FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME220429036M

Original scientific paper

IMPROVING THE MECHANICAL CHARACTERISTICS OF THE 3D PRINTING OBJECTS USING HYBRID MACHINE LEARNING APPROACH

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Abstract. *Production of three-dimensional parts in 3D printing process gains growing importance in various fields, such as: aviation and car industry, architecture, medicine, dentistry, etc. Mechanical performance is an important users' requirement for manufacturers of 3D printed parts. Furthermore, printed part highly depends on process parameters, position and orientation of the printed part, and performances of the 3D printer which prints the part. In this paper, based on experimental results, an artificial neural network has been used for modeling the dependence of process parameters and object orientation during printing, on the one side, and tensile strength as very important mechanical performance, on the other side. After establishing abovementioned dependence, the developed neural network has been used as a fitness function for the genetic algorithm while the genetic algorithm has been created for the optimization process. The result of optimization process was a set of optimal process parameters and part orientation giving the maximum tensile strength. The results have shown acceptable potential of the developed methodology for optimizing the 3D printing process as a complex engineering problem.*

Key Words: *3D Printing, Optimization, Tensile Strength, Neural Network, Genetic Algorithm*

1. INTRODUCTION

3D printing or additive manufacturing is a modern manufacturing process of making a three-dimensional part from a digital 3D model. It allows making the part from several different materials that have different mechanical and physical properties, in a unique

[*]**Received:** April 29, 2022 / Accepted September 12, 2022
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process, usually, layer by layer. Additive manufacturing technologies have been initially used only for prototyping in order to accelerate part development and minimize development costs. However, with the improvement of technology and materials, a development level allowing the production of final, functional parts or tools has been reached. In addition to prototyping, 3D printers offer a great potential for the production of various applications in the field of industrial design, aviation and car industry, architecture, medicine, dentistry, etc.

Fused Deposition Modeling (*FDM*) is one of the most important 3D printing methods which deliver parts made of thermoplastic filaments. The layers are stacked on top of each other in order to create a final 3D part. *FDM 3D* printing process uses different types of plastic materials and composite materials made of plastics and metal particles, ceramics, various carbon fibers, etc. Due to its ease of use and low cost, this method has become very popular and is widely used for prototyping as well as for manufacturing functional industrial products. However, the default settings of printing process parameters, set by a manufacturer in some cases, do not guarantee the quality (dimensional errors and unsatisfactory mechanical characteristics of the part) of the printed part because of a significant number of process parameeters to be taken into consideration. For the parts made in this way to be completely functional, it is necessary to meet the requirements on the mechanical characteristics that depend on choice of basic material, technological process parameters as well as post-processing procedures. *FDM 3D* printing process consists of a fairly large number of parameters that can affect the final appearance and mechanical characteristics of the part. These parameters can be classified into: process parameters, *FDM* printer parameters, 3D model orientation mode, material type, 3D model and environment parameters [1], [2].

Analysis of the process parameters influence on the quality of printed part and its mechanical properties in the *FDM* printing process has been the subject of numerous scientific research papers [3-6]. The most analyzed have been influences of the following parameters: layer thickness, type of internal filling, percentage of internal filling, distance between rasters, raster width, raster angle, material density, part orientation by *x*, *y* and *z* axis, number of contour walls, printer head velocity, nozzle temperature in the printer head, etc. [7-12]. Research that includes testing the influence of all abovementioned parameters and their combinations requires a large number of samples, so the literature usually states the impact of only certain ones [13-18]. Furthermore, due to the complexity of process parameters and an unclear relationship between process parameters and part performances, the influence of each parameter on 3D printed parts has not been universally defined yet. Therefore, it is necessary to consider the method of choosing optimization parameters of process that will improve the quality of 3D printing [19-23]. In previous scientific research papers the mechanical properties of *FDM* printed samples have been most frequently tested by tensing [4,8,10,17,25-29]. Tensile strength testing provides the most complete image of material's mechanical properties. Test samples (test pipes) have been defined by relevant standards. During testing, forces in the direction of the axis are acting on test pipe, tending to extend and break it. Tensile testing machines, also known as tension test machines, have been used for this type of testing.

After selecting the appropriate influential process parameters, it is possible to improve quality and mechanical properties of 3D printed part by their optimization. Optimization of process parameters is a research challenge that has been addressed by many researchers [7,30-32]. The research field of this challenge is wide because a significant number of process parameters and their combinations lie in a design of the experiment while a range of materials to be processed is wide. It is also important to note that every 3D printer has its own specifics.

The present paper deals with the influence that process parameters and test specimen orientation in 3D printer's workspace have on the mechanical characteristics, in particular case – on the tensile strength. This paper represents in a way an improvement over research studies that have been investigating only the influence of certain process parameters without taking into account the orientation of the test specimen in the 3D printer workspace. The present paper is divided into four chapters. After *Introduction*, the second chapter describes the experimental part related to 3D printing and mechanical testing. The second chapter describes the process parameters and test specimen orientations used in the design of the experiment and their influence on tensile strength. Then follows the mechanical testing of tensile strength. In the third chapter of the paper, a hybrid intelligent neuro-genetic system for the selection of process parameters and test specimen orientation that provides the best mechanical characteristics of the printed part has been developed. Conclusions on the application of such a hybrid intelligent system for optimization the process parameters in order to maximize the tensile strength of the part made by 3D printing, are given in the fourth chapter.

2. Experimental Setup

2.1 3D Printing process parameters and conditions

For the purposes of the experiment, at first a 3D model of a standard test specimen, *type 1BA* (for tensile tests, according to ISO 527-2:2012, Annex A) has been created, from which an *STL* file have been obtained (Fig. 1). The *STL* file has been imported into *CreatWare* software, in which the *G*-code has been generated. Each *G*-code consisted of 3 test specimens that were positioned on a base at an angle 0, 45° and 90° to the *y*-axis (Fig. 2), in order to determine how the direction of printing affects the tensile strength of the printed model. Along with three different angles, the experiment has been repeated with different parameters of print speed, printer head temperature and print density. Speed has varied from 40 to 80 mm/s, temperature from 200 °C to 220 °C and print density from 5 to 25%. Thus 81 samples are obtained. The samples have been sorted and marked. A *CreatBot DX2 3D* printer, that uses *FDM* printing technology, has been used for making the samples. *PLA* plastics in the form of a wire (3 mm diameter) have been used as a material. All input data, i.e. process parameters, are displayed in the diagram at Fig. 3.

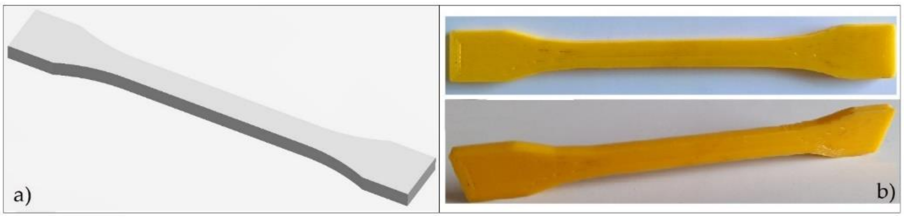

Fig. 1 Test specimen: a) *STL* model; b) a sample made on a 3D printer

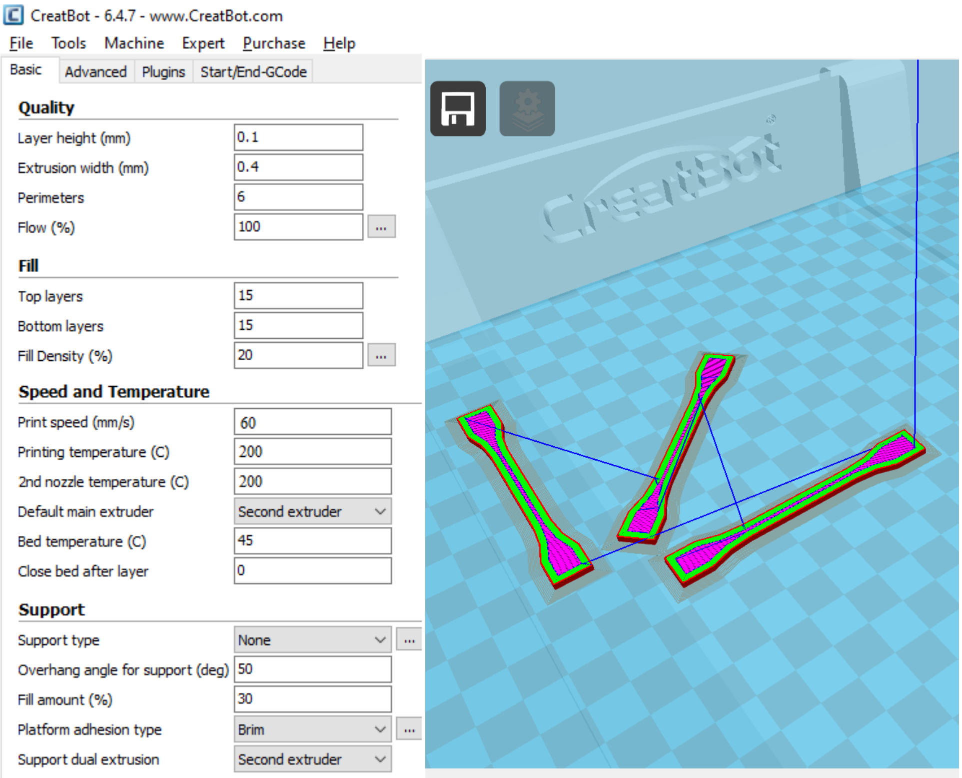

Fig. 2 Generation of the *G*-code in the *CreatWare* software of the *CreatBot DX2 3D* printer

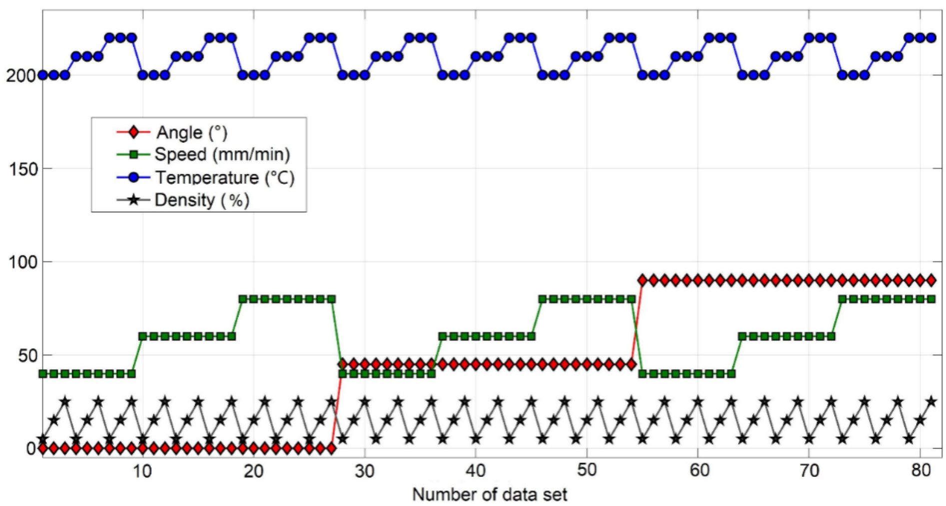

Fig. 3 Input data – Process parameters

2.2 Tensile strength testing procedure

For determination of tensile strength of printed test pipes have been used tensile load tests in accordance with requirements defined by ISO 527-1:2019 (*Plastics – Determination of tensile properties – General principles*) and ISO 527-2:2012 (*Plastics – Determination of tensile properties – Test conditions for molding and extrusion plastics*). A machine type *SKAZ 2000* has been used for testing, equipped with 1st class force-measuring cell up to 20 kN in accordance with ISO 7500-1:2018 and 1st class extensometer in accordance with ISO 9513:2012. The appropriate software generated a dependence diagram of tensile force on deformation, the value of tensile strength as well as the relative elongation when tearing the test specimen for each test sample. Tensile strength values for all tested samples are given in the diagram shown in Fig. 4.

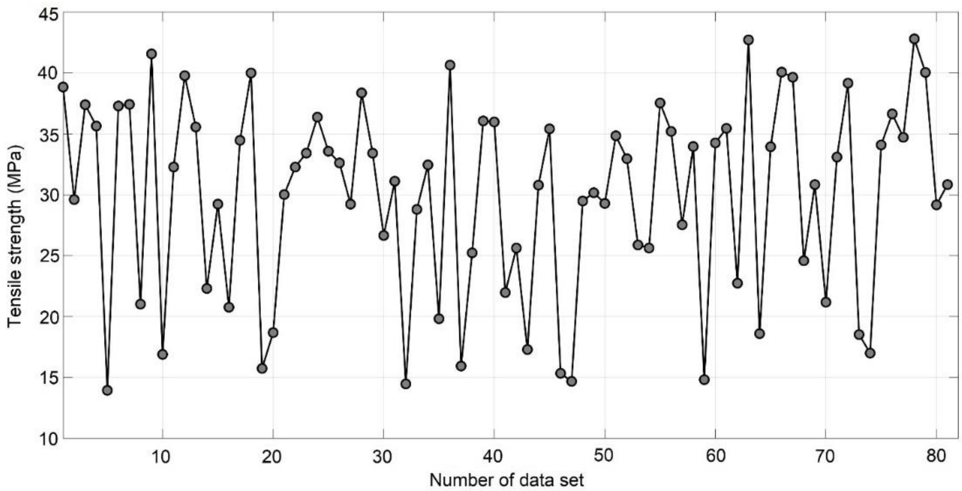

Fig. 4 Output data - Tensile strength

3. Neuro-Genetic Optimization of Process Parameters

3.1 Tensile strength prediction model

A neural network is a massively parallelized distributed processor with a natural ability to store experiential knowledge and ensure its use. Through the training process, synaptic weights are systematically changed in an artificial neural network in order to achieve the desired network performance. The basic computing power of neural networks is massive parallelism, the ability to train and generalize. In order for the system modeling process through training to be as high quality as possible, it is necessary to cover the widest possible range of operating modes of the dynamic system. A neural network architecture consists of an input layer, one or more hidden layers, and an output layer. The most commonly used algorithm for training multilayer neural networks with a supervisor is error propagation backwards and is only applicable to feedforward networks. The basic idea is that the input signal propagates forward, from the input to the output layer while the error signal propagates backwards, from the output to the input layer, changing the weights of the network in that order. The structure of the *i*-th artificial neuron with *r* inputs $x_1, x_2, ..., x_r$ multiplied by appropriate weighting coefficients $\varpi_{i,1}, \varpi_{i,2}, ..., \varpi_{i,r}$ and added bias can be represented in the following from [33]:

$$a_i = x_1\varpi_{i,1} + x_2\varpi_{i,2} + ... + x_r\varpi_{i,r} + b_i \tag{1}$$

where a_i represents argument of transfer function (called activation function). The *i*-th neuron produces output data y_i

$$y_i = f\left(a_i\right) = f\left(\sum_{j=1}^{r} x_j \varpi_{i,r} + b_i\right) \tag{2}$$

This output then represents the input for the neurons of the next layer or represents an element of the output vector of the artificial neural network. In this paper, the *Levenberg-Marquardt* backpropagation algorithm has been used to train neural networks. This algorithm is a standard method for minimizing the mean square error (*MSE*) criterion and is characterized by fast convergence and robustness [34]. The *MSE* is calculated as follows:

$$MSE = \frac{1}{Q}\sum_{k=1}^{Q} e\left(k\right)^2 = \frac{1}{Q}\sum_{k=1}^{Q}\left(t\left(k\right) - y\left(k\right)\right)^2 \tag{3}$$

where *Q* denotes number of experiments, *e*(*k*) denotes error, *t*(*k*) denotes target values, while *y*(*k*) are predicted values. Updating the weights of network with the *Levenberg-Marquardt* algorithm [35] is presented by the equation:

$$w_{k+1} = w_k - \left(J_k^T J_k + \mu I\right)^{-1} J_k e_k \tag{4}$$

which is based on the approximation of *Hessian matrix H*.

$$H = JJ^T + \mu I \tag{5}$$

where *I* is identity unit matrix, μ is a learning parameter and *J* is the *Jacobian matrix* (the *Levenberg-Marquardt* algorithm requires the computation of the Jacobian *J* matrix at each iteration step and the inversion of J^TJ square matrix, the dimension of which is $N \times N$).

To predict the tensile strength, the feedforward backpropagation neural network described above has been developed, whose training algorithm is the *Levenberg–Marquardt* algorithm. A set of data (81 samples) was used for the development of neural networks, which has been divided into three groups: training 80% (65 samples), validation 10% (8 samples) and testing 10% (8 samples). Several different neural network architectures have been developed (with different number of hidden layers and neurons in them), and network performance has been evaluated based on mean squared error. The best performance in the prediction of tensile strength was shown by a network with one hidden layer and 12 neurons in the hidden layer (Fig. 5). The neurons in input and hidden layers of neural networks had the sigmoid transfer function, while the neuron of the output layer has the linear transfer function.

The process of creating a neural network ends in 15 epochs when the values of the mean square error are in the phase of training, validation and testing: 0.34, 5.17 and 9.25, respectively (Fig. 6).

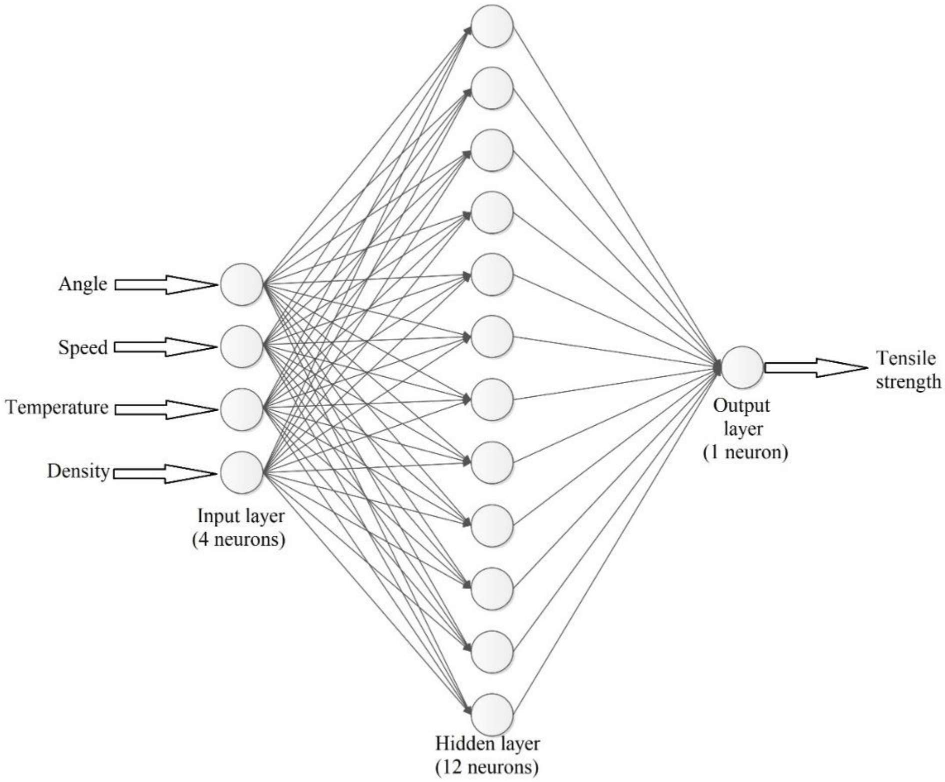

Fig. 5 Neural Network Architecture 4-12-1

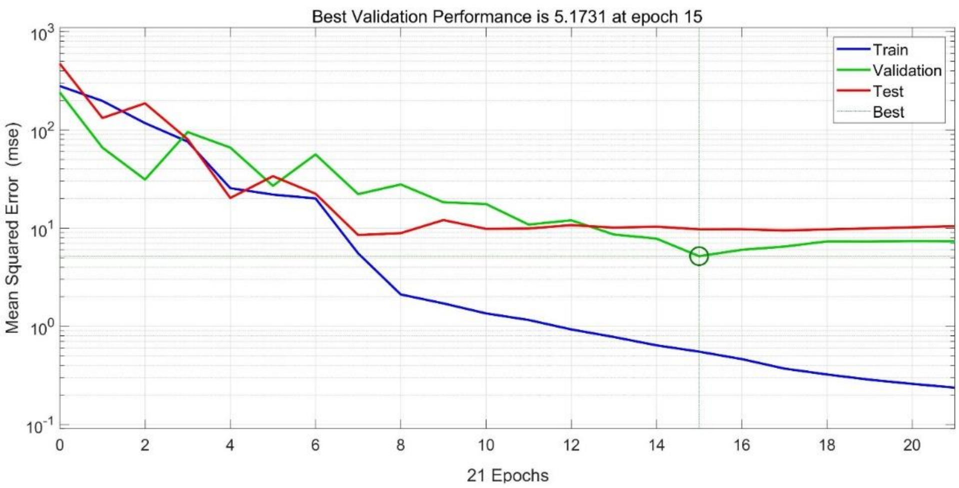

Fig. 6 Mean square error during the epochs

As another criterion for confirming the validity of the created neural network, the *Regression criterion* has been used, which compares the outputs from the neural network and the target outputs (tensile strength values obtained by experimental testing) in the training, validation, training and total in all phase. A graphical presentation of the *Regression criterion* in the training, validation and testing phase as well as the total for all the above phases, is given in Fig. 7.

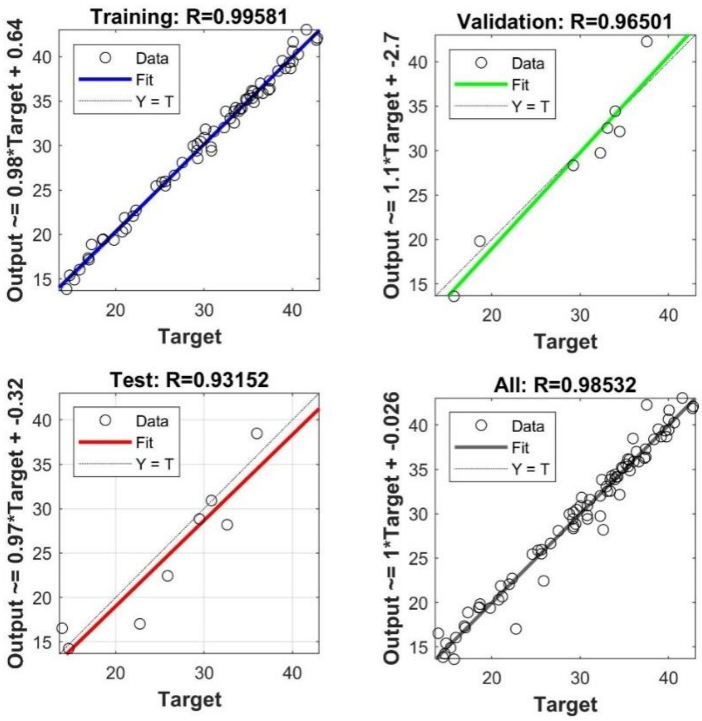

Fig. 7 *Regression criterion* as an assessment of neural network performance

The listed performances of the neural network ANN 4-12-1 are given in Table 1.

Table 1 Performance of the neural network 4-12-1

	Mean Squared Error (MSE)	Regression
Training	0.34	0.996
Validation	5.17	0.965
Testing	9.25	0.931

The created neural network ANN 4-12-1 is used below as a fitness function of the genetic algorithm for optimization of the process parameters with the aim of maximizing tensile strength.

3.2 Optimization of 3D printing process parameters

Genetic algorithms (*GA*) are a search technique that uses heuristic optimization methods to find an exact or approximate solution simulating the mechanism of natural evolution. The algorithm uses four genetic operators: selection, reproduction, crossover and mutation. The second basic component of the genetic algorithm is the fitness function, which is a quantitative measure of quality, i.e., correctness of the proposed solution. The strength of the algorithm lies in its ability to determine the position of the global optimum in a space with multiple local extremes in the so-called multidimensional space. Unlike most deterministic algorithms, the characteristic of genetic algorithms is that they begin the search for the optimal solution from a series of possible solutions that represent the initial population of the genetic algorithm. It is common to generate the initial population (initialization) by randomly selecting solutions from the domain. This includes defining individuals and associating them with possible solutions. Genetic algorithms use individuals that describe a set of objects. Each individual is assigned a fitness score that evaluates the quality of a given individual. The genetic algorithm must provide a way to continuously improve, from generation to generation, the absolute adaptation of each individual in the population as well as the mean adaptation of the entire population. This is achieved by successive application of genetic operators of selection, crossing and mutation, which provides better solutions to a given specific problem (Fig. 8).

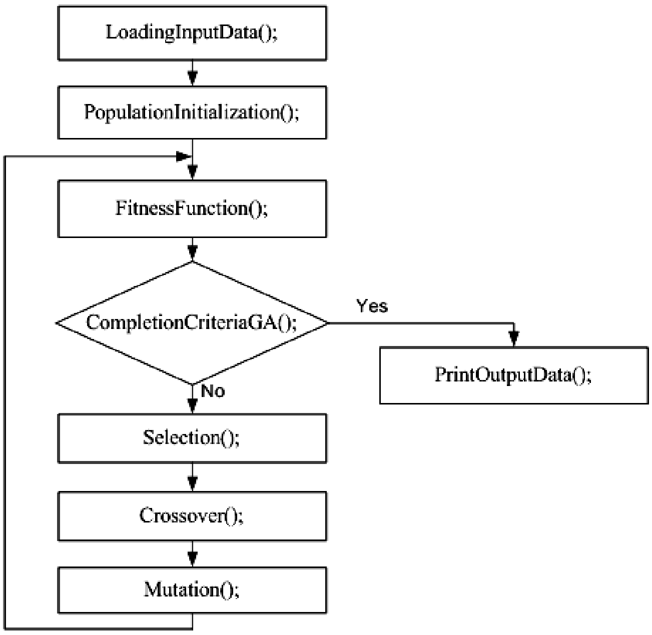

Fig. 8 Flowchart of genetic algorithm

The main disadvantage of *GA* is that the speed of convergence close to the global optimum can be quite slow. If the population has become sufficiently similar, but an optimal solution has not been reached, the mean fitness of all individuals in the population is large, and the differences between the best individual and other individuals in the population are small. Therefore, there is an insufficient gradient in the fitness function that would help the genetic algorithm to reach the optimal value. To overcome the above-mentioned anomalies simple *GA* and the successful execution of the genetic algorithm used various techniques adapted to the nature of the problem to solve. These are: various types of coding, customized more complex genetic operators, several types of fitness functions, generation replacement policy, fixed or adaptive parameter change during *GA* execution. Methods of calculating the fitness function can also greatly affect *GA* performance. More detailed descriptions and analysis of the operation principles of genetic algorithms are given by References [36-39].

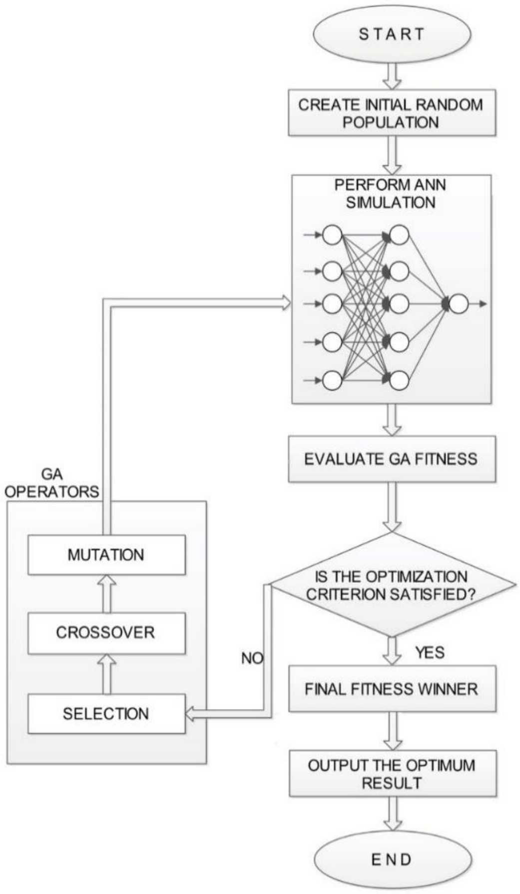

Fig. 9 *GA/ANN*-based optimization algorithm [40]

The principle of hybrid neuro-genetic combination for optimization of 3D printing process parameters in order to maximize tensile strength is shown in Fig. 9. The selection of the initial population is generated randomly. The fitness function of the genetic algorithm is the neural network (ANN 4-12-1), described in the previous section of this paper. The fitness of each member of the initial population is calculated using the *ANN* model and is followed by selection, crossing and mutation as parts of the reproduction process of a new generation. The process is repeated until one of the multiple requirements for termination of *GA* is satisfied.

The population range is 30 individuals, with 100 generations at maximum. Stochastic universal sampling algorithm is used in the selection. Uniform crossover served as the crossing operator. The coefficient of the crossover fraction is 0.8. Crossover fraction defines a portion of the new population derived from a crossing (non-elite individuals), its value being between 0 and 1. Not more than two elite individuals are to be transferred to the next generation. The optimization ends in 53 iterations (Fig. 10), and gives us a maximized value of tensile strength of 46.47MPa, and the values of the parameters are angle = 0.005 (°), speed = 69.36 (mm/min), temperature 218 (°C), density 24 (%).

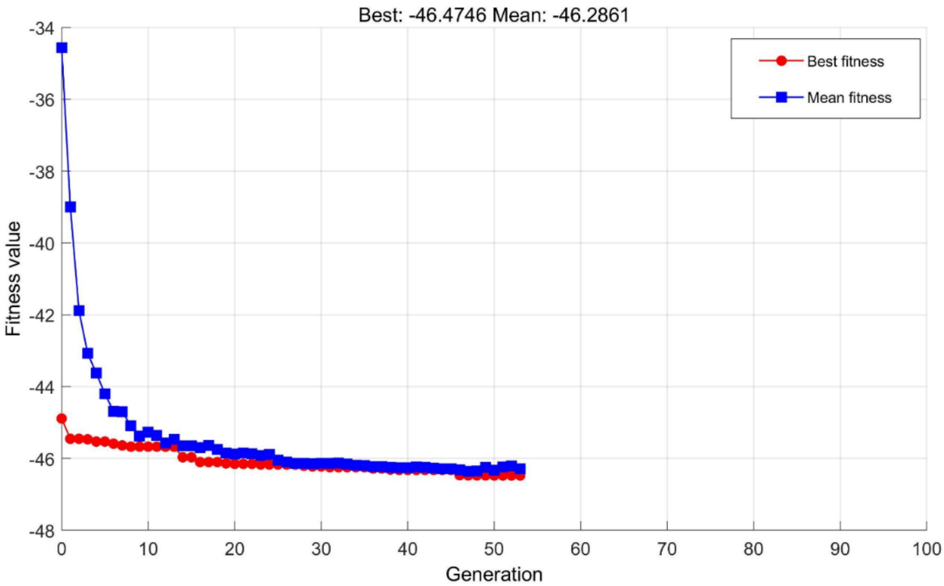

Fig. 10 Optimization process during iterations

The optimization results indicate that by increasing the velocity by 10 and slightly shifting the temperature and density, *GA* has found the maximum function generated by the neural network ANN 4-12-1.

4. CONCLUSION

The present study describes a joint influence of process parameters and part orientation on the tensile strength as a very important mechanical characteristic of the part made bay 3D printing process. In order to establish a connection between inputs (process parameters and part orientation) and outputs (tensile strength), and based on experimental results, a neural network has been developed that showed a high degree of efficiency in establishing correlations between inputs and outputs. The best performance (MSE=0.931 in testing phase) has been shown by a neural network with 12 neurons in a hidden layer and it was determined as a fitness function for the optimization process resulting in a set of process parameters (speed = 69.36 (mm/min), temperature 218 (°C), density 24 (%)) and part orientation (angle = 0.005 (°)) for which the tensile strength has maximum value. The genetic algorithm has been used as an optimization technique and it showed great potential in optimizing the process parameters of 3D printing and the orientation of the part being created. The very special importance of the present paper is that it considers a joint influence of process parameters and orientation of the part to be printed on the tensile strength. It is also of a great importance for practical workers who set 3D printer settings and prepare process, and who need to know the influence of process parameters on mechanical characteristics of the part. The application of the presented methodology eliminates the expensive principles of "trial and error" to achieve high product quality.

Thus, the study promotes the methodology of obtaining a set of process parameters and the orientation of the part for which the tensile strength is the maximum value. In practice, maximum mechanical characteristics are often not required, so some other values of process parameters can produce an acceptable printed part. The application of the neural network model developed in this study for any set of input parameters (within defined limits) gives a stable and relatively accurate prediction of tensile strength. This practically means that the developed neural network can be used separately as a high-precision model of 3D printing process in the cases when maximum tensile strength is not sought, which gives the presented study additional significance.

Future research will be directed in three research directions. The first one is to increase the precision of the process model through a larger number of experiments. The second one will include a wider class of materials used in 3D printing technology, while the third one will include the application of the presented methodology to other processes from the family of Rapid prototyping technology.

Acknowledgements: *This study was supported by the Ministry of Education, Science and Technological Development of the Republic of Serbia, Grant No. 451-03-68/2022-14/200132 with University of Kragujevac - Faculty of Technical Sciences Čačak.*

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