Pressure stress modeling on expanded polystyrene materials using genetic programming

Ermin Bajramović, Bahrudin Hrnjica, Redžo Hasanagić and Emir Bajramović
University of Bihac, Faculty of Technical Engineering, Bosnia and Herzegovina

E-mail: ermin.bajramovic@unbi.ba

Abstract. In the production of expanded polystyrene, the standards are very high in terms of thermal, fire, dimensional, and mechanical characteristics, because each of the characteristics is a condition for achieving quality that allows competitiveness in the market. To ensure high-quality products, it is necessary to achieve optimal performance and product quality through carefully adjusted input parameters of production. Since the production of expanded polystyrene is specific in several ways, an experimental study was conducted in which the basic parameters affecting product quality were detected and through which a series of experiments were performed to prove product quality. Experimental research for this work was conducted on three types of expanded polystyrene samples whose purpose is to insulate floors exposed to pressure. The samples were made of the same material of different densities and aging times for which the pressure stress at a deformation of 10% was tested. After the experimental phase, the modeling of the output parameters was performed. Modeling involved the development of a model that describes a given problem and the obtained modeled values were analyzed and compared with the experimental one. The modeling method used genetic programming using the GPdotNET software package. The goal of modeling with the GpdotNET tool is to obtain a realistic model that would give the value of the compression stress at a deformation of 10% as an output variable in materials made of expanded polystyrene.

1. Introduction

Depending on the purpose, products made of expanded polystyrene (EPS) need to be subjected to various tests in order to prove their quality. The most common tests being performed are those on thermal, fire, dimensional and mechanical characteristics such as compression strength, bending, tensile and shear strength. These tests are usually being performed and controlled by experimental methods directly in laboratories using specialised equipment with appropriate software.

As experimental methods require high costs there is a need to determine the properties and indirect methods. Thus, the standard EN 13163 specifies indirect methods of mathematical calculation through input parameters as well as other forms of mathematical proofs.

Mathematical modeling is not excluded as one of the methods also if the obtained model gives a high degree of reliability for the problem under research.

With the development of computer science artificial intelligence also developed, which found its application in solving engineering problems. Artificial intelligence is a broad field in which methods based on biological evolution have their place. All methods based on the biological principle of survival and reproduction are called evolutionary algorithms (EA). By using them in different areas of research they have evolved into special methods for solving engineering problems, so they are also called...
evolutionary methods. One of the evolutionary methods is a genetic programming, which will be used in this paper.

Automatic problem solving with the help of computers is a central part of artificial intelligence; machine learning is wide area covered machine intelligence, as Turing called it (Turing 1950). Genetic programming and evolutionary programs were mentioned at the later stage. In the book Genetic Programming - On the Programming of Computers by Means of Natural Selection, 1992 John R. Koza talks about computer-aided programming through natural selection.[1]

The development of new methods was accompanied by the development of tools for modeling engineering problems, so the authors M. Jurković and B. Hrnjica wrote about modeling and optimisation of tool stresses in the drilling process using evolutionary algorithms [2]. B. Hrnjica talks in his paper about mathematical modeling of engineering problems using the method of genetic programming with GPdotNET tools. In his doctoral dissertation he used a numerical-evolutionary approach to determining the parameters of vessels' fracture mechanics under pressure [3, 4].

Moreover the authors E. Nezirević et al. in their paper Modeling of Pressing Forces using Genetic Programming demonstrated the application of genetic programming using the GPdotNET tool [5]. Authors B. Hrnjica and A. Danandeh Mehr explored new possibilities of application of optimised application for genetic programming [6]. R.Hasanagić presented modeling of fracture force on tensile strength of solid wood elements by genetic programming [7].

M. Kovacic and U. Župerl talked about the application of genetic programming in the steel industry to predict the diversity of serial processes and equipment that affected the properties, quality and final price of the product [8]. M. Semenkina et al. in their paper they wrote about the evolution of a model based on genetic programming [9]. All these papers indicate that genetic programming is being increasingly used in all areas of engineering and respective problems.

Many authors have used various methods in their research to analyse, model and simulate the mechanical properties of expanded polystyrene. Authors N. Tang et al. in Mechanical performance of polystyrene foam (EPS): Experimental and numerical analysis performed a series of tests to characterise the mechanical properties of polystyrene foam (EPS), including uniaxial compression tests, uniaxial stress tests and three-point bending tests [10].

L.G. Sun et al. In the paper Mechanical analysis and numerical simulation of EPS exterior decorative element, did perimental studies covering tensile, compression and bending tests of expanded polystyrene foam material used as a component of EPS decorative line thus obtaining the basic parameters of mechanics [11].

A. Krundaeva et al. in the paper Dynamic compressive strength and crushing properties of expanded polystyrene foam for different strain rates and different temperatures, performed static and dynamic tests of compression and crushing on expanded polystyrene foam to characterise the material at high stress rates in order to obtain a stress-strain curve for different temperatures and densities. They presented a methodology for processing experimental data for use in finite elements' modeling (FE).[12]

This paper aims to present the possibility of application and reliability of the genetic programming method using GPdotNET tools for creating GP models based on the obtained experimental values.

2. Materials and methods

2.1. Materials and equipment

The experimental research was carried out on three types of products made of expanded polystyrene marked EPS 100, EPS 150, and EPS 200 of different densities. The aim of the test was to check the pressure stress $S$ (kPa) at a deformation of 10% as a function of input parameters. Density $\rho$ (kg/m$^3$), aging time $\omega$ (d), relative humidity $\phi$ (%) and temperature $T$ (°C) were taken as input parameters.

EPS 100, EPS 150 and EPS 200 of different densities were depending on their purpose. The aim of the research was to test the pressure stress $S$ (kPa) at a deformation of 10% as a function of input parameters. The density $\rho$ (kg/m$^3$), aging time $\omega$ (d), relative humidity $\phi$ (%) and temperature $T$ (°C) were taken as input parameters.
The test was performed in laboratory controlled conditions on highly sophisticated equipment, electromechanical press labelled ES10 connected to the monitoring program, digital scale, thermometer labelled PCE-T311 with probe for measuring temperature in the product and hygrometer labelled FMC with probe for measuring humidity in the product. The following methods were used in the preparation and performance of the experiment: normative, empirical, measurement method and experimental method. The test was performed on 35 samples of different densities within 15 days.

2.2. Genetic programming method

Genetic programming (GP) is a method based on artificial intelligence with the ability to solve complex engineering problems generally. The real goal of genetic programming is to create computer programs that solve given problems.

The genetic algorithm creates a population of computer programs and through a number of generations improves individuals of the population using conventional genetic operators. The quality of an individual program is reflected in the efficiency in performing the desired task and the best rated program is presented as a result. The quality of the obtained solution is expressed by a predefined fitness function. Based on various parameters it determines the fitness of an individual on which the efficiency of the individual later depends. In evolutionary algorithms and thus genetic programming the most commonly used genetic operators are: reproductions, selections, crossovers and mutations.

In some cases, operators of permutation, swap, inversion, etc. also appear.

The GP algorithm can be controlled by nineteen parameters, as follows:

- two basic parameters that make up the population size and the maximum number of the algorithm generations performance,
- eleven auxiliary parameters that control the performance of the GP,
- six qualitative variables are selected differently from the performance of the genetic programming algorithm.

The optimal selection of GP control parameters is reflected both in the quality of the obtained results and in the performance of the algorithm. Quality results will not always be obtained if all parameters were included in the algorithm. Moreover, a fast and quality result will not be obtained if the number of individuals in the population was set large while solving a simple problem.

Optimal use of GP control parameters is a complex task depending primarily on the experience of the researcher.

3. Experimental research

Measurement and testing of expanded polystyrene products marked EPS 100, EPS 150, and EPS 200 yielded the results used as a substrate in this study, shown in table 1.

| No of exp. | Type   | Density (kg/m³) | Aging time (d) | Humidity (%) | Temperature (°C) | Pressure stress (k Pa) |
|-----------|--------|-----------------|----------------|--------------|------------------|-----------------------|
| 1         | EPS 100| 20              | 5              | 10.5         | 24.1             | 134.03                |
| 2         |        | 20              | 6              | 10.5         | 24.5             | 138.44                |
| 3         |        | 20              | 7              | 10.4         | 24.8             | 138.69                |
| 4         |        | 20              | 8              | 10.4         | 24.8             | 143.09                |
| 5         |        | 20              | 9              | 10.4         | 25.4             | 144.70                |
| 6         |        | 20              | 10             | 10.4         | 25.5             | 146.83                |
| 7         |        | 20              | 11             | 10.3         | 26.8             | 147.21                |
| 8         |        | 20              | 12             | 10.3         | 27.3             | 149.48                |
| 9         |        | 20              | 13             | 10.3         | 27.6             | 149.59                |
| 10        |        | 20              | 14             | 10.3         | 27.8             | 149.02                |
| 11        |        | 20              | 15             | 10.3         | 28.0             | 152.02                |
The table shows the values of input parameters, sample density (kg/m$^3$), sample aging time (d), humidity in the sample before the test (%), sample temperature before the test (°C) as well as output pressure stress values (kPa) for all 35 examined samples over a period of 15 days.

The values of input and output parameters varied in the following intervals:

- density $\rho$, in the interval from 20 ÷ 30 (kg/m$^3$)
- aging time $\omega$, in the interval from 5 ÷ 19 (d),
- relative humidity $\varphi$, in the interval from 10.3 ÷ 10.6 (%),
- temperature $T$, in the interval from 23.8 ÷ 28.0 (°C),
- pressure stress $S$, in the interval from 134.03 ÷ 223.51 (kPa).

The organisation of the data was shown by scatter diagrams that showed the relation between the input and output parameters as well as the input parameters with each other.

![Figure 1](image-url)

**Figure 1.** Scatter diagram EPS 100: (a) pressure stress-aging time; (b) pressure stress-humidity; (c) pressure stress-temperature.
Figure 2. Scatter diagram EPS 150: (a) pressure stress-aging time; (b) pressure stress-humidity; (c) pressure stress-temperature.

Figure 3. Scatter diagram EPS 200: (a) pressure stress-aging time; (b) pressure stress-humidity; (c) pressure stress-temperature.

The diagrams shown in figures 1, 2 and 3 showed the pressure stress as a function of aging time, relative humidity and temperature from which it can be seen that there was an interdependence.

The diagram in figure 4 showed the interdependence of the input parameters temperature as a function of aging time, temperature as a function of relative humidity and relative humidity as a function of aging time for all tested samples.
For a complete picture of the interdependence, a correlation analysis was performed for all input parameters with output parameters as well as input parameters with each other. Correlation analysis for all examined types of EPS showed that the input parameters were in a very significant correlation with each other as well as with the output parameters.

Thus, the regression coefficient was for EPS 100 r above 0.90563, for EPS 150 r in the range from 0.78340 to 0.97080 while for EPS 200 r it was above 0.90942, which showed that over 90% of the variability was achieved by influence and by the action of input parameters (variables).

4. Modeling by GPdotNET tool
In GPdotNET-V5 is a modeling tool currently in the fifth version indicating that it is constantly being improved to make it as easy as possible for use. It contains a set of very complex algorithms for normalising input parameters, algorithms for manipulating binary and multiclass types of input parameters and algorithms to manage missing data.

The data management module is one of the most important modules in GPdotNET. The quality of the obtained solution will depend on which parameters and from which set of functions the genetic programming algorithm will look for solutions. The obtained solution represents a mathematical model that is usually nonlinear.

GPdotNET consists of several user interfaces into which modeling data is to be entered. For GP modeling it is necessary to perform data selection and randomly select data for model training and model testing. The first step is to load test and training data followed by determining the mathematical operations with which the program will work. The most important thing is to set up a data management module in which the parameters of genetic programming are entered based on which the program will offer the best solution, shown in figure 5.
After selecting the functions, entering the input parameters and defining the variable to be modeled, the algorithmic programming program is to be started following the process of obtaining the optimal model that will describe the given problem best, figure 6.

A change in fitness function and prediction as well as a change in the correlation coefficient gives a picture when the model is good. Sometimes it takes more time and attempts with different functions and parameters to get the appropriate model for a given problem.

Figure 5. GPdotNET interface (input of parameters).

Figure 6. Interface display of the best model solution in GPdotNET.
The resulting GP model shown as an expression tree looks as follows:

Figure 7. GP model shown as expression tree.

Taking into account that the constants were \( r_1 = 0.33255 \) and \( r_2 = 0.91284 \), the GP model in figure 7 after the transformations of the initial expression was reduced to the form:

\[
S(\rho, \omega, \phi, T) = 138.44 + 28.29 \left[ \rho + \frac{1}{13}(-6 + \omega) - 0.08 \left( \frac{3.33(-10.3 + \phi) + 0.004}{(-6 + \omega)(-23.8 + T)} \right) \right] \tag{1}
\]

The GP pressure stress model obtained for a particular GP configuration depends on the input parameters, the set of functions and the parameters under which the algorithm would be processed. For the above GP model, the addition, subtraction, multiplication and division functions were used.

The default parameters for which the program found the best solution were: population size 1000, mutation probabilities 0.05, initial level of tree structure 5 and working level 6, and number of generations 100. Change of fitness function showed that 54 iterations were needed and last change on fitness function occurred in the 48th iteration with a stated value of 969.95 out of a maximum of 1000. It also showed in which iteration the GP model that best describes the given problem was obtained.

The parameters can have a wide range of values, which can significantly affect the operation and quality of the solution. On the other hand, if the selection pressure is too low, time is spent on useless iterations because the convergence is too slow in that case. The probability of mutation is a key parameter allowing GP new genetic material to be introduced into the population, and thus the possibility of obtaining better solutions. Therefore, the number of generations should be positively correlated with the quality of the solution and negatively with the speed of the program performance.

5. Results analysis and discussion

Based on the obtained mathematical model, the pressure stress \( S_{GP} \) was calculated for all input parameters in tables 2 and 3.
Table 2. Experimental and GP modeling results for Training data.

| No | $Y_E$ (SE) | $Y_{GP}$ (SGP) | $Y_E - Y_{GP}$ (SE - SGP) |
|----|------------|----------------|--------------------------|
| 1  | 149.02     | 150.85         | -1.83                    |
| 2  | 218.08     | 219.30         | -1.22                    |
| 3  | 169.92     | 174.38         | -4.46                    |
| ...| ...        | ...            | ...                      |
| 25 | 147.21     | 148.00         | -0.79                    |
| 26 | 200.17     | 198.70         | 1.47                     |
| 27 | 149.48     | 148.98         | 0.50                     |

Table 3. Experimental and GP modeling results for Testing data.

| No | $Y_E$ (SE) | $Y_{GP}$ (SGP) | $Y_E - Y_{GP}$ (SE - SGP) |
|----|------------|----------------|--------------------------|
| 1  | 211.49     | 213.79         | -2.30                    |
| 2  | 143.09     | 142.03         | 1.06                     |
| 3  | 166.07     | 167.33         | -1.26                    |
| 4  | 202.98     | 203.05         | -0.07                    |
| 5  | 134.03     | 135.82         | -1.79                    |
| 6  | 176.91     | 181.49         | -4.58                    |
| 7  | 190.92     | 187.45         | 3.47                     |
| 8  | 167.78     | 171.74         | -3.96                    |

It can be seen from the above that the experimental results and the results obtained by the method of genetic programming were close, and the maximum result was -5.91, which is an error of less than 2.75%. The results obtained experimentally and by genetic programming can be presented in the form of graphs showing the pressure stress distribution in figure 8. The graphs also show close experimental values and GP model values.

![GP Model Simulation](image)

![Prediction](image)

Figure 8. Comparison of experimental and GP modeling results of (a) training data ($Y_E$ - $Y_{GP}$); (b) testing data ($Y_E$ - $Y_{GP}$).
From the diagram shown in figure 8 it can be seen that the measured pressure stress by experimental methods (blue line) is close to the values of pressure stress calculated according to GP model (1) (red line).

![Figure 8](image)

Figure 9. Performance models for (a) training and (b) testing data.

After the evaluation of the model, figure 9 shows the basic statistical indicators of the model, where it can be seen that the root mean square error for the trained set was 2.636 while for the validation set was 2.737. The correlation coefficient for the trained and validation set was the same and it was 0.995 and the coefficient of determination 0.991 which showed that the model was well trained.

All the above indicates that the model describes very well the given problem in the observed area. The deviations of the absolute values of the experimental results pressure stress in relation to the results obtained by genetic programming range in intervals in the validation set $S_{GP}=0.07 \div 4.58$ [k Pa] or in the trained set $S_{GP}=0.11 \div 5.91$ [k Pa].

From this it can be seen that the experimental results and the results obtained by the method of genetic programming were close and the maximum result was -4.58 for the trained set and -5.91 for the validation set, which was an error of less than 2.75%.

6. Conclusion

In this paper, experimental research of products from expanded polystyrene was performed, and several input/output parameters were detected. Due to the specificity of the product, the experiments were performed in the laboratory and several parameters were monitored. The experimental part included the measurement of pressure stress for several types of products with different input parameters (density, aging time, relative humidity and temperature). The obtained experimental results were taken as input data for modeling. The modeling phase involved the modeling of pressure stresses during deformation of 10%. Pressure stress modeling was done using the GPdotNET software package. The results of the obtained GP model show close values to the experimental ones. The correlation coefficient between the model and the training set was 0.995 and the correlation coefficient between the model and the validation set was also 0.995 which gave a high degree of reliability to this model. Given this correlation coefficient, the model obtained by the method of genetic programming showed that it was reliable for the researched area.

It can be seen from the presented that genetic programming is a very efficient method of model making, and unlike classical regression analysis there are no restrictions in terms of the degree of polynomials. This method of genetic programming is based on the concept of computer programs and represents an intuitive and simple way of building a model over experimental data that can then be used in future research as a starting point.
References

[1] Koza J R 1992 Genetic Programming: On the programming of computers by means of natural selection (London: Cambridge Massachusetts)

[2] Jurković M, Hrnjica B 2007 Modeling and optimization of the tool stress in drilling process by evolution algorithms 3th International conference on manufacturing science and education (MSE)

[3] Hrnjica B 2016 Matematičko modeliranje inženjerskih problema korištenjem metode genetskog programiranja VI Međunarodni naučni skup o ekonomskom razvoju i životnom standardu (EDASOL 2016)

[4] Hrnjica B 2014 Numeričko-evolucijski pristup određivanja parametara mehanike loma posuda pod pritiskom Doktorska disertacija (Bihać: Univerzitet u Bihaću)

[5] Nezirević E, Hrnjica B and Hodžić A 2016 Modeling of Pressing Forces using Genetic Programming 20th International Research/Experts Conference (TMT 2016)

[6] Hrnjica B and Danandeh Mehr A 2019 Optimized genetic programming applications Advances in Medical Technologies and Clinical Practice DOI:10.4018/978-1-5225-6005-0

[7] Hasanagić R 2018 Modeling and prediction of fracture force to tighten solid wood elements by genetic programming Tehnika 73 653–7 DOI:10.5937/tehnika1805653H

[8] Kovačič M and Župerl U 2020 Genetic programming in the steelmaking industry Genetic Programming and Evolvable Machines 21 99–128 DOI: 10.1007/s10710-020-09382-5

[9] Semenkina M, Burlacu B and Affenzeller M 2020 Genetic programming based evolution of models of models Computer Aided Systems Theory – EUROCAST 2019 387–95 DOI:10.1007/978-3-030-45093-9_47

[10] Tang N, Lei D, Huang D and Xiao R 2019 Mechanical performance of polystyrene foam (EPS): Experimental and numerical analysis Polymer Testing 73 359-65 DOI:10.1016/J.POLYMERTESTING.2018.12.001

[11] Sun L G, Du C B and Wang D P 2013 Mechanical analysis and numerical simulation of EPS exterior decorative element Journal of Building Materials 16-4 637-41+56 DOI:10.3969/j.issn.1007-9629.2013.04.015

[12] Krundaeva A, De Bruyne G, Gagliardi F and Van Paepegem W 2016 Dynamic compressive strength and crushing properties of expanded polystyrene foam for different strain rates and different temperatures Polymer Testing 55 61-8 DOI:10.1016/j.polymertesting.2016.08.005

[13] Bajramović E and Đuzelić R 2018 Influence of production and products of Expanded Polystyrene (EPS) on leaf and living organisms 6th International Scientific and Professional Conference “5 June - World Environmental Day” Proc. 6-2018 ISSN 2566-4530

[14] Awol T 2012 A Parametric Study of Creep on EPS Geofoam Embankments, Norwegian

[15] European standrad EN 13163 2012 Thermal insulation products for buildings – Factory made expanded polystyrene (EPS) products – Specification