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МОДЕЛИРОВАНИЕ КАЧЕСТВА ПОКРЫТИЙ, ФОРМИРУЕМЫХ ИМПУЛЬСНЫМ ЛАЗЕРНЫМ ИЗЛУЧЕНИЕМ НА СТАЛИ 30ХГСН2А С ИСПОЛЬЗОВАНИЕМ НЕЧЕТКИХ МОДЕЛЕЙ

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FUZZY LOGIC-BASED MODELING OF COATING QUALITY UNDER PULSED LASER RADIATION ON 30ХГСН2А STEEL

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Аннотация. Высокая нелинейность процессов при импульсной лазерной наплавке затрудняет прогнозирование свойств поверхностного слоя, особенно в условиях малых выборок экспериментальных данных. В данной работе предложен подход к моделированию процесса импульсной лазерной наплавки высокопрочной стали 30ХГСН2А нихромом с использованием математического аппарата нечеткой логики. На основе экспериментальных данных построена экспертная система нечеткого вывода типа Мамдани, связывающая параметры лазерного излучения (энергию, длительность и частоту импульсов) с геометрией наплавленного валика, микротвердостью и дефектностью (наличием трещин и пор). Прогностическая ценность модели оценивалась на независимой тестовой выборке. Результаты показали достаточную точность. Использование алгоритмов нечеткой интерполяции с переходом к целочисленным значениям позволило создать физически адекватную систему прогнозирования дефектов. Разработанная модель может применяться в качестве интеллектуального ядра для оптимизации технологических режимов импульсной лазерной наплавки.

Ключевые слова: *лазерная наплавка*, *сталь*, *нечеткая логика*.

Для цитирования: *Моделирование качества покрытий, формируемых импульсным лазерным излучением на стали* 30ХГСН2А *с использованием нечетких моделей* / Ю. В. Никитюк, Л. Н. Марченко, Г. А. Баевич, В. А. Прохоренко, А. В. Максименко // Проблемы физики, математики и техники. – 2026. – № 3 (68). – С. 72–78. – DOI: https://doi.org/10.54341/20778708_2026_3_68_72. – EDN: LAGKPK

Abstract. The high nonlinearity of pulsed laser cladding processes poses significant challenges for predicting coating quality, particularly when dealing with small experimental datasets. This paper proposes a fuzzy logic-based modeling approach for pulsed laser cladding of high-strength 30ХГСН2А steel with nichrome. Using the experimental data, a Mamdani-type fuzzy inference expert system was constructed, linking the laser radiation parameters (pulse energy, duration, and repetition rate) with the geometry of the deposited bead, microhardness, and defectiveness (presence of cracks and pores. The predictive performance of the model was assessed on an independent test dataset, demonstrating satisfactory accuracy. Furthermore, the application of fuzzy interpolation algorithms with integer-valued outputs enabled the development of a physically consistent defect prediction system. The resulting model can serve as an intelligent decision-making core for optimizing process parameters in pulsed laser cladding.

Keywords: *laser cladding*, *steel*, *fuzzy logic.*

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Introduction

High-strength structural steels, such as 30ХГСН2А, are extensively employed in the aerospace and power engineering industries for components that operate under cyclic loading and at elevated temperatures. During operation, the surface layers of these components experience severe abrasive wear and corrosion, creating a need for reliable protective coatings that can improve corrosion resistance and ensure the required surface performance. Pulsed laser cladding has emerged as a highly efficient method for depositing such coatings onto high-strength steels, allowing precise control over coating geometry and physico-mechanical properties [1]–[5].

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Producing high-quality coatings on high-strength steels entails several challenges. The high heating and cooling rates inherent in the process give rise to steep thermal gradients within the laser-affected zone, resulting in the development of considerable thermal stresses and, consequently, coating defects. At the same time, the deposited layer thickness and surface microhardness must be maintained at specified levels. These quality attributes exhibit a complex nonlinear dependence on the key laser processing parameters, namely, pulse energy, pulse duration, and repetition rate [6]–[8].

Pulsed laser cladding of high-strength steels thus represents a complex problem in which heat transfer, phase transformations, melt pool hydrodynamics, and thermoelastic stress generation and relaxation all occur concurrently. Finite element simulations for predicting laser processing outcomes are computationally expensive. A viable alternative is the construction of surrogate models (metamodels), i. e., mathematical approximations trained on limited experimental data that capture the underlying input → output relationships with sufficient accuracy for practical engineering purposes. The conventional approach to process parameter optimization in laser processing relies on experimental design techniques followed by the construction of regression models. However, second-order polynomial approximations often fail to capture the nonlinear thermophysical phenomena occurring in the melt pool with sufficient accuracy. While modern machine learning techniques, such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests, can deliver high predictive accuracy, they often come at the cost of model interpretability. The process engineer is thus left with a "black box" that obscures the underlying physical mechanisms linking the input parameters to the output, thereby hindering informed decision-making, particularly when extrapolating beyond the training data range [9]–[12].

A compelling alternative is fuzzy logic, introduced by L. Zadeh in 1965 and further expanded for control applications by E. Mamdani [13], [14]. Fuzzy models operate with linguistic variables, such as "low energy" or "high frequency", and IF – THEN rules, which facilitates the seamless integration of expert knowledge. Fuzzy inference systems have been successfully employed for modeling laser processing operations [15]–[20], offering an attractive trade-off between predictive accuracy and transparency of the decision-making logic.

In our earlier research, we explored the application of adaptive neuro-fuzzy inference systems (ANFIS) and Mamdani-type models to describe the laser alloying of 30ХГСН2А steel [18]. Nonetheless, the intelligent models in that research were trained on numerically generated data, and the predicted outputs were limited to thermal fields. While temperature predictions were highly accurate, thermophysical modeling by itself cannot directly assess the resultant physico-mechanical properties of the surface layer or the probability of defect emergence. In contrast to our earlier research, the present study relies exclusively on experimental data from physical experiments. The focus has shifted from computing theoretical temperature fields to directly forecasting actual quality characteristics, and further extends to the challenging task of predictive analytics for discrete macrodefects using a modified fuzzy inference algorithm.

This paper presents the development and experimental validation of a Mamdani-type fuzzy model for predicting the geometry, mechanical properties, and defects of nichrome coatings deposited on 30ХГСН2А steel by pulsed laser radiation, providing an effective trade-off between predictive accuracy and result interpretability.

1 Experimental investigation of pulsed laser cladding of nichrome coatings on 30ХГСН2А steel

Pulsed laser cladding of nichrome coatings was performed using a TL-400 processing facility equipped with a solid-state Nd:YAG laser. The active medium comprises yttrium aluminum garnet (YAG) crystals doped with trivalent neodymium ions, emitting at a wavelength of $\lambda = 1.064$ μm, with crystal dimensions of 6.3×130 mm. The system delivers an average output power of up to 400 W, and the laser beam diameter at the output is 8 mm.

High-strength structural steel 30ХГСН2А blanks served as substrates. Nichrome grade Х20Н80 was used as the coating material. Metallographic specimens of the clad beads were prepared by sequential grinding and polishing with abrasive papers of decreasing grit size: 60–40 μm, 10–17 μm, 7–5 μm, 1 μm, and 0.1 μm. The procedure persisted until a surface roughness of $Ra \leq 0.2$ μm was attained. The microstructure of the substrate, the heat-affected zone (HAZ), and the clad layer was revealed by chemical etching in a 3–5% solution of nitric acid in ethanol (nital). Morphological and geometric features of the coatings were examined with an EPIQUANT automatic structure analyzer (Carl Zeiss, Jena) at ×100 magnification. Quantitative measurements of the clad layer thickness and HAZ depth were carried out on digital images using a stage micrometer with a scale division of 0.01 mm. Coating defectiveness was evaluated by counting pores and microcracks in the bead cross-sections. Microhardness of the structural zones was measured by the Vickers method on a Kason-59-HV microhardness tester under an indenter load of 0.4905 N with a dwell time of 10 s. Indentation diagonals were measured at ×400 magnification.

A *D*-optimal experimental design was employed for the three input parameters: pulse

duration *t*, pulse energy *E*, and pulse repetition rate *f* (Table 1.1). The response parameters measured were *h* (deposited layer thickness), *HV* (surface microhardness), *Nc* (number of cracks), and *Np* (number of pores).

Table 1.1 – Experimental design and measured responses

N	*t*, ms	*E*, J	*f*, Hz	*h*, μm	*HV*, kgf/mm^2	*Nc*	*Np*
1	4	6.4	2	40	224	1	0
2	4	12.9	2	200	191	0	3
3	4	12.9	3	220	209	4	0
4	4	6.4	5	50	201	0	4
5	4	12.9	5	250	186	3	0
6	6	4.6	2	30	213	0	0
7	6	12.6	2	220	205	0	1
8	6	9.1	4	130	214	0	0
9	6	4.6	5	40	192	0	0
10	6	12.6	5	260	208	2	3
11	8	9.8	2	30	193	0	0
12	8	12.8	2	120	217	2	3
13	8	12.8	4	130	194	2	3
14	8	9.8	5	40	189	0	0
15	8	12.8	5	140	228	0	1

2 Fuzzy modeling of pulsed laser cladding parameters

The surrogate model was developed in Python using the scikit-fuzzy library. A Mamdani-type fuzzy inference system was implemented. The architecture of the developed fuzzy model is illustrated in Figure 2.1 [21], [22].

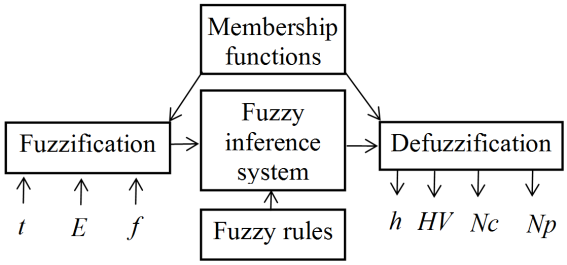


Figure 2.1 – Structure of the fuzzy system used for modeling pulsed laser cladding (*h*, *HV*, *Nc*, *Np*)

Triangular membership functions with three linguistic terms (Low, Medium, High) were defined for each input variable *t*, *E*, and *f*. This choice reflects the discrete nature of the process parameter settings in the experimental design. For the output variables *h*, *HV*, *Nc*, and *Np*, Gaussian membership functions with nine terms (T1–T9) were employed (see Figure 2.2), which provide smooth variation of the predicted outputs and improved approximation of the experimental data.

To predict the geometric characteristics, mechanical properties, and defect formation of nichrome coatings deposited on 30ХГСН2А steel by pulsed laser radiation, we constructed four IF-THEN rule bases from the experimental data (Table 2.1). These rule sets were designed to reflect the underlying physical mechanisms governing the coating formation process.

The rule bases for each output parameter are presented below:

```
rules_HV = [
ctrl.Rule(t['L']&E['L']&f['L'], HV['T8']),
ctrl.Rule(t['L']&E['H']&f['L'], HV['T2']),
ctrl.Rule(t['L']&E['H']&f['M'], HV['T6']),
ctrl.Rule(t['L']&E['L']&f['H'], HV['T4']),
ctrl.Rule(t['L']&E['H']&f['H'], HV['T1']),
ctrl.Rule(t['M']&E['L']&f['L'], HV['T7']),
ctrl.Rule(t['M']&E['H']&f['L'], HV['T5']),
ctrl.Rule(t['M']&E['L']&f['H'], HV['T2']),
ctrl.Rule(t['M']&E['H']&f['H'], HV['T6']),
ctrl.Rule(t['H']&E['M']&f['L'], HV['T2']),
ctrl.Rule(t['H']&E['H']&f['L'], HV['T7']),
ctrl.Rule(t['H']&E['H']&f['M'], HV['T3']),
ctrl.Rule(t['H']&E['M']&f['H'], HV['T2']),
ctrl.Rule(t['H']&E['H']&f['H'], HV['T9']),
ctrl.Rule(t['M']&E['M']&f['M'], HV['T7']),
ctrl.Rule(t['M']&E['H']&f['M'], HV['T4']),
ctrl.Rule(t['H']&E['M']&f['M'], HV['T3'])
]

rules_NC = [
ctrl.Rule(t['L']&E['L']&f['L'], NC['T3']),
ctrl.Rule(t['L']&E['H']&f['L'], NC['T1']),
ctrl.Rule(t['L']&E['H']&f['M'], NC['T9']),
ctrl.Rule(t['L']&E['L']&f['H'], NC['T1']),
ctrl.Rule(t['L']&E['H']&f['H'], NC['T7']),
ctrl.Rule(t['M']&E['L']&f['L'], NC['T1']),
ctrl.Rule(t['M']&E['H']&f['L'], NC['T1']),
ctrl.Rule(t['M']&E['L']&f['H'], NC['T1']),
ctrl.Rule(t['M']&E['H']&f['H'], NC['T5']),
ctrl.Rule(t['H']&E['M']&f['L'], NC['T1']),
ctrl.Rule(t['H']&E['H']&f['L'], NC['T5']),
ctrl.Rule(t['H']&E['H']&f['M'], NC['T5']),
ctrl.Rule(t['H']&E['M']&f['H'], NC['T1']),
ctrl.Rule(t['H']&E['H']&f['H'], NC['T1']),
ctrl.Rule(t['M']&E['M']&f['M'], NC['T1']),
ctrl.Rule(t['M']&E['H']&f['M'], NC['T3']),
ctrl.Rule(t['H']&E['M']&f['M'], NC['T1'])
]

rules_Np = [
ctrl.Rule(t['L']&E['L']&f['L'], Np['T1']),
ctrl.Rule(t['L']&E['H']&f['L'], Np['T7']),
ctrl.Rule(t['L']&E['H']&f['M'], Np['T1']),
ctrl.Rule(t['L']&E['L']&f['H'], Np['T9']),
ctrl.Rule(t['L']&E['H']&f['H'], Np['T1']),
ctrl.Rule(t['M']&E['L']&f['L'], Np['T1']),
ctrl.Rule(t['M']&E['H']&f['L'], Np['T3']),
ctrl.Rule(t['M']&E['L']&f['H'], Np['T1']),
ctrl.Rule(t['M']&E['H']&f['H'], Np['T7']),
ctrl.Rule(t['H']&E['M']&f['L'], Np['T1']),
ctrl.Rule(t['H']&E['H']&f['L'], Np['T7']),
ctrl.Rule(t['H']&E['H']&f['M'], Np['T7']),
ctrl.Rule(t['H']&E['M']&f['H'], Np['T1']),
ctrl.Rule(t['H']&E['H']&f['H'], Np['T3']),
ctrl.Rule(t['M']&E['M']&f['M'], Np['T1']),
ctrl.Rule(t['M']&E['H']&f['M'], Np['T5']),
ctrl.Rule(t['H']&E['M']&f['M'], Np['T5'])
]
```

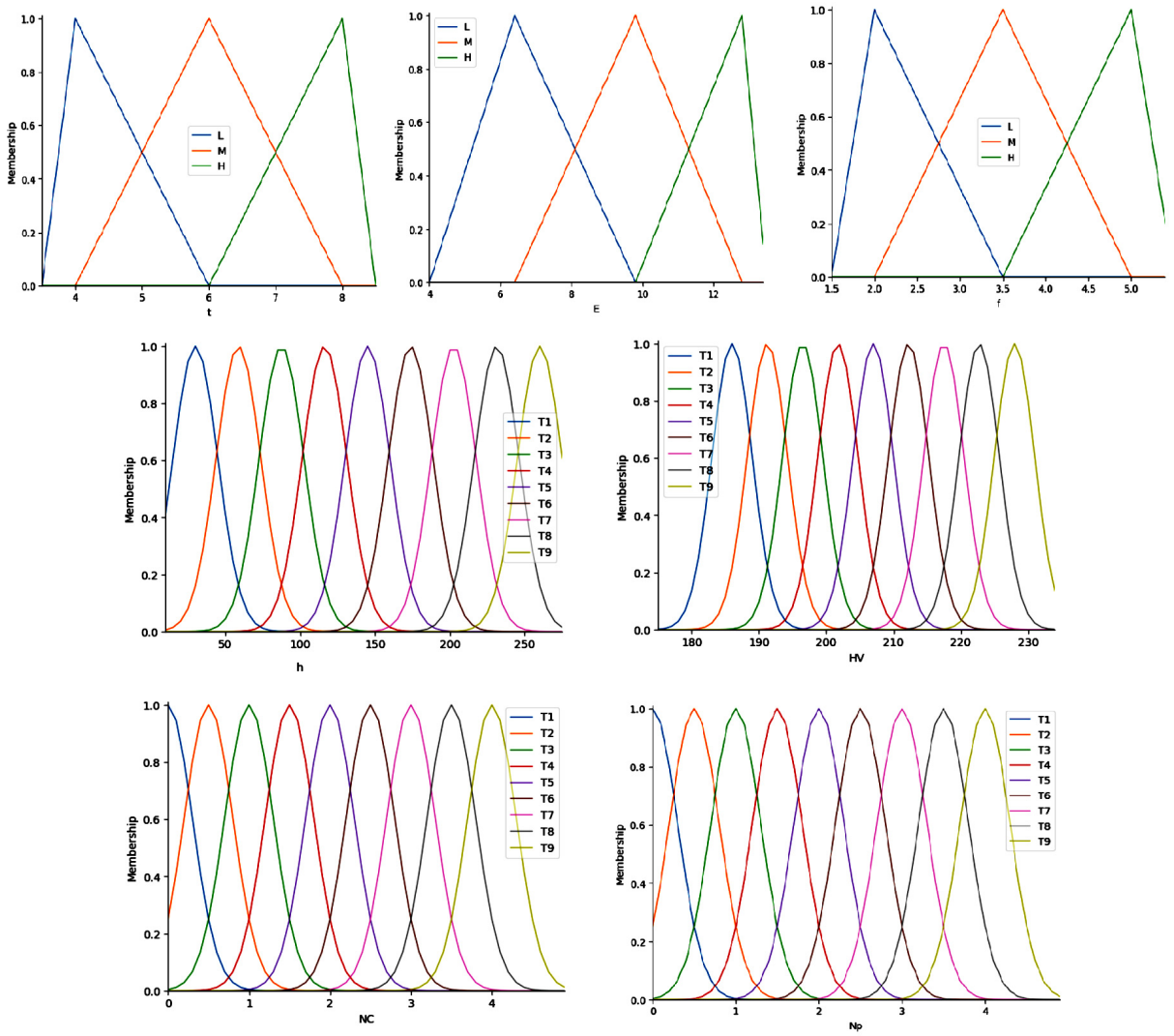


Figure 2.2 – Membership functions of the input and output linguistic variables

```
rules_h = [
ctrl.Rule(t['L']&E['L']&f['L'], h['T1']),
ctrl.Rule(t['L']&E['H']&f['L'], h['T7']),
ctrl.Rule(t['L']&E['H']&f['M'], h['T8']),
ctrl.Rule(t['L']&E['L']&f['H'], h['T2']),
ctrl.Rule(t['L']&E['H']&f['H'], h['T9']),
ctrl.Rule(t['M']&E['L']&f['L'], h['T4']),
ctrl.Rule(t['M']&E['H']&f['L'], h['T8']),
ctrl.Rule(t['M']&E['L']&f['H'], h['T1']),
ctrl.Rule(t['M']&E['H']&f['H'], h['T9']),
ctrl.Rule(t['H']&E['M']&f['L'], h['T1']),
ctrl.Rule(t['H']&E['H']&f['L'], h['T4']),
ctrl.Rule(t['H']&E['H']&f['M'], h['T4']),
ctrl.Rule(t['H']&E['M']&f['H'], h['T1']),
ctrl.Rule(t['H']&E['H']&f['H'], h['T5']),
ctrl.Rule(t['M']&E['M']&f['M'], h['T4']),
ctrl.Rule(t['M']&E['H']&f['M'], h['T6']),
ctrl.Rule(t['H']&E['M']&f['M'], h['T3'])
]
```

To finalize the fuzzy modeling process, defuzzification was carried out to produce quantitative values for the output variables. Since defect formation, specifically, the number of pores and cracks, is inherently discrete and expressed as integer counts, a rounding function was applied to the defuzzified outputs for *Nc* and *Np* to ensure physically meaningful predictions.

The three-dimensional response surfaces shown in Figure 2.3 illustrate the influence of pulse energy and pulse duration on the geometric characteristics, hardness, and defect formation of the clad bead at a fixed pulse repetition rate of $f = 3$ Hz. The response surfaces for macroscale geometry and hardness (Figure 2.3 *a*, *b*) are smooth and indicate that the maximum coating thickness is obtained at high pulse energies and short pulse durations, whereas microhardness is strongly governed by the laser exposure time. In contrast, the response surfaces for defect prediction (Figure 2.3 *c*, *d*) exhibit a pronounced step-like behavior, which is associated with the integer values of the defect counts.

The performance, adequacy, and predictive capability of the developed fuzzy model were evaluated on an independent test dataset (Table 2.2).

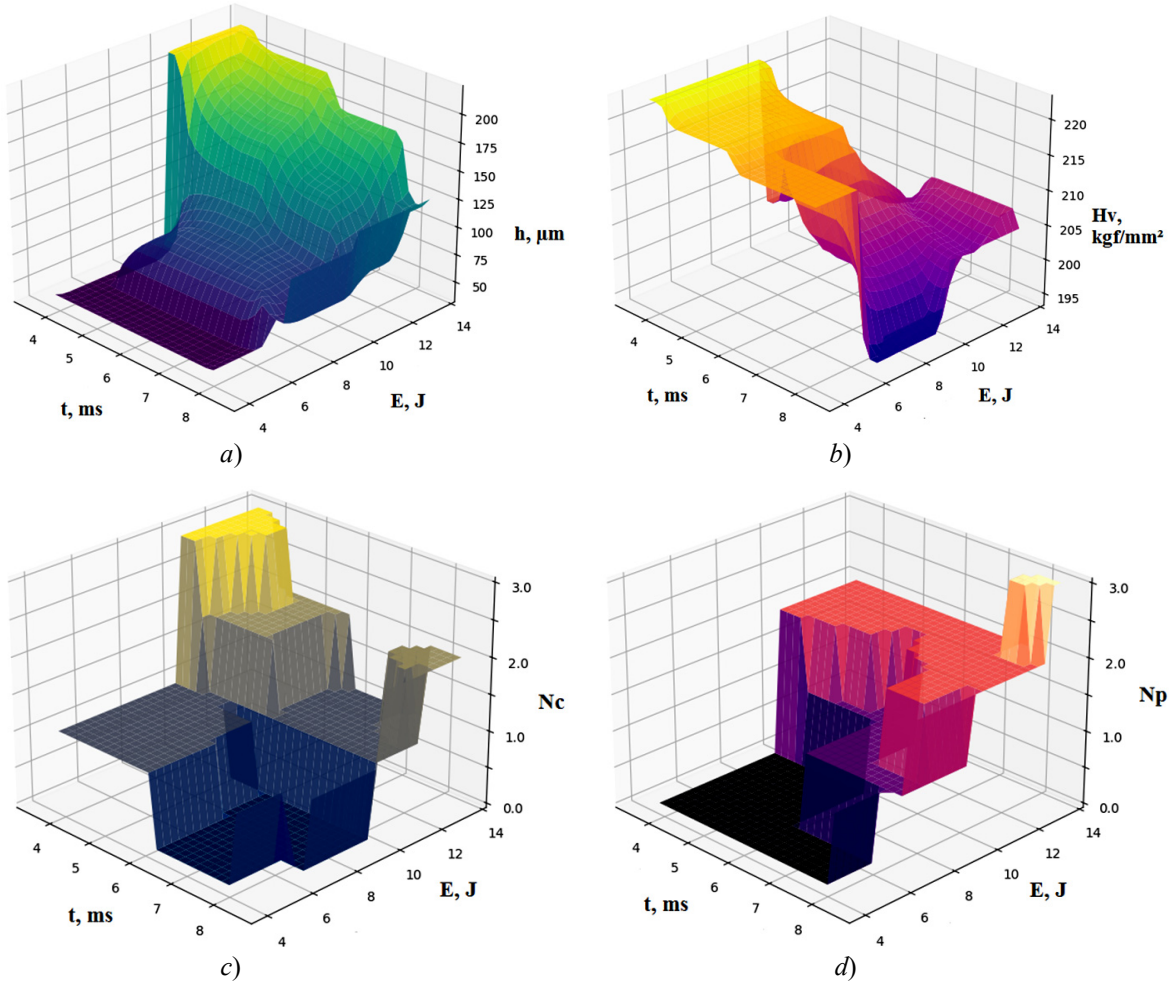


Figure 2.3 – Response surfaces of the fuzzy model showing the effect of pulse energy (E) and pulse duration (t) at f = 3 Hz on: (*a*) coating thickness (h), (*b*) microhardness (HV), (*c*) number of cracks (Nc), and (*d*) number of pores (Np)

Table 2.2 – Test dataset

№	t, ms	E, J	f, Hz	h, μm	HV, kgf/mm^2	Nc	Np
1	5.0	8.0	3.0	90	222	2	0
2	7.0	11.5	4.0	130	207	1	2
3	5.0	12.5	2.0	230	202	0	2
4	7.0	6.0	4.0	40	179	0	0
5	8.0	11.0	3.0	90	214	1	3

The predictive performance of the developed fuzzy model was assessed using the following metrics:

– coefficient of determination

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{i=1}^{n}(d_i - y_i)^2}{\frac{1}{n}\sum_{i=1}^{n}(d_i - \bar{d})^2},$$

– mean absolute error (*MAE*)

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

– root mean square error (*RMSE*)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - y_i)^2},$$

where d_i and y_i denote the observed and model-predicted response values, respectively.

The evaluation results for the fuzzy model are summarized in Table 2.3.

Table 2.3 – Performance evaluation results for the fuzzy model

Criterion	h	HV	Nc	Np
RMSE	7.9	7.8	0.5	0.5
MAE	7.3	6.1	0.2	0.2
R^2	0.9845	0.7160	0.6429	0.8611

The model exhibits good predictive accuracy for the output parameters. On the test dataset, it reproduces the geometric response and pore count satisfactorily, whereas the predictions for microhardness and, particularly, the number of microcracks are subject to higher relative uncertainty. The obtained performance metrics confirm that fuzzy modeling is capable of delivering sufficiently accurate predictions for laser cladding processes even when experimental data are limited.

Conclusion

A multi-output Mamdani-type fuzzy model was developed based on the results of a full-scale *D*-optimal experiment. The model directly relates the pulsed laser processing parameters *t*, *E*, and *f* to the final quality characteristics of nichrome coatings on 30ХГСН2А steel, namely coating thickness *h*, microhardness *HV*, number of cracks *Nc*, and number of pores *Np*. The model was validated against five process regimes not included in the training dataset, demonstrating satisfactory interpolation performance, particularly for coating thickness and pore count.

The proposed model can serve as an interpretable decision-support tool for preliminary parameter selection and multi-criteria ranking of process regimes in pulsed laser cladding of nichrome coatings on 30ХГСН2А steel.

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