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OPTIMIZATION OF LASER ALLOYING PARAMETERS OF 30ХГСН2А STEEL USING A GENETIC ALGORITHM AND NEURAL NETWORK MODELING

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The process of laser alloying of structural steel with chromium has been optimized using a genetic algorithm and neural network modeling. Finite element modeling of the process of laser alloying of 30ХГСН2А steel was performed in the ANSYS Workbench software environment taking into account the temperature dependence of the thermophysical properties of materials. A face-centered version of the central compositional design of the experiment was used to construct a surrogate model of laser alloying. Time intervals corresponding to the durations of three laser pulse fronts and the peak power densities of these fronts were selected as experimental factors. Maximum temperatures in the processing zone were analyzed as responses. The process was optimized taking into account the limiting values of the maximum temperatures in the processing zone for three moments in time corresponding to the ends of the laser pulse fronts, at two points of the finite element model. The parameters obtained as a result of optimization were compared with the parameters calculated based on the finite element modeling data. The maximum relative error of temperature values obtained using the genetic algorithm was no more than 4.0 %.

Keywords: laser alloying, optimization, MOGA, ANSYS.
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ОПТИМИЗАЦИЯ ПАРАМЕТРОВ ЛАЗЕРНОГО ЛЕГИРОВАНИЯ СТАЛИ 30ХГСН2А С ИСПОЛЬЗОВАНИЕМ ГЕНЕТИЧЕСКОГО АЛГОРИТМА И НЕЙРОСЕТЕВОГО МОДЕЛИРОВАНИЯ

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Проведена оптимизация процесса лазерного легирования хромом конструкционной стали с использованием генетического алгоритма и нейросетевого моделирования. Конечно-элементное моделирование процесса лазерного легирования стали 30ХГСН2А выполнялось в программной среде ANSYS Workbench с учетом температурной зависимости теплофизических свойств материалов. Для построения суррогатной модели лазерного легирования использован гранецентрированный вариант центрального композиционного плана эксперимента. В качестве факторов эксперимента были выбраны временные интервалы, соответствующие длительностям трех фронтов лазерного импульса, и пиковые плотности мощности этих фронтов. В качестве откликов анализировались максимальные температуры в зоне обработки. Оптимизация процесса осуществлялась с учетом предельных значений максимальных температур в зоне обработки для трех моментов времени, соответствующих завершениям фронтов лазерного импульса, в двух точках конечно-элементной модели. Проведено сравнение параметров, полученных в результате оптимизации, с параметрами, рассчитанными по данным конечно-элементного моделирования. Максимальная относительная погрешность температурных значений, полученных с использованием генетического алгоритма, составила не более 4,0 %.

Ключевые слова: лазерное легирование, оптимизация, MOGA, ANSYS.

Для цитирования. Оптимизация параметров лазерного легирования стали 30ХГСН2А с использованием генетического алгоритма и нейросетевого моделирования / Г. А. Баевич, Ю. В. Никитюк, А. В. Максименко [и др.] // Вестник Гомельского государственного технического университета имени П. О. Сухого. – 2025. – № 2 (101). – С. 23–32. – DOI 10.62595/1819-5245-2025-2-23-32

Introduction

Nowadays, multiple technological methods, such as ion, gas-flame, and electron-beam processing, are employed to achieve the desired properties of the surface layer of products while preserving the characteristics of the original material. Laser technologies stand out as a highly promising option for the processing of mechanical-engineering components.

The unique features of laser technologies include the capability to create coatings from a range of materials, high application flexibility, impressive productivity, and the ability to process items of nearly any size and geometric configuration. The classification of these technologies is based on the mechanism through which they affect the material, which is influenced by the energy density of the laser radiation and the duration of its application. The primary methods include heating, melting, and applying shock loading to the material.

Among the various technologies used in laser processing, the most prevalent include alloying, hardening, and cladding. Laser alloying serves as an effective technique for enhancing the surface characteristics of metals. The distinctiveness of this approach is found in its ability to facilitate precise alterations in the composition and structure of the surface layer through high-energy laser impact, resulting in enhanced processing accuracy and notable advancements in the material's performance characteristics [1, 2].

The distribution of temperature within the material during laser exposure is a key characteristic, the assessment of which is essential for optimizing the parameters of technological processes. Finite element analysis software, particularly ANSYS, is extensively utilized for modelling temperature fields in the context of laser processing.

Furthermore, artificial neural networks have demonstrated their efficacy as a valuable resource in the examination of laser processing. In several instances, a combined approach that integrates the finite element method with artificial neural networks is employed to enhance the precision and flexibility of simulations. This method facilitates the consideration of intricate physical processes and the variability of processing parameters [3–12].

Determination of optimal parameters for laser alloying of 30ХГСН2А steel with chromium

The temperature fields were determined through the application of finite element analysis utilizing the ANSYS Workbench software. The developed finite-element model was verified using experimental data collected from a pulsed YAG : Nd^{3+}-laser operating in free generation mode, along with an IT-3SM thermal imager. The error in assessing the peak temperatures on the sample surface was under 5 % [10].

The design model consisted of a plate made from 30ХГСН2А steel, measuring 3×3×1 mm, with its surface coated by a 100 μm thick layer of additive material that included an alloying component. The simulation parameters facilitated the creation of a consistent melted layer with a thickness of h_{al}. The model geometry comprised 12.768 finite elements of Solid90 type and 51.624 nodes. Figure 1 illustrates the interaction of laser radiation with the surface of the additive coating material.

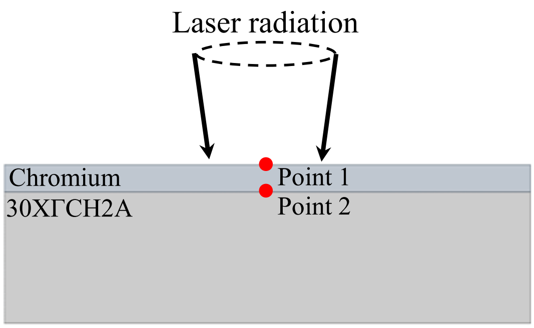


Fig. 1. Schematic illustrating the effects of laser radiation on the surface of the additive coating material

Metamodeling is now widely used to create models of complex systems based on data obtained from computational experiments. Such models, referred to as surrogate or metamodels, are characterized by significantly higher computational efficiency compared to the original finite element models.

The primary function of surrogate modelling involves the estimation of system output parameters using provided input data, eliminating the necessity for comprehensive calculations. The generated metamodels are used to optimize the parameters of technological processes, incorporating artificial intelligence methods, including genetic algorithms [12, 13].

The multicriteria optimization of the parameters for laser alloying of 30ХГСН2А steel was conducted implementing the DesignXplorer module, following the procedural steps outlined in [14].

A six-factor face-centered variant of the central composite experimental design was employed in the metamodeling process. The time intervals t_1, t_2, t_3, which correspond to the durations of three laser pulse fronts, along with the peak power densities p_1, p_2, p_3 of these fronts, served as experimental factors (Fig. 2).

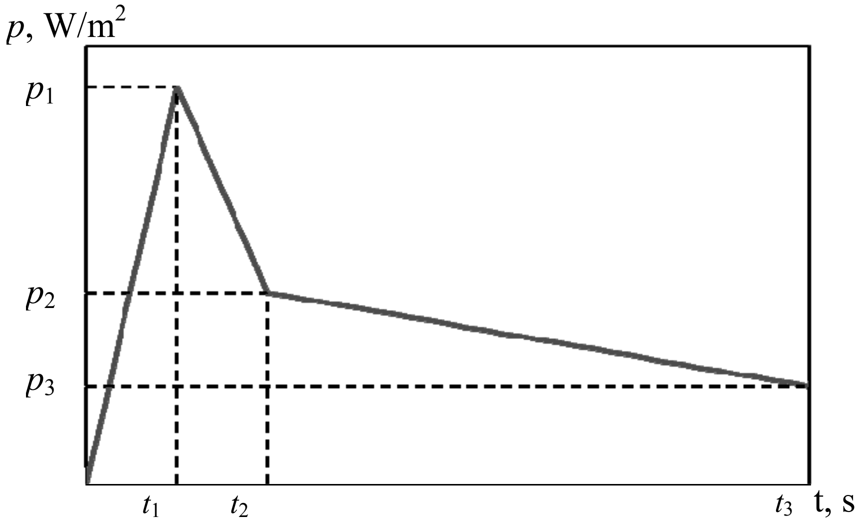


Fig. 2. Pulse shape of laser radiation

The study employed temperature indices in the processing area as response variables. T1, T2, and T3 represent the temperatures on the surface of the deposited coating layer that contains the alloying component. These temperatures are measured at the time points corresponding to the completion of the first, second, and third fronts of the laser pulse, respectively. *T*4 indicates the temperature at a depth of 100 µm, recorded at the time point corresponding to the completion of the third front of the laser pulse (Table 1).

Table 1

Experimental design and calculation results

P1 t_1, ms	P2 t_2, ms	P3 t_3, ms	P4 p_1, W/m^2 · 10^9	P5 p_2, W/m^2 · 10^9	P6 p_3, W/m^2 · 10^9	P7 T1, °C	P8 T2, °C	P9 T3, °C	P10 T4, °C
1.25	8.00	2.25	3.50	0.55	2.55	6379	2657	4735	2192
0.50	8.00	2.25	3.50	0.55	2.55	6178	2611	3608	2146
2.00	8.00	2.25	3.50	0.55	2.55	6548	2703	5774	2238
1.25	1.00	2.25	3.50	0.55	2.55	6379	3755	4735	3135
1.25	15.00	2.25	3.50	0.55	2.55	6379	2681	4735	2227
1.25	8.00	0.50	3.50	0.55	2.55	5338	2460	4735	1993
1.25	8.00	4.00	3.50	0.55	2.55	6781	2833	4735	2368
1.25	8.00	2.25	1.00	0.55	2.55	4846	2491	1369	2025
1.25	8.00	2.25	6.00	0.55	2.55	7911	2824	8101	2360
1.25	8.00	2.25	3.50	0.10	2.55	6379	1641	4735	1535
1.25	8.00	2.25	3.50	1.00	2.55	6379	3674	4735	2849
1.25	8.00	2.25	3.50	0.55	0.10	2333	1544	4735	1104
1.25	8.00	2.25	3.50	0.55	5.00	10425	3771	4735	3280
0.50	1.00	0.50	1.00	0.10	0.10	713	378	1046	293
2.00	1.00	0.50	1.00	0.10	5.00	6050	3300	1665	2834
0.50	15.00	0.50	1.00	0.10	5.00	5733	2333	1046	2228
2.00	15.00	0.50	1.00	0.10	0.10	1030	350	1665	269
0.50	1.00	4.00	1.00	0.10	5.00	10311	5065	1046	4572

Final part of table 1

P1 t_1, **ms**	**P2** t_2, **ms**	**P3** t_3, **ms**	**P4** p_1, **W/m^2 · 10^9**	**P5** p_2, **W/m^2 · 10^9**	**P6** p_3, **W/m^2 · 10^9**	**P7 T1, °C**	**P8 T2, °C**	**P9 T3, °C**	**P10 T4, °C**
2.00	1.00	4.00	1.00	0.10	0.10	747	559	1665	477
0.50	15.00	4.00	1.00	0.10	0.10	688	381	1046	300
2.00	15.00	4.00	1.00	0.10	5.00	10370	2648	1665	2543
0.50	1.00	0.50	6.00	0.10	5.00	8675	3987	6169	3499
2.00	1.00	0.50	6.00	0.10	0.10	5555	2110	9883	1989
0.50	15.00	0.50	6.00	0.10	0.10	3655	401	6169	320
2.00	15.00	0.50	6.00	0.10	5.00	10575	2533	9883	2428
0.50	1.00	4.00	6.00	0.10	0.10	3035	1837	6169	1746
2.00	1.00	4.00	6.00	0.10	5.00	13011	6674	9883	6173
0.50	15.00	4.00	6.00	0.10	5.00	12659	2937	6169	2833
2.00	15.00	4.00	6.00	0.10	0.10	3387	810	9883	730
0.50	1.00	0.50	1.00	1.00	5.00	5733	4338	1046	3221
2.00	1.00	0.50	1.00	1.00	0.10	1030	1714	1665	974
0.50	15.00	0.50	1.00	1.00	0.10	713	2588	1046	1784
2.00	15.00	0.50	1.00	1.00	5.00	6050	4614	1665	3786
0.50	1.00	4.00	1.00	1.00	0.10	688	1699	1046	963
2.00	1.00	4.00	1.00	1.00	5.00	10370	6299	1665	5153
0.50	15.00	4.00	1.00	1.00	5.00	10311	4887	1046	4060
2.00	15.00	4.00	1.00	1.00	0.10	747	2660	1665	1856
0.50	1.00	0.50	6.00	1.00	0.10	3655	2401	6169	1639
2.00	1.00	0.50	6.00	1.00	5.00	10575	6070	9883	4917
0.50	15.00	0.50	6.00	1.00	5.00	8675	4665	6169	3837
2.00	15.00	0.50	6.00	1.00	0.10	5555	2788	9883	1984
0.50	1.00	4.00	6.00	1.00	5.00	12659	7577	6169	6422
2.00	1.00	4.00	6.00	1.00	0.10	3387	3307	9883	2565
0.50	15.00	4.00	6.00	1.00	0.10	3035	2950	6169	2146
2.00	15.00	4.00	6.00	1.00	5.00	13011	5317	9883	4490

A response surface was constructed using the non-parametric regression method to describe the relationship between output parameters (T1, T2, T3, T4) and factors $(t_1, t_2, t_3, p_1, p_2, p_3)$.

An analysis was conducted on how input factors affect output parameters. The temperature T1 in the processing zone is significantly affected by the power density of the first front of the laser pulse p_1. The temperature T2 is primarily influenced by the power density of the second front p_2, whereas the temperature T3 is significantly affected by the power densities of both the second and third fronts, p_2 and p_3, respectively. The temperature T4 is significantly influenced by the power density of the second front p_2, as illustrated in Fig. 3.

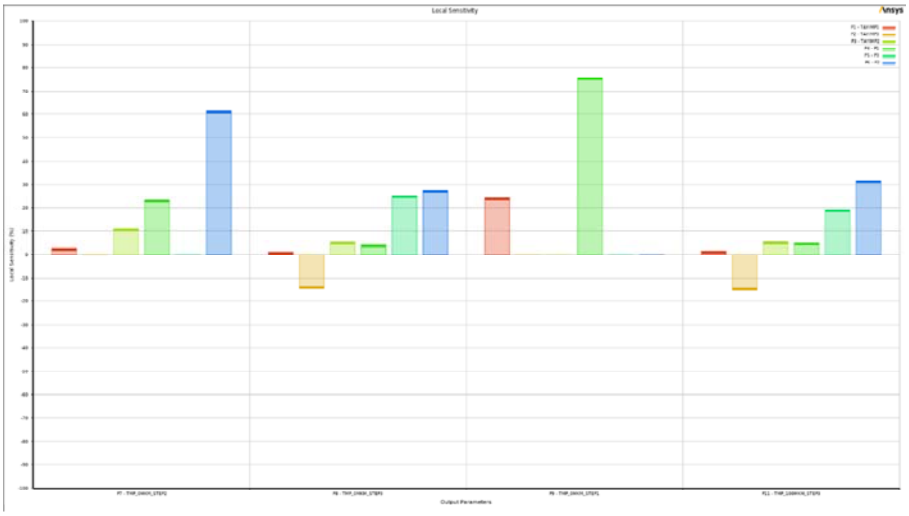


Fig. 3. Sensitivity diagram of optimized parameters:
$P1 - t_1$, $P2 - t_3$, $P3 - t_2$, $P4 - p_1$, $P5 - p_3$, $P6 - p_2$,
P7 – T1, P8 – T2, P9 – T3, P11 – T4

Figure 4 illustrates the relationships between the input parameters and the output parameters.

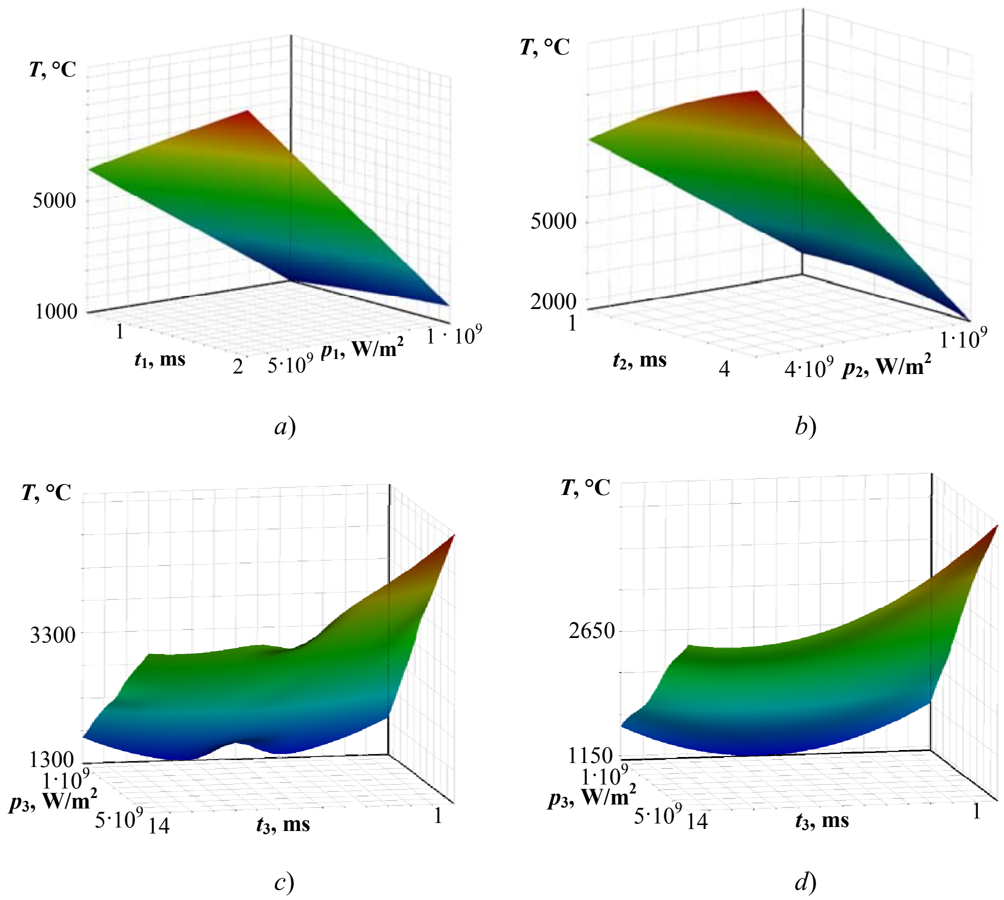


Fig. 4. Input parameters versus output parameters:
a – temperature T1 vs. processing parameters t_1 and p_1;
b – temperature T2 vs. processing parameters t_2 and p_2;
c – temperature T3 vs. processing parameters t_3 and p_3;
d – temperature T4 vs. processing parameters t_3 and p_3

The calculations involved 100 variants of input parameters, with 95 used alongside 45 variants of experimental design for the training of artificial neural networks, while the remaining 5 were reserved for testing (Table 2).

The Adam optimizer, MSE (Mean Squared Error) loss function, and ReLU activation function were used in the process of constructing the artificial neural networks. The neural network underwent training for a total of 300 epochs. As a result, 25 artificial neural networks were created with the number of neurons in two hidden layers ranging from 5 to 20, with an interval of 5.

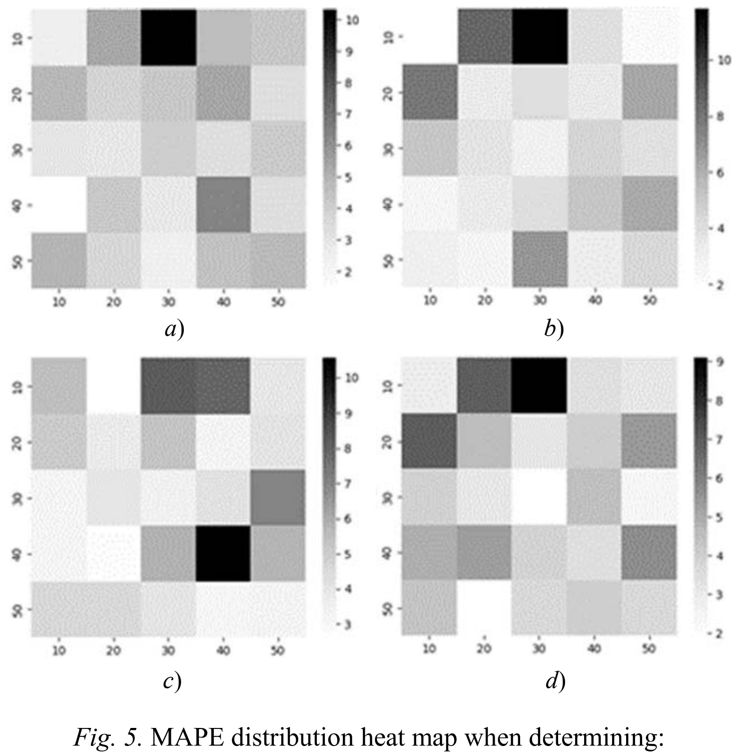
Table 2

Test dataset

P1 t_1, ms	P2 t_2, ms	P3 t_3, ms	P4 p_1, W/m^2 · 10^9	P5 p_2, W/m^2 · 10^9	P6 p_3, W/m^2 · 10^9	P7 T1, °C	P8 T2, °C	P9 T3, °C	P10 T4, °C
1.05	14.51	3.14	4.33	0.90	4.63	10831	4587	5467	3842
1.59	3.45	2.62	2.13	0.46	2.28	5268	2545	3049	2106
1.54	13.95	3.88	2.43	0.14	0.52	2355	793	3577	677
0.81	11.57	1.08	5.88	0.64	1.20	5688	2259	7116	1732
0.73	8.63	1.01	5.73	0.47	3.90	8646	2984	6375	2559

The quality of the generated models was evaluated using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and the coefficient of determination R^2 [15].

Figure 5 presents heat maps illustrating the distribution of validation errors MAPE in determining the maximal values of temperature T1, T2, T3 and T4 in the processing area. The number of neurons in the first and second hidden layers of the artificial neural network are shown by the vertical and horizontal axes, respectively. The intensity of color coding represents the extent of error: the error increases from light to dark.



a) *b*) *c*) *d*)

Fig. 5. MAPE distribution heat map when determining:
a – T1; *b* – T2; *c* – T3; *d* – T4

The artificial neural network with the architectures [6-40-10-4], [6-10-50-4], [6-40-20-4], [6-50-20-4] demonstrated the most favorable results when determining the values of maximum temperatures T1, T2, T3, T4 in the processing area.

Table 3 presents the estimation results of the respective neural network models, and Table 4 displays the model derived from the non-parametric regression approach.

Table 3

Assessment outcomes of the neural network model

Criterion	T1	T2	T3	T4
RMSE, K	122.5	63.9	158.5	32.8
MAE, K	93.4	47.6	122.9	29.7
MAPE, %	1.4	2.2	2.7	1.9
R^2	0.9982	0.9973	0.9898	0.9990

Table 4

Assessment outcomes of the model derived from the non-parametric regression approach

Criterion	T1	T2	T3	T4
RMSE, K	211.4	127.5	149.7	97.7
MAE, K	182.0	118.8	106.5	79.4
MAPE, %	3.4	7.5	2.1	6.1
R^2	0.9948	0.9891	0.9909	0.9911

The assessment outcomes of the developed models indicate their alignment with the data obtained from finite element calculations. The data presented in Tables 3 and 4 indicate that neural network models exhibit greater efficiency in predicting the output parameters associated with the laser alloying process of steel 30ХГСН2А.

The optimization procedure was performed via the MOGA (Multi-Objective Genetic Algorithm) within the DesignXplorer module, with the initial population size of 500 individuals, and the number of individuals per iteration was likewise established at 500.

The optimization of laser alloying of steel 30ХГСН2А with chromium was carried out in accordance with the following problem formulation:

– to minimize metal evaporation during alloying at the termination time of each laser pulse front, it is essential that the surface temperature of the alloying component of the additive coating material (Fig. 1, point 1) be above the melting temperature and below the metal evaporation temperature;

– to ensure the melting of the alloying component layer while minimizing evaporation, it is essential that the entire volume within the laser radiation exposure area be melted by the termination time of the third pulse front. This necessitates that the temperature at the lower surface (Fig. 1, point 2) remain at or above the melting temperature of the additive metal.

The genetic algorithm was employed to determine the optimal duration of pulse fronts for the laser alloying of 30ХГСН2А steel with chromium, as presented in Table 5. The parameter values derived from finite-element calculations are presented in parentheses. The maximum percentage error of temperature values calculated using the genetic algorithm remained below 4 %.

Table 5

Optimization results

P1 t_1, **ms**	**P2** t_2, **ms**	**P3** t_3, **ms**	**P4** p_1, **W/m^2 · 10^9**	**P5** p_2, **W/m^2 · 10^9**	**P6** p_3, **W/m^2 · 10^9**	**P7 T1, °C**	**P8 T2, °C**	**P9 T3, °C**	**P10 T4, °C**
1.63	8.68	1.15	1.01	1.09	0.75	1526 (1542)	2311 (2227)	2271 (2260)	1653 (1650)

Conclusion

This paper presents a finite element modeling of the laser alloying of 30ХГСН2А steel with chromium. A surrogate model of the process under study was developed utilizing artificial neural networks and the non-parametric regression approach. The demonstration of multicriteria optimization for the parameters of pulsed laser cladding of steel through the genetic algorithm is presented. The maximum percentage error in the prediction of temperature values within the laser processing area does not surpass 4 %. The laser pulse parameters were established through multi-criteria optimization, leading to a practical application that enhances the efficiency of the laser cladding process for 30ХГСН2А steel.

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