Optimization of the Parameters Technological Operation of Laser Cutting of Silicate Glass Using a Genetic Algorithm and Neural Networks

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***Abstract*—This paper presents the process of numerical modeling and optimization of the dual-beam laser cleaving process for silicate glasses. Technological parameters enabling effective separation of glass plates under the action of two laser beams are identified. Temperature fields and thermoelastic stresses were computed using the finite element method in a quasi-static formulation, implemented in Python with the FEniCS library. Process optimization was carried out using a modified genetic algorithm, with the objectives of maximizing tensile stress and processing speed. The varied parameters included laser power, processing speed, and laser spot radius (wavelength 10.6 µm). The responses considered were the maximum temperatures and stresses within the laser-affected zone. A regression model of the process was developed. The error of the results when using a neural network approximation did not exceed 4% for temperature and 5% for stress. The paper also describes a real-time adaptive control approach based on neuroregulators, which ensures high precision and stability of the processing operation.**

***Keywords*—control adaptation system, neural network modeling, synthesis of the structure of the neuroregulator, stabilization of the parameters of a technological operation**

I. Introduction

One of the promising methods for the separation of silicate glasses is laser cleaving, which relies on the controlled formation of a crack induced by localized thermal loading from laser irradiation, followed by rapid cooling of the processing zone using a coolant [1–3]. This thermomechanical approach ensures high precision and cleanliness of the cut, while also enhancing the mechanical strength of the resulting components. In a range of technological applications, the effectiveness of this method is significantly improved by employing dual-beam laser configurations, which allow for optimization of the temperature-stress distribution in the interaction zone.

A key direction in enhancing the efficiency of laser processing technologies lies in the optimization of process parameters. In this context, artificial intelligence methods—particularly genetic algorithms—have gained considerable relevance due to their ability to effectively search for the global optimum of objective functions [4]. Genetic algorithms are based on the principles of natural selection and evolution, incorporating mechanisms of inheritance, mutation, and selection, which impart an adaptive character to the search process and strong resilience against local minima.

However, even when optimal parameters are determined during the planning stage, the actual technological process remains susceptible to a variety of external and internal disturbances, including instability of the laser sources, fluctuations in the properties of the processed material, and environmental influences. Under such conditions, the development of adaptive control systems capable of responding in real time to changes in both external and internal environments becomes a critical challenge for ensuring the stability and reproducibility of laser processing outcomes [5].

An adaptive control approach based on the use of neuroregulators has been developed, enabling corrective actions to be applied to a set of control variables within the technological process. The system operates under conditions of external control actions and random disturbances, maintaining the stability of laser cutting parameters.

II. Finite Element Analysis

To determine the temperature field and the distribution of thermoelastic stresses arising during dual-beam laser cleaving of silicate glass (Figure 1), a computational program was developed in a quasi-static formulation within the framework of an uncoupled thermoelasticity problem. Numerical modeling was performed using the Python programming language and the open-source finite element library FEniCS [6].

The initial simulations were carried out for a glass plate with geometric dimensions of 30×40×4 mm. For thermal and mechanical analysis, a finite element model was constructed, consisting of approximately 25,520 elements. Optimization of the technological parameters was performed according to a defined algorithmic sequence, employing multi-objective optimization methods [7].

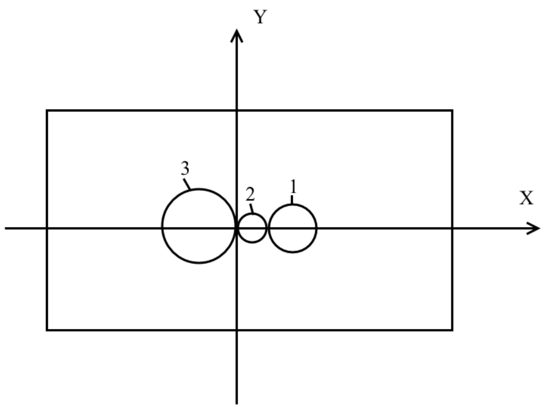

Fig. 1. Scheme of the laser cutting process, top view: 1 – zone affected by laser with a wavelength of 10.6 µm, 2 – zone affected by laser with a wavelength of 1.06 µm, 3 – zone affected by refrigerant; the laser beam and coolant spot move from left to right.

The factors influencing the considered technological process include:

- the movement speed of the laser beams and the coolant (v);
- the power of the laser with a wavelength of 10.6 µm (P_0);
- the power of the laser with a wavelength of 1.06 µm (P_1);
- the beam spot radius of the 10.6 µm wavelength laser (R_0);
- the coolant spot radius (R_2);
- the beam spot radius of the 1.06 µm wavelength laser (R_1).
- The process responses (target characteristics) considered were:
- the maximum tensile stress (σ_{yy});
- the maximum temperature in the processing zone (T_{max}).

The beam spot radius of the laser with a wavelength of 1.06 µm was fixed at 1 mm. The coolant spot radius was also set to 1 mm. The remaining factors were subject to optimization by the genetic algorithm. For this purpose, neural network approximators were constructed. A total of 375 finite element simulation experiments were conducted, in which the values of the variable factors were varied within the following ranges:

- movement speed of the laser beams and coolant: 0.005–0.05 m/s;
- power of the 10.6 µm wavelength laser: 4–20 W;
- power of the 1.06 µm wavelength laser: 20–80 W;
- beam spot radius of the 10.6 µm wavelength laser: 1–4 mm.

III. Neural Network Approximation of Responses

During the simulation stage, data were collected to train neural network approximators for the response values of maximum temperature and tensile stress in the processing zone. Multilayer perceptron (MLP) architectures were employed for this task. The neural network models were developed using the open-source Keras library in Python.

Optimal network architectures were selected based on training followed by cross-validation of candidate three-layer models, evaluated using the mean squared error (MSE) and the coefficient of determination (R^2) as performance metrics. The architectures considered included three layers, with varying numbers of neurons in the first and second hidden layers [8].

Figure 2 presents heatmaps of the average MSE values for the neural network approximators of maximum tensile stress (left) and maximum temperature in the processing zone (right). Based on the numerical experiments, the architectures 120-60-1 (for maximum tensile stress) and 100-80-1 (for maximum temperature) were selected as optimal. Figure 3 shows the evolution of model evaluation metrics during the training process of the neural network approximators. Figure 3 shows changes in metrics when neural network approximator is trained.

IV. Optimization of Process Parameters

In the optimization of process parameters for dual-beam laser glass cleaving using a multi-objective genetic algorithm, the number of individuals in the initial population and per generation was set to 250. The objective function of the genetic algorithm incorporated two criteria: maximizing tensile stress and maximizing processing speed. The optimization was constrained by two conditions: (1) the values of the process parameters must remain within the ranges used for training the neural network approximators, and (2) the thermal conditions of laser-induced thermal cleaving of silicate glass must be maintained, specifically with a maximum temperature not exceeding 789 K.

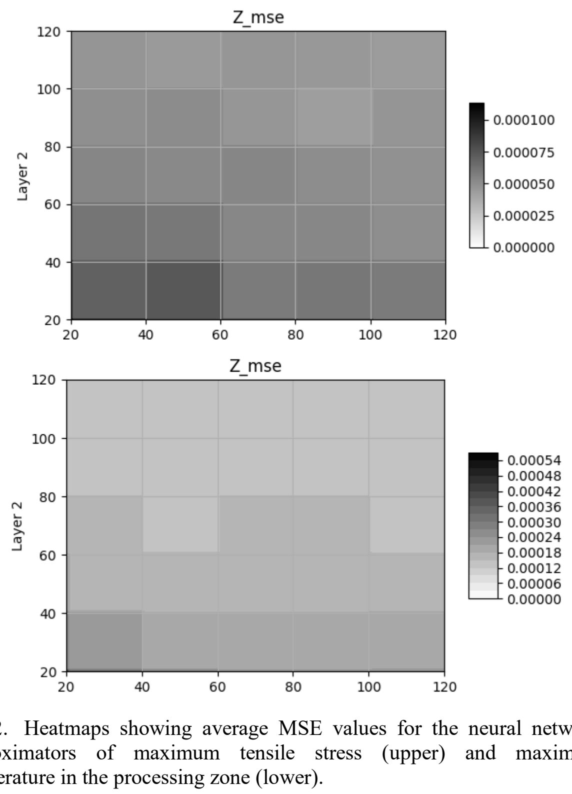

Fig. 2. Heatmaps showing average MSE values for the neural network approximators of maximum tensile stress (upper) and maximum temperature in the processing zone (lower).

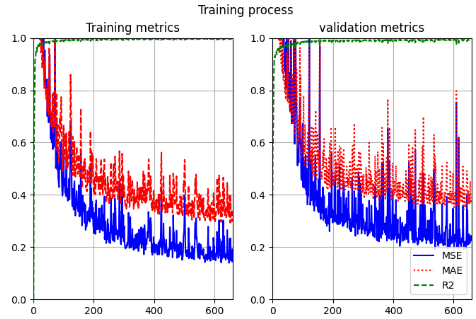

Fig. 3. Metrics of a neural network approximator during training.

The optimization results are presented in Table 1. The values in parentheses represent the parameters obtained from finite element simulations. The maximum relative error in the results obtained using the genetic algorithm with neural network approximation did not exceed 4% for temperatures and 5% for thermoelastic stresses.

TABLE I. OPTIMIZATION RESULTS

P_0	P_1	R_1	σ_{yy}	T_{max}
15.8	79.7	0.0032	125 MPa	776 K
			(126.3 MPa)	(748 K)

V. ADAPTIVE CONTROL OF THE DUAL-BEAM LASER CLEAVING PROCESS

The algorithm for constructing the neuroregulator [5] includes the following sequence of steps: the user defines a system of adaptation quality criteria, followed by model training and validation based on a sample dataset. The adaptation quality criterion focuses on ensuring the stability of the technological process, which entails preventing the controlled parameters from exceeding the permissible ranges while simultaneously maintaining the maximum values of processing speed and tensile thermoelastic stresses in the affected zone.

To build the neuroregulator, reinforcement learning algorithms were used, which allow for the consideration of user-defined adaptation quality criteria [9-10]. A simulation model [5] based on the constructed neuroregulators was employed as the environment for reinforcement learning. The dynamics of the average adaptation quality evaluation function are shown in Figure 4.

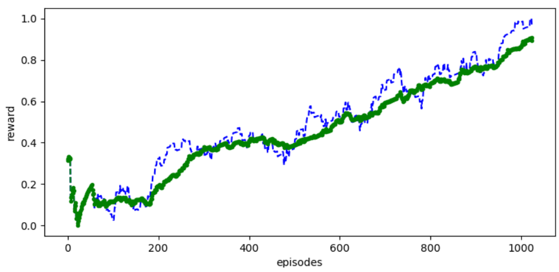

Fig. 4. Dynamics of the average adaptation quality evaluation function.

VI. CONCLUSION

A computational model was developed using the finite element method in a quasi-static formulation and the FEniCS library, allowing the determination of temperature fields and thermoelastic stresses in the laser-affected zone. Within the framework of multi-objective optimization, implemented through a modified genetic algorithm, the technological parameters that ensure effective separation of silicate glass plates were identified. The optimization was performed based on the criteria of maximizing tensile stresses and processing speed, while varying laser power, movement speed, and laser spot radius.

Based on the numerical calculations, a regression model was constructed, the adequacy of which was confirmed by comparing with the results of neural network approximation, demonstrating errors of no more than 4% for temperature and 5% for stresses. Furthermore, an approach to adaptive control of the technological process in real time using neuroregulators was proposed and implemented. The developed system ensures the stabilization of laser cutting parameters in the presence of external and internal disturbances.

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