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НЕЙРО-НЕЧЕТКОЕ И НЕЧЕТКОЕ МОДЕЛИРОВАНИЕ ЛАЗЕРНОГО ЛЕГИРОВАНИЯ СТАЛИ 30ХГСН2А

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NEURO-FUZZY AND FUZZY MODELING OF LASER ALLOYING OF STEEL 30ХГСН2А

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Аннотация. Работа посвящена построению нейро-нечетких и нечетких моделей лазерного легирования хромом конструкционной стали 30ХГСН2А на основе результатов численного эксперимента. Конечно-элементное моделирование лазерного легирования стали 30ХГСН2А выполнено с учетом зависимости теплофизических свойств материалов от температуры и плотностей на языке программирования APDL с использованием гранецентрированного варианта центрального композиционного плана эксперимента. В качестве факторов эксперимента использовались временные интервалы, соответствующие длительностям трех фронтов лазерного импульса, и пиковые плотности мощности этих фронтов, в качестве – максимальные температуры в зоне обработки. Оценка качества моделей осуществлялась по статистическим метрикам *RMSE*, *MAE*, *MAPE*, R^2 на тестовом наборе данных. Выявлена более высокая эффективность нейро-нечетких моделей при прогнозировании параметров лазерного легирования стали в сравнении с нечеткими моделями.

Ключевые слова: *лазерное легирование*, *нечеткий вывод Мамдани*.

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Abstract. The study focuses on developing neuro-fuzzy and fuzzy models for laser alloying of structural steel 30ХГСН2А with chromium, based on numerical experiment results. Finite element modeling of laser alloying for steel 30ХГСН2А was performed using APDL programming language, accounting for temperature-dependent thermophysical material properties and power densities, and employing a face-centered central composite experimental design. The experimental factors included time intervals corresponding to the durations of three laser pulse fronts and their peak power densities, while the response variables were maximum temperatures in the processing zone. The model quality was evaluated using statistical metrics (*RMSE*, *MAE*, *MAPE*, R^2) on a test dataset. The results demonstrate the superior predictive accuracy of neuro-fuzzy models over conventional fuzzy models for laser alloying parameters.

Keywords: *laser alloying*, *Mamdani fuzzy inference.*

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Introduction

Modern technologies, particularly laser processing, enable targeted modification of surface properties without affecting the base material. The key advantages of laser processing are its versatility and precision, which allow for coating deposition with various materials and treatment of components with virtually any geometry or size.

Among laser processing technologies, laser alloying has gained widespread adoption as an effective method for enhancing metal surface properties. This technique enables precise modification of a component's surface layer composition and microstructure through laser irradiation, offering high processing accuracy and improved material performance characteristics [1], [2].

The application of artificial intelligence methods, particularly fuzzy logic and adaptive neuro-fuzzy inference systems, enables optimization of laser processing parameters. This approach is especially relevant for investigating laser alloying of steels such as 30ХГСН2А. The formation of fuzzy rules through integration of artificial neural networks into fuzzy inference systems allows training such systems without expert involvement. Hybrid networks combine the advantages of both approaches, thereby overcoming the fundamental limitations of each individual method [3]–[5].

Our analysis shows that reference [6] examined neural networks with genetic optimization and adaptive neuro-fuzzy systems for laser forming processes, while the work in [7] developed a neuro-fuzzy model that accurately predicts geometric parameters of laser-clad layers.

This study aims to develop fuzzy and neuro-fuzzy models of chromium laser alloying for structural steel 30ХГСН2А.

1 Research results

Temperature determination was performed using the ANSYS finite element analysis software. The computational model consisted of a 30ХГСН2А steel plate with dimensions of 3 × 3 × 1 mm, coated with a 100 μm thick flux layer containing the alloying component that ensured formation of a uniformly melted layer. Figure 1.1 illustrates the laser irradiation scheme applied to the treated surface.

The numerical experiment employed a six-factor face-centered central composite design [8]. The experimental factors consisted of time intervals t_1, t_2, and t_3 (corresponding to the durations of three laser pulse fronts) and peak power densities p_1, p_2, and p_3 of these fronts (Figure 1.2). The model responses were temperatures in the processing zone: $T1$, $T2$, and $T3$ represented surface temperatures of the alloying-component flux layer at the completion times of the first, second, and third laser pulse fronts, respectively, while $T4$ denoted the temperature at 100 μm depth upon completion of the third front. The finite element analysis, implemented via APDL programming language, generated a dataset for constructing and validating neuro-fuzzy models [8].

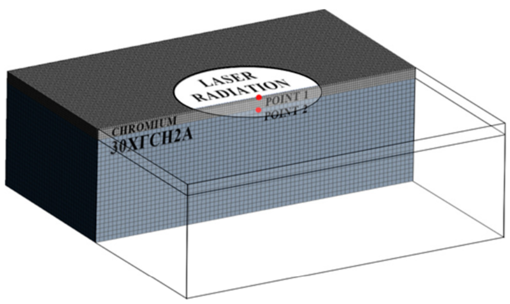

Figure 1.1 – Schematic of laser irradiation impact

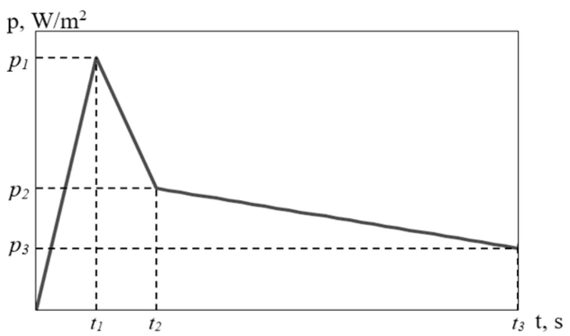

Figure 1.2 – Laser pulse waveform

The neuro-fuzzy model was developed using ANFIS (Adaptive Neuro-Fuzzy Inference System), a hybrid architecture combining neural networks and fuzzy logic. For training, we employed a hybrid learning algorithm integrating gradient descent with least squares estimation [9]. During the first stage, premise parameters were fixed while consequent parameters were optimized using least squares. In the second stage, consequent parameters remained fixed while premise parameters were refined through gradient descent.

The neuro-fuzzy model approximating the relationships between maximum temperatures ($T1$, $T2$, $T3$, $T4$) and laser pulse front durations (t_1, t_2, t_3) with their corresponding power densities (p_1, p_2, p_3) was trained over 20 epochs. The model testing was performed using a test dataset (Table 1.1), which was also generated through finite element analysis employing the APDL programming language.

Table 1.1 – Test dataset

N	1	2	3	4	5
t_1, ms	1.05	1.59	1.54	0.81	0.73
t_2, ms	14.51	3.45	13.95	11.57	8.63
t_3, ms	3.14	2.62	3.88	1.08	1.01
p_1, W/m^2·10^9	4.33	2.13	2.43	5.88	5.73
p_2, W/m^2·10^9	0.90	0.46	0.14	0.64	0.47
p_3, W/m^2·10^9	4.63	2.28	0.52	1.20	3.90
$T1$, °C	10831	5268	2355	5688	8646
$T2$, °C	4587	2545	793	2259	2984
$T3$, °C	5467	3049	3577	7116	6375
$T4$, °C	3842	2106	677	1732	2559

The neuro-fuzzy model's performance was evaluated using the following statistical metrics: the coefficient of determination (R^2), Mean Absolute Error (*MAE*), Root Mean Square Error (*RMSE*), and Mean Absolute Percentage Error (*MAPE*).

Table 1.2 – Performance evaluation metrics of neuro-fuzzy models

Statistical Metric	Model Response			
	$T1$	$T2$	$T3$	$T4$
RMSE	411 K	169 K	250 K	149 K
MAE	355 K	150 K	218 K	133 K
MAPE	6.7%	5.3%	5.0%	6.4%
R^2	0.9802	0.9808	0.9747	0.9795

The metric values demonstrate sufficient agreement between the neuro-fuzzy model and the finite element analysis results. As an example, Figure 1.3 shows the derived relationship between the maximum temperature $T1$ and the processing parameters t_1 and p_1.

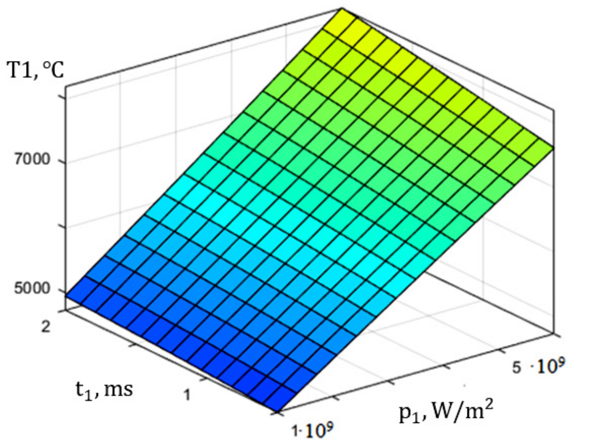

Figure 1.3 – Dependence of temperature $T1$ on processing parameters t_1 and p_1 derived using the neuro-fuzzy model

The fuzzy model establishing relationships between maximum temperatures ($T1$, $T2$, $T3$, $T4$) and laser pulse front durations (t_1, t_2, t_3) with their corresponding power densities (p_1, p_2, p_3) was developed using the same numerical experiment data generated via APDL programming [8]. The fuzzy system implementation employed Python's Scikit-Fuzzy library, where input parameter fuzzification utilized triangular membership functions (Figure 1.4), while Gaussian membership functions were selected for output fuzzification due to their smoothness and superior ability to approximate nonlinear dependencies (Figure 1.5).

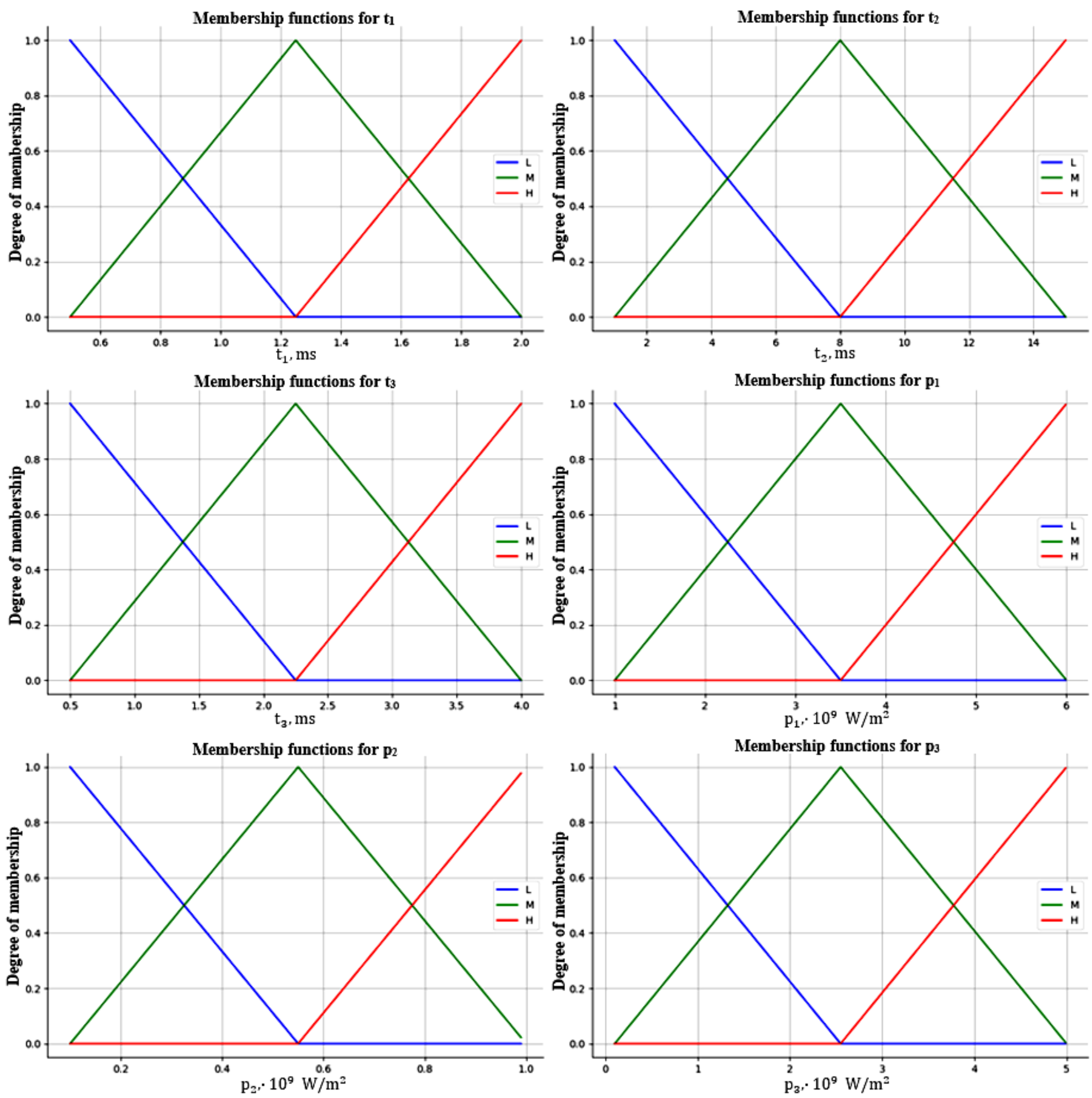

Figure 1.4 – Membership functions of linguistic variables for input parameters t_1, t_2, t_3 and p_1, p_2, p_3

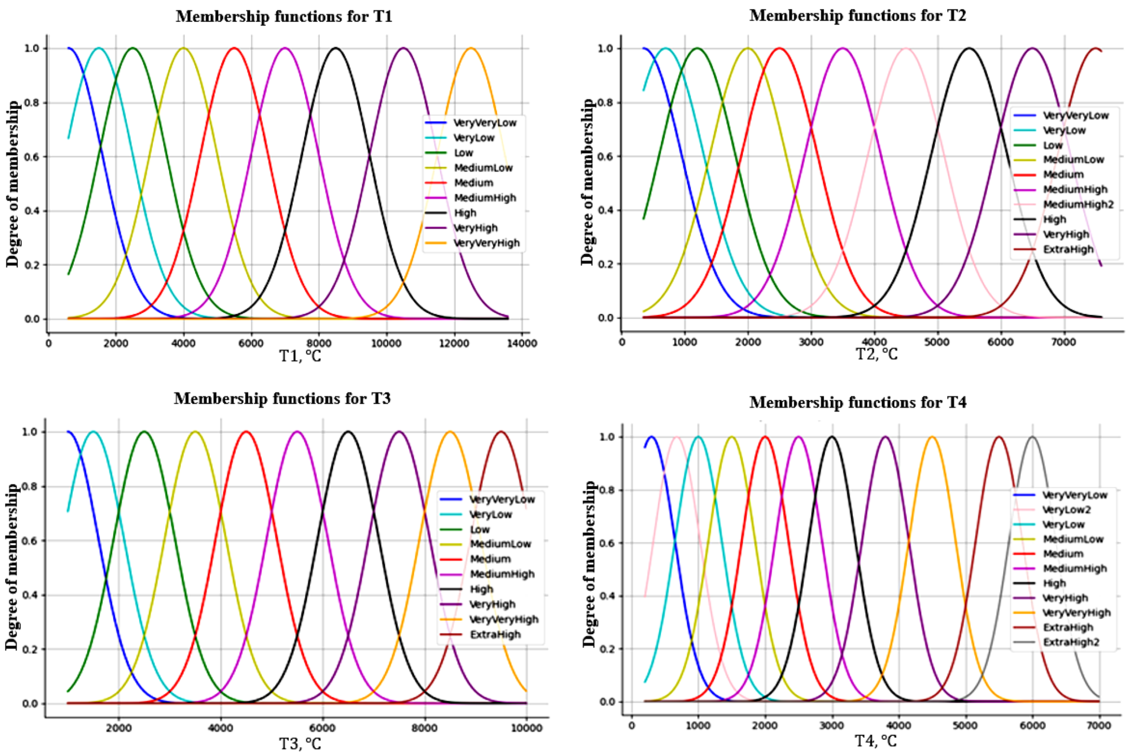

Figure 1.5 – Membership functions of linguistic variables for output parameters *T*1, *T*2, *T*3, and *T*4

2 Mamdani fuzzy inference algorithm

The fuzzy modeling of laser alloying for steel 30ХГСН2А is based on the Mamdani fuzzy inference algorithm [3]. Specifically, the generated rules for determining temperatures T1 in the processing zone are formulated as follows:

```
rule1 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule2 = ctrl.Rule(t1['L'] & t2['M'] &
t3['M'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule3 = ctrl.Rule(t1['H'] & t2['M'] &
t3['M'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule4 = ctrl.Rule(t1['M'] & t2['L'] &
t3['M'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule5 = ctrl.Rule(t1['M'] & t2['H'] &
t3['M'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule6 = ctrl.Rule(t1['M'] & t2['M'] &
t3['L'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['MediumLow'])
rule7 = ctrl.Rule(t1['M'] & t2['M'] &
t3['H'] & p1['M'] & p2['M'] & p3['M'],
T_ctrl['Medium'])
rule8 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['L'] & p2['M'] & p3['M'],
T_ctrl['Low'])
rule9 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['H'] & p2['M'] & p3['M'],
T_ctrl['High'])
rule10 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['M'] & p2['L'] & p3['M'],
T_ctrl['Medium'])
rule11 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['M'] & p2['H'] & p3['M'],
T_ctrl['Medium'])
rule12 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['M'] & p2['M'] & p3['L'],
T_ctrl['VeryLow'])
rule13 = ctrl.Rule(t1['M'] & t2['M'] &
t3['M'] & p1['M'] & p2['M'] & p3['H'],
T_ctrl['VeryHigh'])
rule14 = ctrl.Rule(t1['L'] & t2['L'] &
t3['L'] & p1['L'] & p2['L'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule15 = ctrl.Rule(t1['H'] & t2['L'] &
t3['L'] & p1['L'] & p2['L'] & p3['H'],
T_ctrl['Low'])
rule16 = ctrl.Rule(t1['L'] & t2['H'] &
t3['L'] & p1['L'] & p2['L'] & p3['H'],
T_ctrl['Low'])
rule17 = ctrl.Rule(t1['H'] & t2['H'] &
t3['L'] & p1['L'] & p2['L'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule18 = ctrl.Rule(t1['L'] & t2['L'] &
t3['H'] & p1['L'] & p2['L'] & p3['H'],
T_ctrl['VeryHigh'])
rule19 = ctrl.Rule(t1['H'] & t2['L'] &
t3['H'] & p1['L'] & p2['L'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule20 = ctrl.Rule(t1['L'] & t2['H'] &
t3['H'] & p1['L'] & p2['L'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule21 = ctrl.Rule(t1['H'] & t2['H'] &
t3['H'] & p1['L'] & p2['L'] & p3['H'],
T_ctrl['VeryHigh'])
rule22 = ctrl.Rule(t1['L'] & t2['L'] &
t3['L'] & p1['H'] & p2['L'] & p3['H'],
T_ctrl['High'])
rule23 = ctrl.Rule(t1['H'] & t2['L'] &
t3['L'] & p1['H'] & p2['L'] & p3['L'],
T_ctrl['Low'])
```

```
rule24 = ctrl.Rule(t1['L'] & t2['H'] &
t3['L'] & p1['H'] & p2['L'] & p3['L'],
T_ctrl['Low'])
rule25 = ctrl.Rule(t1['H'] & t2['H'] &
t3['L'] & p1['H'] & p2['L'] & p3['H'],
T_ctrl['VeryHigh'])
rule26 = ctrl.Rule(t1['L'] & t2['L'] &
t3['H'] & p1['H'] & p2['L'] & p3['L'],
T_ctrl['Low'])
rule27 = ctrl.Rule(t1['H'] & t2['L'] &
t3['H'] & p1['H'] & p2['L'] & p3['H'],
T_ctrl['VeryVeryHigh'])
rule28 = ctrl.Rule(t1['L'] & t2['H'] &
t3['H'] & p1['H'] & p2['L'] & p3['H'],
T_ctrl['VeryVeryHigh'])
rule29 = ctrl.Rule(t1['H'] & t2['H'] &
t3['H'] & p1['H'] & p2['L'] & p3['L'],
T_ctrl['Low'])
rule30 = ctrl.Rule(t1['L'] & t2['L'] &
t3['L'] & p1['L'] & p2['H'] & p3['H'],
T_ctrl['Low'])
rule31 = ctrl.Rule(t1['H'] & t2['L'] &
t3['L'] & p1['L'] & p2['H'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule32 = ctrl.Rule(t1['L'] & t2['H'] &
t3['L'] & p1['L'] & p2['H'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule33 = ctrl.Rule(t1['H'] & t2['H'] &
t3['L'] & p1['L'] & p2['H'] & p3['H'],
T_ctrl['Low'])
rule34 = ctrl.Rule(t1['L'] & t2['L'] &
t3['H'] & p1['L'] & p2['H'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule35 = ctrl.Rule(t1['H'] & t2['L'] &
t3['H'] & p1['L'] & p2['H'] & p3['H'],
T_ctrl['VeryHigh'])
rule36 = ctrl.Rule(t1['L'] & t2['H'] &
t3['H'] & p1['L'] & p2['H'] & p3['H'],
T_ctrl['VeryHigh'])
rule37 = ctrl.Rule(t1['H'] & t2['H'] &
t3['H'] & p1['L'] & p2['H'] & p3['L'],
T_ctrl['VeryVeryLow'])
rule38 = ctrl.Rule(t1['L'] & t2['L'] &
t3['L'] & p1['H'] & p2['H'] & p3['L'],
T_ctrl['Low'])
rule39 = ctrl.Rule(t1['H'] & t2['L'] &
t3['L'] & p1['H'] & p2['H'] & p3['H'],
T_ctrl['VeryHigh'])
rule40 = ctrl.Rule(t1['L'] & t2['H'] &
t3['L'] & p1['H'] & p2['H'] & p3['H'],
T_ctrl['High'])
rule41 = ctrl.Rule(t1['H'] & t2['H'] &
t3['L'] & p1['H'] & p2['H'] & p3['L'],
T_ctrl['Low'])
rule42 = ctrl.Rule(t1['L'] & t2['L'] &
t3['H'] & p1['H'] & p2['H'] & p3['H'],
T_ctrl['VeryVeryHigh'])
rule43 = ctrl.Rule(t1['H'] & t2['L'] &
t3['H'] & p1['H'] & p2['H'] & p3['L'],
T_ctrl['Low'])
rule44 = ctrl.Rule(t1['L'] & t2['H'] &
t3['H'] & p1['H'] & p2['H'] & p3['L'],
T_ctrl['Low'])
rule45 = ctrl.Rule(t1['H'] & t2['H'] &
t3['H'] & p1['H'] & p2['H'] & p3['H'],
T_ctrl['VeryVeryHigh'])
```

Similar Mamdani-type fuzzy inference rules were also constructed for *T*2, *T*3, and *T*4.

The models were tested using the test dataset (Table 1.1). The fuzzy models' performance evaluation results, including statistical metrics *RMSE*, *MAE*, *MAPE*, and R^2, are presented in Table 2.1.

Table 2.1 – Fuzzy models performance evaluation results

Statistical Metric	Model Response			
	*T*1	*T*2	*T*3	*T*4
RMSE	922 K	468 K	463 K	376 K
MAE	916 K	389 K	345 K	320 K
MAPE	17.2%	26.1%	8.9%	19.9%
R^2	0.9005	0.8530	0.9130	0.8680

The best results were obtained for *T*3 (minimum *MAPE* = 8.9% and maximum $R^2 = 0.9130$), with all metric values confirming the fuzzy model's satisfactory accuracy against finite element analysis. Upon comparing the outcomes of neuro-fuzzy modelling within the ANFIS framework for the laser alloying of steel 30ХГСН2А (Table 1.2) with those of fuzzy modelling (Table 2.1), it is evident that all *RMSE*, *MAE*, and *MAPE* metrics of the neuro-fuzzy model were inferior to their fuzzy model counterparts, whereas the R^2 determination coefficients were superior.

Figure 2.1 illustrates the graph depicting the relationship between maximum temperature *T*1 and the processing parameters t_1 and p_1, as derived from the fuzzy model.

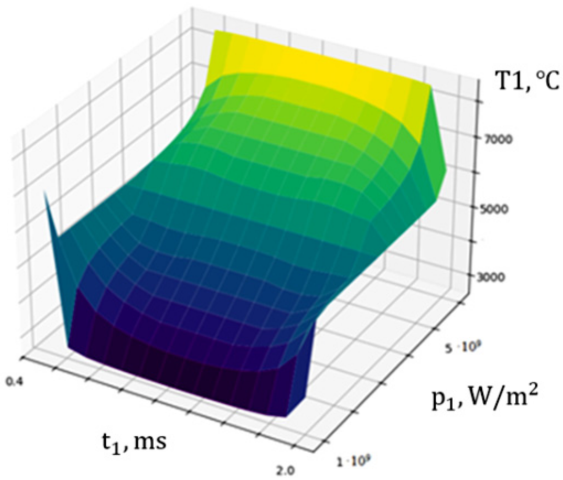

Figure 2.1 – Dependence of temperature *T*1 on processing parameters t_1 and p_1 as determined by the fuzzy system

Conclusion

This study conducted comparative modeling of the laser alloying process for 30ХГСН2А structural steel with chromium using two approaches: an adaptive neuro-fuzzy inference system (ANFIS) and fuzzy logic. The modeling was based on finite element analysis data and aimed to establish relationships between pulsed laser parameters and temperatures in the processing zone.

Neuro-fuzzy and fuzzy models were developed to predict key thermal parameters (maximum surface temperatures *T*1, *T*2, *T*3 and subsurface temperature *T*4) during laser alloying of 30ХГСН2А steel.

Both models demonstrated agreement with finite element analysis results, confirming their validity.

A comparative accuracy assessment of the models was conducted on the test dataset using statistical metrics (*RMSE*, *MAE*, *MAPE*, R^2), revealing that the neuro-fuzzy model achieves significantly higher predictive accuracy than the Mamdani fuzzy logic model. The determination coefficient R^2 for neuro-fuzzy models ranged between 0.9747 and 0.9808 compared to 0.8530–0.9130 for fuzzy models, while the mean absolute percentage error (MAPE) of neuro-fuzzy models remained below 7%, demonstrating their strong agreement with experimental data.

The study confirmed that hybrid systems combining neural networks and fuzzy logic serve as effective tools for modeling complex nonlinear processes, including laser material processing. The neuro-fuzzy systems' capability to learn and automatically adjust membership functions based on experimental data eliminates the reliance on expert knowledge inherent in conventional fuzzy inference systems, while significantly improving prediction accuracy.

The developed models can be used to optimize laser alloying process parameters for fabricating surface layers with tailored performance characteristics. Future research will focus on adapting this approach for other steel grades and alloying elements.

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