ФИЗИКА

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ОПРЕДЕЛЕНИЕ ПАРАМЕТРОВ УПРАВЛЯЕМОГО ЛАЗЕРНОГО РАСКАЛЫВАНИЯ СИЛИКАТНЫХ СТЕКОЛ С ИСПОЛЬЗОВАНИЕМ РЕГРЕССИОННЫХ, НЕЙРОСЕТЕВЫХ И НЕЧЕТКИХ МОДЕЛЕЙ

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DETERMINATION OF PARAMETERS FOR CONTROLLED LASER CLEAVING OF SILICATE GLASSES USING REGRESSION, NEURAL NETWORK AND FUZZY MODELS

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Аннотация. Представлен один из вариантов решения научно-прикладной задачи прогнозирования характеристик лазерного раскалывания силикатных стекол. Результаты численного эксперимента, реализованного на языке программирования APDL, были использованы для построения регрессионных, нейросетевых и нечетких моделей управляемого лазерного раскалывания силикатных стекол. В качестве варьируемых факторов рассматривались скорость обработки, радиус и мощность лазерного пучка, а в качестве откликов – максимальная температура и термоупругие напряжения растяжения в зоне лазерной обработки. По результатам гранецентрированного варианта центрального композиционного плана эксперимента оценена регрессионная модель откликов лазерной резки стеклянных пластин при заданном уровне значимости. Построены и обучены искусственные нейронные сети зависимости откликов от входных факторов. На основе тепловых карт средней абсолютной процентной ошибки определены наиболее эффективные нейросетевые модели максимальной температуры и термоупругих напряжений растяжения в зоне лазерной обработки. Нечеткое моделирование управляемого лазерного раскалывания силикатных стекол осуществлено по разработанным лингвистическим переменным входных и выходных параметров. Сравнение результатов регрессионного, нейросетевого, нечеткого моделирования проведено на основе критериев точности, при этом выявлена наиболее эффективная модель. Результаты исследований могут быть рекомендованы для прикладного использования аппроксимации максимальной температуры и термоупругого напряжения растяжения в зоне лазерной обработки.

Ключевые слова: *лазерная резка*, *нечеткая логика*, *искусственная нейронная сеть*, *ANSYS – универсальная программная система анализа методом конечных элементов.*

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Abstract. This study proposes a solution to the applied research problem of predicting the characteristics of laser cleaving of silicate glasses. The results of a numerical experiment conducted in APDL (Ansys Parametric Design Language) were used to build regression, neural network and fuzzy models for the controlled laser cleaving of silicate glasses. The processing speed, radius, and power of the laser beam were considered as variable factors, whereas the maximum temperature and thermoelastic tensile stresses in the laser-treated area were regarded as responses. The regression model for the responses of laser cutting of glass plates at a specified significance level was estimated using the findings from the face-centered version of the central composite design experiment. Artificial neural networks that exhibit response dependence on input factors were created and trained. The most effective neural network models of the maximum temperature and thermoelastic tensile stresses in the laser-treated area were determined using MAPE (mean absolute percentage error) heat maps. Fuzzy modeling of controlled laser cleaving of silicate glasses was conducted according to the developed linguistic variables of input and output parameters. An evaluation was performed to compare the results of regression, neural network, and fuzzy modelling based on accuracy criteria, ultimately identifying the most effective model. The research findings can be suggested for practical application in approximating the maximum temperature and thermoelastic tensile stress in the laser-treated area.

Keywords: *laser cutting*, *fuzzy logic*, *artificial neural network*, *ANSYS – Universal Finite Element Analysis Software System.*

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Introduction

Silicate glasses are exceptionally well-suited for industrial applications due to their inherent properties. The primary procedure involved in the manufacturing of glass products is cutting, and controlled laser cleaving has multiple advantages compared to conventional methods of dimensional processing. The controlled laser cleaving technology was established in the latter part of the twentieth century. Nevertheless, even today, research on the laser cleaving processes involving various brittle nonmetallic materials remains relevant [1]–[5].

Artificial neural networks have the potential to effectively simulate complex relationships between inputs and outputs of the system; their extensive application stems from their capability to determine nonlinear dependencies in multidimensional datasets [6], [7]. Artificial neural networks are presently being effectively employed to simulate laser processing of materials, including laser cleaving methods [6]–[18]. Regression models of laser processing are also successfully used in modeling the processes under consideration [10]–[20]. The comparison between neural network and regression models for laser cutting of materials was conducted in [10], [20].

The implementation of a fuzzy approach for modelling real processes has been essential to enhancing prediction accuracy. This approach is founded on the concept of fuzzy description of systems and objects. Fuzzy logic is a means of representing the uncertainties of the real world, which are close to human thinking and natural languages [21].

Professor Lotfi Zadeh developed the theory of fuzzy sets in 1965, which serves as the mathematical foundation for fuzzy modelling. In 1994, Professor Bart Kosko demonstrated the theorem of fuzzy approximation, which states that any mathematical system may be approximated by a system that relies on fuzzy logic. Thus, fuzzy set theory allows for the representation of an arbitrary "input – output" relationship without the need for complicated mathematical methods. Fuzzy modelling is particularly beneficial when the processes under study are challenging to analyze using conventional methods [21]–[24].

The use of fuzzy modelling has proven to be effective in determining the parameters of laser processing of materials [25]–[27]. The study described in paper [27] presents the outcomes of a comparison between neural network, fuzzy, and regression models for predicting laser cutting parameters of AISI304 steel.

The present research focuses on developing and comparing the effectiveness of regression, neural network, and fuzzy models in identifying the parameters for controlled laser cleaving of silicate glasses.

1 Finite element analysis

Finite element calculations of temperature and thermoelastic stress fields that arise during controlled laser cleaving in glass plates (Figure 1.1) were performed using APDL as part of the unlinked task of thermoelasticity in a quasi-static formulation.

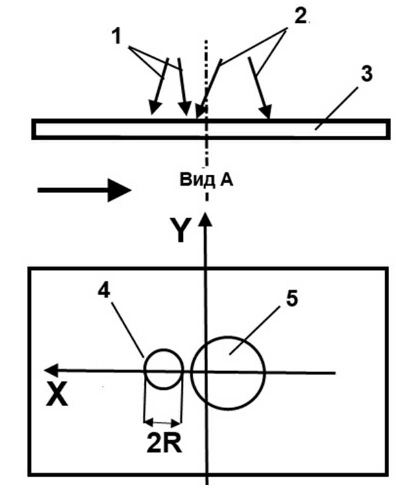

Figure 1.1 – Schematic of mutual arrangement of exposure areas to laser and refrigerant

Position 1 represents the laser beam with a wavelength of 10.6 μm, position 2 indicates the refrigerant, position 4 denotes the cross-section of the laser beam with a wavelength of 10.6 μm, and position 5 represents the refrigerant exposure area. The silicate glass plate under treatment is identified as position 3.

Calculations were performed for a plate with geometric dimensions of $35 \times 25 \times 2$ mm. The model that was created had 36960 Solid 70 elements for thermal analysis and Solid 185 elements for strength analysis. The properties of silicate glass provided in [2] were used in the modeling process. The cutting speed was assumed to be $V = 0.02$ m/s. The parameters of the laser beam with the radiation wavelength $\lambda = 10.6$ μm were as follows: the radius of the beam radiation spot $R = 0.002$ m and the radiation power $P = 10$ W.

It was assumed that the impact of the refrigerant provides cooling of the glass surface with a heat transfer coefficient equal to 8,000 W/m^{2}K. Figures 1.2 and 1.3 depict the distributions of temperature and thermoelastic stress fields that are typical of the controlled laser cleaving process applied to glass plates. For the calculated parameters, the values of maximum tensile stresses in the treatment zone σ_{yy} and maximum temperatures T are equal to 25.9 MPa and 481 K, respectively, with permissible temperature values not exceeding the glass transition temperature of 789 K [2].

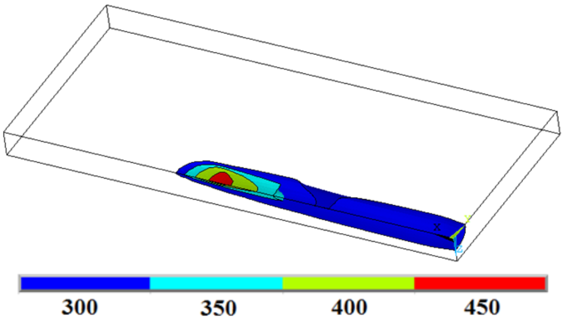

Figure 1.2 – Temperature distribution T throughout the sample's volume, ° K

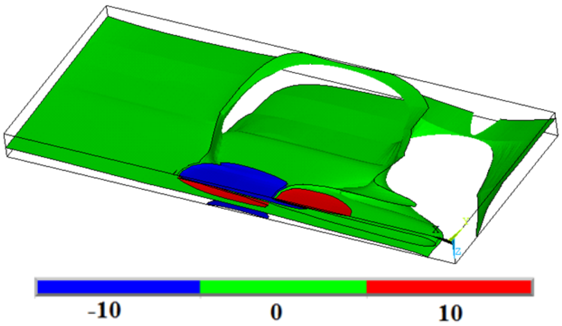

Figure 1.3 – Distribution of stresses σ_{yy} throughout the sample's volume, MPa

2 Regression model

A face-centered version of the central composite design experiment was generated in the DesignXplorer module of the ANSYS software for three factors ($P1$–$P3$): $P1$ represents the processing speed V, $P2$ represents the laser power P, and $P3$ denotes the radius of the radiation spot R of the beam. The calculations were performed for 15 combinations of input parameters, as specified by the experimental design (Table 2.1).

Table 2.1 – Experimental design and calculation results

№	$P1$ V, m/s	$P2$ P, W	$P3$ R, m	$P4$ T, °K	$P5$ σ_{yy}, MPa
1	0.03	10	0.002	481	25.9
2	0.025	10	0.002	504	30.9
3	0.035	10	0.002	464	22.0
4	0.03	5	0.002	387	12.9
5	0.03	15	0.002	576	38.8
6	0.03	10	0.0015	558	33.5
7	0.03	10	0.0025	435	20.9
8	0.025	5	0.0015	442	20.1
9	0.035	5	0.0015	412	14.2
10	0.025	15	0.0015	741	60.3
11	0.035	15	0.0015	651	42.7
12	0.025	5	0.0025	372	12.5
13	0.035	5	0.0025	358	8.9
14	0.025	15	0.0025	530	37.4
15	0.035	15	0.0025	487	26.8

The maximum temperature T in the laser-treated area and the maximum tensile stresses σ_{yy} in the treatment zone were considered as output parameters.

The response functions that establish a relationship between the input factors V, P, R and the output parameters T, σ_{yy} at a significance level of 0.05 are expressed as follows:

$$T = 538 + 62.2P - 2.81 \cdot 10^5 R + 6.74 \cdot 10^7 R^2 -$$
$$-356VP + 7.69 \cdot 10^5 VR - 12500PR,$$
$$\sigma_{yy} = -4.02 \cdot 10^5 + 8.7 \cdot 10^6 P - 3.3 \cdot 10^9 R -$$
$$-1.12 \cdot 10^8 VP + 1.12 \cdot 10^{11} VR - 1.29 \cdot 10^9 PR.$$

3 Neural network model

The creation of artificial neural networks with two hidden layers (see Figure 3.1) was implemented via the TensorFlow library in Python, following the algorithm provided in [10].

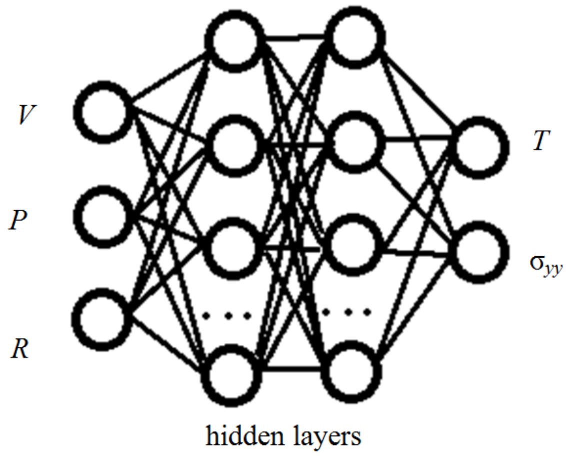

Figure 3.1 – Artificial neural network architecture

The training and test sets were generated by solving the corresponding problems using the finite element method, with 15 combinations of the central composite design experiment being supplemented by 50 combinations of calculations. Thus, the neural networks were trained using a dataset that comprised 60 combinations of controlled laser cleaving parameters. The neural networks were tested using a sample of 5 parameter combinations (see Table 3.1). It is important to mention that this test dataset was also used to assess regression and fuzzy models.

Table 3.1 – Test dataset

№	$P1$ V, m/s	$P2$ P, W	$P3$ R, m	$P4$ T, °K	$P5$ σ_{yy}, MPa
1	0.033	12.9	0.0025	466	24.5
2	0.026	7.3	0.0015	506	28.2
3	0.025	10.7	0.002	518	33.1
4	0.03	8.9	0.002	461	23
5	0.029	9.3	0.002	472	24.9

The Adam optimizer, ReLU activation function, and *MSE* loss function were used in the process of constructing the artificial neural networks. The neural network underwent training for a total of 500 epochs. As a result, 16 artificial neural networks were created with the number of neurons in two hidden layers ranging from 5 to 20, with an interval of 5.

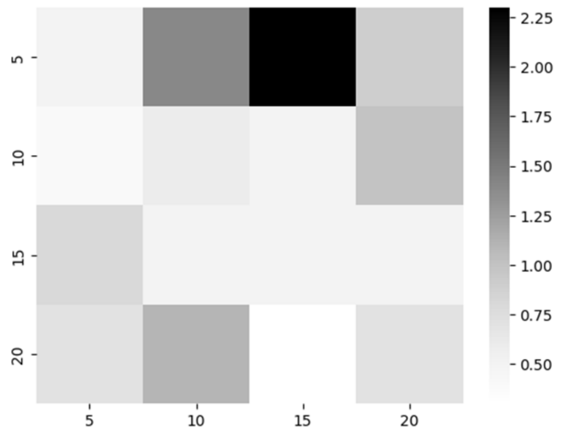

Figure 3.2 – Heat map of *MAPE* distribution when determining *T*

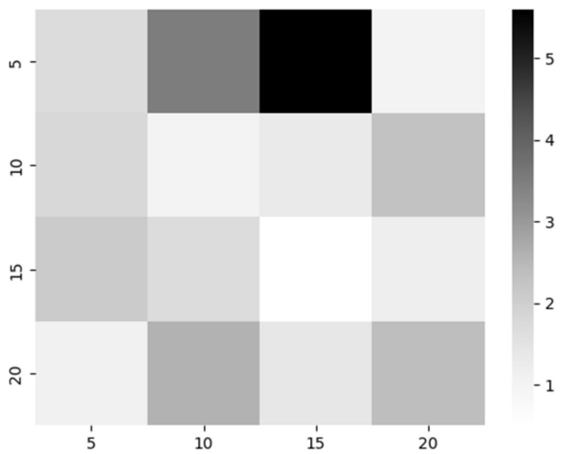

Figure 3.3 – Heat map of *MAPE* distribution when determining σ_{zz}

Figures 3.2 and 3.3 illustrate heat maps of the distribution of mean absolute percentage errors (*MAPE*) in determining the maximum values of temperature and tensile stresses during the controlled laser cleaving of glass plates. The vertical axis represents the number of neurons in the first hidden layer, while the horizontal axis shows the number of neurons in the second hidden layer of the neural network. The intensity of color coding represents the extent of error: the error increases from light to dark.

The neural network with the architecture [3-20-15-2] demonstrated superior performance in predicting the values of maximum temperatures *T* in the treatment zone, whereas the neural network with the architecture [3-15-15-15-2] achieved the highest accuracy in calculating the maximum tensile stresses σ_{yy}.

4 Fuzzy model

The fuzzy system depicted in Figure 4.1 was employed to do fuzzy modelling of the controlled laser cleaving process on silicate glasses. The fuzzy system was implemented using the Scikit-Fuzzy library in Python.

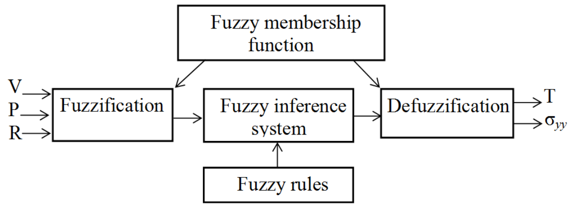

Figure 4.1 – Structure of the fuzzy system employed to simulate controlled laser cleaving

Fuzzification is the procedure of converting exact input variables into fuzzy variables via appropriate membership functions. This paper employed triangular functions to specify the membership of input parameters to fuzzy sets, whereas Gaussian functions were used to define the membership of output parameters to fuzzy sets (Figure 4.2). The following linguistic variables were defined for the input and output parameters.

Input parameters:

V = { L – little, M – medium, H – high};

P = { L – little, M – medium, H – high};

R = { L – little, M – medium, H – high}.

Output parameters:

T = { VVL – very very little, VL – very little, L – little, M – medium, VH – very high, VVH –very very high};

σ_{yy} = { VVL – very very little, VL – very little, L – little, M – medium, VH – very high, VVH – very very high}.

```
rule1 = ctrl.Rule(V['L'] & P['L'] & R['L'],
T_ctrl['V_L'])
rule2 = ctrl.Rule(V['L'] & P['L'] & R['H'],
T_ctrl['VV_L'])
rule3 = ctrl.Rule(V['L'] & P['M'] & R['M'],
T_ctrl['M'])
rule4 = ctrl.Rule(V['L'] & P['H'] & R['L'],
T_ctrl['VV_H'])
rule5 = ctrl.Rule(V['L'] & P['H'] & R['H'],
T_ctrl['M'])
rule6 = ctrl.Rule(V['M'] & P['L'] & R['M'],
T_ctrl['VV_L'])
rule7 = ctrl.Rule(V['M'] & P['M'] & R['L'],
T_ctrl['H'])
rule8 = ctrl.Rule(V['M'] & P['M'] & R['M'],
T_ctrl['L'])
rule9 = ctrl.Rule(V['M'] & P['M'] & R['H'],
T_ctrl['V_L'])
rule10 = ctrl.Rule(V['M'] & P['H'] & R['M'],
T_ctrl['H'])
rule11 = ctrl.Rule(V['H'] & P['L'] & R['L'],
T_ctrl['V_L'])
rule12 = ctrl.Rule(V['H'] & P['L'] & R['H'],
T_ctrl['VV_L'])
rule13 = ctrl.Rule(V['H'] & P['M'] & R['M'],
T_ctrl['L'])
rule14 = ctrl.Rule(V['H'] & P['H'] & R['L'],
T_ctrl['V_H'])
rule15 = ctrl.Rule(V['H'] & P['H'] & R['H'],
T_ctrl['L'])
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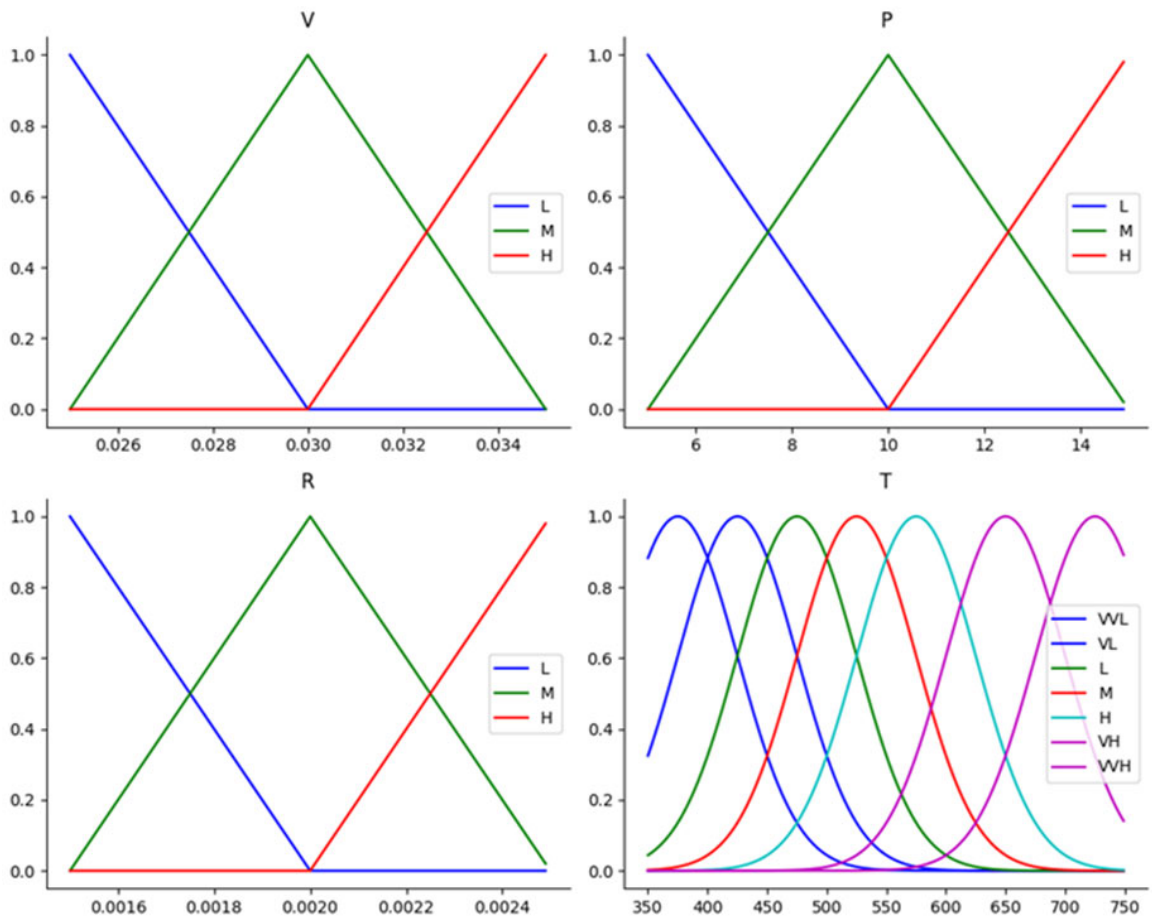

Figure 4.2 – Membership functions of linguistic variables of input and output parameters

The fuzzy inference process is an algorithm used to derive fuzzy conclusions from fuzzy rules. Mamdani fuzzy inference method was used in the fuzzy modeling of controlled laser cleaving, primarily selected for its versatility and simplicity.

Based on the data provided in Table 2.1, a total of 15 rules were derived to ascertain the maximum temperatures in the treatment zone:

Similarly, a set of 15 rules were developed to determine the values of maximum tensile stresses σ_{yy} within the treatment zone.

In order to complete the fuzzy modeling process for the controlled cleaving of silicate glasses involving the center of gravity method, defuzzification was performed to produce numerical values for the output variables.

3 Results and discussion

The following criteria were used to evaluate the resulting regression, neural network and fuzzy models:

– Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(d_i - y_i\right)^2}, \quad (3.1)$$

– Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|d_i - y_i\right|, \quad (3.2)$$

– Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{d_i - y_i}{d_i}\right| \cdot 100. \quad (3.2)$$

Here, d_i represents the calculated values determined via the finite element method as a result of a numerical experiment, while y_i stands for the model values obtained on the basis of regression, neural network and fuzzy models.

The values of criteria (3.1)–(3.3) used for evaluating the models are given in Table 3.1.

Table 3.1 – Evaluation results of regression, neural network and fuzzy models

Criterion	Regression model		Neural network model		Fuzzy model	
	T	σ_{yy}	T, K	σ_{yy}	T	σ_{yy}
RMSE	3.2	1.12	1.9	0.19	14.6	1.9
MAE	2.4	1.11	1.4	0.15	13.2	1.5
MAPE	0.5%	4.3%	0.3%	0.5%	2.7%	5.4%

The evaluation results of the produced models enable us to draw conclusions regarding the required correspondence with the results of finite element calculations. Meanwhile, the *MAPE* values for determining maximum temperatures and tensile stresses in the laser-treated area were the lowest for neural network models. These values were 0.3% for temperatures (T) and 0.5% for tensile stresses (σ_{yy}), respectively. The neural network models exhibited lower values of *RMSE* and *MAE* compared to the corresponding criteria of regression and fuzzy models. Hence, neural network models exhibit superior accuracy in predicting the parameters of the controlled laser cleaving of glass plates.

Conclusion

The study addresses the solution to the applied research problem of predicting the characteristics of laser cleaving of silicate glasses through mathematical modelling. A numerical experiment in APDL (Ansys Parametric Design Language) has been performed for silicate glass. The processing speed, radius, and power of the laser beam were considered as variable factors, whereas the maximum temperature and thermoelastic tensile stresses in the laser-treated area were regarded as responses.

Regression models of the dependence of the maximum temperature T and thermoelastic tensile stress σ_{yy} on the processing speed, radius, and power of the laser beam at a specified significance level of 0.05 were estimated following the results of the face-centered version of the central composite design of the three-factor experiment.

An artificial neural network with two hidden layers was created to predict the maximum values of temperature and tensile stress in the treatment zone while performing controlled laser cleaving of glass plates. The most optimal neural network models were determined based on the heat maps of *MAPE* distribution.

The study employs fuzzy logic to construct a model for estimating the output parameters (maximum temperature and thermoelastic tensile stress) in the area where laser cleaving of glass occurs. This estimation takes place for a set of initial input parameters such as processing speed, radius and power of the laser beam. Triangular functions were employed for the fuzzification of input parameters, while Gaussian membership functions were utilized for the output parameters. The rule base (15) of fuzzy inference systems was developed based on the experimental data. Mamdani method served as the foundation for fuzzy inference. The defuzzification process resulted in obtaining numerical values for the output parameters.

An evaluation was conducted to compare the outcomes of regression, neural network, and fuzzy modelling using accuracy criteria such as *RMSE, MAE*, and *MAPE*. Neural network modeling provided the lowest values of approximation criteria for both experimental and simulated values.

The models that have been developed are suitable for practical application in approximating the maximum temperature and thermoelastic tensile stress in the laser-treated area while performing the controlled laser cleaving of glass plates in various experiments.

REFERENCES

1. *Lumley*, *R.M.* Controlled separation of brittle materials using a laser / R.M. Lumley // Am. Ceram. Soc. Bull. – 1969. – Vol. 48. – P. 850–854.

2. *Machulka*, *G.A.* Laser processing of glass / G.A. Machulka. – Moscow: Sov. radio, 1979. – 136 p. (In Russian)

3. *Nisar*, *S.* Laser glass cutting techniques – A review / S. Nisar // Journal of laser applications. – 2013. – Vol. 25, № 4. – P. 042010-1–11.

4. *Kondratenko*, *V.S.* Precision Cutting of Glass and Other Brittle Materials by Laser-Controlled Thermo-Splitting (Review) / V.S. Kondratenko, S.A. Kudzh // Glass Ceram. – 2017. – Vol. 74. – P. 75–81. – DOI: https://doi.org/10.1007/s10717-017-9932-1.

5. *Nikityuk*, *Yu.V.* Physical regularities of laser thermal cleaving of silicate glasses and alumina ceramics: specialty 01.04.21 “Laser physics”: PhD thesis extended abstract / Nikityuk Yuri Valerievich. – Minsk, 2009. – 24 p. (in Russian)

6. *Golovko*, *V.A.* Neural network data processing technologies: textbook / V.A. Golovko, V.V. Krasnoproshin. – Minsk: BSU, 2017. – 263 p. (in Russian).

7. *Chollet*, *F.* Deep Learning with Python / F. Chollet. – Manning Publications Co., 2018. – 400 p.

8. *A review on applications of artificial intelligence in modeling and optimization of laser beam machining* / A.N. Bakhtiyari, Z. Wang, L. Wang, H. Zheng // Optics & Laser Technology. – 2021. – Vol. 135. – P. 1–18.

9. *Comparison of ANN and finite element model for the prediction of thermal stresses in diode laser cutting of float glass* / M.B. Kadri, S. Nisar, S.Z. Khan, W.A. Khan // Optik – Int. J. Light Electron Optics. – 2015. – Vol. 126, № 19. – P. 1959–1964.

10. *Nikityuk*, *Yu.V.* Determination of the parameters of two-beam laser splitting of silicate glasses using regression and neural network models / Yu.V. Nikityuk, A.N. Serdyukov, I.Yu. Aushev // Journal of the Belarusian State University. Physics. – 2022. – Vol. 1. – P. 35–43. – DOI: https://doi.org/ 10.33581/2520-2243-2022-1-35-43

11. *Application of artificial neural networks and finite element method for determining parameters of quartz sol-gel glass processing by elliptical laser beams* / Yu.V. Nikityuk, A.N. Serdyukov, V.A. Prokhorenko, I.Yu. Aushev // Problems of

Physics, Mathematics and Technics. – 2021. – № 3 (48). – P. 30–36. (In Russian).

12. *Nikityuk*, *Yu.V.* Optimization of two-beam laser cleavage of silicate glass / Y.V. Nikityuk, A.N. Serdyukov, I.Yu. Aushev // Journal of Optical Technology. – 2022. – Vol. 89, № 2. – P. 121–125. – DOI: 10.1364/JOT.89.000121.

13. *Nikityuk*, *Yu.V.* Optimization of laser splitting parameters of silicate glasses with elliptical beams in the plane of parallel surface / Yu.V. Nikityuk, A.N. Serdyukov, I.Yu. Aushev // Vestnik of the Sukhoi State Technical University of Gomel. – 2023. – № 3. – P. 17–27.

14. *Nikityuk*, *Yu.V.* Optimization of laser cleaving of silicate glasses with elliptical beams using fracture mechanics parameters / Yu.V. Nikityuk, I.Yu. Aushev // Problems of Physics, Mathematics and Technics. – 2023. – № 4 (57). – P. 36–41.

15. *Nikityuk*, *Yu.V.* Determination of the Parameters of Controlled Laser Thermal Cleavage of Crystalline Silicon Using Regression and Neural Network Models / Yu.V. Nikityuk, A.N. Serdyukov // Crystallography Reports. – 2023. – Vol. 68, № 7. – P. 195–200.

16. *Parametric optimization of silicate-glass-based asymmetric two-beam laser splitting* / Yu.V. Nikityuk, A.A. Sereda, A.N. Serdyukov, S.V. Shalupaev, I.Yu. Aushev // Journal of Optical Technology. – 2023. – Vol. 90, № 6. – P. 296–301. – DOI: https://doi.org/10.1364/JOT.90.000296.

17. *Nikityuk*, *Yu.V.* Optimization of laser cleaving of silicate glasses by elliptical beams under additional influence of hot air flow / Yu.V. Nikityuk, A.N. Serdyukov, I.Yu. Aushev // Proceedings of F. Skorina Gomel State University. – 2023. – № 6 (141). – P. 110–116. (in Russian)

18. *Optimisation of parameters for laser cleaving of silicate glasses using U-shaped beams* / Yu.V. Nikityuk, A.N. Serdyukov, J. Ma, L. Wang, I.Y. Aushev // Vestnik of the Sukhoi State Technical University of Gomel. – 2023. – № 4. – P. 30–39.

19. *Multiparametric optimization of laser cutting of steel sheets* / A.E. Gvozdev, I.V. Golyshev, I.V. Minaev, N.N. Sergeev, I.V. Tikhonova, D.M. Khonelidze, A.G. Kolmakov // Inorganic Materials: Applied Research. – 2015. – Vol. 6, № 4. – P. 305–310.

20. *Madić*, *M.* Comparative modeling of CO_2 laser cutting using multiple regression analysis and artificial neural network, International Journal of Physical Sciences / M. Madić, M. Radovanović // International Journal of Physical Sciences. – 2012. – Vol. 7 (16). – P. 2422–2430.

21. *Emelyanov*, *S.G.* Automated fuzzy-logical control systems: Monograph / S.G. Emelyanov, V.S. Titov, M.V. Bobyr. – Moscow: INFRA-M, 2011. – 176 p.

22. *Klir*, *G.* Fuzzy sets and fuzzy logic / G. Klir, B. Yuan. – New Jersey: Prentice hall, 1995. – 574 p.

23. *Rutkovskaya*, *D.* Neural networks, genetic algorithms and fuzzy systems / D. Rutkovskaya, M. Pilinski, L. Rutkovsky. – Moscow: Goryachaya Liniya-Telecom, 2013. – 384 p. (In Russian)

24. *Shtovba*, *S.D.* Design of fuzzy systems by means of MATLAB / S.D. Shtovba. – Moscow, Goryachaya Liniya, 2007. – 284 p. (in Russian)

25. *Bakhtiyari*, *A.N.* A review on applications of artificial intelligence in modeling and optimization of laser beam machining / A.N. Bakhtiyari // Optics & Laser Technology. – 2021. – Vol. 135. – P. 106721.

26. *Fuzzy Logic Approach for the Prediction of Dross Formation in* CO_2 *Laser Cutting of Mild Steel* / M. Madić [et al.] // Journal of Engineering Science & Technology Review. – 2015. – Vol. 8, № 3. – P. 143–150.

27. *Madić*, *M.* Comparison of fuzzy logic, regression and ANN laser kerf width models / M. Madić, Ž. Ćojbašić, M. Radovanović // UPB Scientific Bulletin, Series D: Mechanical Engineering. – 2016. – Vol. 78. – P. 197–212.

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