Crashworthiness Design for Cylindrical Tube using Neural Network and Genetic Algorithm

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Abstract

In this article, the multi-objective optimization of cylindrical aluminum tubes under axial impact load is presented. Absorbed energy and specific absorbed energy are considered as objective functions while the mean crush load should not exceed allowable limit. The geometric dimensions of tubes including diameter, length and thickness are chosen as design variables. The Non-dominated Sorting Genetic Algorithm –II (NSGAII) is applied to obtain the Pareto optimal solutions. A back-propagation neural network (ANN) is constructed as the surrogate model to formulate the mapping between the variables and the objectives. The finite element software ABAQUS/Explicit is used to generate the training and test sets for the ANNs. Validating the results of finite element model, several impact tests are carried out using drop hammer.

Keywords: Circular tube, Energy absorption, Neural networks, Multi-objective optimization.

1. INTRODUCTION

Lately, the studies on optimization of crashworthiness in mechanical structures have increased mainly thanks to faster computers and better algorithms. Nevertheless, few works have been done on the optimization of energy absorber tubes. The first time, (Yamazaki and Han 2000) optimized crashworthiness of cylindrical tubes so as to maximize their crushing energy while the limit was the mean crash load on a certain value. Based on numerical analysis, the crush responses of tubes were determined and response surface approximation method (RSM) has been applied to construct an approximating design sub-problems. (Zarei and Kroger 2006) represented the multi-objective optimization of aluminum tubes with the purpose of maximizing absorbed energy and specific absorbed energy by MATLAB. They

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also used the scalar weighting function method to aggregate the multi-objective optimization problem into a simple optimization. The D-optimal design of the experiment and RSM has been utilized to construct sub-problems in sequential optimization procedure. (Hou et al. 2007; Liu 2008) presented optimal designs of multi-corner structures with sound crush performances.

By and large, it is conventional to employ the nonlinear finite element method (FEM) in optimization of crashworthiness problems to create the design samples because of complex material constitutive relationships and large deformations.

Since it is not affordable to employ FEM to evaluate the objective and the constraint values from a computational point of view, the global approximation methods like RSM (Yamazaki and Han 2000; Zarei and Kroger 2006; Hou et al. 2007; Liu 2008), artificial neural networks (ANNs) (Hajela and Lee 1997; Lanzi et al. 2004) and the radial basis functions (RBF) (Lanzi et al. 2004; Fang et al. 2005) are mainly used to construct the responses of tube crashworthiness parameters. Comparing these metamodels, (Stander et al. 2004) demonstrated in the optimization of nonlinear problems, ANNs method has a better efficiency.

In this paper, the multi-objective optimization of cylindrical aluminum tubes under impact axial load is performed by Non-dominated Sorting Genetic Algorithm-II (NSGA-II) which is a fast and elitist genetic algorithm proposed by (Deb 2002). In view of the fact that the goal of this survey is to find tubes with dimensions that have maximum energy absorption capacity besides weight efficiency, the multi-objective optimization procedure has been applied to maximize the absorbed energy and the specific absorbed energy. The diameter, length and thickness of the tubes were optimized while the applied mean crush load should not exceed allowable limit.

To this end, at the first step, the crush behavior of tubes has been simulated by finite element software ABAQUS/Explicit. Then, several impact tests are carried out to validate the results of simulation. The approximating design sub-problem is constructed with the use of ANNs. Finally, the Pareto solution sets will be presented.

2. NUMERICAL SIMULATIONS

2.1. Finite element modeling

With the aim of carrying out the numerical simulations of axial crushing of cylindrical tubes under impact loading, the FE code ABAQUS/Explicit is used. While axial crushing of tubes includes buckling, it is essential to perturb the initial mesh of the tube by the buckling modes. Thus, before performing crushing analysis, the buckling analysis is carried out to find the first ten elastic buckling modes using the FE code ABAQUS/Standard.

For axial crushing simulation, a cylindrical tube is placed between two rigid walls, the lower wall is fixed and the upper wall is constrained in all degrees of freedom except the axial displacement. A point mass equal to 140 kg is attached to the upper wall and an initial velocity is defined for the upper wall just before the collision.

Four-noded shell elements, suitable for large deformation analysis is used to model tubes. Five integration points are used through the shell thickness to model bending. The mesh sensitivity analysis indicates that an element size of 3 mm is adequate to produce suitable results.

Self-contact with a friction coefficient equal to 0.2 is defined for the inner and the outer surfaces of tubes. And surface-to-surface contact with friction coefficient equal to 0.2 is defined between the tube and the rigid walls.
2.2. Material properties

Mechanical properties of the aluminum tubes are determined from standard tensile testing of coupons cut from several tubes. The elastic modulus of this material is $E=70$ GPa, the density is $\rho = 2700\text{kg/m}^3$ and the Poisson ratio is $\nu = 0.3$. The material model are defined as linear elastic followed by non-linear isotropic work hardening in the plastic region, as shown in Table 1.

Table 1: True stress-strain data points used for aluminium in numerical simulations

<table>
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<th>85</th>
<th>90</th>
<th>98</th>
<th>103.75</th>
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3. EXPERIMENTAL RESULTS

With the intention of validating numerical simulations, five impact tests are carried out on aluminum tubes under axial crashes. The tests are conducted using the vertical drop-test machine which is installed in impact mechanic laboratory in Amirkabir University. Impact loads are applied to the specimens using a drop hammer with constant mass of 140 kg. The maximum drop height is 5 m and the maximum impact velocity is 9.9 m/s. A dynamic acceleration gauge is attached to the drop mass to measure acceleration of impact event. Crush load is calculated by multiplying the drop mass and acceleration. The instantaneous crush displacement is obtained by twice numerically integrating the acceleration-time curve. The crush load-displacement curves of the specimens are obtained by cross plotting the displacement-time and load-time values. The area under the crush load-displacement curves equals the absorbed energy. The ratio of the absorbed energy to the mass of the tube is specific energy (SEA).

The tubes have been made of aluminum alloy. The material properties of this alloy have been described in section 2. The dimensions of specimens and impact velocity for each test are presented in Table 2. The collapsed modes of specimens obtained by numerical simulation and experimental tests are compared in Figure 1. This figure shows that the FE modeling can simulate the collapsing shape of the tube with sufficient accuracy. Typically, a crush load-displacement curve obtained from the experimental and numerical results is shown in Figure 2. Table 2 shows the values of the crashworthiness parameters obtained from FE simulation and experimental tests. It is obvious from Figures 1 and 2 and Table 2 that numerical simulation can predict the collapsing shape and the crashworthiness parameters of tubes with a great accuracy.

Table 2: Results from the impact tests and numerical simulation

<table>
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<tr>
<th>Test no.</th>
<th>$t$ (mm)</th>
<th>$D/t$</th>
<th>$L/D$</th>
<th>$V_0$ (m/s)</th>
<th>$F_{\text{max}}$ (KN)</th>
<th>$F_{\text{mean}}$ (KN)</th>
<th>$SAE (\text{KJ/Kg})$</th>
<th>$\delta_{\text{max}}$ (mm)</th>
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4. NEURAL NETWORKS TO REPRODUCE THE CRUSH BEHAVIOUR OF TUBE

As was mentioned earlier, the aim of this article is the optimization behavior of thin-walled tubes under axial crushing. For this purpose, plenty of numerical simulations are needed to define a design domain. On the other hand, performing all these simulations by the FEM method is very costly and time consuming from the computational point of view because of the complexity of the FEM models required to predict behavior of structures. Thus, the ANNs are used to reproduce crashworthiness parameters of
tubes under impact load. For this purpose, a set of the MLP neural networks, with two hidden layer is
developed and trained by a finite number of FEM simulations.

In this study, two distinct neutral networks are designed to reproduce the values of the absorbed energy
and the mean force during axial crushing of tubes with impact velocity fixed at 10m/s. A proper structure
of the network needs to be found considering the training efficiency and accuracy. Since the number of
input variables and output variables determine the neurons as well as the transfer functions for these two
layers, it is necessary to define a proper structure for the hidden layers. The most common approach to
attain an optimal network topology so far is still the trial-and-error method, i.e. comparing the
performances of different networks. Based on this ground, the architecture is obtained to be 3-15-15-1
and the transfer functions for the four layers are "tangent sigmoid", "tangent sigmoid", "tangent sigmoid"
and "linear" respectively.

The training and test sets are defined in the range of 50mm < D < 150mm , 100mm < L < 300mm and
1mm<t<3mm, which will also be the optimization domain. The training set consists of 50 samples chosen
to guarantee a random and homogeneous allocation inside the design domain. The test set consists of 20
samples randomly selected inside the design domain. A total number of 70 ABAQUS/Explicit runs were
then performed. After training both of the networks, the test sets are used to find the error of each network.
The maximum percentage error obtained by each network is within 12%.

5. CRASHWORTHINESS OPTIMIZATION

5.1. Problem formulation

Several problems of crashworthiness optimization may be considered even for a simple structure under
impact load. Owing to the variety of the parameters that affect the response of the structure subject to
dynamic loading, different classes of the optimization problems may be introduced. In the present study
the optimization problem is applied to the maximization of absorbed energy and specific absorbed energy
under axial impact load. Design variables are diameter and length of the tubes. The crush load constraint
is usually required to reduce the occupant injury when passenger vehicles are considered. Hence, in the
optimization process, the mean crush load should not exceed the allowable limit. The design variable
domain is also limited so that the crushing of tube in concertina or diamond mode is guaranteed. Thus, the
optimization problem is defined as

\[
\max \{ E(D,L), SEA(D,L) \} 
\]

\[ P_{\text{mean}} \leq 40KN \]  \hspace{1cm} (2)

\[ 20 \leq \frac{D}{t} \leq 150 \]  \hspace{1cm} (3)

\[ 1 \leq \frac{L}{D} \leq 4 \]  \hspace{1cm} (4)

5.2. Multi-objective genetic algorithm (MOGA)

GA is an optimization method based on the process of evolution in biological population. In the first
step of GA, a random population in the design variable domain is generated and in the next steps,
successively new populations are produced using the previous individuals in such a way that each new
population is modified and evolves towards an optimal solution. For crashworthiness problems that the objective function is highly non-linear with respect to the design variables, unlike the other standard optimization methods, the GA can be applied with sufficient accuracy.

In most cases, design problems frequently contain multiple conflicting objectives, leading to a set of Pareto optimal solutions. One of these solutions cannot be considered better than others. MOGAs have been regarded as well-suited to solve multi-objective problems. The main reason for this is their capability to find diverse Pareto optimal solutions in one single simulation run (Deb 2002). From these optimum solutions the designer can choose the final design according to his particular emphasis on certain objective functions.

Over the years, a number of MOGAs have been developed and successfully used (Deb 2001). In this work, the NSGA-II is applied to obtain the Pareto set. The main features of NSGA lie in that it ranks solutions with non-dominated sorting and assigns them fitness based on their ranks. While the crossover and mutation operators remain similar to a simple GA, the selection operator distinguishes itself. As an improvement of NSGA, NSGA-II is characterized by a fast non-dominated sorting procedure; an elitist strategy; a parameter-less diversity-preservation mechanism and a simple yet efficient constraint-handling method. Details of NSGA-II are described by (Deb 2002).

5.3. Results of the optimization

Based on the NN model, the multi-objective optimization is performed through NSGA-II. Table 3 contains parameters for NSGA-II, which has been executed several times and provides results with good repeatability.

The outcome of this optimization is displayed in Figure 3. 42 circular points represent the Pareto optimal solutions, which explain the trade-off between the absorbed energy and the specific absorbed energy. It is shown that the two crashworthiness criteria strongly compete with each other: large absorbed energy values go hand in hand with small SEA values. Consequently, if the decision maker wishes to emphasize more on the SEA or weight of the energy Absorbers, the energy absorption must be compromised and become lower, and vice versa. Note that the Pareto front spreads over a wide range and each point represents a possible optimal solution with a unique set of design parameters. The points with smaller values of SEA favor the objective of high energy absorption and the points with smaller values of energy absorption favor the minimization of the weight. While the middle points tend to favor the ratio of energy absorption to SEA. To gain more insight into the optimization, the results are demonstrated in Table 4.

Table 3: Parameter specifications for the NSGA-II

<table>
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<th>Parameter</th>
<th>Specification</th>
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<tr>
<td>Population size</td>
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<tr>
<td>Number of generations</td>
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<td>Crossover probability</td>
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<td>Mutation probability</td>
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6. CONCLUSION

This paper presents the crashworthiness design of cylindrical tubes under axial impact load. The design problem is formulated as an optimization procedure with two design variables and two objective
functions. By nonlinear FE technique, the crashworthiness characteristics of different design samples during the crash process are captured in the given domain. Back-propagation neural network is then utilized to establish the surrogate model and acquire the complex relation between the parameters and the response functions. When the BPNN is validated, a multi-objective genetic algorithm is applied to seek for the optimal solutions and as a result, a set of Pareto optimal solutions are visualized. It is noted from the Pareto optima that these two objectives strongly compete with each other and different criteria are emphasized along the Pareto frontier.

Figure 3: Pareto front for the optimization design problem

REFERENCES


Table 4: The optimization results and Pareto solutions

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<th>No.</th>
<th>D(mm)</th>
<th>L(mm)</th>
<th>t(mm)</th>
<th>Absorbed Energy($10^3$ J)</th>
<th>SAE ($10^4$ J/kg)</th>
<th>No.</th>
<th>D(mm)</th>
<th>L(mm)</th>
<th>t(mm)</th>
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