Crushing analysis of energy absorbing materials using artificial neural networks

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Abstract. This article presents the use of artificial neural networks in data analysis. The subject of the research were energy-absorbing materials under oblique loading. The forces obtained during the analysis were used to determine the crushing indicators. The numerical analysis was performed using the FEM Abaqus software. The specimens were loaded with the same force at different angles, i.e. 15, 30, 45, 60 degrees. During the numerical analyses, the normal and shear forces were measured. The tests were carried out under both static and dynamic load. On the basis of the MLP and RBF networks, analyses were carried out to study the relationship between the foam properties and the crushing efficiency indicators.

1. Introduction
The phenomenon of energy absorption, as well as passive safety has been explored since the mid-20th century. The first structural elements in the form of a flat steel bar attached to the longitudinal bars were proposed in Cadillac vehicles. Subsequently, with the development of motor vehicles and the speeds achieved by them, passive safety played a major role [1]. In addition, with the increasing restrictions in the European Union, the manufacturers supplying vehicles to this area were obliged to improve the structural elements of the vehicle responsible for energy dissipation [2, 3]. The energy-absorbing structure in a frontal impact is a crash-box. It is made up of thin-walled elements of a certain stiffness attached to the front beam and stringers. It provides a completely safe crushing to a speed of about 15 km/h. The energy-absorbent profiles in cars most often assume a rectangular cross-section; however, round, omega and hexagonal cross-sections are also well described in the literature and are used in various types of constructions [4, 5]. During crushing, two types of local and global buckling can be distinguished [6, 7]. Depending on the width/diameter, wall thickness and profile height, crushing can be done differently. Most often these are local buckling along the entire length of the profile. In this way, a thin-walled profile is able to absorb the most energy [8, 9]. With the development of technology, the demands placed on motor vehicles have been increasing. Therefore, the ways to improve the energy efficiency of the absorbers were invented. The basic way to control the crushing process is to use a trigger that initiates the crush in the right place. The initiator can take various forms, such as notches or dents on walls or edges [2, 10, 11]. The first type of reinforcement used in columns are the honeycomb structures. The hexagonal shape increases the...
stiffness in the direction of impact and resists the collapse of the walls into the profile, thus absorbing an additional portion of energy [12, 13]. Another way to increase the energy efficiency of the absorber is to use a filling with a porous structure. Thorough research on foamed materials and the characteristics of their destruction began at the turn of the 20th and 21st centuries [14]. With the development of technology, in addition to the use of conventional materials for steel and aluminum profiles, both GFRP and CFRP composite materials have become increasingly popular. There are many publications in the literature describing limit states and propagation of destruction of the columns made of composite materials [15–17]. Nowadays, when analyzing data, a common solution is to use artificial neural networks [18–20]. A statistical method called regression is used in the study of the relationships between the variables. With the use of a function it allows determining the interdependence of data. In the data analysis, two types of networks are used, namely multi-layer perceptron (MLP) and radial base function (RBF). Moreover, the CAD software used in the analysis presented in this article is used to model various types of issues [21–23]. Stress distribution testing is used not only in mechanical engineering applications but also in biomedical engineering [24, 25].

2. Numerical analysis

2.1 Subject of the research
In this article, a 20x20x40 mm foam element was numerically tested. The foam model was loaded in a static and dynamic way. The boundary conditions for restraint were the same for both analyses (Figure 1). The base had all translation degrees blocked and the foam material had frictional contact. The tup had the translation degrees locked in the X and Z direction so that it could only move vertically. The coefficient of friction was specified as 0.3.

![Figure 1](image1.png)

**Figure 1.** a) Boundary conditions of dynamic analysis b) discretized finite element.

The energy during dynamic load was assigned by mass m=50 kg and initial speed V=1.5 m/s. In the static analysis, the load was applied by displacement of the tup insert on the Z direction.

2.2 Research methodology
The tests were carried out for different inclination of the base from 15-60 degrees. The element used as a base and the tup insert were modeled as a discrete rigid i.e. R3D4. Owing to this type of model, the elements are not deformed; however, during dynamic analysis, it is possible to detect the
displacement values and force reactions. In the case of porous material, the type of element used is C3D8R, i.e. a fully deformable element. The output value for neural networks presented in Table 2 was the CLE indicator.

**Table 1.** Material properties of the porous elements [26, 27].

| PET/W AC 135 | “Alporas” Aluminum Foam |
|--------------|-------------------------|
| Density [kg/m³] | 135 | Density [kg/m³] | 270 |
| Young’s Modulus [MPa] | 24.10 | Young’s Modulus [MPa] | 60 |
| Poisson’s ratio v [-] | 0.1 | Poisson’s Ratio [-] | 0.33 |
| Yield strength (compression) [MPa] | 0.77 | Yield strength (compression) [MPa] | 1.702 |
| Poisson's Plastic Ratio [-] | 0.09 | Poisson's Plastic Ratio [-] | 0.015 |

The data presented above were used to model the foam material issue. The analysis was carried out using the Abaqus software. In the field of plasticity, the Crushable Foam option was used. It allows giving the element properties of porous materials. Moreover, quantities such as Young’s module and Poisson’s coefficient were used to model the flexible range.

**Figure 2.** Foam material crushing process for model AL-15.
The graphic above shows an example of a Force-Shortening characteristic. The graph was obtained during dynamic crushing and the foam was on a base inclined at 15 degrees. The five figures correspond to the points marked on the diagram, providing a comprehensive view of the dynamic crushing of the aluminum foam.

3. Results of FEM
This chapter presents the results obtained during two types of analysis. The static and dynamic compression of foamed materials was described in Table 1. For both analyses, the samples were placed on a base inclined at an angle of 15-60 degrees, every 15 degrees so that the distribution of forces over normal and tangential could be measured. Then, on the basis of the quantities measured during numerical analyses, the crushing efficiency coefficients i.e. EA (energy absorbed), CLE (crush load efficiency) were determined and characteristic forces such as PCF (peak crushing force) and MCF (mean crushing force) were determined. The input data was the type of foam and the angle of base inclination, and the output was EA or CLE indicator.

![Figure 3. Results of numerical analysis showing the amount of energy absorbed for static and dynamic test.](image3)

![Figure 4. Numerical analysis results showing the CLE for static and dynamic test.](image4)
The quantities obtained using the finite element method shown in Figures 3 and 4 show the effect of the base angle inclination on the absorbed energy and the crushing performance determined by the CLE indicator, respectively. The crush load efficiency shows a significantly higher performance under static load. This is due to the lack of initial impact, which can occur in case of kinetic energy assignment.

4. Neural networks
Numerically acquired quantities were used to create the neural networks and perform the regression analyses. The neural networks were created on the basis of the PET foam data, which is characterized by better energy absorption capacity. The MLP type networks were used to study the dependencies and their description is presented in the table 2. The networks have achieved a high quality of learning as well as testing and validation and low error rate, which makes the results obtained from these networks highly probable.

The table below shows the parameters of neural networks used to analyze the data obtained during a static load test. The presented data show the high quality of the neural network, which allows confirming that the relationships determined by it are correct. Due to the divergent nature of the static and dynamic analyses, the analysis of the data from both tests was performed using separate neural networks.

| Network | Static | Dynamic |
|---------|--------|---------|
|         | MLP 2-6-1 | MLP 2-4-1 | MLP 2-7-1 | MLP 2-4-1 | MLP 2-4-1 |
| Quality (Training) | 0.99504 | 0.99577 | 0.99392 | 0.922736 | 0.955467 |
| Quality (Testing)  | 0.892413 | 0.924975 | 0.874137 | 0.85366 | 0.86344 |
| Quality (Validation)| 0.934591 | 0.917324 | 0.892496 | 0.99751 | 0.99751 |
| Error (Training)    | 0.00104 | 0.00010 | 0.00064 | 0.000284 | 0.000475 |
| Error (Testing)     | 0.000137 | 0.000193 | 0.000054 | 0.000042 | 0.000046 |
| Error (Validation)  | 0.002087 | 0.000290 | 0.001328 | 0.001842 | 0.002451 |
| Learning algorithm  | BFGS 4 | BFGS 38 | BFGS 6 | BFGS 6 | BFGS 17 |
| Error              | SOS | SOS | SOS | SOS | SOS |
| Activation (hidden) | Exponential | Exponential | Gauss | Exponential | Exponential |
| Activation (Output) | Tanh | Logistic | Exponential | Logistic | Logistic |
Figure 5. Predicted CLE values for the static analysis, linearly approximated.

Observing the predicted values in Figure 5 show a value match. For the CLE values, the accuracy is very high and almost perfectly matches the linear approximation shown in Figure 6. Table 2 shows a description of the neural networks used for data analysis. Out of a hundred, five were selected for the best quality of training, testing, validation and error, which ensures the best results. The neural networks achieved a quality of learning, testing and validation higher than 85%. The lower value of test quality is due to the small number of samples; however, observing all the parameters of the neural network, the appropriate quality is found for further analysis. The learning error in both cases was very low and did not exceed 1%. The table 2 also shows the functions that use the neural networks.

Figure 6. Predicted CLE values for the dynamic analysis, linearly approximated.
Figure 6 show the prediction of artificial neural networks for data obtained during dynamic analysis. In the case of prediction of the CLE (Crush Load Efficiency) values two, main data clusters can be seen, but both of them are very accurate in their approximate linear function. In addition, global sensitivity analyses was performed for the neural networks, which show that the type of porous material filling used has the greatest influence on CLE. The inclination of the base also has lesser influence on stress distribution.

5. Conclusions
In the presented studies, the subject matter was compressed foams. The foam elements were modeled as Crushable Foam in order to test their energy-absorbing properties in the elastic-plastic range. Two types of foams were numerically analyzed: metal (aluminum ALPORAS) and polymer (PET). Observing the behavior of the foams, one can see that the energy absorbed by the PET foam increases significantly, i.e. up to 50%, along with the angle of inclination. In the case of the AL foam, the increase of absorbed energy is max. 15%. This indicates very good energy-absorbing properties of the PET foam in the tangential direction. During shearing, the foam shows good properties which increase its efficiency. The quality of neural networks is very high, the learning error reached a low value. The value adjustment for CLE reaches high accuracy and oscillates around the approximate function indicated in the graph. The approximation of the linear function is good due to the exact distribution of values around. There is a much higher CLE in the static analysis, due to the absence of impact during the first crushing stage. It can be clearly stated that both foams have good energy-absorbing properties, and the use of neural networks is a very good tool to analyze its behavior.

References
[1] Macaulay M 1987 Introduction to Impact Engineering vol 9 (Dordrecht: Springer Netherlands)
[2] Ferdynus M, Kotelko M and Urbaniak M 2019 Crashworthiness performance of thin-walled prismatic tubes with corner dents under axial impact - Numerical and experimental study Thin-Walled Struct. 144
[3] Rogala M 2020 Neural networks in crashworthiness analysis of thin- walled profile with foam filling . Adv. Sci. Technol. Res. J.14
[4] Zhang Y, He N, Song X, Chen T and Chen H 2020 On impacting mechanical behaviors of side fractal structures Thin-Walled Struct.
[5] Kopczyński A and Rusiński E 2010 Passive safety. Energy absorption by thin-walled profiles (Wroclaw: Publishing House of the Wroclaw University of Technology)
[6] Kubiak T 2013 Static and dynamic buckling of thin-walled plate structures vol 9783319006
[7] Falkowicz K and Debski H 2020 The post-critical behaviour of compressed plate with non-standard play orientation Compos. Struct.252, https://doi.org/10.1016/j.compstruct.2020.112701
[8] Rogala M, Gajewski J and Ferdynus M 2019 Numerical analysis of the thin-walled structure with different trigger locations under axial load IOP Conf. Ser. Mater. Sci. Eng.710 012028
[9] Ferdynus M and Rogala M 2019 Numerical Crush Analysis of Thin-Walled Aluminium Columns with Square Cross-Section and a Partial Foam Filling Adv. Sci. Technol. Res. J.13 144–51
[10] Alavi Nia A, Fallah Nejad K, Badnava H and Farhoudi H R 2012 Effects of buckling initiators on mechanical behavior of thin-walled square tubes subjected to oblique loading Thin-WalledStruct. 5987–96
[11] Kotelko M, Ferdynus M and Jankowski J 2018 Energy absorbing effectiveness - Different approaches Acta Mech. Autom.12 54–9
[12] Ha N S and Lu G 2020 A review of recent research on bio-inspired structures and materials for energy absorption applications Compos. Part B Eng.181
[13] Wei L, Zhao X, Yu Q and Zhu G 2020 A novel star auxetic honeycomb with enhanced in-plane crushing strength Thin-Walled Struct.
[14] Hanssen A G, Langseth M and Hopperstad O S 1999 Static crushing of square aluminium extrusions with aluminium foam filler Int. J. Mech. Sci.41 967–93
[15] Debski H, Rozylo P and Teter A 2020 Buckling and limit states of thin-walled composite columns under eccentric load Thin-Walled Struct.\textbf{149} 106627
[16] Wysmulska P, Debski H and Falkowicz K 2020 Stability analysis of laminate profiles under eccentric load Compos. Struct.\textbf{238} 111944
[17] Rozylo P and Debski H 2020 Effect of eccentric loading on the stability and load-carrying capacity of thin-walled composite profiles with top-hat section Compos. Struct.\textbf{245} 112388
[18] Vališ D, Gajewski J and Žák L 2019 Potential for using the ANN-FIS meta-model approach to assess levels of particulate contamination in oil used in mechanical systems Tribol. Int.\textbf{135} 324–34
[19] Gajewski J and Vališ D 2017 The determination of combustion engine condition and reliability using oil analysis by MLP and RBF neural networks Tribol. Int.\textbf{115} 557–72
[20] Hasilová K and Gajewski J 2019 The use of kernel density estimates for classification of ripping tool wear Tunn. Undergr. Sp. Technol.\textbf{88} 29–34
[21] Karpiński R, Jaworski Ł, Szala M and Maňko M 2017 Influence of patient position and implant material on the stress distribution in an artificial intervertebral disc of the lumbar vertebrae ITM Web Conf.\textbf{15} 07006
[22] Falkowicz K and Dębski H 2017 Postbuckling Behaviour of Laminated Plates oith a Cut-Out Adv. Sci. Technol. Res. J.\textbf{11} 186–93, DOI: 10.12913/22998624/68283
[23] Falkowicz K 2017 Stability of rectangular plates with notch using FEM ITM Web Conf.\textbf{15} 07013, https://doi.org/10.1051/itmconf/20171507013
[24] Karpiński R, Jaworski, Łukasz, Jonak J and Krakowski P 2019 Stress distribution in the knee joint in relation to tibiofemoral angle using the finite element method MATEC Web Conf.\textbf{252} 07007
[25] Karpiński R, Jaworski L, Jonak J and Krakowski P 2019 The influence of the nucleus pulposus on the stress distribution in the natural and prosthetic intervertebral disc MATEC Web Conf.\textbf{252}07006
[26] Xu A, Vodenitcharova T, Kabir K, Flores-Johnson E A and Hoffman M 2014 Finite element analysis of indentation of aluminium foam and sandwich panels with aluminium foam core Mater. Sci. Eng. A \textbf{599} 125–33
[27] Costas M, Diaz J, Romera L E, Hernández S and Tielas A 2013 Static and dynamic axial crushing analysis of car frontal impact hybrid absorbers Int. J. Impact Eng.\textbf{62} 166–81