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НЕЙРОСЕТЕВОЕ МОДЕЛИРОВАНИЕ ПАРАМЕТРОВ ЛАЗЕРНОЙ ОБРАБОТКИ АЛМАЗОВ В ТЕХНОЛОГИЯХ ЭЛЕКТРОНИКИ

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NEURAL NETWORK MODELING OF LASER PROCESSING PARAMETERS FOR DIAMONDS IN ELECTRONICS TECHNOLOGIES

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Аннотация. С помощью сочетания искусственных нейронных сетей и аналитической модели движущегося теплового источника выполнено моделирование процесса лазерной обработки алмазов. Обучающая выборка и массив данных для тестирования нейронных сетей были сформированы с использованием математического пакета Mathcad. Расчеты были выполнены для 1152 вариантов входных параметров, 50 из которых были использованы для тестирования искусственных нейронных сетей. Установлены параметры искусственных нейронных сетей, обеспечивающие лучшие результаты при прогнозировании температур, формируемых лазерным излучением в алмазах. Полученные результаты могут быть использованы при определении технологических параметров процессов лазерной обработки алмазов.

Ключевые слова: *лазерная резка*, *алмаз*, *искусственная нейронная сеть*.

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Abstract. This study employs a combined approach of artificial neural networks (ANN) and an analytical moving heat source model to simulate the laser processing of diamonds. The training and testing datasets for the neural networks were generated using Mathcad, with calculations performed for 1,152 input parameter combinations, including 50 dedicated to ANN validation. Optimal ANN configurations were identified to achieve high-precision predictions of laser-induced temperature distributions in diamonds. The results provide a basis for optimizing technological parameters in diamond laser processing for electronic applications.

Keywords: *laser cutting, diamond, artificial neural network.*

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Introduction

The unique properties of diamonds ensure stable operation of diamond-based electronic components and devices under extreme conditions. This makes diamonds a promising material for developing next-generation electronic systems [1].

Laser processing of diamonds offers several distinct advantages, such as the potential for full process automation, ease of adjusting key laser parameters, and the capacity to achieve narrow cut widths while maintaining high processing speeds during laser separation [2].

Artificial neural networks (ANNs) have found successful applications across various scientific and engineering domains, including laser processing research [3]–[6]. A defining characteristic of ANNs is their data-driven learning capability, i. e., rather than being explicitly programmed, they are trained on specific datasets. Once trained, the neural network can efficiently determine optimal laser processing parameters when analyzing new data. Moreover, in certain cases, neural network models demonstrate superior computational efficiency compared to the original physical models used for generating the training data set [7].

The authors' earlier research has explored the laser processing of diamonds, using methods that integrate finite element modeling with artificial neural network simulations [8]–[14]. The combination of neural network modeling with appropriate analytical models appears particularly relevant for predicting optimal laser processing parameters of diamonds.

1 A mathematical model of the diamond laser processing process and the formation of a training set

The distribution of the temperature field in diamond when subjected to laser radiation provides insights into the necessary laser exposure parameters required to achieve critical temperatures in the processing zone within specified timeframes. Specifically, one can identify the parameters sufficient to induce either diamond fracture or phase transformations (e. g., graphitization).

To calculate the temperature field, it is necessary to solve the heat conduction boundary value problem in a moving coordinate system (see Figure 1.1) for a laser beam with Gaussian spatial energy distribution [10]:

$$\frac{c\rho}{\lambda}\cdot\frac{\partial T}{\partial \tau}-\frac{v_x c\rho}{\lambda}\cdot\frac{\partial T}{\partial \tau}=\frac{\partial^2 T}{\partial x^2}+\frac{\partial^2 T}{\partial y^2}+\frac{\partial^2 T}{\partial z^2}, \quad (1.1)$$

$$-\lambda\left.\frac{\partial T}{\partial z}\right|_{z=0}=I_0 e^{-k\cdot\left(x_0^2+y_0^2\right)}, \quad (1.2)$$

$$\begin{aligned}&T(\infty,y,z,t)=T(x,\infty,z,t)=\\&=T(x,y,\infty,t)=T(x,y,z,0)=T_0.\end{aligned} \quad (1.3)$$

Equations (1.1)–(1.3) incorporate the following physical parameters: T is the target temperature, λ is the thermal conductivity coefficient, c is the heat capacity, ρ is the material density, I_0 is the power density of the surface, k is the Gaussian beam concentration coefficient (exponential term coefficient). The laser beam velocity vector is directed along the x-axis.

Subsequently, using the coordinate transformation method from a moving to a stationary reference frame, we express the solution of the system (1.1)–(1.3) in the following form:

$$T=T_0+\frac{I_0\sqrt{a}}{4\sqrt{\pi}k\lambda}\sum_{n=0}^{N}F\left(x_n-v_x t,y_n,z,t\right), \quad (1.4)$$

where

$$F_N=\sum_{n=0}^{N}F\left(x_n-v_x t,y_n,z,t\right)=$$

$$=\int_0^t\sum_{n=0}^{N}\exp\left\{\left[-\frac{y_n^2+\left(x_n-\omega v_x\right)}{4\left[a\left(t-\omega\right)+1/\left(4k\right)\right]}-\frac{z^2}{4a\left(t-\omega\right)}\right]\times\right.$$

$$\left.\times\frac{d\omega}{\left[a\left(t-\omega\right)+1/\left(4k\right)\right]\sqrt{t-\omega}}\right\}. \quad (1.5)$$

In expressions (1.4)–(1.5): a is the thermal diffusivity coefficient, ω is the integration variable.

Computations using expressions (1.4)–(1.5) were performed for 1,152 input parameter combinations, including 50 cases reserved for neural network training. The parameters employed in modeling diamond laser processing are provided in Table 1.1.

The presented example outlines the application of equations (1.4)–(1.5) to determine six temperature values at varying distances from the laser beam center along its propagation axis, evaluated at depths up to 0.1 mm. For artificial neural network validation, 50 parameter combinations from Table 1.2 were employed in the computational testing protocol.

Table 1.1 – Parameters of diamond laser processing

Parameters	Value range
Cutting speed V, mm/s	3–8
Laser power density P_0, 10^{11} W/m^2	0.5–1.2
Laser beam radius R, mm	2–7

Table 1.2 – Input parameters of the model and calculated temperature values in the diamond laser processing zone for the test dataset

N	V, m/s	R, mm	P_0, 10^{11} W/m^2	z, mm	T_1, K	T_2, K	T_3, K	T_4, K	T_5, K	T_6, K
1	5	3	0.4	1.1	459	618	777	935	1092	1249
2	4	3	0.3	1.0	445	590	735	879	1023	1165
3	3	6	0.2	1.0	446	591	735	876	1015	1150
4	6	5	0.4	0.5	372	445	516	587	657	726
5	3	4	0.4	1.0	445	589	733	876	1018	1158
6	6	2	0.2	0.9	431	562	693	823	954	1084
7	8	3	0.1	0.9	431	563	693	824	954	1082
8	3	2	0.2	0.5	373	446	518	591	663	735
9	8	7	0.1	0.9	431	562	691	818	941	1060
10	5	7	0.2	0.9	431	562	690	817	940	1058
11	4	2	0.3	0.7	402	503	605	706	807	908
12	4	4	0.3	1.0	445	590	735	878	1020	1161
13	3	6	0.1	0.7	402	504	605	704	802	896
14	6	6	0.2	0.5	373	445	517	588	658	725
15	8	2	0.2	0.5	373	446	518	591	663	735
16	5	2	0.3	0.6	387	474	561	648	735	821

N	V, m/s	R, mm	P_0, 10^{11} W/m^2	z, mm	T_1, K	T_2, K	T_3, K	T_4, K	T_5, K	T_6, K
17	4	6	0.1	0.5	373	446	518	589	658	726
18	3	4	0.1	0.6	388	475	562	649	734	819
19	3	2	0.1	0.9	431	563	694	825	955	1085
20	8	4	0.1	1.2	475	650	824	997	1168	1338
21	8	2	0.3	0.7	402	503	605	706	807	908
22	5	2	0.2	1.1	460	620	780	940	1099	1258
23	8	3	0.1	0.7	402	504	606	707	808	909
24	3	6	0.3	1.0	445	590	733	875	1013	1148
25	4	4	0.1	1.2	475	650	824	997	1168	1338
26	6	7	0.1	1.1	461	620	778	933	1083	1228
27	5	3	0.1	1.1	461	621	781	940	1099	1256
28	8	5	0.1	0.6	388	475	562	648	732	815
29	3	3	0.1	0.5	373	446	519	591	663	735
30	5	2	0.2	1.0	446	591	736	882	1026	1171
31	5	3	0.4	0.8	416	531	647	762	876	990
32	4	7	0.4	0.9	430	560	688	814	936	1054
33	5	2	0.1	0.6	388	475	563	650	737	824
34	4	3	0.3	1.2	474	648	822	995	1167	1338
35	7	6	0.2	1.2	475	649	821	991	1158	1320
36	4	2	0.1	1.1	461	621	781	941	1101	1260
37	8	5	0.4	1.2	474	647	819	990	1158	1323
38	5	2	0.3	0.5	373	445	518	590	662	734
39	8	3	0.3	0.5	373	445	517	590	661	733
40	3	6	0.4	1.2	474	647	818	988	1153	1315
41	7	7	0.3	0.9	431	561	689	815	938	1056
42	4	6	0.3	1.1	460	619	777	932	1085	1233
43	4	6	0.1	1.1	461	621	779	935	1088	1237
44	8	4	0.2	0.7	402	504	605	706	805	904
45	8	4	0.2	1.0	446	591	736	880	1022	1163
46	4	7	0.1	1.0	446	591	735	875	1012	1144
47	7	3	0.1	0.9	431	563	693	824	954	1082
48	5	5	0.1	0.6	388	475	562	648	732	815
49	6	7	0.1	0.5	373	446	517	588	656	722
50	6	3	0.4	0.8	416	531	647	762	876	990

2 Building an artificial neural network to solve an optimization problem

To determine temperature values during diamond laser processing, the neural networks with the architecture shown in Figure 2.1 were employed.

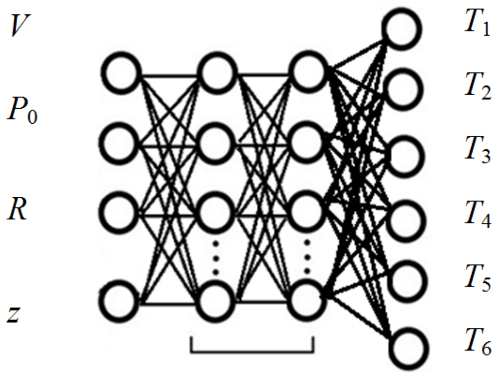

Figure 2.1 – Neural network architecture

The optimal laser processing parameters for diamonds were determined through the implementation of neural networks with various architectures, utilizing TensorFlow, an open-source machine learning library. The networks employed ReLU (Rectified Linear Unit) activation functions, and Adam optimizer (an adaptive stochastic gradient descent extension). The neural networks were generated using mean squared error (MSE) as the loss function, which computes the squared difference between predicted and target values. The networks underwent training for 100 epochs.

The developed regression and neural network models were evaluated using the following performance metrics:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|d_i - y_i\right|$$

is the Mean Absolute Error (*MAE*);

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|d_i - y_i\right|}$$

is the Root Mean Square Error (*RMSE*);

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

is the Mean Absolute Percentage Error (*MAPE*);

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}\left(d_i - y_i\right)^2}{\frac{1}{n}\sum_{i=1}^{n}\left(d_i - \overline{d}\right)^2}$$

is the determination coefficient;
where d_i indicates values calculated using analytical expressions (1.4)–(1.5), y_i stands for values predicted by neural network models.

As a result, 25 artificial neural networks were trained with the number of neurons in two hidden layers ranging from 5 to 25, with an interval of 5.

Figure 2.2 illustrates heatmaps visualizing the distribution of validation errors in output parameter prediction. The vertical and horizontal axes represent the number of neurons in the first and second hidden layers of the artificial neural networks, respectively. The intensity of color coding represents the extent of error: the error increases from light to dark.

The neural network with the architecture [4-10-20-6] demonstrated superior performance in predicting the temperature values.

Table 2.1 presents evaluation results of the corresponding neural network model.

The mean absolute percentage error (*MAPE*) observed during the testing of this network remained below 0.2%, while the mean absolute error (*MAE*) and root mean square error (*RMSE*) were both kept under 1.5 K. The coefficients of determination for the output parameters T and σ_1 exhibit values no less than 0.99995, indicating a strong alignment of the neural network model with the modelling data as described in expressions (1.4)–(1.5).

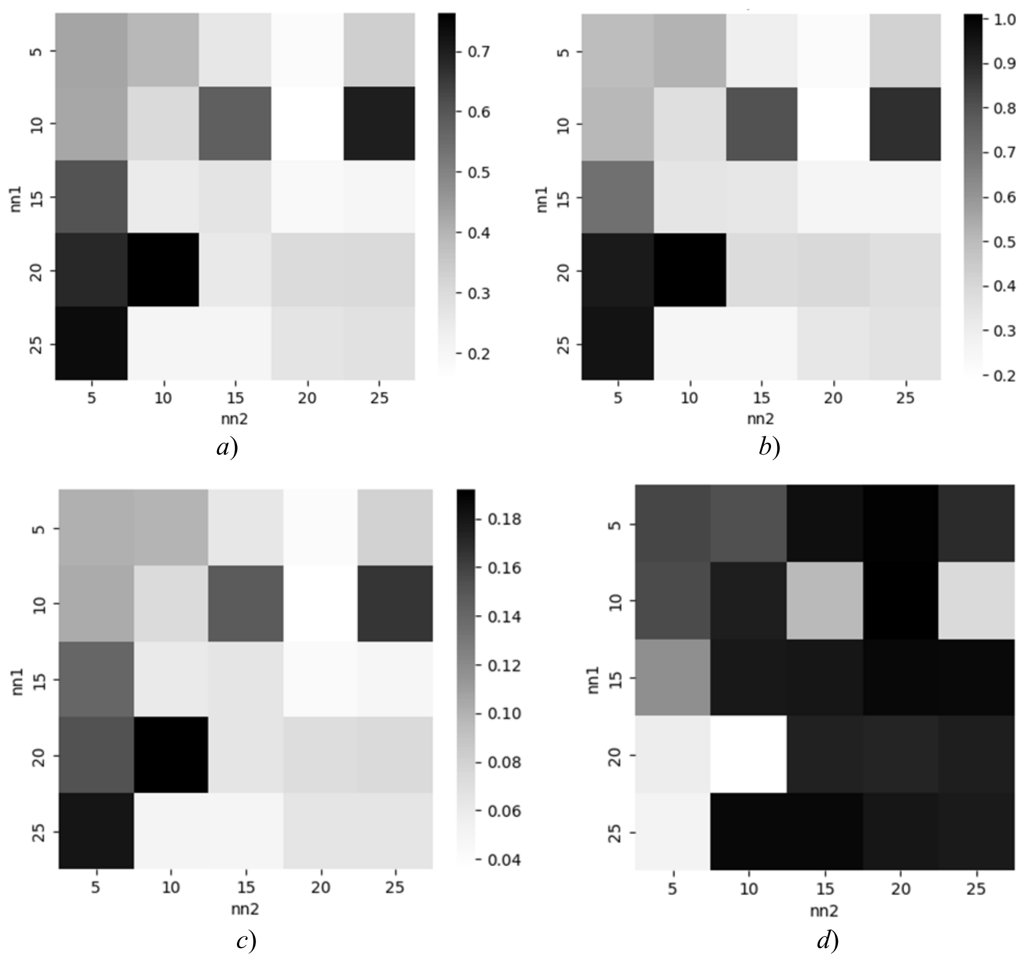

Figure 2.2 – Heatmaps displaying the distribution of *MAE* (*a*), *RMSE* (*b*), *MAPE* (*c*), R^2(*d*) when determining T_1

Table 2.1 – Evaluation results of neural network models

Criterion	T_1	T_2	T_3	T_4	T_5	T_6
MAE	0.16 K	0.26 K	0.36 K	0.65 K	0.83 K	1.19 K
RMSE	0.19 K	0.34 K	0.46 K	0.77 K	1.02K	1.49 K
MAPE	0.04%	0.05%	0.05%	0.08%	0.09%	0.12%
R^2	0.99997	0.99998	0.99998	0.99997	0.99997	0.99995

Conclusion

This study demonstrates the feasibility of predicting diamond laser processing parameters for electronic applications through a combined analytical and artificial neural network (ANN) approach. Numerical experiments identified an optimal neural network architecture that achieves superior accuracy in determining temperature distributions within laser-affected zones. A critical challenge lies in enhancing the efficiency of precision laser machining for diamonds, which can be addressed by optimizing processing parameters to induce controlled graphitization not only in the direct laser interaction zone but also in adjacent treatment areas. This approach eliminates the need for additional processing passes, significantly improving manufacturing productivity [2], [10]. The developed methodology enables determination of optimal laser parameters not only for diamond processing but also for other electronic materials through artificial neural network modeling [15]–[16].

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