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Electrical Properties Research of PA6 Low Warp Composite Material Using Selected Machine Learning Method

Lukáš Vacho [a], *Vladimír* Madola [b,1], *Martin* Barát [c], *Lucia* Boszorádová [c], *Patrik* Kósa [c]

[a] Institute of Electrical Engineering, Automation, Informatics and Physics, Slovak University of Agriculture in Nitra, Tr. A. Hlinku 2, Nitra, Slovakia
[b] Information and Coordination Centre of Research, Faculty of Engineering, Slovak University of Agriculture in Nitra, Tr. A. Hlinku 2, Nitra, Slovakia
[c] Institute of Design and Engineering Technologies, Faculty of Engineering, Slovak University of Agriculture in Nitra, Tr. A. Hlinku 2, Nitra, Slovakia

Abstract. This paper focuses on the study of the electrical properties of PA6 Low Warp material using Artificial Neural Network model. The model classifies the material samples into a given class depending on the time of exposure of the material to increased temperature according to the input electrical properties and the mechanical properties of the material in tension. For the neural network models tested, the primary effectiveness of the ReLu and Tanh activation functions to classify a sample into a given class for a given time interval at an increased environment temperature of 180 °C was examined. The highest classification accuracy of 82.46% was obtained for the model using the Tanh activation function. The results show that in researching the physical properties of engineering materials used in 3D printing using artificial neural networks allows to predict the response of material properties under certain initial ambient conditions.

1 INTRODUCTION

Additive manufacturing technologies (AMT) finds application in the industrial sector as well as in the commercial sphere, where computer-aided design (CAD) enables the simple manufacture of complex parts without the need for elementary manufacturing processes such as moulding or milling. Fused deposition modelling (FDM) uses the polymeric materials as the base material. In most applications, Polylactic Acid (PLA) and Acrylonitrile-Butadiene-Styrene (ABS) are used, where the materials in this case have comparable dielectric properties to those of materials typically used in moulding process [1].

These materials can therefore be used as insulators in various fields. However, their dielectric properties, such as dielectric strength and permittivity, require detailed study [2]. When using PA6 material, it is also necessary to study its dielectric properties and dielectric relaxation, the characteristics of which depend on the drying effect of the material as well as the filler [3]. Quantitative analysis and prediction of the electrical properties of materials used in additive manufacturing technologies requires extensive study of the materials and

[1] Corresponding author: vladimir.madola@uniag.sk

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adequate data acquisition, as well as evaluation. The machine learning algorithms are used for data processing and prediction of characteristic physical properties [4, 5]. The aim of the research was to determine the use of a suitable prediction model for time intervals of a PA6 Low Warp material sample exposed to an increased temperature of 180 °C and changing mechanical properties as well as electrical properties in a specified frequency range.

2 MATERIALS AND METHODS

The electrical properties of solid materials can be measured in a selection of approaches and using a various measuring methods [7].
In the experiment, the electrical properties - series resistance R_s and series capacitance C_s are measured using the parallel plate method using Keysight 4294A (Keysight, USA) impedance analyser for the studied PA6 Low Warp material samples printed by Prusa 3D printer with parameters in print process: nozzle temperature 260 °C, layer height 0.2 mm, nozzle diameter 0.4 mm.

A material sample with a diameter of d= 56 mm and a thickness of h= 6 mm is placed in dielectric test fixture 16451B (Keysight, USA) connected to the analyser by a 4-terminal pair cable assembly (tetrapolar system). The impedance measurement range of this method is from 10 mΩ to 10 MΩ, and its frequency range is up to 110 MHz. The constant voltage was set to 1 Vrms and the frequency range used for the measurements was set to 40 Hz to 110 MHz. For each parameter, the measurements were repeated 201 times.

The standard mathematical technique of descriptive statistics will be used to determine the dependence of the electrical parameters on the mechanical properties, which will be used to show significant differences in the measured data.

Various machine learning methods [8] have been considered for electrical material properties modelling for reasons such as: optimization of computational performance at the expense of sufficient classification accuracy, increased robustness of the models, and efficiency of data evaluation. Artificial Neural networks (ANN) with parameter modification techniques will be used in order to identify nonlinear dependencies between electrical parameter variables. The measured sample was exposed under laboratory conditions to increased temperature to 180 °C using heating chamber at different time intervals: 30 min, 60 min and 100 min, while one sample was not exposed to increased temperature. The samples were then left to cool to 20 °C. The artificial neural network will be used to estimate the time class classification of the sample according to the variation of the electrical parameters (Rs and Cs) and the tensile strength required to break the sample in tension.

The measurement data set was divided into training and test sequences in a 70:30 ratio. The metrics (TP - true positive), (FP - false positive), (FN - false negative), (TN - True negative) as evaluation factor of classifier accuracy, other metrics were used to determine the percentage score of classifier accuracy (Acc) Eq. (1) and F1score (F1S) Eq. (2):

$$A_{CC} = \frac{TP}{TP+FP} \quad (\%) \tag{1}$$

$$F1_S = 2 \cdot \frac{A_{CC} \bullet \left(\frac{TP}{TP+FN}\right)}{A_{CC} + \left(\frac{TP}{TP+FN}\right)} \quad (\%) \tag{2}$$

The scikit-learn library ver. 1.7 was primarily used to pre-process the data with machine learning models and the Python programming language ver. 3.12.3 with the JupyterLab 4.4.2 environment.

3 RESULTS AND DISCUSION

The Shapiro-Wilk test confirmed the normality of the tensile strength measurement data, indicating no significant deviation from the normal distribution of the data in the test set at the 5% significance level ($p > 0.05$).

Table 1. Basic statistical evaluation of tensile strength for tested time interval in increased temperature condition

Time of exposure of the sample to the increased temperature [min]	0	30	60	100
Mean tensile strength [MPa]	45.91	27.72	41.02	27.97
Standard deviation [MPa]	12.46	8.84	16.02	9.55
Standard error of mean [MPa]	± 6.23	± 4.42	± 8.01	± 4.78

To study the effect of 180 °C temperature on the strength of the material in tension, the average tensile strength required to crack the sample at different heating intervals was observed. The impact of increased temperature on the mechanical properties of the material in tension, as determined by the time of exposure of the sample to the increased temperature and the varying average tensile strength required to crack the material sample, was not clearly evident.

Statistical significance of the change in temperature on the change in mechanical properties in tension was tested using Dunnett's multiple comparisons test at a significance level of $p > 0.05$ with respect to samples without temperature loading (0 min).

The results are presented in Table 2, testing was carried out between samples without increased temperature exposure and samples increased temperature exposure at the tested time intervals.

Table 2. Basic statistical evaluation of tensile strength for tested time interval in increased temperature condition

Multiple comparisons	0 vs. 30	0 vs. 60	0 vs. 100

of samples by heating time [min]			
p – value	0.071	0.891	0.136

The p-values of Dunnett's multiple comparisons test are for each sample at increased temperature with respect to time under the significance level examined. The results indicate a statistically insignificant effect of the increased temperature of 180 °C on the PA6 Low Warp material sample and the length of time the sample was exposed to that temperature.

Table 3. Metrics evaluation for NN with different number of neurons in one hidden layer with ReLu activation function and Tanh activation function for classification material properties

Type of activation function	Number of neurons	Accuracy [%]	F1-score [%]	Pearson correlation coefficient
ReLu	5	64.05	63.20	0.613
	10	75.37	75.34	0.777
	15	79.81	79.96	0.844
Tanh	5	68.84	64.03	0.585
	10	78.28	78.48	0.781
	15	82.46	82.67	0.817

The Pearson correlation coefficient values to evaluate the relationship between the type of classification model and the number of neurons are shown in Table 3. The classifier predicted values were the individual time intervals (0- no exposure to elevated temperature, 30 - 30 minutes, 60 - 60 minutes, 100 - 100 minutes) in which the samples were exposed to increased temperature of 180 °C. The input values to the ANN classifier with ReLu function and Tanh function were the measured tensile strength, series resistance R_s, series capacitance C_s. The Pearson correlation coefficient values to evaluate the relationship between the type of classification model and the number of neurons are shown in Table 3.

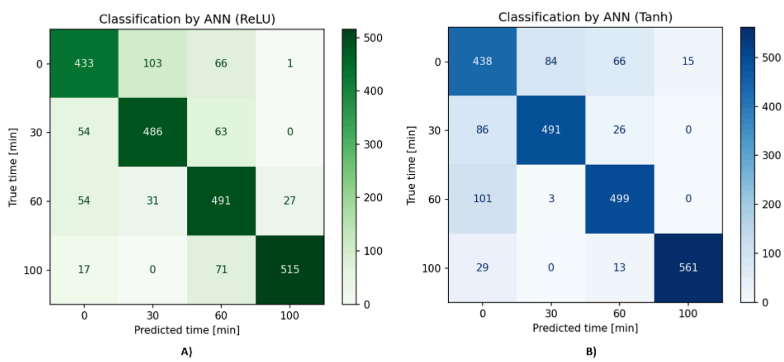

Fig. 1. Confusion matrix of NN with 15 neurons for time label classificator with ReLu activation function A), and Tanh activation function B)

For the case of ANN classifier with ReLu feature, there is a significant high correlation when using 15 neurons. In case of the Tanh activation function, there is an equally high correlation when using 15 neurons. In fact, in both cases the coefficient value is positive, indicating the absence of negative values in the input data of the classifier. The confusion matrix of the classifier time dependent electrical parameters for the case using 15 neurons and with the ReLu activation function is shown in Fig. 1A for the model validation case, similarly Fig. 1B shows the confusion matrix for the Tanh activation function for the validated training set. The classification model with the ReLU activation function of Fig. 1A achieved the highest accuracy when classifying the 100 minutes class, with 515 correctly classified instances. The model with the Tanh function of Fig. 1B reached a higher accuracy for the same class, where 561 cases were correctly classified. For the classified classes of 30 and 60 minutes, the model with Tanh function shows lower number of misclassifications for each class. From the results, it is evident that the ANN model of PA6 Low Warp using Tanh activation function has a higher ability to generalize the input data with more precise classification of the predicted time instances.

The following figures show the metrics (Accuracy, F1 score, Loss function) during training of the neural network with 15 neurons for the activation function ReLu Fig. 2, and Tanh Fig. 3.

In the first case, using the ReLu activation function, an accuracy value of 79.81% was achieved. On the waveform of the function Fig. 2A it is possible to observe the iterations of the model within one epoch, where the model correctly classifies the values without overfitting at a low number of iterations. The F1 score value reached 79.96%, where the level indicates a high level of model performance. The value of the loss function decreases as a function of model learning. In the second ANN network with 15 neurons and Tanh activation function the model reached an accuracy of 82.46%. The accuracy trend over the iterations of

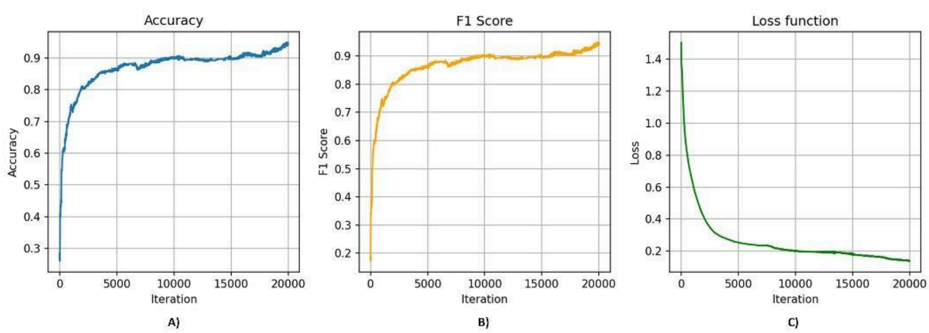

Fig. 2. Evaluation metrics for training performance of ANN model with ReLu activation function for 15 neurons: Accuracy A), F1 Score B), Loss function C)

Fig. 3A within a single epoch shows a more evident classification process achieved with fewer iterations. The F1 score value reached 82.67%, where the value indicates the better performance of the model compared to the previous type. For the classification of individual epochs based on the input values of electrical parameters and tensile strength, the model with hyperbolic activation function shows better generalization [9]. The better parameters of the second model indicate a nonlinear dependence between the individual parameters of studied material PA6 Low Warp.

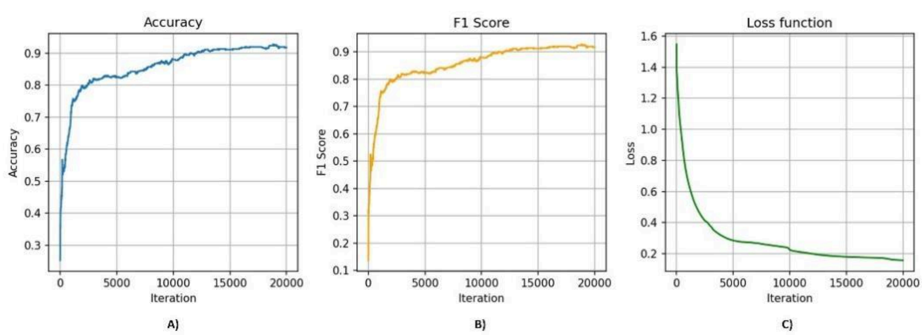

Fig. 3. Evaluation metrics for training performance of ANN model with Tanh activation function for 15 neurons: Accuracy A), F1 Score B), Loss function C)

4 CONCLUSION

In research, ANN model has been investigated for possible to determine, based on the mechanical and electrical properties of the PA6 Low Warp material, the time of exposure of the sample to increased temperature. The sample was tested at an increased temperature of 180°C. Using basic descriptive statistics, there was no clear dependence between the physical parameters studied. The best results of the classification model were obtained when using the Tanh activation function, where the model correctly classified most of the observed time intervals with a significant level of accuracy on value 82.46%.

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