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Multidisciplinary optimization of collapsible cylindrical energy absorbers under axial impact load

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Abstract. In this article, the multi-objective optimization of cylindrical aluminum tubes under axial impact load is presented. The specific absorbed energy and the maximum crushing force are considered as objective functions. The geometric dimensions of tubes including diameter, length and thickness are chosen as design variables. *D/t* and *L/D* ratios are constricted in the range of which collapsing of tubes occurs in concertina or diamond mode. The Non-dominated Sorting Genetic Algorithm-II is applied to obtain the Pareto optimal solutions. A back-propagation neural network is constructed as the surrogate model to formulate the mapping between the design variables and the objective functions. The finite element software ABAQUS/Explicit is used to generate the training and test sets for the artificial neural networks. To validate the results of finite element model, several impact tests are carried out using drop hammer testing machine.

Keywords: cylindrical tube; axial crushing; energy absorption; neural networks; optimization

1. Introduction

Nowadays, using energy absorber systems has grown owing to increase of vehicles' speed in order to lessen human suffering and financial burdens. The energy absorber systems are devices which transform the whole or just a part of kinetic energy into another form of energy. They are generally called mechanical energy absorbers. In a general classification, the energy absorbers are divided into two categories, reversible energy absorbers like elastic damper dashpots and collapsible energy absorbers which absorb the energy by plastic deformation of thin-walled structures. The collapsible energy absorbers can be made of different materials such as metal, composite, polymer, or combination of them called hybrid. Metal thin-walled structures such as circular and square tubes, corrugate tubes, frusta, tapered tubes, octagonal cross-section tubes, honeycomb cells and S-shaped frames form the most widespread shapes of collapsible energy absorbers which have got excellent energy absorption capabilities (Alghamdi 2001).

Among the aforesaid structures, circular metal tubes have attracted the most attention of design engineers and researchers due to their ease of manufacture and low cost. These tubes absorb the energy under axial load, in different modes like axial crushing, in-out inversion, axial splitting,

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lateral crushing and etc. Tube axial crushing is the most prominent mode from the energy absorption point of view and occurs in two major modes: axisymmetric or concertina, non-axisymmetric or diamond. Empirical and numerical studies reveal that different parameters affect the collapsing mode such as geometric dimensions (Guillow and Grzebieta 2001), impact velocity (Karagiozava and Jones 2000), material properties (Hsu and Jones 2004) and end condition of tube (Shakeri *et al*. 2007, Shakeri *et al*. 2004), although geometric dimensions plays a more important role among these factors.

In last decades, studies on optimization of structural crashworthiness have increased mainly due to faster computers and better algorithms. Nevertheless, a few works have been carried out on the optimization of tubular energy absorbers. The first time, Yamazaki and Han (2000) optimized crashworthiness of cylindrical tubes so as to maximize the absorbed energy while the mean crash load was limited not to exceed a certain value. Diameter and thickness of the tube are chosen as design variables and response surface approximation method (RSM) has been applied to construct an approximating design sub-problem based on numerical simulation results. Lee *et al*. (2002) used the response surface method based on stochastic modeling process in order to maximize the energy absorption of cylindrical aluminum tubes. Lanzi *et al*. (2004) applied genetic algorithm and neural networks to optimize the absorbed energy per unit mass of a helicopter sub-floor. Zarei and Kroger (2006) represented the first multi-design optimization of circular and square aluminum tubes with the purpose of maximizing absorbed energy and specific absorbed energy (SAE) by MATLAB. They also used the scalar weighting function method to convert the multi-objective optimization problem into a single-objective one. The D-optimal design of experiment and RSM methods have been utilized to construct sub-problems in sequential optimization procedure. Of course, sequential optimization procedure may lead into local optimum results. Hou *et al*. (2007) and Liu (2008) presented optimal designs of multi-corner structures with sound crush performances. A non-constraint optimization of circular tubes crashworthiness parameters was presented by the present authors (Shakeri *et al*. 2007) using genetic algorithm (GA). In this research, artificial neural networks (ANNs) were used to reproduce the crushing characteristics of tubes, which are often non-smooth and highly non-linear in terms of non-dimensional ratios D/t and L/D. Also, they used scalar weighting function to covert the multi-objective optimization problem to single-objective. Jiang and Gu (2010) represented optimization of the ship fender structure with the purpose of maximizing the SAE and minimizing the maximum crush load under lateral impact loading. They applied neural network and genetic algorithm to obtain Pareto optimal solution. Bi *et al*. (2010) have optimized the foam-filled and empty single and triple-hexagonal columns for maximizing SAE with consideration of section geometry, tube thickness and foam density. Their results show better weight and SAE efficiency of triple columns than single columns. Hou *et al*. (2011) utilized particle swarm optimization method in multi-objective optimization for different configurations of tapered circular tubes. Acar *et al*. (2011) investigated the crush performance of circular tapered tubes with the purpose of maximizing the crush force efficiency (the ratio of the mean load to the peak load) and SAE by considering circumferential indentations and concluded that indentations improve crush performance of these tubes. Salehghaffari *et al*. (2011) used both single and multi-objective optimization formulation and RSM to optimize the externally stiffened circular crush tubes and showed that stiffened tubes are considerably more efficient in terms of energy absorption, crush force efficiency and structural weight. Yin *et al*. (2011) employed particle swarm optimization method for multi-objective crashworthiness optimization of honeycomb-filled single and bitubular polygonal tubes. Their results reveal better SAE performance of the honeycomb-filled single tubes than the bitubular ones.

Although finite element simulation is an appropriate method to evaluate the objective and the constraint functions in terms of design variables, but it is not affordable to employ FEM alone to calculate these functions from a computational point of view. Therefore global approximation methods like RSM, ANNs and the radial basis functions (RBF) are mainly used to construct the response surfaces of tube crashworthiness parameters. Comparing these meta-models, Stander *et al.* (2004) demonstrated that in the optimization of nonlinear problems, ANNs method has a better efficiency.

As it can be seen, almost in all previous researches on the field of optimization of cylindrical tubes under axial loading, a thorough optimization study is not performed and are restricted to some of the effective design variables on crushing response of the tubes. On the other hand, just a small region of design variables domain is considered in which the concertina mode occurs, whilst the energy absorption capability of the diamond mode is considerable and appropriate for energy absorption purposes. 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). As a matter of fact, the goal of this survey is to find tubes with the maximum SAE while their maximum crushing force is minimum in order to decline imposed damages to the occupants. The geometric dimensions of tubes including diameter, length and thickness are limited in a way which causes the tube collapsing occurs in the concertina or diamond modes that involves the highest capacity of energy absorption. To this goal, at the first step, the crush behavior of tubes has been simulated in 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 back propagation ANNs. Totally, 256 numerical simulations are used for training and testing ANNs. Eventually, the Pareto solution sets are presented and analyzed.

2. Nnumerical simulations

2.1 Finite element modeling

Numerical simulations of axial crushing of the cylindrical tubes under impact loading, are conducted using finite element code ABAQUS/Explicit. Since axial crushing of the tubes includes buckling, it is essential to perturb the initial meshes of the tube by its buckling modes. Thus, before performing crushing analysis, buckling analysis is carried out to find the first ten elastic buckling modes using ABAQUS/Standard.

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

3D four-nodded shell elements, suitable for large deformation analysis are used to model the tubes. Nine integration points are used through the shell thickness to consider bending deformation. After performing the mesh sensitivity analysis, element size of 3 mm is found to be adequate to produce suitable results.

Self-contact algorithm is defined for the inner and the outer surfaces of tubes, and surface-to-

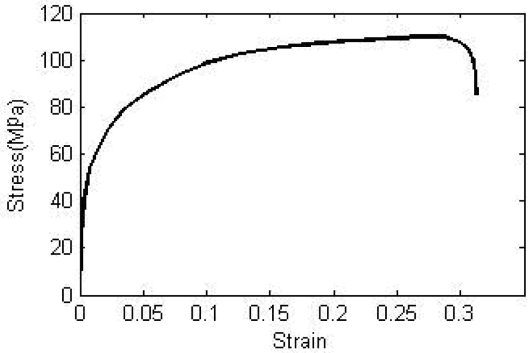


Fig. 1 Engineering static stress-strain curve of the aluminum alloy obtained from experiment

Table 1 Isotropic hardening data for aluminum

σ (N/mm^2)	65	85	90	98	103.75	106.87	110.3
ε_p	0	0.032	0.0463	0.082	0.132	0.182	0.263

surface contact is regarded between the tube and the rigid walls. In all in-contact-surfaces, friction coefficient equals to 0.2.

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 the tube material is E = 70 GPa, the density is $\rho = 2700$ kg/m^3 and the Poisson ratio is $\upsilon = 0.3$. The material model is defined as linear elastic followed by non-linear isotropic work hardening in the plastic region. A typical engineering static stress-strain curve is presented in Fig. 1. This curve is used to introduce the approximated true stress-plastic strain data points needed for the numerical simulations, as shown in Table 1. It is also presumed that the tube material is not sensitive to strain rate effects.

3. Experimental results

In order to validate the numerical simulations, five impact tests are carried out on aluminum tubes under axial crushing load. The tests are conducted using the vertical drop-testing machine. Impact load is 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 by 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 equal to the absorbed energy. The ratio of the absorbed energy to the mass of the tube is SAE.

The tubes have been made of aluminum alloy. The material properties of this alloy have been described in section 2. The geometric dimensions and impact velocity for each specimen are presented in Table 2. Comparisons between the numerical and experimental collapsing modes are shown in Fig. 2. Typically, a crush load-displacement curve obtained from the experimental and numerical results is compared in Fig. 3. Table 2 shows the values of the crashworthiness parameters obtained from simulation and experimental tests. It is clear from Fig. 2, Fig. 3 and Table 2 that numerical simulation can predict the deformation pattern and the crashworthiness characteristics of the tubes with a good accuracy.

Table 2 Results from the impact tests and numerical simulations

Test no.	t (mm)	D/t	L/D	V_0 (m/s)	$F_{\max}$ (kN)		F_{mean} (kN)		SAE (kJ/kg)		$\delta_{\max}$ (mm)	
					Exp.	Sim.	Exp.	Sim.	Exp.	Sim.	Exp.	Sim.
1	3	25	1.53	6.5	68.12	67.35	44.92	43.26	13.86	13.84	65	66.7
2	1.6	45.43	2.05	6.4	26.42	25.58	14.3	13.99	12.89	11.32	130.5	132.2
3	2	36.85	2.03	5.8	37.87	36.59	24.56	23.24	13.79	13.4	102.5	103.03
4	1.8	40.67	3.07	6.6	31.13	30.47	18.17	16.84	13.15	12.2	177.5	179.92
5	2	36.9	2.03	6.8	41.87	39.74	30.02	29.19	17.52	15.75	117	116.14

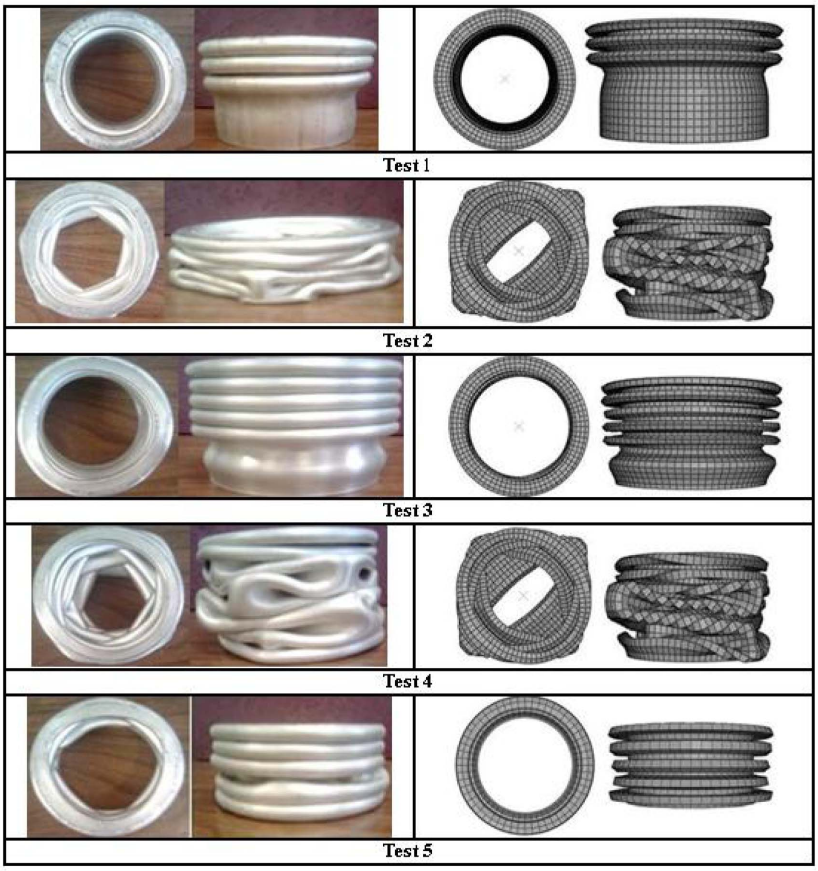


Fig. 2 Comparison of the experimental and numerical collapsing mode of tubes

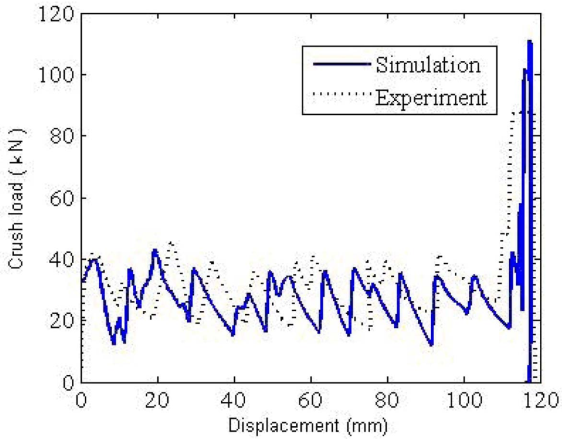


Fig. 3 Comparison of the experimental and numerical crushing load-displacement curve for test no. 5

4. Neural networks to reproduce the crush behavior of the tube

Artificial neural networks are regarded as global approximation tools to solve problems, not only in engineering, science and mathematics, but in medicine, business, finance and literature as well. The history work in the field of neural networks dates back to the late 19th and early 20th centuries which includes predominantly of interdisciplinary work in physics, psychology and neurophysiology.

ANNs comprise several simple computing units called neurons which can be trained to reproduce the response of an input-output system. Neurons are usually arranged in series layers to develop a multi-layer ANN. A multi-layer ANN consists of an input layer, an output layer and one or more layers in the middle called hidden layers. Number of neurons in input and output layers equal to the number of input and output variables. According to Fig. 4, each neuron in the ANN receives sum of the weighted outputs of previous layers and bias, then the output of the neuron is produced by passing through a transfer function which can be any differentiable function. The ANNs must be trained to solve a problem. Training process includes adjusting the weight and the bias parameters for each neuron to conform the network output to a desired value. Relation between input and output is extracted by a set of examples of proper network behavior called training set. After training, in order to approve the accuracy of the network response to new inputs, a verification stage is needed by considering several input/target pairs called test sets.

As was mentioned earlier, the aim of this article is optimization of the crashworthiness characteristics of cylindrical metal 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

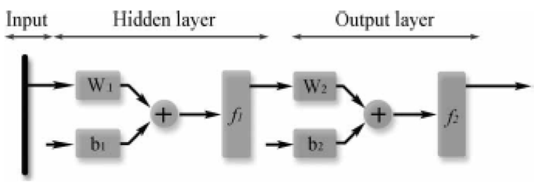


Fig. 4 Schematic of a one hidden-layer network

simulations by the FEM is very costly and time consuming from the computational point of view. Thus, the ANNs are used to reproduce crashworthiness parameters of tubes under axial impact load. So, a set of the MLP neural networks, with two hidden layers is developed and trained using a finite number of numerical simulations.

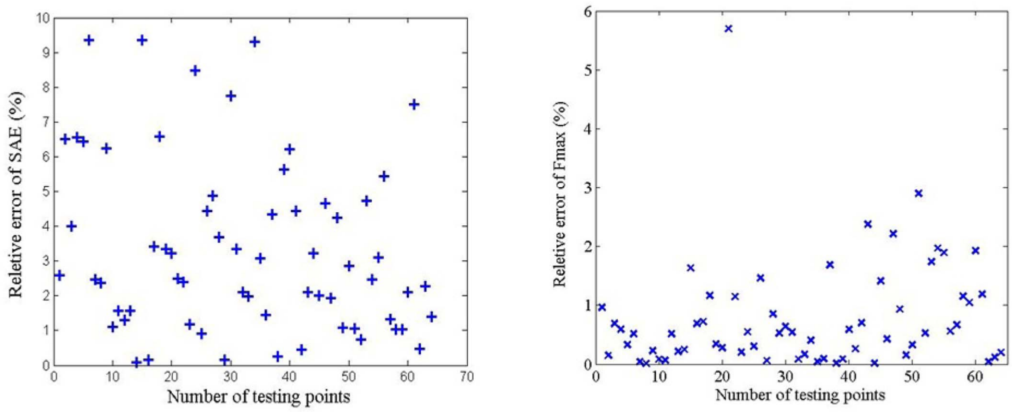
4.1 Design of neural networks

Two distinct neutral networks are designed to reproduce the values of the SAE and the F_{max} during axial crushing of tubes with impact velocity of 10 m/s by MATLAB software. Design variables vector consists of diameter, length and thickness of the tubes.

A proper structure of the network needs to be found considering the training efficiency and accuracy. Since the number of input and output variables determine the number of 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. So the architecture is obtained to be 3-5-5-1 and the transfer functions for the four layers are "tangent sigmoid", "tangent sigmoid", "tangent sigmoid" and "linear" respectively. The training function "trainbr" is used for training all the neural networks (Demuth *et al*. 2007).

4.2 Training and test sets

The performance of the ANNs is highly sensitive to the settlement of the training sets in the design variables domain. A general rule for selecting the location of the training sets in the design variables domain is not still attained. Methods based upon the definition of factorial grid within the desirable region of the domain are frequently used to settle the initial design points. Sadly, these approaches are not easily applicable in crush problems often requiring large number of samples. In the present work, in order to reduce the number of required sample points to train the ANNs, design-of-experiment method is employed. The training and test sets are defined in the range of 50 mm < D < 150 mm, 100 mm < L < 300 mm and 1 mm < t < 3 mm, which will also be the



(a) (b)

Fig. 5 Relative error of test sets (a) SAE, (b) maximum crushing force

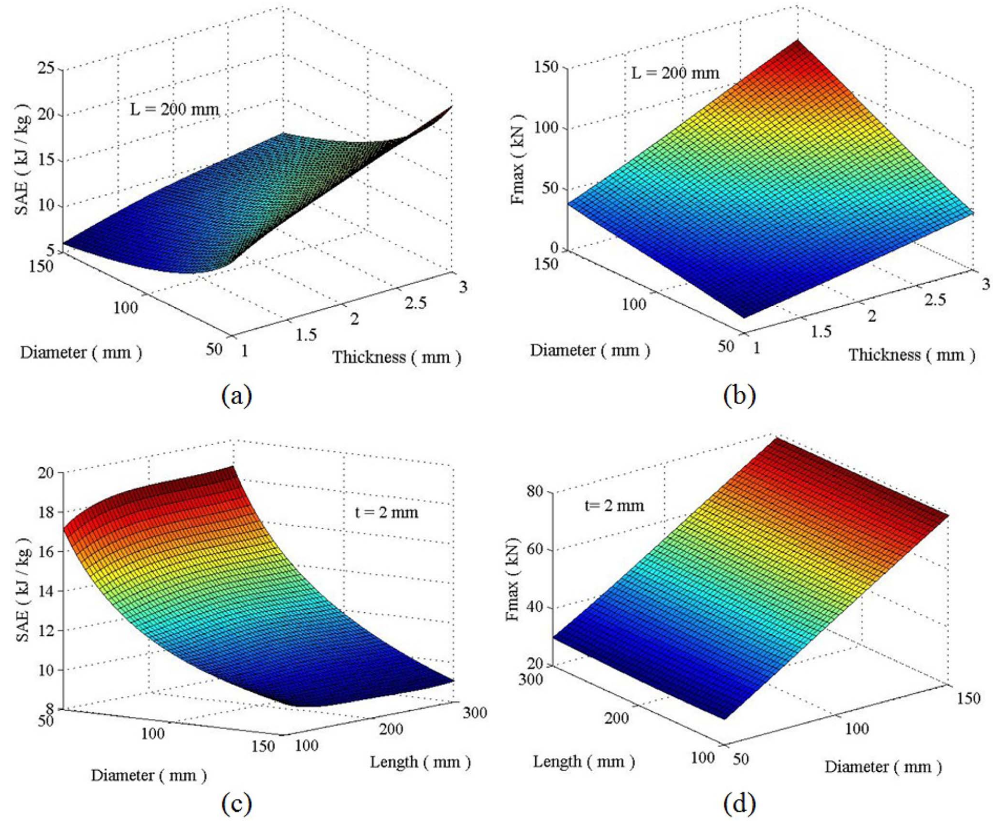


Fig. 6 Response surfaces of crashworthiness parameters of the tubes

optimization domain. Supposing eleven levels for each design variable, 11^3 sample points are required to predict the crashworthiness parameters of tube, while applying design-of-experiment method reduces them to 256 samples with the same precision that training sets consist of 192 samples and the others are used to test the ANNs. The relative error percentage of each network is illustrated in Fig. 5. The average relative error percentage of test sets for the SAE and maximum crushing force fall below 4% and 1%, respectively. To better insight into the behavior crashworthiness parameters against the geometric dimensions of tubes, using trained ANNs, response surfaces of the SAE and maximum crushing force are plotted in Fig. 6. As it is seen from this figure, crashworthiness parameters of tubes show nonlinear behavior in terms of design variables except for $F_{\max}$ in terms of length and diameter, Fig. 6(b). On the other hand, Fig. 6 reveals that geometric parameters have different effects on different crashworthiness characteristics. For instance, according to Figs. 6(a) and (b), by increasing the tube thickness, both crashworthiness parameters increase while by increasing the tube diameter, $F_{\max}$ increases and SAE descends. Also, among the design variables, thickness has got the most significant effect whereas the length shows less influence rather than the others. This subject confirms the necessitation of multi-objective optimization of these structures in order to achieve the best energy absorption requirements.

5. Optimization of crashworthiness characterization

5.1 Definition of problem

Due to the diversity of the parameters that affect the response of the structure subjected to impact loading, different classes of the optimization problems can be introduced. In the present study the optimization problem is applied to the circular metal tubes in order to maximize the SAE while maximum crushing force is minimized to prevent serious damages to the occupants. Geometric dimensions of the tubes including diameter, length and thickness are considered as design variables. The design variables domain is also limited so that the crushing of tube in concertina or diamond mode is guaranteed, (Andrews *et al*. 1983). Thus, the optimization problem can be defined as

$$\text{Maximize:} \quad \left\{ SAE(D,L,t),\ \frac{1}{F_{\max}(D,L,t)} \right\} \tag{1}$$

$$\text{Constraints:} \quad 20 \le \frac{D}{t} \le 150 \tag{2}$$

$$1 \le \frac{L}{D} \le 3 \tag{3}$$

$$\text{Design variables:} \ 50\ \text{mm} \le D \le 150\ \text{mm} \tag{4}$$

$$100\ \text{mm} \le L \le 300\ \text{mm} \tag{5}$$

$$1\ \text{mm} \le t \le 3\ \text{mm} \tag{6}$$

5.2 Multi-objective genetic algorithm (MOGA)

In most crashworthiness problems, lack of accurate analytical models to correspond objective functions to design variables, applying classical optimization methods which need the gradient of function, is not possible. So usages of evolutionary algorithms like GA is extensively developing. The GA is an optimization method based on the process of evolution in biological populations which by selecting a random initial population from design domain and successively improving it, evolves towards an optimal solution.

In most cases, design problems frequently contain multiple conflicting objectives, leading to a set of Pareto optimal solutions. One of these solutions can not be considered better than the other. MOGAs have been regarded as well-suited to solve multi-objective problems. The main advantage of this algorithms is their capabilities 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.

A number of MOGAs have been developed and effectively implemented throughout the years (Deb 2001). In this research, the NSGA-II is applied to attain the Pareto set. The principal features of NSGA lie in that, it ranks solutions with non-dominated sorting and assigns them fitness based on their ranks. The main difference between NSGA and ordinary GA is about their selection operator while the crossover and mutation operators remain analogous. As an improvement of NSGA, NSGA-II is characterized by a rapid non-dominated sorting procedure; an elitist strategy; a parameter-less diversity-preservation mechanism and a straightforward effective constraint-handling approach. Details of NSGA-II are described by Deb (2002).

5.3 Optimization results

Pareto optimization is performed through NSGA-II. Table 3 lists the used parameters in it. In order to obtain results with good repeatability, algorithm is several times executed. Pareto optimal solutions are displayed in Fig. 7 via 47 circular points which explain the trade-off between SAE and F_{max} in such a way that large SAE values go hand in hand with large F_{max} values. Each point in this Figure represents a possible optimal solution with a unique set of design variables. As a result, tubes with high SAE values have got high F_{max} and vice versa. Consequently, each optimum solution is selected to consider crashworthiness requirement of problem. To gain more insight into the optimization, the results are demonstrated in Table 4.

As an alternative method, according to the Fig. 8 and the Fig. 9, the normalized design variable values can be plotted against their positions on the Pareto front (Jiang and Gu 2010). Since the diameter of tubes keeps constant of 50 mm for the whole optimum solutions, it is not shown in the graphs, and these indicate that thicker tubes gain an optimum solution for not only the SAE but also the F_{max} that is not favorable.

It is necessary to validate the obtained optimal solutions of the ANNs in the optimization procedure with the finite element results. So, three points have been evaluated to compare existing errors between optimal results and numerical simulations. Table 5 shows that the optimal solution is authentic.

Table 3 Parameter specifications for the NSGA-II

Population size	300
Number of generations	1000
Crossover probability	70%
Mutation probability	30%

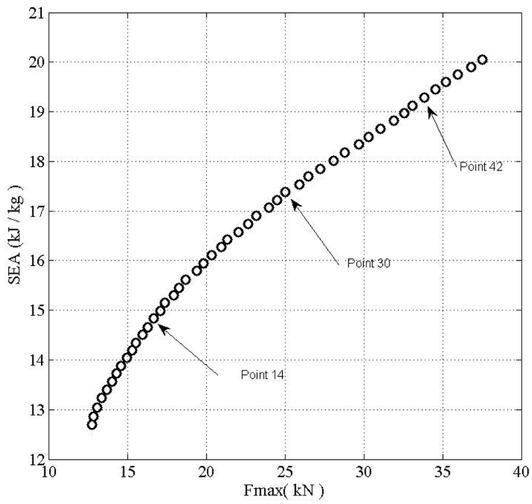


Fig. 7 Pareto front for the optimization design problem

Table 4 The optimization results and Pareto solutions

No.	D (mm)	L (mm)	t (mm)	SAE (kJ/kg)	F_{max} (kN)	No.	D (mm)	L (mm)	t (mm)	SAE (kJ/kg)	F_{max} (kN)
1	50.21	150.5	2.51	20.05	37.51	25	50.21	149.39	1.52	16.27	20.95
2	50.03	147.17	2.47	19.90	36.82	26	50.21	150.53	1.49	16.10	20.37
3	50.08	149.76	2.42	19.74	35.97	27	50.03	143.04	1.46	15.95	19.85
4	50.03	149.39	2.38	19.59	35.23	28	50.21	150.5	1.43	15.80	19.39
5	50.03	149.29	2.34	19.44	34.55	29	50.03	149.29	1.39	15.62	18.69
6	50.03	149.29	2.30	19.29	33.83	30	50.08	147.75	1.36	15.45	18.30
7	50.03	149.21	2.26	19.13	33.09	31	50.21	150.53	1.34	15.30	17.94
8	50.08	147.75	2.23	18.98	32.58	32	50.03	149.29	1.30	15.15	17.39
9	50.21	150.53	2.19	18.82	31.89	33	50.08	146.85	1.28	14.99	17.10
10	50.10	148.00	2.14	18.65	31.06	34	50.08	147.75	1.26	14.83	16.69
11	50.08	146.85	2.10	18.49	30.33	35	50.10	147.75	1.23	14.66	16.30
12	50.21	149.20	2.06	18.34	29.68	36	50.20	150.46	1.21	14.50	15.95
13	50.13	148.46	2.00	18.17	28.78	37	50.03	148.46	1.18	14.35	15.53
14	50.21	150.53	1.96	18.02	28.10	38	50.21	149.29	1.17	14.20	15.32
15	50.08	148.00	1.91	17.85	27.23	39	50.20	150.46	1.14	14.04	14.95
16	50.03	146.94	1.87	17.69	26.47	40	50.20	150.23	1.12	13.87	14.62
17	50.14	147.75	1.83	17.54	25.94	41	50.21	150.53	1.10	13.72	14.32
18	50.03	149.20	1.78	17.38	25.00	42	50.21	150.53	1.08	13.57	14.03
19	50.08	146.85	1.75	17.23	24.50	43	50.20	150.46	1.06	13.39	13.71
20	50.20	148.00	1.71	17.07	23.98	44	50.03	148.46	1.04	13.23	13.39
21	50.10	148.00	1.66	16.90	23.16	45	50.20	150.50	1.02	13.04	13.09
22	50.03	141.67	1.63	16.74	22.64	46	50.10	148.00	1.01	12.86	12.84
23	50.21	149.29	1.59	16.57	22.04	47	50.08	143.73	1.00	12.69	12.77
24	50.08	147.75	1.55	16.42	21.35						

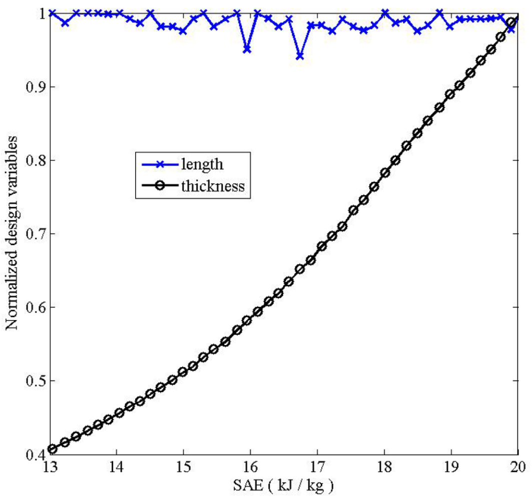


Fig. 8 Variation of the design variables against SAE on the Pareto front

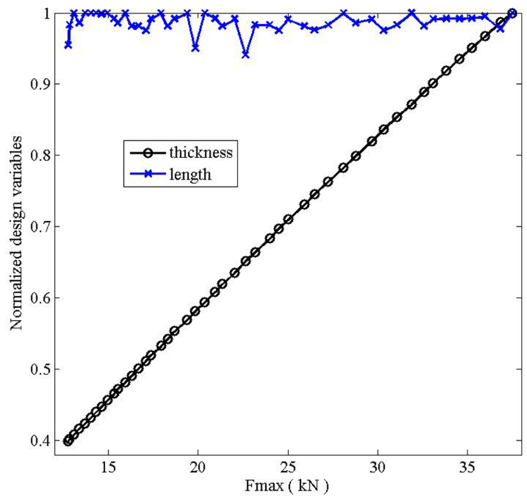


Fig. 9 Variation of the design variables against maximum crushing force on the Pareto front

Table 5 Comparison between the optimum results and the FEM

No.	D (mm)	L (mm)	t (mm)	Optimized solution		FEM		Relative error (%)
				SAE (kJ/kg)	F_{max} (kN)	SAE (kJ/kg)	F_{max} (kN)	
14	50.21	150.53	1.96	18.02	28.10	17.23	27.96	4.5
30	50.08	147.75	1.36	15.45	18.30	14.51	18.95	6.4
42	50.21	150.53	1.08	13.57	14.03	13.42	14.55	1.1

6. Conclusions

This paper presents the crashworthiness design of cylindrical tubes under axial impact load. The design problem is formulated as an optimization procedure with three design variables and two objective functions. Using the numerical simulation, the crashworthiness characteristics of different design samples during the crush process are captured in the given domain. Afterward, in order to establish the surrogate model and achieve the complex relation between the parameters and the objective functions, back-propagation neural network is utilized. When the ANNs are validated, a multi-objective genetic algorithm is applied to search for the optimal solutions and consequently, a set of Pareto optimal solutions is visualized. It can be seen from the Pareto optimal solutions that these two objectives intensely compete with each other and various criteria are highlighted along the Pareto frontier. To gain better insight into the optimum results, the normalized design variables are plotted versus their objective functions. Finally, to validate the optimum sets, the results are compared with the finite element model which shows good accuracy of both ANNs and optimization process.

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