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The fuzzy logic analysis as criterion of hot rolled stainless steel destruction caused by corrosion

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ABSTRACT

This study explores how predictive modeling can be used to assess and improve the corrosion resistance of steels by modifying metal forming parameters. Traditional statistical methods often fall short when evaluating corrosion resistance due to the stochastic nature of structural transformations during plastic deformation. To address this, we applied Fuzzy Logic within the MATLAB environment to uncover the non-linear dynamics between hot rolling conditions, microstructure, and corrosion rates. Drawing on experimental data from AISI 321 and S32750 steels, we constructed Mamdani-based mathematical models to visualize how deformation levels, pass counts, and microalloying affect intergranular and pitting corrosion. Subsequent validation of the models revealed a key finding: high predictive accuracy requires more than just processing parameters and basic structural data. It is critically important to include mechanical properties, namely yield strength and hardness, in the input dataset, since a material's resistance to corrosion-driven degradation is fundamentally tied to its stress-strain state.

KEYWORDS

stainless steel • fuzzy logic • corrosion resistance • hot rolling • thermomechanical processing

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Introduction

Evaluating the operational reliability of modern engineering structures requires a shift from conventional statistical methods to intelligent monitoring systems capable of operating under high uncertainty [1–3]. Because ambiguous and imprecise data are inherent to complex systems, effectively modeling these uncertainties necessitates a deep understanding and rigorous management of input data quality. Fuzzy logic serves as a powerful tool in this regard, striking an optimal balance between data relevance and processing precision [4–6]. It provides a convenient framework for mapping the input parameter space to the output, allowing for the formalization of decision-making processes based on expert linguistic variables ranging from tuning household appliances to controlling sophisticated technical systems. Industrial applications of fuzzy control have proven highly successful in managing complex, non-linear systems [7–9]. Specifically, fuzzy logic models have been widely deployed to predict the mechanical properties and surface quality of metallic materials [10–14].

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Within the broader field of materials science, the degradation of structural integrity in steel components due to corrosion remains a critical challenge [15]. Predictive analysis of these phenomena is complicated by the stochastic nature of structural changes and the inherently blurred boundaries between a material's "safe" and "critical" states [16,17]. Since most components operating in highly aggressive environments are manufactured via plastic deformation, there is an obvious need to establish the non-linear relationships among hot metal forming parameters, microstructure, and corrosion resistance. Conventional analytical techniques often fail to fully capture the stochasticity of structural transformations, such as recrystallization or the evolution of dislocation substructures, thereby making the application of intelligent algorithms highly relevant.

This paper investigates the interplay between the structural state and the corrosion resistance of materials using the mathematical framework of fuzzy logic. Employing fuzzy modeling allows for the formalization of how technological factors and microstructural parameters influence corrosion resistance, ultimately ensuring high predictive reliability.

Materials and Methods

Under normal conditions, hot rolling is usually performed by several passes. At different ranges of strain accumulation schedules, the corrosion-resistant austenitic steel type AISI 321 has been studied. The study evaluated the influence of varying strain (reduction) degrees (ε = 10–50 %) and rolling passes (n = 1–5) during the hot rolling process of AISI 321 stainless steel (Experiment No. 1). In Experiment No. 2, the investigation focused on S32750 steel with diverse rare earth metal (REM) contents (0.00–0.08 wt. %) under different strain accumulation regimes (single-pass vs. fractional) with n = 1–3 passes. The underlying structural transformations occurring during these processes are detailed in [18,19]. Corrosion resistance for the first case was assessed via intergranular corrosion (IGC) testing using the 'DU' method as per GOST 6032 [1]. For the second case, pitting corrosion resistance was analyzed through electrochemical measurements in a 5 % aqueous NaCl solution acidified with CH_3COOH to pH = 3, in compliance with GOST 9.912[2] and ASTM G5[3] standards.

Modeling

This study investigates the correlation between material structure and corrosion resistance utilizing the mathematical framework of fuzzy logic. Computational analyses were executed within the MATLAB environment, specifically employing the Fuzzy Logic Toolbox. Fundamentally, fuzzy modeling encompasses three distinct, sequential phases: fuzzification, the inference mechanism, and defuzzification. Fuzzification refers to the translation of crisp data points into their corresponding fuzzy representations via

[1] International Standard. GOST 6032-2017. *Corrosion-resistant steels and alloys. Test methods of intercrystalline corrosion resistance.* Moscow: Standardinform; 2017. (In Russian)

[2] State Standard of the USSR. GOST 9.912-89. *Unified system of corrosion and ageing protection. Corrosion-resistant steels and alloys. Method of accelerated tests for resistance to pitting corrosion.* Moscow: USSR state committee for product quality management and standards; 1989. (In Russian)

[3] American Society for Testing and Materials. ASTM G5-14. *Standard Reference Test Method for Making Potentiodynamic Anodic Polarization Measurements.* West Conshohocken, PA, USA: ASTM International; 2021.

predefined membership functions. Conversely, defuzzification acts as the inverse operation, converting the aggregated fuzzy sets back into a quantifiable crisp value [20]. The Center of Gravity (COG) approach for defuzzification is widely adopted in Mamdani-type systems and was purposefully selected for the current investigation [21]. At the core of the fuzzy model lies the inference engine, which bridges input and output variables through a set of IF-THEN rules. While the formulation and tuning of these rules are traditionally handled by domain experts, the present work derives them directly from the gathered empirical data [22,23].

Results and Discussion

The results of experiments No. 1 and No. 2 are presented in Tables 1 and 2, respectively. As evidenced by Table 1, the corrosion rate escalates in tandem with an increase in both the single-pass deformation level and the volume fraction of the recrystallized microstructure. Conversely, specimens subjected to an identical total reduction via fractional deformation specifically, over three or five passes demonstrate a different behavior: their corrosion rate shows no significant growth up to a cumulative reduction of 30 %, but more than doubles when the total reduction reaches 50 %. It is noteworthy that the substructure of steel fractionally deformed in three passes (n = 3) to a 30 % reduction achieves a higher degree of structural perfection compared to material treated in a single pass. In this state, dynamic strain aging and the fine, uniform precipitation of carbides throughout the grain volume effectively strengthen both the solid solution and the grain boundaries. Consequently, this structurally and compositionally homogeneous state, characterized by mitigated internal stresses, exhibits reduced electrochemical heterogeneity. This ultimately diminishes the material's susceptibility to localized corrosion phenomena, such as intergranular corrosion (IGC). Among the evaluated factors, recrystallization exerts the most profound impact on IGC susceptibility, with the corrosion rate accelerating as the fraction of recrystallized grains increases. This relationship can be attributed to two primary mechanisms. On the one hand, the nucleation of recrystallized grains and their subsequent growth into adjacent microvolumes induce elevated local microstresses, which stem from the energetic imbalance at the interfaces between the recrystallized and unrecrystallized regions [24]. On the other hand, the recrystallization process inherently yields a multitude of newly formed fine grains, thereby substantially expanding the total grain boundary area. This extensive boundary network compromises the continuity of the protective oxide film, serving as prime initiation sites for corrosive attack [25,26].

Table 1. Results of the Experiment No. 1

Hot-working parameters		***D*, μm**	**Δ*r*, %**	**V_{corr}, g/(m²·h)**
n	**ε, %**			
1	10	48	0	0.70
1	30	24	30	1.74
1	50	30	90	3.85
3	30	39	0	0.70
5	50	17	0	1.38

Table 2. Results of the Experiment No. 2

Hot-working parameters		REM, wt. %	V_γ, %	d, μm	$\sigma_{0.2}$, MPa	σ_u, MPa	$HV_{0.07}$		ΔE, V
n	ε, %						Ferrite	Austenite	
1	45	0.00	47.1 ± 1.7	23.4	566 ± 10	819 ± 13	285 ± 6	304 ± 6	1.231
1	45	0.02	50.7 ± 0.9	24.9	541 ± 30	796 ± 39	282 ± 5	296 ± 5	1.251
1	45	0.05	50.0 ± 1.6	26.9	561 ± 2	857 ± 5	286 ± 4	303 ± 6	1.254
1	45	0.08	50.7 ± 1.7	30.6	554 ± 4	832 ± 3	302 ± 3	305 ± 6	1.289
3	45	0.00	48.7 ± 0.7	31.0	586 ± 2	797 ± 18	297 ± 5	288 ± 6	1.230
3	45	0.02	49.9 ± 1.1	29.7	587 ± 10	800 ± 11	297 ± 5	296 ± 6	1.193
3	45	0.05	50.5 ± 0.9	24.8	597 ± 10	842 ± 12	291 ± 5	300 ± 8	1.127
3	45	0.08	51.0 ± 0.5	30.6	601 ± 24	828 ± 25	298 ± 6	304 ± 4	1.201

*Notation: n, ε are number and degree of workings, respectively; V is volume fraction of austenite; d is average size of austenite regions; $\sigma_{0.2}$ and σ_u are yield strength and ultimate tensile strength, respectively; HV is Vickers hardness; ΔE is pitting resistance base.

The findings from the second experimental series indicate that increasing the rare earth metal (REM) content (from 0.00 to 0.08 wt. %) under constant hot rolling parameters facilitates a gradual growth in the austenite volume fraction, alongside a marginal increase in its average region size. Concurrently, a positive trend in electrochemical properties is evident: elevated REM concentrations enhance the pitting resistance base, thereby signifying improved immunity to pitting corrosion. Furthermore, the mode of strain accumulation significantly impacts the mechanical characteristics. Transitioning from a single-pass to a three-stage deformation regime yields a pronounced increase in yield strength. For instance, in specimens containing the maximum REM concentration (0.08 %), this parameter rises from 554 to 601 MPa. Such an increment underscores the development of a highly strain-hardened microstructural state resulting from fractional deformation.

Table 3. Linguistic variables and rules for two experiments

Linguistic variables	Linguistic rules	Range
Experiment No. 1		
Input parameters		
Number of workings	L_1, L_2, L_3	1.0–5.0
Degree of workings, %	L_1, L_2, L_3	10.0–50.0
Grain size, μm	L_1, L_2, L_3	17.0–48.0
Proportion of recrystallised regions, %	L_1, L_2, L_3	0–90.0
Output parameters		
Corrosion rate, g/(m^2·h)	L_1, L_2, L_3	0.70–3.85
Experiment No. 2		
Input parameters		
Number of workings	L_1, L_2, L_3	1.0–3.0
REM, weight %	L_1, L_2, L_3	0.00–0.08
Volume fraction of austenite, %	L_1, L_2, L_3	47.0–51.0
Average size of austenite regions, μm	L_1, L_2, L_3	23.0–31.0
Yield strength, MPa	L_1, L_2, L_3	541.0–601.0
Ultimate tensile strength, MPa	L_1, L_2, L_3	796.0–857.0
Vickers hardness of ferrite, $HV_{0,07}$	L_1, L_2, L_3	282.0–302.0
Vickers hardness of austenite, $HV_{0,07}$	L_1, L_2, L_3	288.0–305.0
Output parameters		
Pitting resistance base, B	L_1, L_2, L_3, L_4	1.12–1.35

Table 4. Fuzzy logic rules

Number of rules	Condition (IF)	Result (THEN)
Experiment No. 1: x_1 (n); x_2 (ε); x_3 (D); x_4 (Δr), y(V_{corr})		
1	L_1 & L_1 & L_3 & L_1	L_1
2	L_1 & L_2 & L_1 & L_2	L_2
3	L_1 & L_3 & L_2 & L_3	L_3
4	L_2 & L_2 & L_2 & L_1	L_1
5	L_3 & L_3 & L_1 & L_1	L_2
Experiment No. 2: x_1 (n); x_2 (REM); x_3 (V_γ); x_4 (d_γ); x_5 ($\sigma_{0.02}$); x_6 ($\sigma_в$); x_7 (HV_δ); x_8 (HV_γ), y(ΔE)		
1	L_1 & L_1 & L_1 & L_1 & L_2 & L_2 & L_1 & L_3	L_3
2	L_1 & L_2 & L_3 & L_1 & L_1 & L_1 & L_1 & L_2	L_3
3	L_1 & L_3 & L_2 & L_2 & L_2 & L_3 & L_2 & L_3	L_3
4	L_1 & L_3 & L_2 & L_2 & L_2 & L_3 & L_2 & L_3	L_4
5	L_3 & L_1 & L_2 & L_3 & L_3 & L_1 & L_3 & L_1	L_3
6	L_3 & L_2 & L_3 & L_2 & L_3 & L_1 & L_3 & L_2	L_2
7	L_3 & L_3 & L_3 & L_1 & L_3 & L_3 & L_2 & L_2	L_1
8	L_3 & L_3 & L_3 & L_3 & L_3 & L_3 & L_3 & L_3	L_2

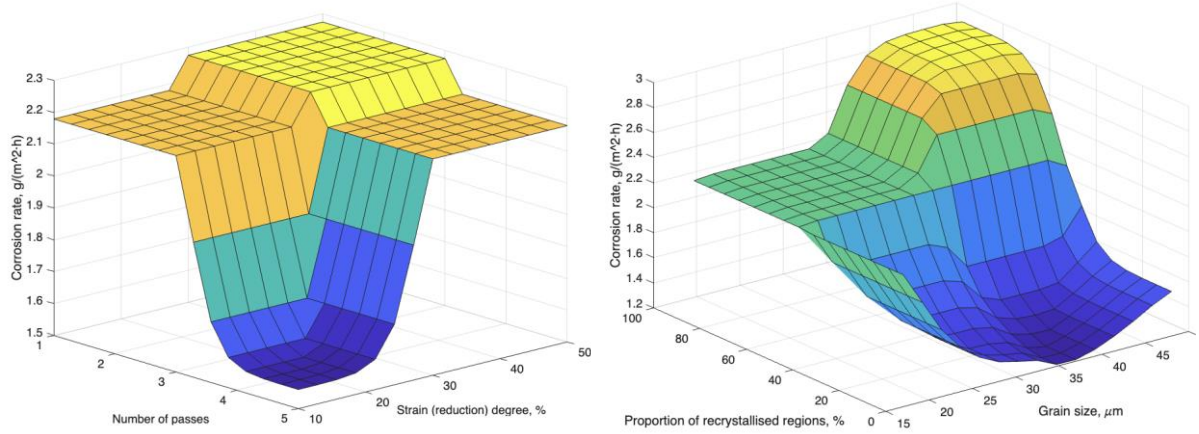
Phase microhardness is distributed unevenly, with the austenite typically registering slightly higher hardness values than the ferrite [27]. Nevertheless, multi-stage deformation promotes a convergence of hardness values between the two phases. Similar to the phenomena detailed in the first case, this homogenization is likely attributable to a more uniform redistribution of internal stresses within the microstructure. In contrast to the initial experiment, however, multi-stage deformation in this scenario leads to a slight reduction in corrosion resistance compared to the single-stage process at identical REM levels. This discrepancy highlights the complex influence of fractional deformation on the pitting potential when alloying micro-additions are present.

The linguistic variables and their defining characteristics for both input and output parameters are summarized in Table 3. The corresponding fuzzy logic rules are outlined in Table 4. Drawing upon the collected experimental data, a fuzzy logic-based mathematical model was developed to visualize the multifaceted impact of processing parameters on the steel's corrosion resistance. The resulting visualizations for the first and second experimental series are presented in Figs. 1 and 2, respectively.

An examination of the response surfaces for the first experimental series (Fig. 1) revealed a pronounced non-linear relationship between the corrosion rate and the material's structural state. The results indicate that the intensification of recrystallization processes under high strain conditions emerges as a destabilizing factor; specifically, the rapid expansion of recrystallized domains leads to a substantial escalation of the corrosion rate.

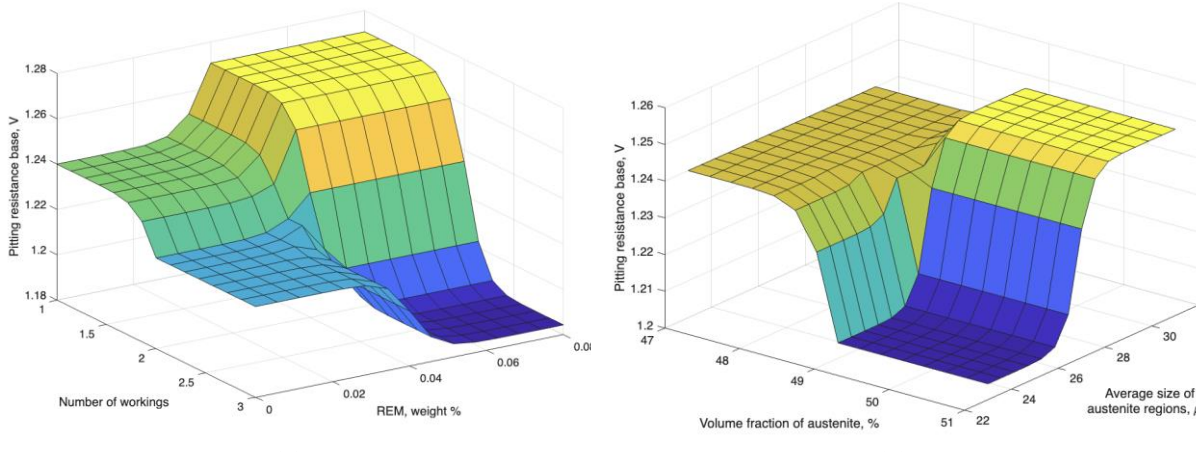
Optimal corrosion resistance metrics are attained at moderate deformation levels (approximately 30 %). In the case of the second experiment (Fig. 2), the pitting resistance base serves as the primary determinant of the material's stability. The generated response surfaces confirm the beneficial impact of microalloying, with peak pitting resistance values observed within a rare-earth metal (REM) concentration range of 0.05 – 0.08 %. Notably, the highest values of the pitting resistance base correlate with regions of enhanced yield strength and ferrite microhardness, a phenomenon detailed in [19].

This suggests that fractional deformation, when combined with REM additions, yields a synergistic effect, simultaneously enhancing both mechanical strength and localized corrosion resistance.

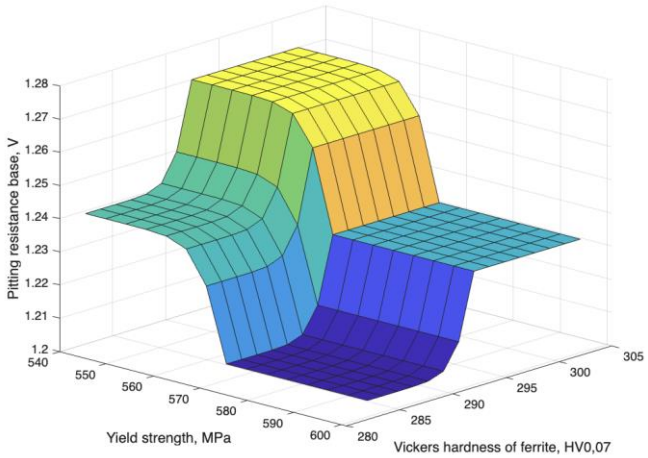


(a) (b)

Fig. 1. The plot of the 3-D surface of the corrosion rate in Experiment 1 as a function of: (a) the number of passes and reduction degree; (b) the fraction of recrystallized regions and grain size



(a) (b)



(c)

Fig. 2. The plot of the 3-D surface of the pitting resistance base in Experiment 2 as a function of: (a) the number of passes and REM content; (b) the austenite volume fraction and the size of austenite regions; (c) the yield strength and ferrite microhardness

The validation of the developed models was performed by benchmarking the calculated predictions against empirical results, as illustrated in Fig. 3.

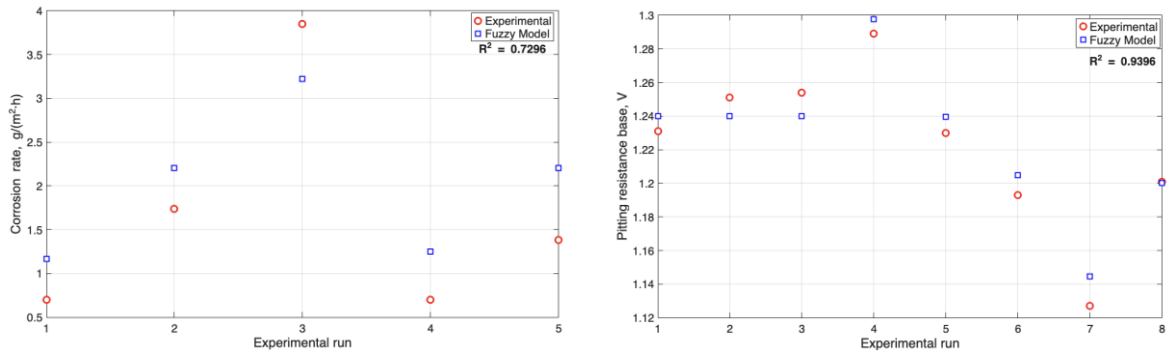


Fig. 3. Validation of the models developed based on the data from Experiment No. 1 (a) and Experiment No. 2 (b)

An analysis of the model derived from Experiment No. 1 data revealed a moderate correlation between calculated and experimental values (R^2 = 0.72). The observed local discrepancies likely stem from the inherent sensitivity of the recrystallization process to microstructural fluctuations, elements not fully captured by the initial variable set or perhaps an insufficient range of input parameters.

In contrast, the model for the second experimental series demonstrated significantly higher precision (R^2 = 0.94), a result of incorporating a more comprehensive array of significant input variables. Specifically, the results underscore that modeling degradation processes necessitates the recognition that corrosion resistance is fundamentally coupled with mechanical properties and the material's stress-strain state. While elevated dislocation density and local microstresses exacerbate structural instability [28,29], recrystallization processes effectively mitigate these stresses, thereby enhancing overall corrosion resistance [30].

Consequently, these findings validate the efficacy of fuzzy logic-based intelligent algorithms for the predictive analysis of corrosion behavior in steels. Despite the stochastic nature of strain-induced structural transformations, Fuzzy Logic provides a robust framework for formalizing the impact of technological parameters with high reliability.

Conclusions

The application of fuzzy logic enables the highly reliable formalization of how thermomechanical processing parameters applied to hot rolling affect steel degradation processes. A comparative analysis of the two developed models highlights a direct relationship between predictive accuracy and the configuration of the input dataset. The first model (Experiment No. 1), which relied primarily on technological and microstructural factors (pass count, recrystallization fraction, and dislocation density), yielded only a moderate correlation with empirical tests (R^2 = 0.72). It was proven that to achieve high predictive accuracy (R^2 = 0.94, as seen in Experiment No. 2), it is essential to

account for the material's mechanical properties, specifically yield strength, tensile strength, and phase microhardness, since corrosion resistance is inextricably linked to the material's stress-strain state.

CRediT authorship contribution statement

Georgij E. Kodzhaspirov: conceptualization, & editing, investigation, supervision; **Vladimir S. Karasev**: writing – review, writing – original draft, investigation, data curation.

Conflict of interest

The authors declare that they have no conflict of interest.

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