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The Optimal Design of Composite Energy Absorptions with Multiple Cell Sections

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Abstract- In this paper the axial impact crushing behavior of the composite tubes are studied by the finite element method using commercial software ABAQUS. Two meta-models based on the evolved group method of data handling (GMDH) type neural networks are then obtained for modeling of both the absorbed energy (E) and the peak crushing force (F max) with respect to geometrical design variables using the training and testing data obtained from the finite element modeling. Using such obtained polynomial neural network models, the multi-objective GA is used for the Pareto-based optimization of the composite tubes considering three conflicting objectives: energy absorption, weight of structure, and peak crushing force. Further evaluations of the design points in the obtained Pareto fronts using the finite element method show the effectiveness of such approach. Moreover, it is shown that some interesting and important relationships as useful optimal design principles involved in the performance of the composite tubes can be discovered by the Pareto-based multi-objective optimization of the obtained polynomial meta-models.

Keywords-: *Composite tubes, Crashworthiness, GMDH, Multi-objective optimization, Genetic Algorithm, Pareto.*

I. INTRODUCTION

Development and analysis of energy-absorbing structures is one of the important issues raised in the mechanical shock and a common example discussed in this context, check the energy absorption due to quasi-static and dynamic load of an body picky. In analyzing the impact in energy absorber , the nature of this response should be investigated energy absorber. Application of this branch of engineering science at the various issues, including vehicle accidents, nuclear reactor safety, coastal structures, etc. is provided. It should be noted that the in the energy absorbed discussion, is a good absorber that can a larger proportion of the kinetic energy is converted to other energies.

Behavior of thin walled structures under impact load and as energy absorber has been studied for many years. Low weight and volume, the availability and cost effectiveness, advantages that have due to research and optimization these structures is still ongoing.

Mamalis and Jones [1] were investigated crushing of aluminum tubes and Frusta under static pressure in action research. They main purpose was to obtain detailed experimental study of failure modes. Mamalis presented a relative theoretical model for Predict the energy and the average load of plastic buckling in crushing of cylindrical thin wall and Frusta in axial symmetric deformation mode. The model by focusing on the plastic used in plastic pipe and amortized in length of material between them, without consideration of their distances. wierzbicki , Abramowicz.[3] their conflict of thin wall structures polygon related to surface components with plastic pipe fixed and narrow areas of tension and bending, analysis existing in structures and for one specific case, average crushing force (Favg) for square deformation calculated as follows:

$$F_{avg} = 9.5Y_t^{5/3}b^{1/3} \qquad (1)$$

Where b is width of square section.

Provide a mathematical relation that amount the energy absorbing by thin wall structures with geometric specific is presented is valuable. for provide this relation can used from other analytical and experimental results.

It is necessary to model a system to know mathematic relation between output-input data clearly [4]. Fuzzy reasoning, neural networks and genetic algorithms, ability to solve non-linear and complex systems and their control [5]. Many efforts has been made for applying the methods of Evolutionary [6]. GMDH (Group Modeling and Data Handling) method first time by Ivakhnenko [7] For modeling complex systems Including a series with several input and output data were used. In fact, main purpose of GMDH network, make function in the network basis on quadratic transfer function. On the recent attempts of the genetic algorithm used for finding the optimum connections for neural network GMDH [8].

In deal with engineering problems often encountered with some objective functions that must be optimum. In this type problem often improve one of objective function made be worst one or several objective functions. In the group of problems is multi-objective optimization problem. In the multi-objective optimization problem introduce groups of optimal design vector as replied of problem that called Pareto. [9] Designer considers with itself attention and degree of important, one of these vectors is chosen.

Genetic algorithms, including evolutionary algorithms that solve optimization problems have been used extensively. Also due to good performance in uncertainties space and direct use from amount of function**,** the growth in the solve of optimal problem.[10,11], multi-objective optimal algorithm basis on genetic algorithm(NSGAII) had been suggested for the solve multi-object optimization problem [11].Because there is problems in the variation of under programming. That algorithm is encountered in solving of problems with two more objective functions. For solve the problems, use from replaced under programs e-elimination. [12, 13]

In this paper, first based on information obtained from finite element modeling, a table of data is generated. Then using the neural networks of type GMDH , energy absorption and maximum force of crushing after crushing to present to polynomials mathematical form with 4variables design include some square section cells, some ply of CFRP, fiber angle of CFRP and width of square section. Number of finite elements model equal 33 that used results of 24models for educate of network and 9 model for analysis model, then use got polynomials for multi-objective optimization basis on Pareto points for finding component of optimal from amount decrease weight and maximum forced of crushing and increase of absorbed energy.

II. FINITE ELEMENT MODELLING OF COMPOSITE ENERGY ABSORPTION

Mamalis and Cooperates (2005) CFRP composite tube with square section with size 100×100 mm with filet 8mm with fiber angle equal to [±0] that shows in figure 1 under static and dynamic loads is experimented . They present the forms of different crushing mode. This experimental considered for quasi-static loads speed equal to 7mm/min and strain speed equal to 2.6×10^{-3} S^{-1} . The main base of our paper this work is considered. [14]

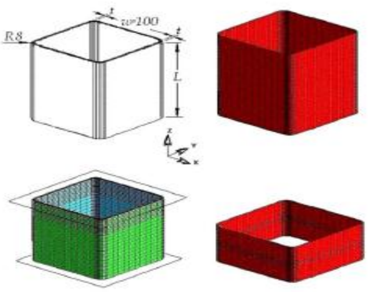

Fig1 - Finite Element of MAMALIS 2005

Non-linear finite element modeling of thin wall tubes and cans under quasi-static and dynamic axial load using commercial software such as ABAQUS, LS-Dyna, Dyna3D, Oasys ,has been studied. In this experiment Using ABAQUS, the piece with weight specified of the distance left to deal with a thin wall Structures. Numerical modeling of these structures, as is done dynamical , as shown in Figure 3 three objects is considered that Object with a certain weight, depending on load, with a certain speed meet with CFRP sample.

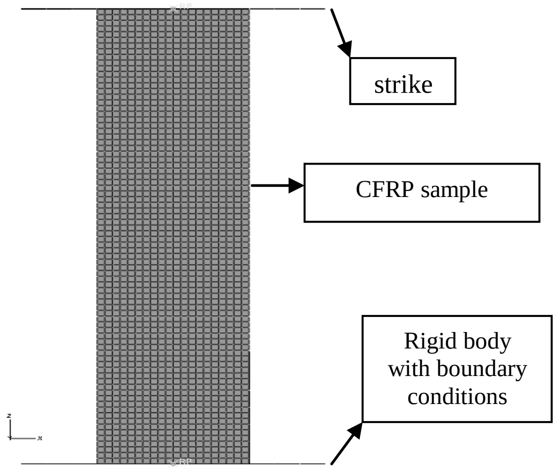

Fig 2 - Dynamic modeling of CFRP tube

The first parameter in the design of thin-walled cells is the number of square cells section. As shown in Figure 3, which is equivalent to:

N = 1 ⟶ 1-cell (Fig 3 - a)
N = 2 ⟶ 4-cells (Fig 3 - b)
N= 3 ⟶ 9-cells (Fig 3 - c)
N= 4 ⟶ 16-cells (Fig 3 - d)
N= 5 ⟶ 25-cells (Fig 3 - e)

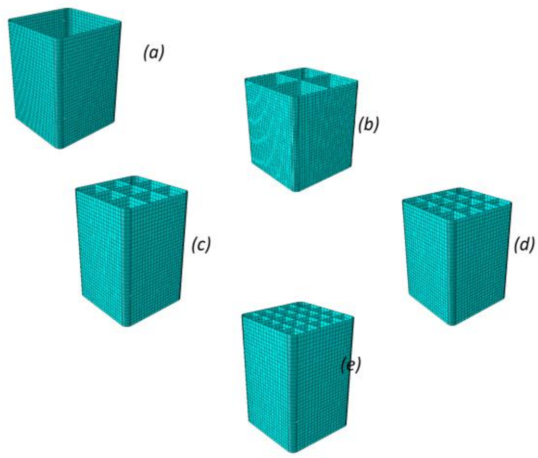

Fig 3 - Finite element modeling a)1-cell b) 4-cells c) 9-cells d) 16-cells e) 25-cells

The second and third parameters of designed are number of layers and angles fiber of sample CFRP that will be presented in modeling the behavior material part. The fourth parameter, c is the width of the thin wall section that its value $0 < c < 6$ (cm) , length of the thin walled equal to L = 15 cm with 8 mm radius filet and thickness of each layer equal to 0.9 mm .

III. MODELIN OF BEHAVIOR MATERIAL CFRP

CFRP composite include of very resistant in the polymer matrix. Poly in composite are a member of porter and resistant and have great rigidity in tension. Polymer matrix, keep poly in the place and optimal arrangement and acts as a load transfer between the fibers. Although they maintain from environmental damage caused by temperature or humidity.

Anisotropic damage model in the ABAQUS basis on Hashin and Rotem (1973) ، Hashin (1980) ، Camanho and Davila. Mechanical properties of materials used are given in Table 1:

Table 1 - Mechanical properties of CPRF

Property	Sign	Amount	Unit
Density	ρ	1549	Kg / m3
Elasticity modulus	E1	145	Gpa
	E2	8.9	Gpa
Poisson ratio	v12	0.33	---
Shear modulus	G12	5.6	Gpa
	G13	5.6	Gpa
	G23	4.48	Gpa

The our second design number of composite fiber that equal n and amount is equal $4 < n < 10$ and third parameter is the fiber alignment angles.

$$[\pm \theta]n \longrightarrow 0 < \theta < 90$$

For sample in model10 presentation that amount θ = 39 and n = 8 and arrangement of layers as follows:

[39˚, -39˚, 39˚, -39˚, 39˚, -39˚, 39˚, -39˚]

Dynamic modeling of composite structures in the ABAQUS/Explicit. In Step modulus is chosen the type of Dynamic Explicit analysis. For introduce the contact between tube and itself caused by crushing, the surfaces introduce that take out both of inter and outside of piece thin wall. Whereas during the crushing process maybe contact other member together. For that introduce self contact. For this contact Tangential behavior includes Penalty friction formulation and Coefficient of friction 0.1. For the disturbances in the head ¬ mainly composed of two rigid definition on one side of the tube is connected to the plates by the Tie and Equivalent mass 300kg with speed 10m/s for stimulating dynamic to rigid a reference point . Surface attached to the tube except for the line speed are bounded. Other Surface rigid in all directions is bound. That element is S4R. Finally with job introduction and that execution crushing force and The amount of absorbed energy are examined in different modes.

To evaluate the effect of design variables on energy absorption behavior of 33 different finite element models created by the software ABAQUS / Explicit have been analyzed. Different design variables for the 33 models in the table below.

Table 2 - Composite energy absorbing design dimension and some results of finite element

Model Num	*Input Data*				*Output Data*		
	N	*n*	*θ(deg)*	*c (cm)*	*E (j)*	*F max(N)*	*W(Kg)*
1	1	6	56	9	1089.46	285.91	4.34
2	1	8	26	8	1462.5	144.66	5.12
3	1	9	86	10	1176	107.80	7.27
....							
13	3	5	53	6	1233.54	323.45	4.87
14	3	6	33	12	4441.18	729.21	11.87
...							
31	5	7	60	11	6358.78	617.77	19.12
32	5	9	30	10	7374.46	917.08	22.32
33	5	9	50	7	6786	792.49	15.55

IV. FINITE ELEMENT SIMULATION RESULTS

The results of finite element models of 33 and 9 is shown below:

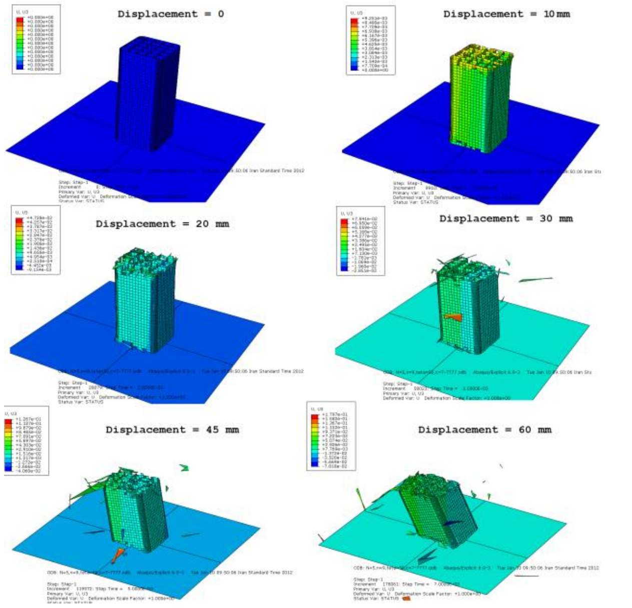

Fig 4 - Crushing model number 33 in different displacement

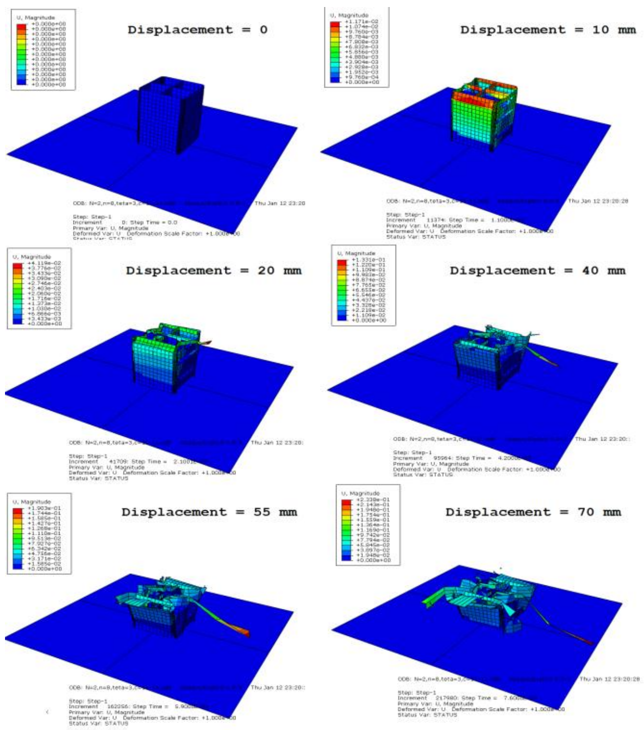

Fig 5 - Crushing model number 9 in different displacement

V. Modeling Using Neural Network Type

By means of GMDH algorithm a model can be represented as set of neurons in which different pairs of them in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function fˆ so that it can be approximately used instead of actual one, f , in order to predict output ˆy for a given input vector X = (x1, x2, x3, . . . , xn240) as close as possible to its actual output y. Therefore, given M observation of multi-input–single-output data pairs so that

yi = f (xi1, xi2, xi3, . . . , xin) (i = 1, 2, . . .,M), (2)

it is now possible to train a GMDH-type neural network to predict the output values ˆyi for any given input vector

X = (xi1, xi2, xi3, . . . , xin), that is,

i = fˆ(xi1, xi2, xi3, . . . , xin) (i = 1, 2, . . . , M). (3)

Now the problem is to determine a GMDH-type neural network so that the square of difference between the actual output and the predicted one is minimized, that is,

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}) - y_i]^2 \rightarrow \min . \quad (3)$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra functional series in the form of

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \cdots , \quad (4)$$

There are two main concepts involved within GMDH type neural networks design, namely the parametric and the structural identification problems. In this way, some works by Nariman-zadeh et al[17]. Present a hybrid GA and singular value decomposition (SVD) method to optimally design such polynomial neural networks. The methodology in these references has been successfully used in this paper to obtain the polynomial model of the thin-walled structures box beam crash behavior with minimum training errors. The obtained GMDH-type polynomial models have shown very good prediction ability of the unforeseen data pairs during the training process.

Parameters which effect on amount of energy absorbing of the some input and only one output are: number of cell section, number of composite layer, and angle of CFRP fiber and width of square section test with four input parameters have done. Energy absorption and maximum crushing load considered as output and measured for all tests. SVD and direct method were used for find coefficients of polynomial and finally me found SVD method was better than others.

Result for initial number 30, summation possibility equal to 0.7, rising possibility of 0.07 and with 200 repeats were taken.

For evaluating power of neural network experimental data divided to two parts which are training and testing set. 24 from 33 experimental data considered as training and 9 else as testing sets.

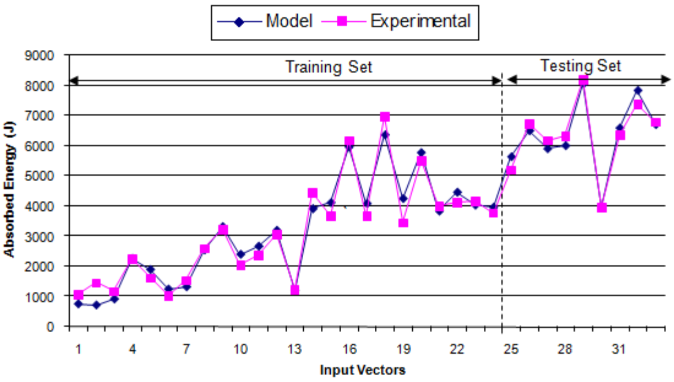

Fig 6 - Comparison between finite element and GMDH model for amount energy absorption

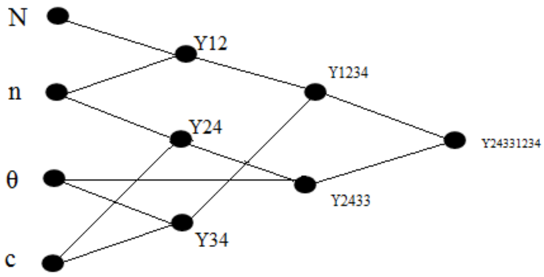

Fig 7 - Neural network structure for modeling the energy absorption

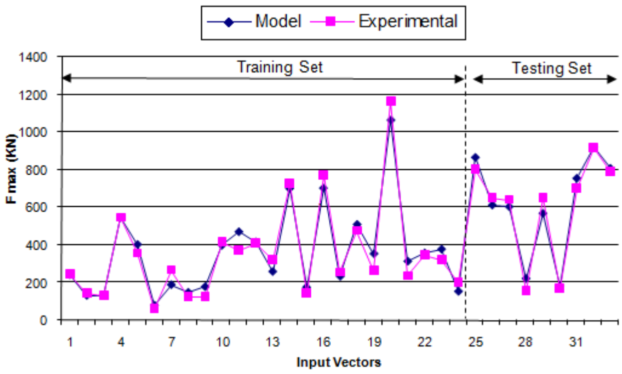

Fig8 - Comparison between finite element and GMDH model for amount maximum crushing force

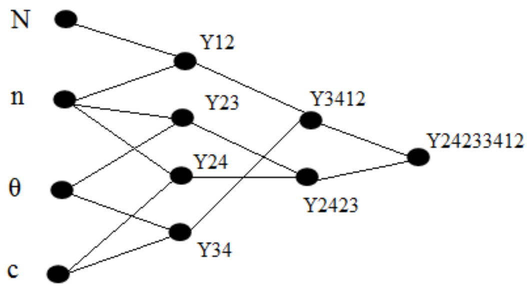

Fig 9 - Neural network structure for modeling the maximum crushing force

VI . MULTI-OBJECTIVE OPTIMIZATION OF ENERGY ABSORBING

In this multi-objective optimization problem, increase the energy absorption, reducing the maximum force and weight are optimized at one time. This means that the energy absorbing composite having less weight and maximum crushing force, able to maximize the energy absorbed.

Maximize $E = f1 (N , n , \theta , c)$
Minimize $Fmax = f2 (N , n ,\theta , c)$
Minimize $W = f3 (N ,n ,\theta , c)$

$1 < N < 5$
$4 < n < 10$
$0 < \theta < 90$
$6 < c < 12$

To solve the optimization problem, uses from modified algorithm NSGAII [16]. Initial number 30, summation possibility of 0.7, rising possibility of 0.07 and with 200 reports were taken. For to calculate amount of energy absorption and maximum crushing force uses of polynomial model from GMDH.

Improved Pareto curve for the three objective function in Fig 10 - 11 - 12 has been shown, The Figure is determined that variables designed to improve the selection of a certain amount of objective functions, can undermine the other objective function. In the case, none of Pareto points does not upset the superiority and if you select any of these points have been used in optimal conditions.

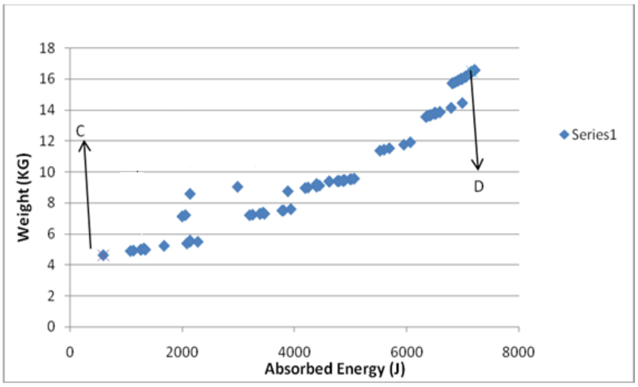

Fig 10 - Graph Pareto Tuesday purpose: energy absorbed to the weight of structure

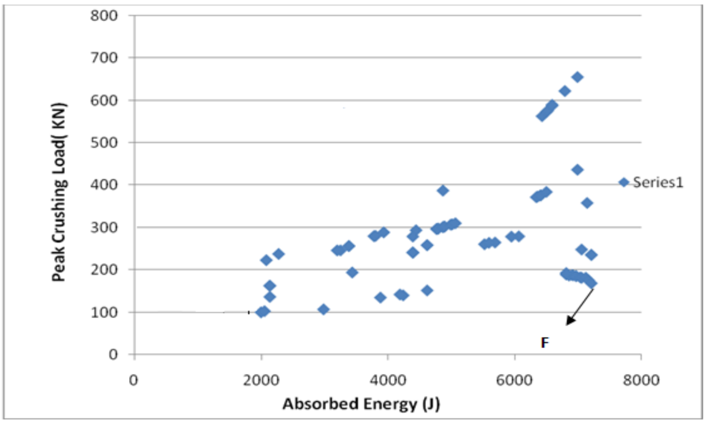

Fig 12 - Graph Pareto Tuesday purpose: energy absorbed to the peak crushing load

Choice point D, the resulting single-objective optimization of energy absorption and also the C point, the result of single-optimization goal is Weight. Points profile is presented in Table 3.

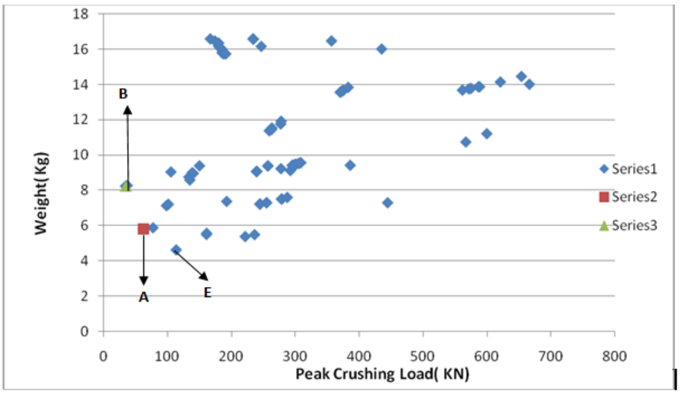

Fig 11 - Graph Pareto Tuesday purpose: peak crushing force to the weight of structure

Point A is optimal point of the Mapping Method and Point B is optimal point of the Near to Ideal Point Method. According to Figure 11 points, these points are favorable point In terms of weight and peak crushing load, because, relative to other points have less weight and peak crushing load. E point most favorable point of In terms of weight and is ideal in terms of maximum force. Point E is same point C in Figure 10.

In Figure 12, point E is breaking point of Curved two-Objective Pareto, energy absorption to peak crushing load. This point has High energy absorption than other points with less maximum forced.

Table 3 - Design parameters and results related to the points discussed

	N	n	θ	c	E(j)	Fmax(N)	W(kg)
A	2	8	32.9	6	1576.26	62.94	5.79
B	2	10	10.1	6.79	1802.34	35.6	8.23
C , E	1	5	1.99	11.39	594	114.63	4.62
D	4	7	1.99	11.38	7159.065	175.25	16.45
F	4	7	1.99	11.46	7202.385	167.96	16.57

VII. Conclusion

In this paper, was presented the relationship between design variables and the energy absorption and peak crushing load as a mathematical mode. For this work, GMDH neural network optimized with genetic algorithm was used that results showed high accuracy in modeling. This mathematical relations are used for multi-Objective optimization algorithm is modified by NSGAII. So Pareto optimal points respective for above objective functions. By using this point, there are the possibility of compromise on the opposite objective functions, the selection of point with designer, which just is possible by using of multi- objective optimization.

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