Determination and optimization of the parameters of the technological operation of two-beam laser cutting of silicate glass using a genetic algorithm and neural networks

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***Abstract**. This work investigates the numerical modeling and optimization of dual-beam laser cleaving for silicate glasses. Thermoelastic stresses and temperature fields were computed via quasi-static finite element analysis using FEniCS. A modified genetic algorithm optimized laser power, speed, and spot radius to maximize tensile stress and processing speed. Neural network approximations yielded errors below 4% for temperature and 5% for stress. A real-time adaptive control method based on neuroregulators was developed to maintain processing precision and stability.*

I. Introduction

Laser cleaving of silicate glasses relies on localized thermal loading and rapid cooling to induce controlled cracks, offering high precision and structural integrity [1–3]. Dual-beam laser setups enhance process efficiency by improving temperature-stress distribution. Optimization of processing parameters using genetic algorithms allows effective global search for maximum performance [4]. Despite optimal preplanning, external and internal disturbances—such as laser instability and material variability—can compromise results. To address this, a neuroregulator-based adaptive control system was developed to ensure stable, real-time correction under fluctuating conditions [5].

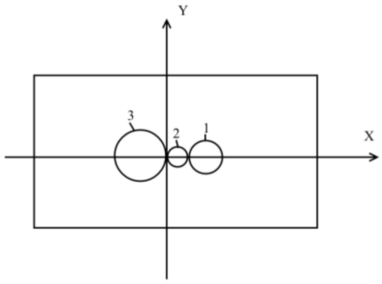

Fig.1. Scheme of the laser cutting process, top view: 1 – zone affected by laser with a wavelength of 10.6 µm, 2 – zone affected by laser with a wavelength of 1.06 µm, 3 – zone affected by refrigerant; the laser beam and coolant spot move from left to right

II. Finite Element Analysis

Thermoelastic stresses and temperature fields during dual-beam laser cleaving were computed using a quasi-static, uncoupled thermoelasticity formulation. Numerical modeling was implemented in Python with FEniCS [6]. Simulations used a 30×40×4 mm glass plate discretized into ~25,520 finite elements. Multi-objective optimization methods were applied to refine technological parameters [7].

Key process parameters included movement speed (v), laser powers at 10.6 µm (P_0) and 1.06 µm (P_1), and beam spot radii (R_0 for 10.6 µm, R_1 for 1.06 µm, R_2 for coolant). Target responses were maximum tensile stress (σ_{yy}) and maximum temperature (T_{max}). R_1 and R_2 were fixed at 1 mm; v, P_0, P_1, and R_0 were optimized using a genetic algorithm supported by neural network approximators. A total of 375 finite element simulations were performed, varying parameters within: v = 0.005–0.05 m/s, P_0 = 4–20 W, P_1 = 20–80 W, and R_0 = 1–4 mm.

III. Neural Network Approximation of Responses

Neural network approximators for maximum temperature and tensile stress were trained on simulation data using multilayer perceptrons implemented in Keras. Candidate three-layer architectures with varying neuron counts in the first two hidden layers were evaluated by cross-validation, optimizing mean squared error (MSE) and coefficient of determination (R^2) to select optimal models [8].

Figure 2 shows heatmaps of average MSE values for neural network approximators of maximum tensile stress (left) and maximum temperature (right). Based on the results, architectures 120-60-1 and 100-80-1 were selected for σ_{yy} and T_{max}, respectively. Figure 3 displays the evolution of evaluation metrics during training of the neural network models.

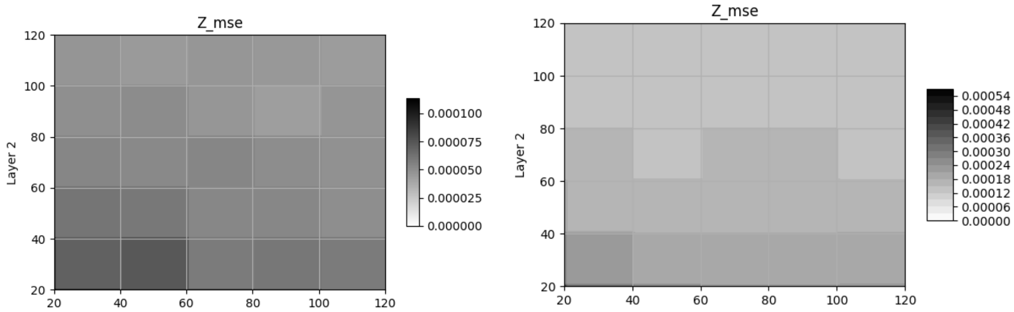

Fig.2. Heatmaps showing average MSE values for the neural network approximators of maximum tensile stress (left) and maximum temperature in the processing zone (right)

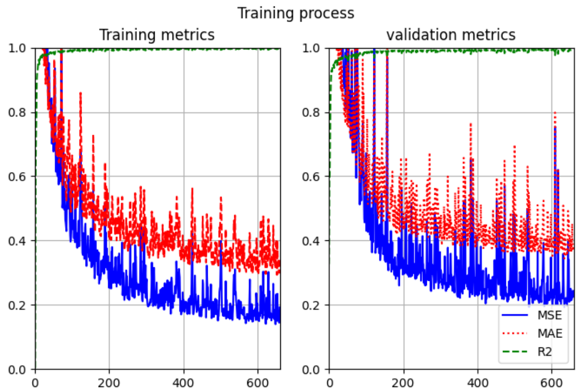

Fig.3. The example Metrics of a neural network approximator during training

IV. Neural Network Approximation of Responses

Process parameters were optimized using a multi-objective genetic algorithm with a population size of 250 per generation. The objective function targeted maximization of tensile stress and processing speed. Constraints included adherence to the parameter ranges used for neural network training and a temperature limit of 789 K to ensure valid thermal cleaving conditions.

Optimization results are shown in Table 1, with values in parentheses indicating those from finite element simulations. The maximum relative error between genetic algorithm outputs and FEM results did not exceed 4% for temperature and 5% for thermoelastic stress.

Table 1. 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 neuroregulator construction algorithm [5] follows a sequence starting with the definition of adaptation quality criteria, model training, and validation on a sample dataset. The criterion focuses on maintaining process stability while optimizing processing speed and tensile stress. Reinforcement learning algorithms [9-10] were used to build the neuroregulator, with the simulation model [5] serving as the environment for learning. The dynamics of the average adaptation quality evaluation function are shown in Figure 4.

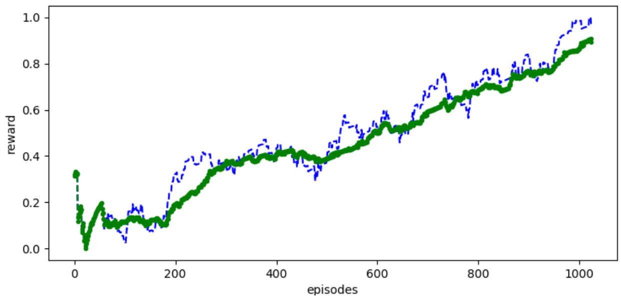

Fig.4. Dynamics of the average adaptation quality evaluation function

VI. Conclusion

A computational model was developed using the finite element method in a quasi-static formulation and the FEniCS library to determine temperature fields and thermoelastic stresses in the laser-affected zone. A modified genetic algorithm was used for multi-objective optimization to identify parameters for effective silicate glass separation, focusing on maximizing tensile stresses and processing speed. A regression model was constructed, showing errors of no more than 4% for temperature and 5% for stresses compared to neural network approximations. Additionally, an adaptive control approach using neuroregulators was proposed to stabilize laser cutting parameters under variable conditions.

References

[1] *R.M. Lumley*, "Controlled separation of brittle materials using a laser," Am. Ceram. Soc. Bull., vol. 48, pp. 850–854, 1969.

[2] *S. Nisar, L. Li, M. Sheikh*, "Laser glass cutting techniques—a review," *J. Laser Appl*., vol. 25, no. 4, pp. 042010-1–11, 2013.

[3] *J. Junke, W. Xinbing*, "Cutting glass substrates with dual-laser beams," *Opt. Lasers Eng*., vol. 47, pp. 860–864, 2009.

[4] *P. Parandoush, A. Hossain*, "A review of modeling and simulation of laser beam machining," *Int. J. Mach. Tools Manuf.,* vol. 85, pp. 135–145, 2014.

[5] V.*A. Prokhorenko, Y.V. Nikitjuk, V.S. Smorodin*, "Adaptive control system for technological operation of laser processing of brittle non-metallic materials," *Probl. Phys. Math. Tech*., vol. 4, no. 61, pp. 78–81, 2024. *https://doi.org/10.54341/20778708_2024_4_61_78.*

[6] FEniCS Project, *https://fenicsproject.org*, accessed January 3, 2025.

[7] Y.*V. Nikitjuk, V.A. Prokhorenko, A.I. Kulyba*, "Multi-criteria optimization of quartz glass laser cutting parameters using neural network simulation and genetic algorithm," *Probl. Phys. Math. Tech*., vol. 3, pp. 26–31, 2023. https://doi.org/10.54341/20778708_2023_3_56_26.

[8] *Y.V. Nikitjuk, A.V. Semchenko, V.V. Sidsky, et al.,* "Prediction of the properties of semiconductor $ZnMgO_{XY}$ sol-gel layers using artificial neural networks," Probl. Phys. Math. Tech., vol. 1, pp. 28–32, 2022. *https://doi.org/10.54341/20778708_2022_1_50_28.*

[9] *R.S. Sutton, A.G. Barto*, Reinforcement Learning: An Introduction, 2nd ed., Cambridge: MIT Press, 2018, 552 p.

[10] *S. Amin, M. Gomrokchi, H. Satija, et al.,* "A survey of exploration methods in reinforcement learning," arXiv preprint, 2021. *https://arxiv.org/abs/2109.00157.*