Multi-Criteria Optimization of Quartz Glass Laser Cleaving Parameters via Neural Network Simulation and Genetic Algorithm

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***Abstract*— The current paper uses neural network modeling and a genetic algorithm to determine the values of technological parameters that ensure effective laser cleaving of quartz glass when exposed to a laser beam with a wavelength equal to 10.6 µm and a refrigerant. Multi-criteria optimization of laser cleaving of quartz plates was performed according to the criteria of maximum tensile stresses and maximum processing speed.**

Keywords—neural network, genetic algorithm, laser cleaving, optimization

I. Introduction

The main methods of separating brittle nonmetallic materials are cutting with diamond discs, mechanical and laser scribing. Another effective method of cutting such materials, including quartz glass, is controlled laser cleaving. The implementation of this technology is based on the formation of a certain spatial localization of thermoelastic stresses in the processed material, which ensures the formation of a separating crack with specified parameters The advantages of this technology include high accuracy and high speed of laser-induced cuts [1-3].

Currently, artificial neural networks are successfully used for modeling the laser processing of materials [4-6]. An important way to improve the efficiency of laser technology application is to optimize the corresponding technological parameters. The examples of optimization implementation including the use of genetic algorithms are presented in [7–9]. Genetic algorithms are a special case of evolutionary methods, which are based on collaborative learning within a population and use simulation of natural selection. Genetic algorithms provide the search for better solutions by inheriting and enhancing beneficial properties of many objects in the process of simulating their evolution [10].

This paper uses neural network simulation and the authors' version of the modified genetic algorithm (MGA) to perform a multi-criteria optimization of laser cleaving of quartz plates [11].

II. Neural Network Aproximation

The calculations of temperature fields and thermoelastic stress fields performed in [6] were used to generate the data for training and validating neural networks. The total number of samples was 875. All data were normalized and adjusted to specific range [0;1]. The following factors were used in the problem under consideration: V is the cutting speed, A and B are the semi-axes of the elliptical laser beam, P is the power of the laser radiation. The following responses were selected for study: σ_{yy} — the maximum tensile stresses, T — the maximum temperature. This study involved the construction of neural network approximators for the parameters σ_{yy} and T.

When addressing problems through the use of neural network simulation tools, a crucial consideration relates to the selection of an appropriate neural network architecture. The process of choosing the appropriate neural network architecture in each case is complex. The simplest approach to handling this issue is to implement a search scheme that explores several candidate architectures and assesses their effectiveness in resolving the specific problem via cross-validation.

The procedure for identifying the optimal neural network architecture through a search process encompasses the subsequent stages:

1) Preparation of input data for training and validating neural networks.

2) The process of generating a set of architectures and corresponding candidate models for the purpose of conducting a search.

3) Training and cross-validation of neural network models.

4) Selection of the optimal architecture based on the specified criteria following the calculated cross-validation metrics.

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Neural networks as well as their training algorithms and cross-validation algorithms are implemented using the Keras library in Python.

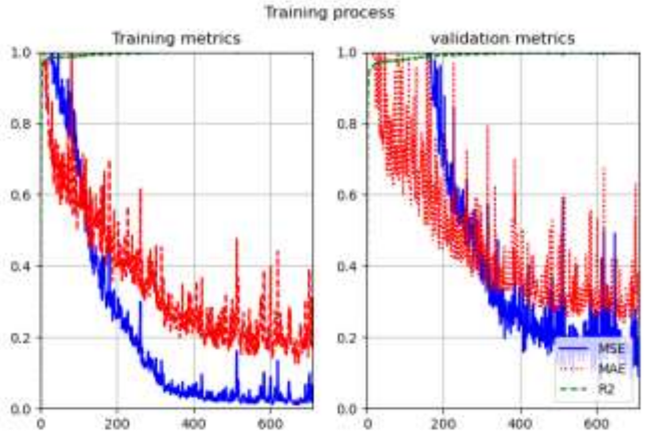

Fig. 1. Example of training and validation metrics (MSE, MAE, R^2) changes when training a model-candidate for σ_{yy} approximation within a single cross-validation experiment

Three-layer perceptrons of different configurations were compared to select optimal neural network architectures for approximating σ_{yy} and T responses. The number of neurons in the first and second hidden layers was searched in the range of 8 to 96 with an incremental step-size 4. A five-fold cross-validation procedure was conducted for each candidate architecture, whereby the input data were divided into five subsets and randomly mixed prior to analysis. The metrics MSE (mean square error), MAE (mean absolute error), R^2 (determination coefficient) were averaged over all experiments. Figure 1 depicts a typical example when the metrics of a neural network model undergo modifications throughout the training process.

Figures 2 and 3 present the heat maps depicting the distributions of MSE and R^2 values for the approximators of σ_{yy} and T, respectively. The horizontal axis represents the number of neurons in the first hidden layer, while the vertical axis denotes the number of neurons in the second hidden layer. Table 1 provides examples of metric values for the most optimal architectures of the σ_{yy} response approximator.

TABLE I. VALUES OF MSE, MAE AND R^2 METRICS FOR THE MOST OPTIMAL CANDIDATE ARCHITECTURES OF THE σ_{yy} APPROXIMATOR..

Neural network architecture	***MSE***	***MAE***	***R^2***	***Number of epochs***
[88-84-1]	4.103e-05	0.00267	0.9969	608.04
[88-88-1]	4.138e-05	0.00266	0.9968	595.88
[96-76-1]	4.490e-05	0.00287	0.996	559.4

The numerical experiments revealed that the artificial neural network with [64-56-1] architecture provides the most accurate results when approximating σ_{yy}, and the artificial neural network with [88-84-1] architecture shows the best results when approximating temperature T.

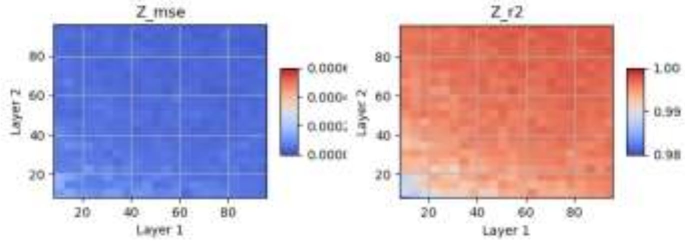

Fig. 2. Temperature maps showing MSE (left) and R^2 (right) distributions for the cross-validated σ_{yy} approximators (x axis represents number of neurons in the first hidden layer, y axis represents number of neurons in the second hidden layer)

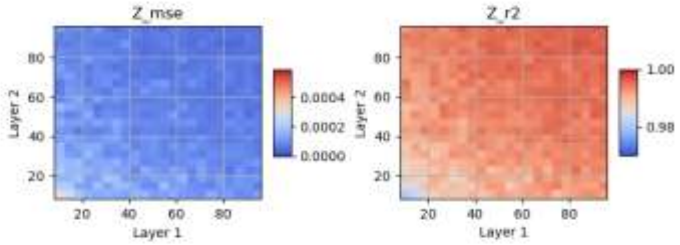

Fig. 3. Temperature maps showing MSE (left) and R^2 (right) distributions for the cross-validated T approximators (x axis represents number of neurons in the first hidden layer, y axis represents number of neurons in the second hidden layer)

III. DETERMINING THE OPTIMAL PARAMETERS FOR THE LASER CLEAVING PROCESS OF QUARTZ PLATES

Using neural networks with architectures [64-56-1] for approximating σ_{yy} and [88-84-1] for approximating T, a search was conducted for the values of factors that provide the maximal values of stresses σ_{yy} provided $V \to$ max and under the temperature constraint $T<1473\ K$. Restrictions were also imposed on factor values going outside the ranges in the training set of neural network approximators.

The authors' version of the modified genetic algorithm (MGA) was developed in Python [11]. The process of creating further generations of the population was derived from the genome crossing technique outlined in reference [11]. Additionally, genome mutation was achieved by introducing random changes in factors within the range of [0.0001,0.1] with the probability $p = 0.5$.

The objective function included the σ_{yy} and T values and the V factor predicted by neural network approximators. Furthermore, penalties were included for exceeding permissible ranges of factors and maximum temperature values:

$$L(A,B,V,P) = -(\alpha_1\sigma_{yy} + \alpha_2 V) + \beta_1 E_1 + \beta_2 E_2 + \beta_3 E_3 + \beta_4 E_4 + \beta_5 E_5,$$

$$E_1 = \{1, A \notin [0,1]\ 0, A \in [0,1]\ , E_2 = \{1, B \notin [0,1]\ 0, B \in [0,1]\ , E_3 = \{1, V \notin [0,1]\ 0, V \in [0,1]\ , E_4 = \{1, P \notin [0,1]\ 0, P \in [0,1]\ ,$$

$$E_5 = \{1, T \geq 1473K\ 0, T < 1473K\ ,$$

$$\alpha_1 = \alpha_2 = 0.5, \beta_i = 1.0,\ i = \underline{1,5}$$

An alternative objective function is also considered:

$$L(A,B,V,P) = -\sqrt{((\alpha_2\sigma_{yy})^2 + (\alpha_2 V)^2)} + \beta_1 E_1 + \beta_2 E_2 + \beta_3 E_3 + \beta_4 E_4 + \beta_5 E_5,$$

$$E_1 = \{1, A \notin [0,1]\ 0, A \in [0,1]\ , E_2 = \{1, B \notin [0,1]\ 0, B \in [0,1]\ , E_3 = \{1, V \notin [0,1]\ 0, V \in [0,1]\ , E_4 = \{1, P \notin [0,1]\ 0, P \in [0,1]\ ,$$
$$E_5 = \{1, T \geq 1473K\ 0, T < 1473K\ ,$$
$$\alpha_1 = \alpha_2 = 0.5, \beta_i = 1.0,\ i = \underline{1,5}$$

Figure 4 depicts the process of multi-criteria optimization using the authors' genetic algorithm. The graph illustrates a monotonic decrease in the values of the objective function (solid line) for the best genome within the population denoted by points (A,B,V,P). The increase in the average value of the objective function over the population (dashed line) at the conclusion of the algorithm operation can be attributed to the genomes approaching the specified boundaries (especially by temperature) and, consequently, to the output penalties $\beta_i E_i$. No significant difference in the convergence rate and quality of the algorithms was found when comparing the provided objective functions.

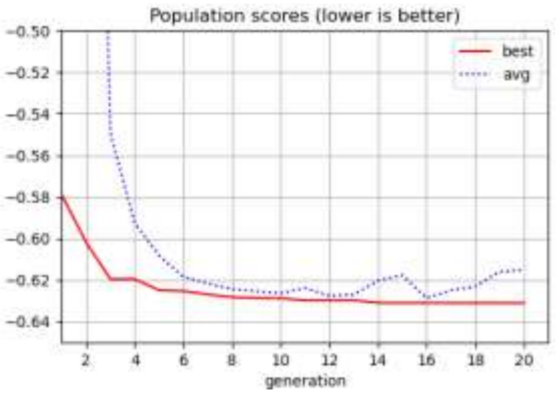

Fig. 4. The convergence procedure of the genetic algorithm when solving the problem of multicriteria optimisation of quartz plate cleaving parameters.

The use of genetic algorithms led to the identification of the optimal values of the factors, as presented in Table 2. A finite element calculation was conducted to investigate the laser cutting process of a quartz plate with the optimal values of the factors. It is demonstrated that the values of stress σ_{yy} and temperature T established by the approximators and MGA are determined with errors of 0.1% and 2.5%, respectively.

TABLE II. MULTICRITERIA OPTIMIZATION RESULTS.

V mm/s	*A mm*	*B mm*	*P W*	*T K*	*σ_{yy}, MPa*
70	1.4	0.8	299	1471	7.2

V mm/s	*A mm*	*B mm*	*P W*	*T K*	*σ_{yy}, MPa*
69.9	1.35	0.8	299.9	1472.45	7.24
				(1435.31)	(7.23)

(нижняя таблица содержит результаты из ПМФТ, вторая строка – проверенные в ансисе значения. верхняя – из тезисов, более ранние результаты – В.П.)

IV. CONCLUSION

This study presents a multicriteria optimization of the responses of the laser cutting process for quartz plates using neural network simulation. The optimal values of laser cutting factors for quartz plates have been determined and the correspondence between the model and the results of finite element analysis has been established. A search method with cross-validation was used to describe the algorithms for selecting the optimal neural network architecture. The optimal neural network architectures have been determined for approximating the maximum of tensile stresses and the maximum of temperature when performing laser cutting of quartz plates.

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