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Multi-objective Optimization of Crashworthiness of Cylindrical Tubes as Energy Absorbers

In this article, the multi-objective optimization of cylindrical aluminum tubes under axial impact load is presented. The absorbed energy and the specific absorbed energy (SEA) are considered as objective functions while the maximum 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 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.

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

1 Introduction

At the present time, using energy absorber systems has grown owing to increase of vehicles' speed in order to lessen human suffering and financial burdens, have found greater importance. 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. 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 the thin-walled structure. Collapsible energy absorbers have various types such as circular and square tubes, corrugate tubes, frusta, tapered tubes, octagonal cross-section tubes, honeycomb cells and S-shaped frames [1].

Thanks to efficient energy absorbing, easy manufacturing and low cost, circular metal tubes represent one of the most famous energy absorbers which absorb the energy under axial load, in different modes like in-out inversion, axial splitting, lateral indentation and axial crushing.

Tube axial crushing is more significant due to high crushing efficiency and energy absorption. These structures may crush in different modes including: axisymmetric or concertina, non-axisymmetric or diamond, mix mode and Euler. Among the various collapsing modes, concertina mode is better than other modes because of progressive and stable

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collapsing. The empirical and numerical studies reveal that different parameters affect the collapsing mode such as geometric dimensions [2], impact velocity [3], material properties [4] and end condition of tube [5,6].

Lately, the studies on optimization of crashworthiness in mechanical structures have increased mainly due 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 [7] optimized crashworthiness of cylindrical tubes so as to maximize their crushing energy while the limit was the maximum 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-problem. Zarei and Kroger [8] represented the multi-objective optimization of aluminum tubes with the purpose of maximizing absorbed energy and specific absorbed energy by MATLAB. They 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. [9] and Liu [10] presented optimal designs of multi-corner structures with sound crush performances. Non-constraint optimization of tube crashworthiness parameters was presented by the authors before [5]. Artificial neural networks (ANNs) were used to reproduce the crushing behavior of tubes, which are often non-smooth and highly non-linear in term of design variables (diameter and length of tube) and single-objective optimization was carried out using the genetic algorithm (GA).

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 [7-10], (ANNs) [11-12] and the radial basis functions (RBF) [13-14] are mainly used to construct the response surfaces of tube crashworthiness parameters.

Comparing these meta-models, Stander et al. [15] demonstrated in the optimization of nonlinear problems, that 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 [16]. 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 (SEA) of cylindrical tubes subject to axial impact. The diameter, length and thickness of the tubes were optimized while the applied maximum crush load should not exceed allowable limit.

To this end, 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 ANNs. Finally, the Pareto solution sets are 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 m=140 kg is attached to the upper wall and an initial velocity is defined for the upper wall just before the collision.

Four-nodded shell elements, suitable for large deformation analysis is used to model tubes. Nine integration points are used through the shell thickness to model bending. The Element size for each tube is obtained after performing the mesh sensitivity analysis. It 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 $\rho = 2700\ \mathrm{kg/m^3}$ 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 Figure 1. This curve is used to introduce the approximated true stress-plastic strain data points in the numerical simulations, as shown in Table 1. It is also presumed that this material is not sensitive to strain rate.

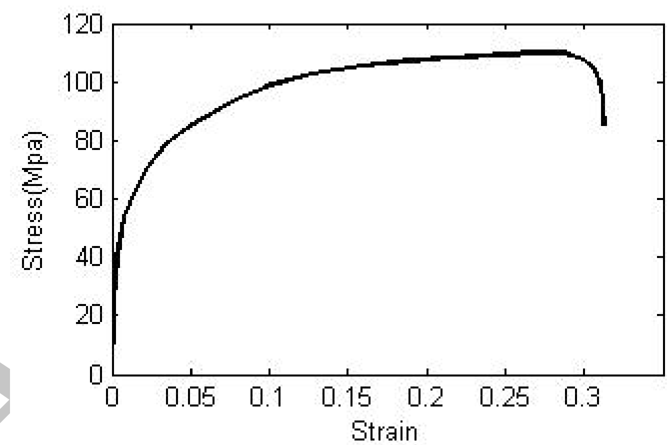

Figure 1 Engineering static stress-strain curve of the aluminum alloy obtained from experiment

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

$\sigma(\mathrm{N/mm^2})$	65	85	90	98	103.75	106.87	110.3
ε_p	0	0.032	0.463	0.082	0.132	0.182	0.263

3 Experimental results

With the intention of validating numerical simulations, five impact tests are carried out on aluminum tubes under vertical 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 drop mass is elevated by an electric winch and released via an electromechanical system from different heights. 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 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 2. 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 3. Table 2 shows the values of the crashworthiness parameters obtained from FE simulation and experimental tests. It is obvious from Figure 2, Figure 3 and Table 2 that numerical simulation can predict the collapsing shape and the crashworthiness parameters of tubes with a great accuracy.

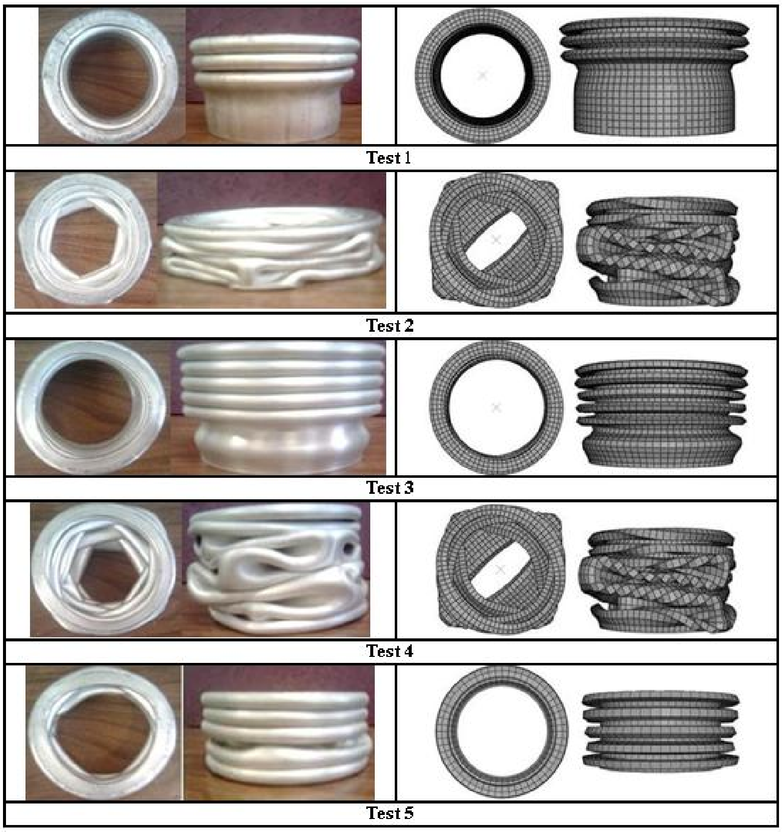

Figure 2 Comparison of the results for tubes collapsing mode under axial impact load obtained from experimental tests and numerical simulations

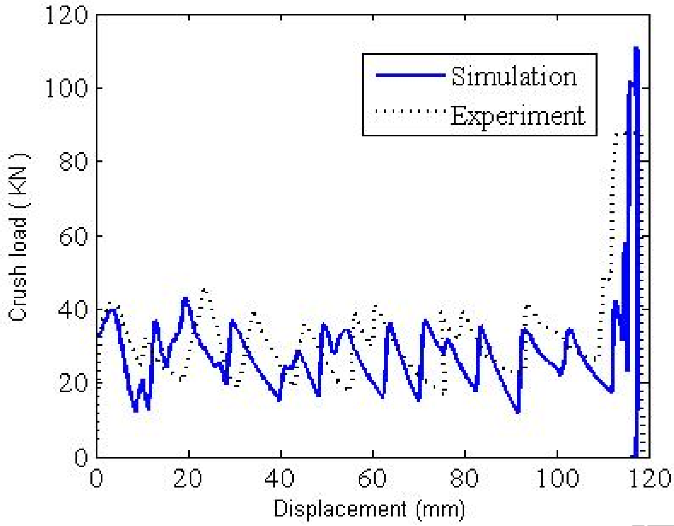

Figure 3 Comparison of the crush load-displacement curve obtained from experimental test and numerical simulation for test no. 5

Table 2 Results from the impact tests and numerical simulation

Test no.	t (mm)	D/t	L/D	V_0 (m/s)	$F_{max}(KN)$		$F_{mean}(KN)$		SAE(KJ/Kg)		δ_{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

4 Neural networks to reproduce the crush behavior of the tube

Currently, the artificial neural networks are regarded as global approximation tools to solve problems, not just 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. Nevertheless, the first practical application of ANNs was introduced in the late 1950s, with the invention of the perceptron network by Frank Rosenblatt [17], which was just applied to a linearly separable problem. Later, the multi-layer perceptron (MLP) networks were put forward with back-propagation learning rule to surmount these limitations in the 1980s [18].

As a point of fact, the ANNs comprise several simple computing units called neurons which can be trained to reproduce the response of input-output systems. 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 layer in between called hidden layers. Number of neurons in input and output layer equals to the number of input and output variables. According to Figure 4, each neuron in the ANN receives the sum of the weighted outputs of previous layer and bias then produces output of the neuron by passing the result through a transfer function. Any differentiable function can be used as a transfer 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 in precisely predicting the solution to the new inputs, a verification stage is needed by considering several input/target pairs called test sets.

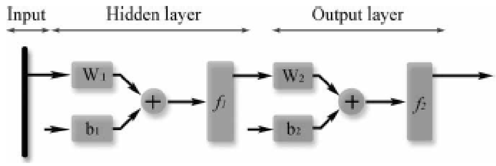

Figure 4 Schematic of a one hidden-layer perceptron network

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 is very costly and time consuming from the computational point of view because of the complexity of the FE models required predicting 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 the FE simulations.

4.1 Design of neural networks

In this study, two distinct neutral networks are designed to reproduce the values of the absorbed energy and the maximum force during axial crushing of tubes with impact velocity fixed at 10m/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 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 3-5-5-1 and the transfer functions for the four layers are "tangent sigmoid", "tangent sigmoid", "tangent sigmoid" and "linear" respectively. The Levenberg – Marquardt algorithm is used for training all the neural networks [19].

4.2 Training and test sets

The ultimate performance of the neural networks 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 to crash problems often requiring large number of examples.

The method used in this research is based on a different concept. The settlement of the training patterns is carried out beginning from an initial random allocation of points in a normalized domain in a way that each design variable ranges from 0 to 1. The idea is then to modify the initial positions so as to acquire a homogeneous and not systematic allocation inside the normalized domain [12].

In the present study, 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 optimization domain. The training set consists of 150 samples chosen to guarantee a random and homogeneous allocation inside the design domain and change the design variable values. The initial and final positions of the samples are compared in Figure 5. The test set consists of 50 samples uniform selected inside the design domain. A total number of 200 ABAQUS/Explicit runs were then performed. The training process continues until the mean square errors decrease less than 0.0008. After training both of the networks, the test sets are used to find the error of each network. The maximum percentage relative error obtained by each network is within 8%.

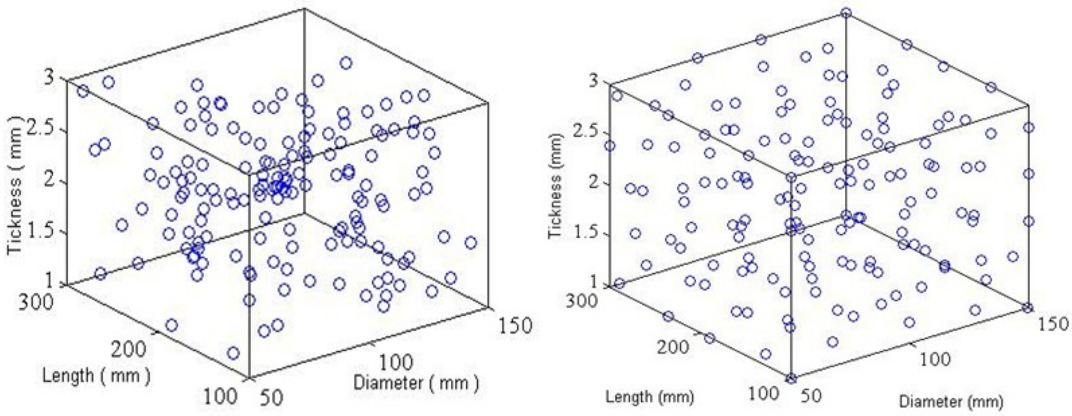

Figure 5 Settlement of the training set (a): initial positions (b): final positions

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 influence the response of the structure subject to dynamic loading, different classes of the optimization problems may be introduced. However, generally the problem can be formulated as:

Objective function: $$\{f_i(x)\} \tag{1}$$

Constraints: $$g_i(x) \le 0, i = 1,...N_c \tag{2}$$

Design variables: $$x_{il} \le x_i \le x_{iu}, i = 1,..., N_d \tag{3}$$

Where the parameters x_{il} and x_{iu} are the lower and upper bounds of the design variable domain, N_c is number of constraints and N_d is number of design variables.

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, length and thickness of the tubes. The crush load constraint is usually required to reduce the occupant injury. Hence, in the optimization process, the maximum 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:

Maximize: $$\{\text{Absorbed energy}(D,L,t), SEA(D,L,t)\} \tag{4}$$

Constraints: $$F_{max} \le 60 \text{ KN} \tag{5}$$

$$20 \le \frac{D}{t} \le 150 \tag{6}$$

$$1 \le \frac{L}{D} \le 4 \tag{7}$$

Design variable: $$50mm \le D \le 150mm \tag{8}$$

$$100mm \le L \le 300mm \tag{9}$$

$$1mm \le t \le 3mm \tag{10}$$

5.2 Multi-objective genetic algorithm (MOGA)

The GA is an optimization method based on the process of evolution in biological population. In the first step of the 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 the 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 the other. 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 [16]. 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 [20]. In this research, the NSGA-II is applied to attain the Pareto set. The principal features of NSGA (Non-dominated Sorting Genetic Algorithm) lie in that it ranks solutions with non-dominated sorting and assigns them fitness based on their ranks. The selection operator distinguishes itself while the crossover and mutation operators remain analogous to an ordinary GA. 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 yet effective constraint-handling approach. Details of NSGA-II are described by Deb [16].

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.

Table 3 Parameter specifications for the NSGA-II

Population size	300
Number of generations	2000
Crossover probability	80%
Mutation probability	20%

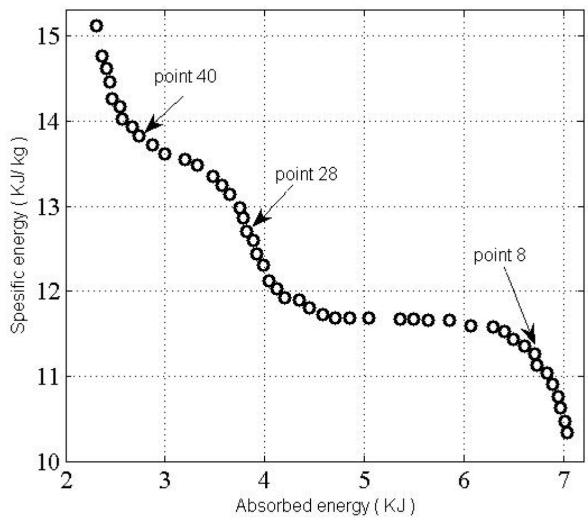

Figure 6 Pareto front for the optimization design problem

The outcome of this optimization is displayed in Figure 6. 48 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. As a result, 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. Pay attention 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 energy absorption and SEA. To gain more insight into the optimization, the results are demonstrated in Table 4. The optimum values are listed with respect to their absorbed energy. In this table, the points from 13 to 20 are considered weak Pareto solutions, because SEA values keep constant when the absorbed energy varies.

Table 4 The optimization results and Pareto solutions

No.	*D(mm)*	*L(mm)*	*t(mm)*	*Absorbed Energy(KJ)*	*SAE (KJ/kg)*	*No.*	*D(mm)*	*L(mm)*	*t(mm)*	*Absorbed Energy(KJ)*	*SAE (KJ/kg)*
1	89.57	298.81	3.00	7.04	10.34	25	59.94	225.05	3.00	4.12	12.03
2	88.25	298.07	3.00	7.01	10.47	26	60.77	215.82	3.00	4.04	12.13
3	86.59	297.52	3.00	6.96	10.63	27	60.01	212.29	3.00	3.99	12.30
4	84.74	299.15	3.00	6.94	10.76	28	62.40	198.21	3.00	3.92	12.44
5	83.00	299.15	3.00	6.89	10.90	29	60.36	200.74	3.00	3.88	12.60
6	81.34	299.21	3.00	6.83	11.03	30	60.98	194.39	2.99	3.82	12.70
7	79.66	299.75	2.99	6.73	11.13	31	60.32	191.85	3.00	3.78	12.86
8	78.08	299.61	3.00	6.71	11.27	32	60.05	188.84	3.00	3.75	12.98
9	76.77	298.63	2.99	6.60	11.35	33	59.75	183.50	2.99	3.65	13.14
10	75.52	296.10	2.99	6.50	11.44	34	60.08	176.95	2.99	3.57	13.25
11	74.17	294.91	3.00	6.40	11.52	35	60.01	171.48	2.99	3.49	13.35
12	73.11	292.35	3.00	6.30	11.58	36	59.97	161.76	2.99	3.32	13.48
13	72.06	286.54	2.99	6.07	11.59	37	59.99	154.87	3.00	3.20	13.55
14	70.35	281.29	3.00	5.86	11.65	38	60.19	143.89	3.00	3.00	13.61
15	69.04	275.96	2.99	5.64	11.66	39	59.94	137.26	3.00	2.87	13.72
16	68.12	271.93	3.00	5.49	11.67	40	59.97	130.17	2.99	2.74	13.83
17	67.28	268.79	3.00	5.36	11.67	41	59.99	125.53	3.00	2.67	13.93
18	65.17	260.48	3.00	5.04	11.68	42	60.88	118.42	2.99	2.57	14.03
19	64.13	254.79	3.00	4.86	11.68	43	59.97	117.80	2.99	2.54	14.16
20	63.31	250.17	3.00	4.71	11.69	44	60.51	112.81	2.98	2.46	14.26
21	62.33	247.64	2.99	4.58	11.72	45	60.12	110.66	3.00	2.44	14.46
22	61.06	243.25	2.99	4.45	11.80	46	59.94	108.19	3.00	2.41	14.61
23	60.01	239.46	3.00	4.35	11.90	47	59.97	105.42	2.99	2.37	14.76
24	60.34	229.96	3.00	4.21	11.92	48	59.95	100.28	3.00	2.31	15.12

As an alternative method, according to the Figure 7 and the Figure 8, the normalized design variable values can be plotted against their positions on the Pareto front [21]. Since the thickness of tubes keeps constant of 3mm for the whole optimum solutions, it is not shown in the graphs, and it indicates, the thicker tubes gain an optimum solution for the maximum absorbed energy and SEA. These graphs also reveal the behavior of diameter and length of tubes against the absorbed energy and SEA. For instance, the Figure 8 divides into two clusters, in either of which only one design variable varies. While SEA is lower than 11.5 KJ, just the diameter of tube decreases accorded on growing SEA. While SEA is larger than 11.5 KJ, decreasing the length of tube, SEA grows. In either cluster, the emphasis on the maximization of absorbed energy is gradually tends to SEA.

It is necessary to validate the obtained optimal solutions of the ANN in the optimization procedure with FEM results. In order to, three points have been evaluated to compare existing errors between optimal results with FEM. Table 5 is shown that the optimal solution is actual.

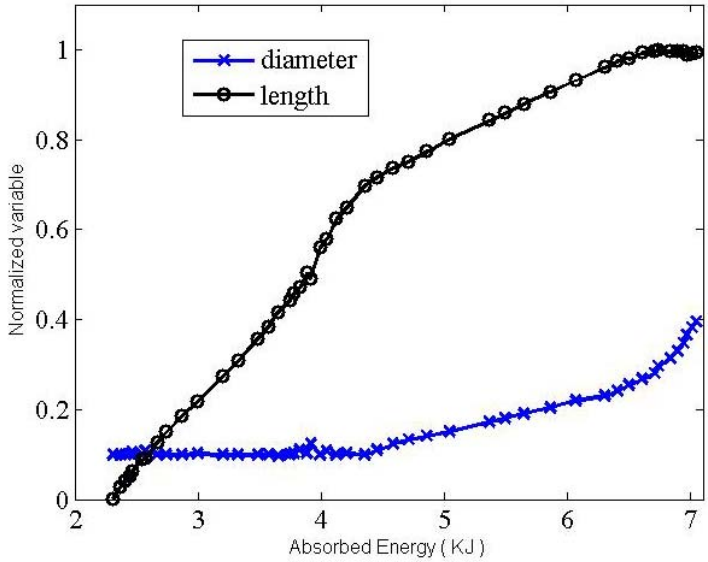

Figure 7 Variation of the design variable against absorbed energy on the Pareto front

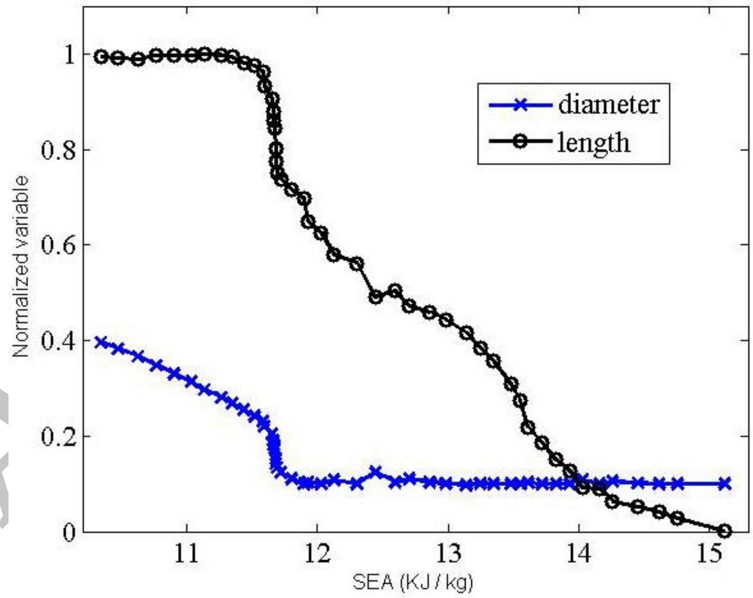

Figure 8 Variation of the design variable against the SEA on the Pareto front

Table 5 Comparison between the optimum results and the FEM

No.	*D(mm)*	*L(mm)*	*t(mm)*	Optimized solution		FEM		Relative error (%)
				Absorbed Energy(KJ)	*SAE (KJ/kg*	*Absorbed Energy(KJ)*	*SAE (KJ/kg*	
8	78.08	299.61	3.00	6.71	11.27	6.89	11.57	2.4
28	62.40	198.21	3.00	3.92	12.44	3.97	12.61	1.2
40	59.97	130.17	2.99	2.74	13.83	2.91	14.69	5.8

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 nonlinear FE technique, the crashworthiness characteristics of different design samples during the crash 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 response functions, back-propagation neural network (BPNN) is utilized. When the BPNN is 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 optima that these two objectives intensely rival 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 against their objective functions. Finally, to validate the optimum sets, the results are compared with the FEM model.

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Nomenclature

D	:	mean diameter of tube
E	:	elastic modulus
$f_i(x)$	:	objective function
$F_{\max}$	:	maximum crushing load

$g_i(x)$	:	constraint equation
L	:	length of tube
m	:	mass
N_c	:	number of constraints
N_d	:	number of design variables
x_i	:	design variable
x_{il}	:	lower bound of design variable
x_{iu}	:	upper bound of design variable

Greek symbols

ε_p	:	plastic strain
σ	:	stress
ρ	:	density
υ	:	Poisson ratio

چکیده

در این مقاله بهینه سازی چند منظوره لوله های آلومینیومی استوانه ای تحت بار محوری ضربه به روش الگوریتم ژنتیک ارائه می گردد. انرژی جذب شده و انرژی ویژه به عنوان توابع هدف در نظر گرفته می شوند. متغیر های طراحی شامل قطر، طول و ضخامت لوله در محدوده ای در نظر گرفته می شوند تا فروریزش لوله به شیوه چیندار والماسی که از قابلیت جذب انرژی بیشتری برخوردار می باشند انجام گردد. همچنین حداکثر نیروی لهیدگی مقید می شود تا از صدمه دیدن سرنشینان وسیله نقلیه اجتناب گردد. به منظور یافتن رابطه بین متغیرهای طراحی با توابع هدف وحداکثر نیروی لهیدگی از شبکه های عصبی پس انتشار استفاده می شود. همچنین جهت آموزش وتست شبکه های عصبی از ۲۰۰ شبیه سازی عددی لهیدگی محوری لوله در نرم افزار المان محدود Abaqus/Explicit استفاده می گردد. جهت معتبر سازی نتایج شبیه سازی تعداد محدودی آزمایش ضربه توسط دستگاه سقوط وزنه انجام می شود.