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СИСТЕМА АДАПТИВНОГО УПРАВЛЕНИЯ ТЕХНОЛОГИЧЕСКОЙ ОПЕРАЦИЕЙ ЛАЗЕРНОЙ ОБРАБОТКИ ХРУПКИХ НЕМЕТАЛЛИЧЕСКИХ МАТЕРИАЛОВ

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ADAPTIVE CONTROL SYSTEM FOR TECHNOLOGICAL OPERATION OF LASER PROCESSING OF BRITTLE NON-METALLIC MATERIALS

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Аннотация. В работе представлена компьютерная система адаптивного управления технологической операцией лазерной резки хрупких неметаллических изделий. Описаны процедуры синтеза структуры нейрорегулятора параметров технологической операции резки и автоматизированного выбора оптимальной архитектуры нейронной сети на основе заданных критериев качества адаптации управления. Стабилизация параметров технологической операции лазерной резки методом термораскалывания приведена на примере обработки силикатных стекол эллиптическими лазерными пучками.

Ключевые слова: *система адаптации управления*, *нейросетевое моделирование*, *синтез структуры нейрорегулятора*, *стабилизация параметров технологической операции.*

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Abstract. This paper presents a computer system for adaptive control of the technological operation of laser cutting of fragile non-metallic products. The procedures for synthesizing the structure of the neural regulator of the parameters of the technological operation of cutting and the automated selection of the optimal architecture of the neural network based on the specified criteria for the quality of control adaptation are described. Stabilization of the parameters of the technological operation of laser cutting by the method of thermal splitting is given on the example of processing silicate glasses with elliptical laser beams.

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

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Introduction

This paper describes an approach to constructing a computer system for adaptive control of the technological operation of laser cutting of fragile non-metallic products based on the technology of constructing mathematical models of complex technical objects [1].

Laser splitting is an effective method of special processing of brittle non-metallic materials. When implementing this technology, it is important to form a specified mode of heating and cooling of the workpiece, especially at the upper limit of the maximum permissible temperature, which has a direct impact not only on the quality of processing, but also on the fundamental possibility of forming a laser-induced crack [2]. At the same time, various external factors can affect the temperature values of the workpiece during cutting. Thus, the task of developing algorithms for taking into account destabilizing effects in real time is relevant.

The developed control adaptation system is based on the use of neuroregulators and allows for corrective actions on the set of control variables of a technological operation, in the presence of external control actions and random disturbances, ensuring stabilization of laser cutting parameters.

Figure 0.1 shows a diagram of the laser cleavage process of a silicate glass plate using an elliptical laser beam.

The factors in the process under consideration include:

– laser beam and coolant speed (V);

– laser radiation power (P);

– semi-axes of the elliptical beam (A, B).

Responses: maximum tensile stresses (σ_{yy}); maximum temperature in the processing zone ($T_{\max}$).

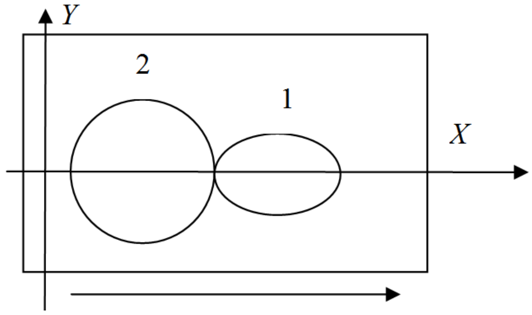

Figure 0.1 – Scheme of the laser cutting process, top view: 1 – zone affected by laser radiation, 2 – zone affected by refrigerant; the laser beam and coolant spot move from left to right

1 Simulation modeling of laser cutting operation control system

The simulation model of the control system uses signal generators for the responses of the physical laser cutting process (maximum tensile stress (σ_{yy}) and maximum temperature in the processing zone ($T_{\max}$)). The operation of the generators is provided by neural network approximation [3]. A feature of neural network approximation of responses in the context of this work is the use of not only the problem factors but also the response values at previous points in time as input signals of neural networks. The data set for constructing neural network response approximators was obtained using finite element modeling of the physical process of laser cutting using software tools developed by the authors [4]. When implementing the finite element model, a change in the values of control variables was simulated by randomly changing the values of the problem factors V and P.

Using the procedure for selecting optimal neural network architectures [3], neural network response approximators with architectures [80-40-1] for σ_{yy} and [60-50-1] for $T_{\max}$ were constructed (Figure 1.1).

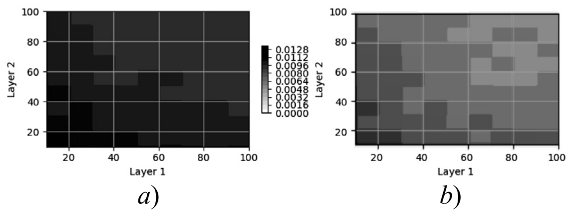

Figure 1.1 – Heat maps of the distributions of the mean square error (MSE) values obtained as a result of cross-validation of three-layer candidate architectures of neural network response approximators σ_{yy} (*a*) and T (*b*)

The simulation model of the cutting process control system includes (the diagram is shown in Figure 1.2):

– random disturbance generator $GENSGN_{\varepsilon}$ and response generators $GENSGN_{\sigma}$ and $GENSGN_{T}$, based on the operation of neural network approximators σ_{yy} and $T_{\max}$, which accept the values of the current set of problem factors determined by the control variables, and the values of the approximated responses at the current and previous time steps;

– executors EX_{1-4}, responsible for the execution of microtechnological operations [1] for setting the values of the control variables $\{U_P, U_V\}$ (change with a given step towards an increase or decrease).

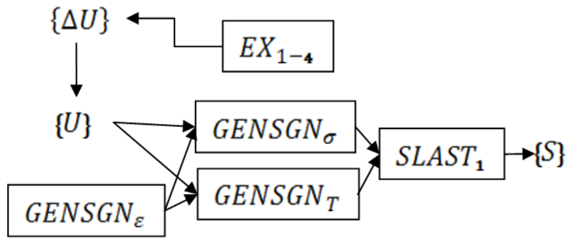

Figure 1.2 – Fragment of the signal generation circuit in the simulation model of the laser cutting technological operation

2 Implementation of the technological operation control loop

In the control loop of the laser cutting process operation, the values of the control variables responsible for the factors of the physical process of laser cutting are set. The control variables $\{U\}$ of the software and technological complex for optimizing the parameters of cutting non-metallic products include the speed of the laser beam and coolant (U_V), the power of the laser radiation (U_P), and the semi-axes of the elliptical laser beam (U_A, U_B). In this case, $\{U_P, U_V\}$ – the power of the laser radiation and the speed of the laser beam – are available for adjustment in real time.

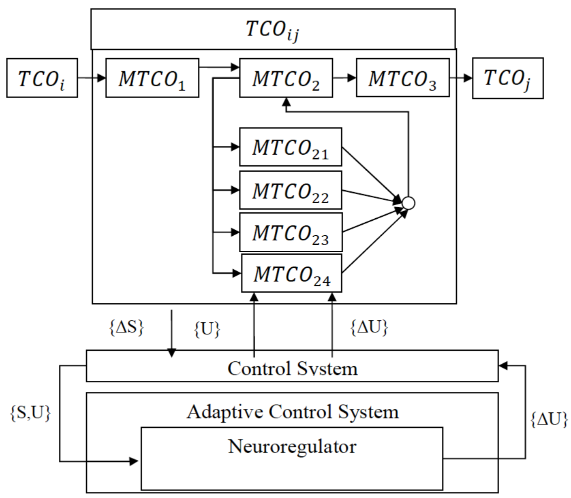

Figure 2.1 – Scheme of adaptation of control of technological operation of laser cutting

The technological operation diagram of laser cutting includes microtechnological operations presented in Figure 2.1. Operations $MTCO_{1-3}$ are responsible for starting cutting, performing cutting and stopping cutting; operations $MTCO_{21-24}$ are responsible for setting the cutting parameters V, P, A, B.

Within the developed control adaptation system, the required stabilization of laser cutting parameters is carried out by constructing a neuroregulator using reinforcement learning algorithms [5], [6].

3 Procedure for synthesizing a neuroregulator of technological operation parameters

The neuroregulator generates signals that have corrective effects on the set of control variables. It has 5 outputs, i. e. inaction, or changes in one of the available control variables in the direction of increase or decrease with a step determined by the implementation of the corresponding microtechnological operation. The maximum output of the neuroregulator determines the activated microtechnological operation.

The scheme of the procedure for synthesizing a neuroregulator is shown in Figure 3.1. The algorithm for constructing a neuroregulator includes the following stages: determination by the user of the system of criteria for the quality of adaptation; search for the optimal architecture of the neuroregulator, training and validation.

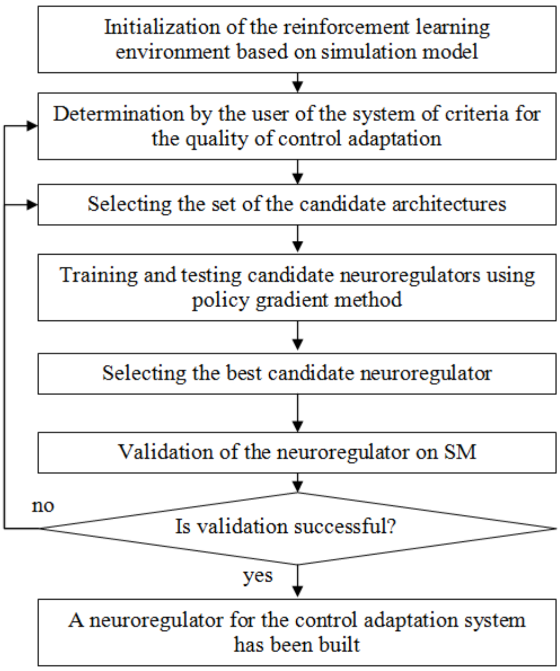

Figure 3.1 – Schematic diagram of the algorithm for synthesizing a neuroregulator using reinforcement learning

In this work, a multilayer perceptron is used as a neuroregulator. The adaptation quality criteria are set by defining the reward function in the reinforcement learning procedure.

The search for the optimal architecture of the neuroregulator is implemented using a scheme for enumerating candidate architectures with varying the number of neurons in the layers. For each architecture, a reinforcement learning procedure is performed with subsequent testing of the model for 128 episodes. The criterion for selecting a candidate architecture is the average reward value obtained as a result of testing.

The policy gradient [7], [9] with the softmax [8] learning scheme was used as a reinforcement learning algorithm. The described simulation model is used as the environment for training the agent. In the process of interacting with the environment, the neuroregulator has access to factors and responses at the current and previous simulation steps: $T^{t}_{\max}$, $T^{t-1}_{\max}$, σ^{t}_{yy}, σ^{t-1}_{yy}, V, P, P_{t-1}. At each step the neuroregulator has access to 5 actions to change the control variables $\{U_P, U_V\}$ or to do nothing.

The training of the neuroregulator is carried out over 512 episodes of interaction with the environment with random initial values of the control variables $\{U\}$. The agent's reward function when implementing the reinforcement learning algorithm is the adaptation quality assessment function, which allows taking into account the user's requirements for control adaptation:

$$R = \alpha_1 R_T + \alpha_2 R_V + \alpha_3 R_\sigma,$$

where R_T – component for assessing whether the temperature is maintained within the acceptable range; R_V – cutting speed assessment component; R_σ – component of the maximum tensile stress assessment.

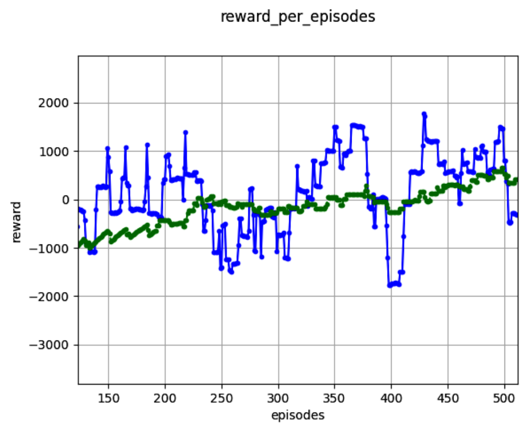

Figure 3.2 –Dynamics of changes in the value of the quality of control adaptation during the training of the neuroregulator

To select the optimal architecture of the neuroregulator, the candidate architectures are trained and tested. Based on the results of the procedure (Figure 3.4), a neuroregulator with the architecture [7-80-64-32-5] was selected.

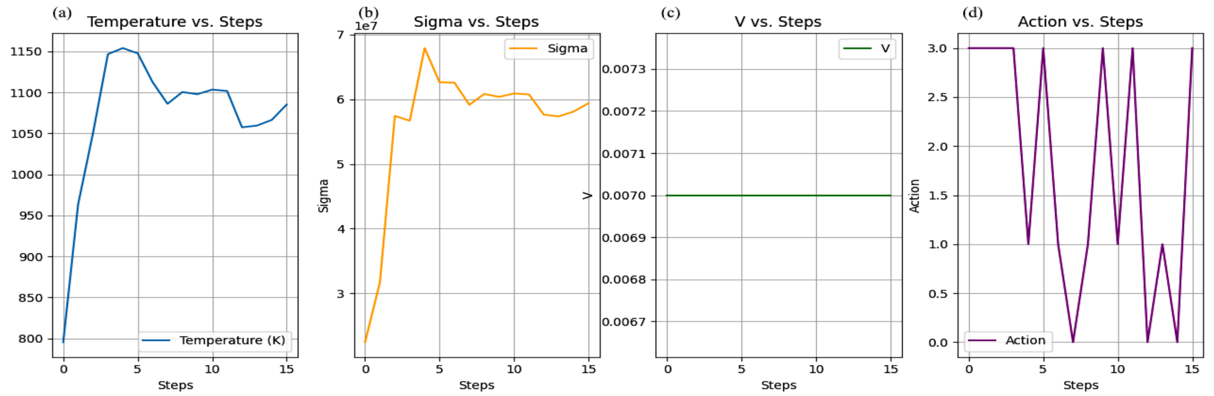

Figure 3.3 – Response values (*a*, *b*), control variable (V) (*c*), selected actions (*d*) in the process of implementing the stabilization of parameters by the constructed neuroregulator

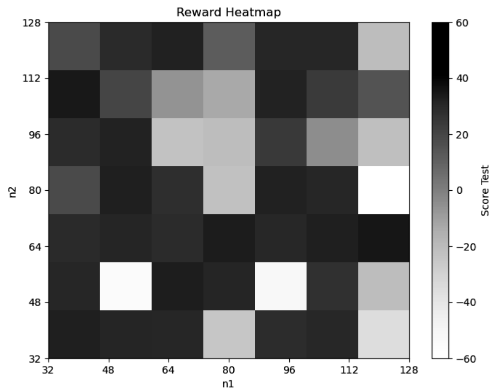

Figure 3.4 – Heat map of the mean test reward values obtained for the selected 4-layer perceptrons

A neuroregulator has been constructed that provides corrective effects on control variables $\{U\}$ (Figure 3.3) with the implementation of the requirement to prevent the parameters of the laser cutting technological process (maximum temperature $T_{\max}$) from going beyond the permissible interval. from going beyond the permissible interval. Figure 3.2 shows a graph of the change in the agent metrics under the control of the neuroregulator in the process of reinforcement learning.

Conclusion

A control adaptation system for the technological operation of laser cutting of fragile non-metallic materials based on the use of neuroregulators has been developed. A procedure for synthesizing the structure of a neuroregulator is described, which ensures the stabilization of the parameters of the technological operation according to the specified criteria of the quality of control adaptation in the presence of random disturbances and external control actions. The application of the developed control adaptation system is shown using the example of stabilizing the parameters of the technological operation of cutting silicate glasses with elliptical laser beams.

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