaptive structures. Arora et al [3] developed simplified models to match the required and critical response from the exact analysis by minimizing the error between them. Diaz and Soto [4] used lattice models for optimizing the topology of impact resistant structure in the conceptual design stage. Among other indirect techniques mentioned before, Yamazaki and Han [5] directly combined the optimization process with the explicit finite element code to maximize the crushing energy on simple tubes. Mayer, Kikuchi and Scott [6] also used homogenization methods to maximize the absorption energy of an automobile rear rail. These publications either worked on the simplified mathematical model, or on the physical model that was not likely to diverge during the repeated reanalysis cycles. However in industry design, applying the optimization directly on the physical model is desired, and the model frequently suffers numerical difficulty for crashworthiness analysis due to its complexity.

On the other hand, there are no or few papers available today dealing with using genetic algorithms for impact structure optimization. This may be due to the fact that the genetic algorithms require a larger amount of function evaluations then the traditional NLP techniques. This nature makes the use of GA for crashworthiness optimization unreasonable. However, the global searching capability of GA also makes it an attractive candidate for this problem.

This paper deals with the problems mentioned above and tries to take advantage of GA without adding too much unreasonable analysis iterations. The specific tasks, methodologies, and GA enhancements are discussed next.

2. Crashworthiness and Impact Structure Optimization

Several unique problems exist in crashworthiness optimization. They are usually due to the nature of the problem or the limitation on the available analysis tools. For industrial applications, these problems

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may become even more critical. This chapter discusses the general problem and formulation of crashworthiness and impact structure optimization.

2.1. Problem Formulation

The formulation of crashworthiness optimization can be very problem dependent Usually it will depend on the requirements of the design and the design variation allowed. However, generally they can be formulated as demonstrated below.

$$
\begin{array}{lll}
\text{Find} & \{X\} & \\
\text{To minimize} & f(\{X\}) & \\
\text{Subjected to} & g_i(\{X\}) \le (g_i)_{allowable} & i = 1, \ldots\ldots NCON \\
 & x_j^L \le x_j \le x_j^U & j = 1, \ldots\ldots, NDV
\end{array}
\qquad (1)
$$

The constraint and objective functions may contain crashworthiness measurements, maximum displacement, structural integrity, stresses and other application dependent requirements. Usually each company has its own way of formulating the design criteria. While sometimes it is not easy to get a good formulation for the nature of the specific problem, it is usually critical to the success of the optimization process.

2.2 Computational Expense Consideration

Traditionally, optimization is done by means of repeating design-analysis cycles, as shown in Figure 1. However this approach is not acceptable in crashworthiness optimization. Although there has been some commercial codes around for crashworthiness analysis, the computational time is usually much more expensive then implicit analysis. This prompted the necessity of reducing the frequency of analysis iterations. (Also it is usually expected to predict further response according to only limited data). Parallel or distributed processing may be encouraging or acceptable because multiple licenses may be available within the company. However since it is very difficult to incorporate and integrate all the machines in an automatic manner, the traditional process is still prohibited.

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2.3 *Analysis Stability Consideration*

Compared with implicit FEM, the explicit FEM codes available today are relatively unstable. It is possible that with only changes on model design variables, some of the control parameters of the program will have to be changed for a feasible result. Should the analysis terminate prematurely, or unexpectedly, the optimization process is likely to crash too. The instability of analysis will also induce numerical noise. Due to these problems, the optimization process will need to interact with engineering judgement sometimes, without much extra redundant time cost. It will not be acceptable for a human to sit before the screen and constantly act as part of the online real time optimization process.

3. The Robust Genetic Algorithms

The simple GA, while powerful, is perhaps too general to be efficient and robust for structural design problems. First, function (or, fitness) evaluations are computationally expensive since they involve finite element analysis. Second, the design space may contain many local minima. The proposed improvements to the simple GA, which is called the Robust Genetic Algorithm, are discussed next.

3.1 *Adaptive Penalty Function for Constraints*

GAs were developed to solve unconstrained optimization problems. However, engineering design problems are usually constrained. They are solved by transforming the problem to an unconstrained problem. The transformation is not unique and one possibility is to use the following strategy.

$$\begin{aligned} &\text{find:} \quad \mathrm{x} = \left\lfloor {}^{b}x_1,\ldots,{}^{b}x_{NBDV};\, {}^{i}x_1,\ldots,{}^{i}x_{NIDV};\, {}^{s}x_1,\ldots,{}^{s}x_{NSDV} \right\rfloor \\ &\text{minimize:} \quad f(\mathbf{x}) + \sum_i c_i \cdot \max(0, g_i) + \sum_j c_j \cdot \left| h_j \right| \end{aligned} \qquad (2)$$

The variables c_i and c_j are penalty parameters used with inequality and equality constraints. Determining the appropriate penalty weights c_i and c_j is always problematic. An algorithm was proposed by Chen and Rajan [7,8] where the penalty weight is computed automatically and adjusted in an adaptive

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manner. In the problem formulation, the constraints are normalized so that the numerical values of the constraints do not adversely affect the solution. First the objective function is modified as follows.

$$f(\mathbf{x}) + c_a \cdot \left(\sum_i \max(0, g_i) + \sum_j |h_j| \right) \tag{3}$$

Then the following rules are used to select c_a.

(1) If there are feasible designs in the current generation, c_a is set as the minimum *f* among all feasible designs in the current generation. The rationale is that for the design with minor violations and a smaller objective value, the probability of survival is not eliminated. If, on the other hand, the maximum *f* among all feasible designs is used, infeasible designs will have a smaller probability to survive even if the constraint violations are small.

(2) If there is no feasible design, c_a is set as the *f* that has the least constraint violation. This has the effect of both pushing the design into the feasible domain as well as preserving the design with the smallest fitness.

3.2 Improving Crossover Operators Using the Association String

To implement this strategy, the author used an additional string called the *association string* that was introduced by Chen and Rajan [7,8,9]. The details of this scheme can be found in our previous publications. The purpose of this scheme is to automate the ordering of design variables and the probability of crossover operators. Results show that the association string improves the robustness of the solution process.

3.3 Mating Pool Selection

In this paper, the tournament selection [10] is used. There are at least two reasons for this choice. First, tournament selection increases the probability of survival of better strings. Second, only the relative fitness values are relevant when comparing two strings. In other words, the selection depends on individual fitness rather than ratio of fitness values. This is attractive since in this research, the fitness value contains the penalty function and does not represent the true objective function.

3.4 Elitist Approach

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The elitist approach was proposed by De Jong [11]. Research [8,9] has shown GA with the incorporation of the elitist approach can be more reliable and efficient than the ones without. This approach is used in the current research.

3.5 Population Size and Stopping Criteria

Previous publications suggest that the population size and the number of generations should be *at least* n [7,8,9] (where n is the length of chromosome). Also it was suggested that using population and generation size of *2n* leads to reasonable results efficiently [7,8,9]. These rules are adopted in this paper.

3.6 The Improved GA Optimizer

As mentioned before, selective improvement can be made to obtain a more robust solution methodology for a class of problems. The primary focus of this research is to make the GA a powerful and reliable optimizer for structural optimization problems. Table 1 shows the proposed improvements.

	Traditional GA	**Enhanced GA**
Penalty Function	ad hoc	Automatic
Schema	ad hoc	Ordered
Cross-over Probability	ad hoc	Adaptive
Population/Max Generation Size	ad hoc	Suggested as *2n*

Table 1 Differences Between Traditional and Enhanced GA

4. Proposed Algorithms and Process

Due to the nature and problems of crashworthiness optimization, an open-looped approach was proposed. The idea was to construct a simplified mathematical model first to replace some of the exact analysis. However, in order to perform optimization directly on the model, the mathematical model must present the exact model directly with the design parameters. This method is commonly used in industry for

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studying sensitivity of variables with respect to the response when the analytical solution is neither available nor possible. With so many methodologies available, DOE (Design of Experiment) is probably the most widely used one.

4.1 Proposed Algorithm

As mentioned above, unexpected or premature termination of the analysis may happen during any iteration. This forces us to develop an optimization algorithm that can interact with human judgement off-line without adding too much extra redundant time. That is, a traditional fully-integrated, close-looped optimization process (Figure 1) cannot be used.

The basic idea of the current approach is to evaluate a group of sample points first, and use these sample points to construct a mathematical model to replace the exact analysis. A Design of Experiments matrix is used to construct this model. Special techniques were used to correct the approximate model with the exact analysis as well as approach the optimum. The procedure is proposed as follows.

Step 1 Construct the basic geometry. Identify the critical design variables, the design objective function, and the constraints.

Step 2 Construct a DOE (Design Of Experiment) matrix for the design variables, the objective function and the constraints.

Step 3 Evaluate the DOE matrix. Set NAPX=0.

Step 4 Do a Response Surface Fit for the objective and constraint functions.

Step 5 Set NAPX=NAPX+1. Do optimization based on the results from Step 4. Get the predicted optimum design.

Step 6 Verify the optimum design by exact analysis (LS-DYNA). If the predicted constraint values are identical with the results from LS-DYNA, or the estimated optimum design is satisfactory enough, exit the loop. Otherwise, modify the constraint bounds by calculating the corrected constraints bounds, $(g_i)_{NAPX,\,Allowable}$, and go to step 4.

The conceptual flow chart of the process is shown in Figure 2. Details of Step 4, Step 5 and Step 6 will be explained below.

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4.2 Building The Simplified Mathematical Model Using DOE

Among some of the popular DOE methods, the Full Factorial Experiment seems attractive to the problem of crashworthiness optimization. The Full Factorial Experiment, while usually more computationally expensive, can usually fit the exact response better than other methods. This is desired for impact problems, which usually involve plastic behavior of material, and are much more complicated than standard linear static analysis. The better accuracy also allows the system to be modeled directly by the design variables, which means direct optimization on the model.

In the Full Factorial Experiment all combinations of all inputs (or factors) are studied at different levels. The formulation of the approximated function is very similar to Lagrangian interpolation. For the case with three independent variables, it can be formulated as the following:

$$u(\xi,\eta,\varsigma)=\sum_{k}^{M3}\sum_{j}^{M2}\sum_{i}^{M1}N_{1i}\cdot N_{2j}N_{3k}\cdot u_{ijk} \tag{4}$$

$$N_{1i}=\prod_{l=1}^{\substack{(l\neq i)\\M1}}\frac{(\xi-\xi_l)}{(\xi_i-\xi_l)} \tag{5}$$

$$N_{2j}=\prod_{l=1}^{\substack{(l\neq j)\\M2}}\frac{(\eta-\eta_l)}{(\eta_j-\eta_l)} \tag{6}$$

$$N_{3k}=\prod_{l=1}^{\substack{(l\neq k)\\M3}}\frac{(\varsigma-\varsigma_l)}{(\varsigma_k-\varsigma_l)} \tag{7}$$

where u_{ijk} is the value of the function on the sample points $(\xi_i,\eta_j,\varsigma_k)$. The independent variables ξ,η,ς of matrix dimension $M1\times M2\times M3$. $M1, M2$ and $M3$ are the studied levels of the variables ξ,η,ς. In this paper, the design variables will replace the independent variables directly.

4.3 Approximated Function Correction

Once the objective and constraints functions were obtained from Lagrangian Interpolation, the problem can be formulated as:

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$$
\begin{array}{lll}
\text{Find} & \{X\} & \\
\text{To minimize} & f(\{X\}) & \\
\text{Subjected to} & g_i^*(\{X\}) \le (g_i)_{Allowable} & i = 1, \ldots\ldots, NCON \\
 & x_j^L \le x_j \le x_j^U & j = 1, \ldots., NDV
\end{array}
\tag{8}
$$

In industrial applications, the feasibility of optimization depends on the accuracy and reliability of the analysis. Inaccurate analysis not only prevents practical optimization results, but also wastes resources. This problem becomes even more serious when response surface approximation is used. While the discrepancy between an approximated result and exact analysis is always expected, the correction process is usually critical, and can be time-consuming. Currently the goal is to match approximated results with exact analysis using the least amount of computational time, while still keeping the optimum design in a feasible domain. For this purpose, equation (8) is modified as:

$$
\begin{array}{lll}
\text{Find} & \{X\} & \\
\text{To minimize} & f(\{X\}) & \\
\text{Subjected to} & g_i^*(\{X\}) \le (g_i)_{NAPX,\,Allowable} & i = 1, \ldots\ldots, NCON \\
 & x_j^L \le x_j \le x_j^U & j = 1, \ldots., NDV
\end{array}
\tag{9}
$$

Here $(g_i)_{NAPX,\,Allowable}$ is calculated as:

$$
(g_i)_{NAPX+1,Allowable} = (g_i)_{NAPX,\,Allowable} - (\Delta g_i)_{NAPX} \tag{10}
$$

$$
(\Delta g_i)_{NAPX} = \alpha \cdot \left((g_i)_{NAPX,\,Exact\ Analysis} - (g_i)_{1,\,Allowable} \right) \tag{11}
$$

In the above equation, *NCON* is the number of inequality constraints, *NDV* is the number of design variables, and *NAPX* is the number of iterations for correcting constraint bounds. g_i^* is the approximated function of g_i approximated by Lagrangian interpolation.

Also $0 \le \alpha \le 1$, and $(g_i)_{1,\,Allowable} = (g_i)_{Allowable}$ is the original allowable value of the constraint.

4.4 The reason for using Genetic Algorithms

The above optimization problem was solved by the Robust Genetic Algorithms (RGA) due to the following reasons.

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1. As the design space becomes more and more complex, it may be desired to search globally for the optimum. When a full orthogonal experiment is used, usually several local minimum exist and a global optimization algorithm will be necessary. GA is suitable for global optimization.

2. Since the response function was obtained from an approximation, the explicit expression exists. This will dramatically reduce the computational expense. Therefore GA can be considered as an optimization process candidate without worrying about the huge amount of function evaluations it needs.

3. GA can handle discrete design variables efficiently.

4.5 Convergence Properties

Convergence of this algorithm involves both the correction of the response surface function and the robustness of the Robust Genetic Algorithms. The convergence properties of the Robust Genetic Algorithms were discussed in the previous publication [7,8]. The convergence properties of the response surface function correction will be discussed here.

In equation (10), $\left(\Delta g_i\right)_{NAPX}$ has the effect of pushing the approximated surface closer to the exact analysis result. However, since it is a linear correction, sometimes the modified approximated response shown in equation (9) may not have a feasible solution, due to the modification of constraint bounds. Under this situation, the user can release the constraint by dividing α by 2.0, and resolve equation (9), until a feasible and optimum solution can be obtained. If a solution cannot be obtained with even a very small α, it is possible that the either the problem does not have a feasible solution or the approximated function is too different from the real response. The approach will converge only when the approximated function is close enough to the real response. The iteration is terminated when the exact analysis result matches closely enough to the approximated function.

4.6 Advantages of the Proposed Algorithms

While the algorithm above cannot be used for problems with too many design variables, it is usually very powerful in the preliminary design stage. Especially for crashworthiness optimization, it is usually very difficult even for the design to decide a reasonable starting point. Therefore using GA can be beneficial. Also there are some other advantages as stated below.

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1. Step 2 of the algorithms can be executed by different machines or persons. Therefore the most intensive effort is distributed and can be executed in a parallel sense. This is likely to reduce computation time.

2. The frequency of interaction between human and the optimizer is greatly reduced, which reduces the redundant time. Furthermore, separating the optimization and function evaluation processes eliminates the failure of the optimization process, due to the instability in function evaluation.

3. Engineering judgement is allowed during the process.

4. A parametric model is not required.

5. Design sensitivity analysis is available from the DOE results.

6. Using response surface approximation reduces numerical noise between each analysis. This feature is important for crashworthiness analysis.

7. Using DOE and Lagrangian interpolation as a function fit algorithm allows adaptive accuracy of the function.

8. The number of function evaluations in step 3 is readily known, which makes the project management easier.

4.7 Disadvantages of the Proposed Algorithms

As mentioned before, this algorithm is more proper for preliminary design and for crucial understanding of the system response. There are also some other disadvantages.

1. Usually the full-factorial DOE matrix requires more function evaluations than a non-full-factorial function fit. The computational expense will become even more significant as the problem becomes larger.

2. The correction process for the response surface fit does not guarantee convergence. The method is useful only when the approximate function is close enough to the exact response.

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5. Numerical Example : Ballistic Shield Weight Optimization

5.1 Problem Description

A ballistic shield is to be designed to resist the impact of a projectile. The ballistic shield must satisfy the following conditions:

1. The projectile shall not penetrate the shield. No holes or open cracks may be created after impact.
2. The displacement of the shield should be limited, such that instrumentation on the other side of the shield won't be hit during and after impact.

The goal is to design this shield for minimum weight and satisfy all requirements. These requirements are quantified as the following constraints.

1. Penetration Energy < 0.0.
2. Max Lateral Displacements < D cm

The Penetration Energy is defined as the residual energy of the projectile at 5.0 milli-seconds of simulation time. If the shield is penetrated, the residual energy is defined as positive, and negative if the fragment bounced back. If a hole is created, but without penetration, the user may have to penalize the residual energy by a certain value, so that only when there was no hole or crack on the shield would the penetration energy be negative or zero. The geometry layout of the ballistic shield is shown in Figure 3.

5.2 Problem Formulation

The problem was formulated as

$$\begin{aligned}
&\text{find} && \{X\} = \{DV1,\ DV2,\ DV3\} \\
&\text{tominimize} && \text{Weight of the shield} \\
&\text{subjected to} && \text{MaxUY} \le \text{D} \\
& && K_e \le 0.0 \\
& && t \le DV1 \le 3 \cdot t \\
& && t \le DV2 \le 3 \cdot t \\
& && t \le DV3 \le 3 \cdot t
\end{aligned} \tag{12}$$

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5.3 DOE Matrix

The model design was optimized by selecting thickness at different locations as design variables, as shown in Figure 3. The thickness of the shield flange was taken as t. A DOE of 3 factors was evaluated, with 3 levels on each factor for a full quadratic fitting.

Table 2 shows the final results of the DOE. The 27 jobs were distributed to 3 HP C3000 workstations, therefore the computation time was greatly reduced. Total computational time took about 1 day.

Some interesting observations can be obtained from the DOE matrix:

1. For preventing total penetration and cracks/holes, a shield thickness around 3*t cm is required. A 2*t cm thick shield will not be penetrated, but will have either a hole or a crack.
2. The displacement constraint is usually more critical than the penetration constraint.
3. The DOE matrix gave only 4 feasible designs : Optm09, Optm18, Optm26, Optm27. The minimum weight was W kilo-grams. See table 2.

Figure 4 shows the simulation of design Optm0201, which was penetrated by the projectile.

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	Shield Face						
	Btm	Mid	Top	Flange			
Design	R75	R76	R77	R78	Weight	Max UY	Ke
Optm0201	t	t	t	t	0.44*W	1.41*D	0.529210
Optm0202	t	t	2*t	t	0.50*W	1.93*D	0.028052
Optm0203	t	t	3*t	t	0.57*W	2.19*D	0.027494
Optm0204	t	2*t	t	t	0.66*W	1.48*D	-0.055938
Optm0205	t	2*t	2*t	t	0.72*W	1.31*D	-0.058635
Optm0206	t	2*t	3*t	t	0.79*W	1.19*D	-0.059581
Optm0207	t	3*t	t	t	0.87*W	1.15*D	-0.108070
Optm0208	t	3*t	2*t	t	0.94*W	1.01*D	-0.107580
Optm0209	**t**	**3*t**	**2*t**	**t**	1.00*W	**0.95*D**	**-0.108010**
Optm0210	2*t	t	t	t	0.47*W	1.84*D	0.054722
Optm0211	2*t	t	2*t	t	0.53*W	1.58*D	0.027064
Optm0212	2*t	t	3*t	t	0.60*W	1.21*D	0.029805
Optm0213	2*t	2*t	t	t	0.69*W	1.49*D	-0.055759
Optm0214	2*t	2*t	2*t	t	0.75*W	1.32*D	-0.059497
Optm0215	2*t	2*t	3*t	t	0.82*W	1.16*D	-0.060556
Optm0216	2*t	3*t	t	t	0.90*W	1.13*D	-0.107690
Optm0217	2*t	3*t	2*t	t	0.97*W	1.02*D	-0.107640
Optm0218	**2*t**	**3*t**	**2*t**	**t**	**1.03*W**	**0.93*D**	**-0.107920**
Optm0219	3*t	t	t	t	0.50*W	1.43*D	0.061396
Optm0220	3*t	t	2*t	t	0.57*W	1.57*D	0.027677
Optm0221	3*t	t	3*t	t	0.63*W	1.22*D	0.023429
Optm0222	3*t	2*t	t	t	0.72*W	1.46*D	-0.055640
Optm0223	3*t	2*t	2*t	t	0.78*W	1.28*D	-0.059782
Optm0224	3*t	2*t	3*t	t	0.85*W	1.07*D	-0.060008
Optm0225	3*t	3*t	t	t	0.94*W	1.13*D	-0.107960
Optm0226	**3*t**	**3*t**	**2*t**	**t**	**1.0*W**	**1.00*D**	**-0.107600**
Optm0227	**3*t**	**3*t**	**2*t**	**t**	**1.06*W**	**0.92*D**	**-0.107900**

Table 2 DOE Results on Thickness Distribution for Dsgn01

5.4 Optimization Based on DOE Matrix

Table 2 was fed into an in-house optimization program and a commercial package for optimization. Note that the commercial package uses a quadratic fit instead of Lagrangian Interpolation. Two optimization algorithms were tested using the in-house program, the Method of Feasible Direction (MFD) and the Robust Genetic Algorithm. Since the commercial package does not provide a very satisfactory GA, the Method of Feasible Direction was used instead. Note that the commercial package used the quadratic fit instead of the full-factorial DOE. Also, the Method of Feasible Direction requires an initial starting point. Table 3 shows the optimum solution.

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		DV1, DV2, DV3		Predicted Value		
Function Fit	Optimizer	Starting Point	Optimum	Weight	UY	Ke
full-factorial DOE	RGA	N/A	t, 2.55t, 2.7t	0.89W	D	-0.084
full-factorial DOE	MFD	2t, 2t, 2t	2t, 2.9t, 2.45t	0.98W	D	-0.002
full-factorial DOE	MFD	3t, 3t, 3t	3t, 3t, 3t	1.06W	0.91D	-0.110
quadratic	MFD	t, t, t,	3t, 2.15t, 3t	0.88W	D	-0.060
quadratic	MFD	2t, 2t, 2t	3t, 2.15t, 3t	0.88W	D	-0.060
quadratic	MFD	3t, 3t, 3t	3t, 2.15t, 3t	0.88W	D	-0.060

Table 3 Optimum Solution, Using Table 3 As Data Points

5.5 Comparison of Algorithms Used

The optimum solutions and predicted responses in Table 3 were evaluated by exact analysis. Note that although the quadratic function fit with MFD gave a result with lower objective weight, the optimum solution was verified to be a non-contained shield. That is, the optimum design from the quadratic fit with MFD was found to be penetrated under the given projectile impact. This meant the approximation was too far away from the exact response. A correction between the approximation response and the exact analysis would require far more effort than expected. Therefore the commercial package was abandoned at this point.

Another interesting observation was that the MFD algorithm seemed to be "trapped" inside the local minimum when the full-factorial DOE was used. As can be seen in Table 4, the result highly depends on the starting point. Note that the commercial package was not trapped inside the local minimum because it does random sweeping in the design space, which is an ad-hoc approach. This observation further convinced us to use RGA for impact structural optimization.

5.6 Approximation Modification and Correction

Table 4 shows the iterations performed to complete the correction process. Note that in the first iteration α was set to 0.5, because 1.0 will make the optimization problem infeasible. Since the constraint is active and critical, and the DOE showed that the problem did have feasible solutions, it was natural to release α so that a feasible solution could be obtained. Since only the displacement constraint seems to control the design, the residual energy is not included in the correction iteration. Each iteration for the optimum solution, exclusive of the exact analysis, took only a few seconds.

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The optimum solution was obtained at the 3rd iteration, with a weight of 0.95W kilo-grams and a displacement of D cm. Figure 5 shows the simulation of the projectile impact.

NAPX	NAPX Allowable	DV1	DV2	DV3	Weight	Exact Anls	Exact-Allow	Alpha
1	1.00D	1.0t	2.55t	2.70t	0.89W	1.08D	0.08D	0.50
2	0.96D	t	2.8t	2.7t	0.94W	1.009D	0.009D	1.00
3	0.95D	t	2.8t	2.8t	0.95W	D	0.00	

Table 4 Iterations for the Approximation Correction, Dsgn01

6. Conclusion

In this research, the Genetic Algorithm was successfully applied to impact structural optimization. Particular attention is paid to instability and premature termination of the explicit finite element analysis. As evidenced by the result in the numerical example, the developed methodologies show promise in implementing impact structure optimization.

It was also found during this research, that the crashworthiness properties of the structures seemed to perform extreme nonlinearity even with small changes to the design variables. This was even more significant when the structure was in the nearly-penetrated zone. As most of today's structural optimization algorithms still focus on local optimum with well-behaved structural response, a further study on the design sensitivity of the physical phenomena seems to be necessary.

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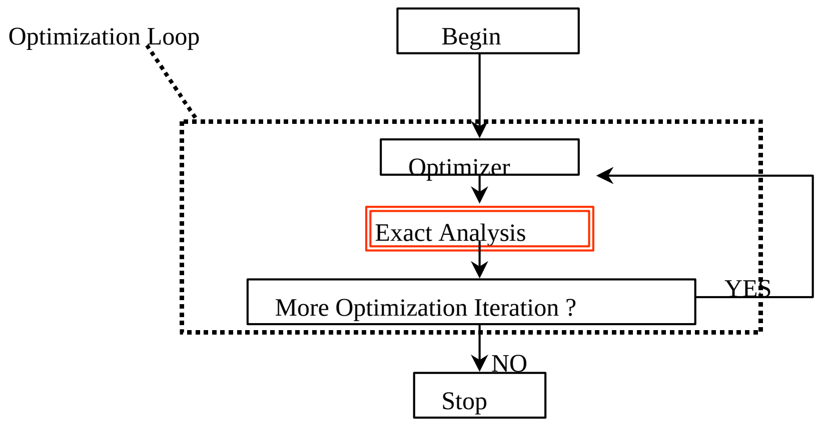

Figure 1 Traditional Optimization Process, Exact Analysis Done Inside Optimization Loop

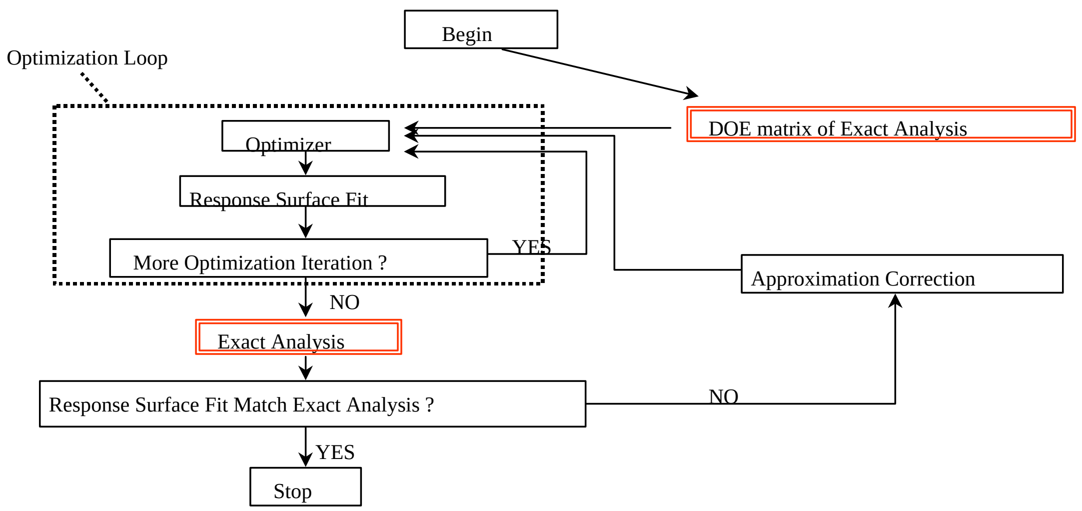

Figure 2 New Optimization Process, Exact Analysis Done Outside Optimization Loop

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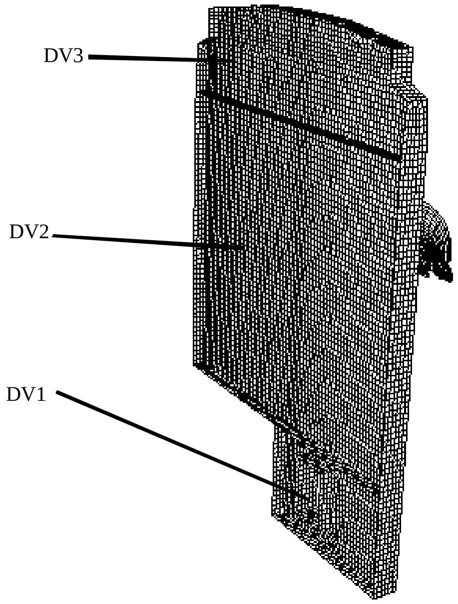

Figure 3 Geometry Configuration and Design Variables Linking of the Shield

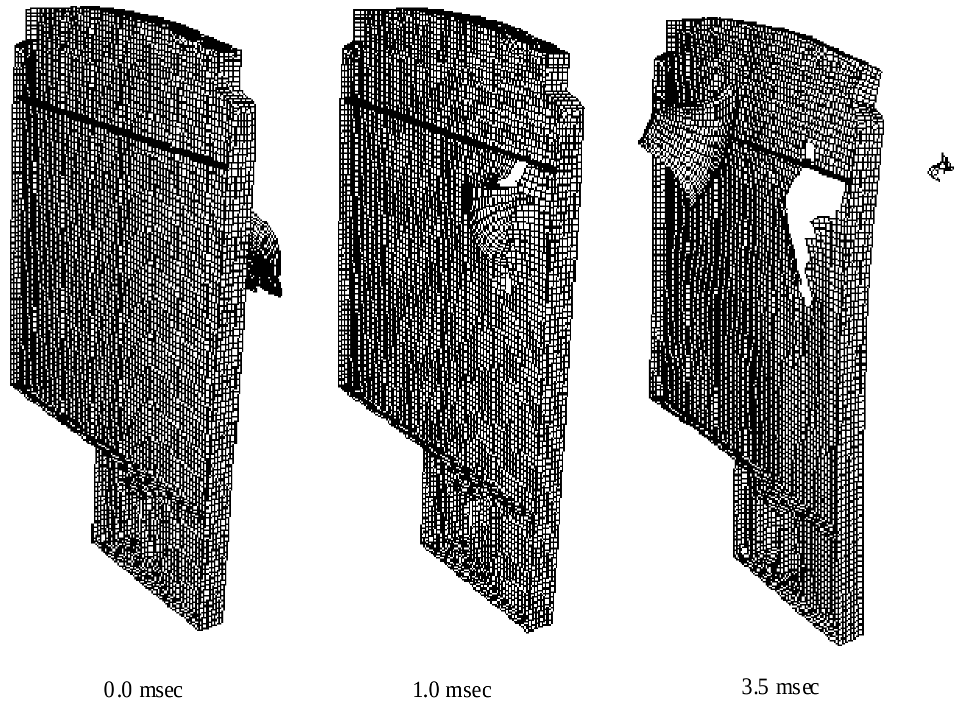

Figure 4 Simulation of the Projectile Penetrating the Shield, Design Optm0201

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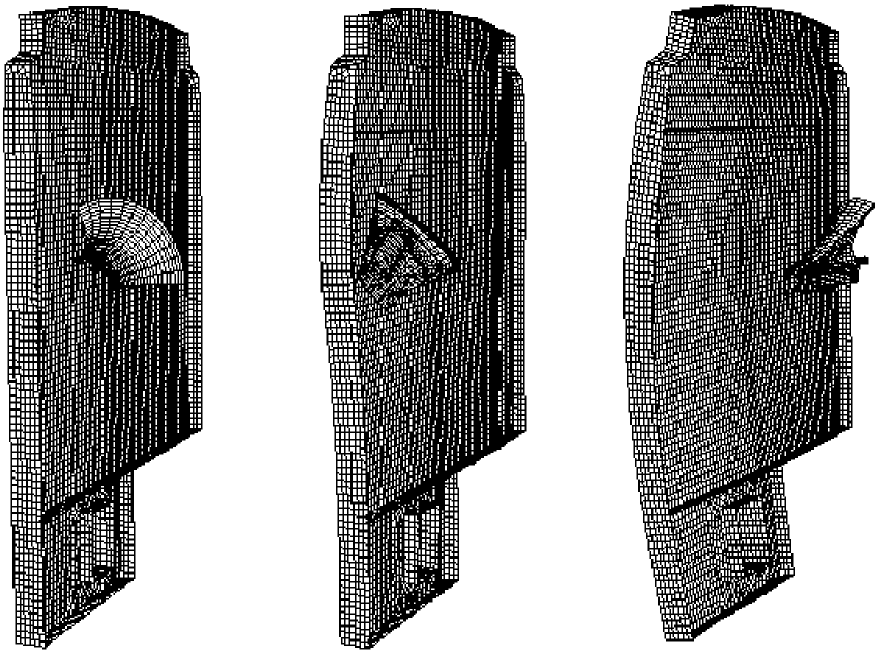

0.0 msec 1.0 msec 3.5 msec

Figure 5 Simulation of the Projectile Impacting the Shield, Final Optimum Design

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