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TYPE-1 FUZZY LOGIC MODELING OF FINAL DENSITY IN CERAMIC COATINGS FOR SAND CORE PACKAGES

Felipe Alberto Jáuregui Elizalde
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Gerardo Daniel Olvera Romero
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Jesús Salvador Luna Álvarez
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Felipe de Jesús García Vázquez
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Rolando Javier Praga Alejo
Facultad de Sistemas, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Jafeth Rodríguez Ávila
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Juan Carlos Ortiz Cuellar
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Carlos Rodrigo Muñíz Valdez
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

Jesús Fernando Martínez Villafañe
Facultad de Ingeniería, Universidad Autónoma de Coahuila, Ciudad Universitaria
Coahuila, México

ABSTRACT: This study evaluates the performance of a multiple linear regression model and several Type-1 Fuzzy Logic Systems (T1 FLS) in predicting the "Final Density" of a ceramic coating applied to sand core packages for iron casting. The coating preparation process exhibits high variability, nonlinear behavior, and decisions based on operator expertise, which makes it difficult to represent using strictly linear models. Experimental data were obtained from an industrial prototype that reproduces the real coating adjustment procedure, considering four input variables ("Initial amount", "Paste", "Water", and "Initial Density") and one output variable ("Final Density"). The regression model achieved moderate performance with , and only "Initial Density" was statistically significant. Fifty-eight T1 FLS models were constructed by varying membership function types, extreme shapes, and range partitioning strategies. The results show that configurations with five membership functions per variable, combining triangular and trapezoidal shapes with open extremes, produced the most accurate fits. The PX-8 model reached , clearly outperforming the regression model. Overall, the findings indicate that T1 FLS better capture the nonlinear and empirical nature of the ceramic coating preparation process. Future work includes exploring alternative modeling approaches such as neural networks and Type-2 fuzzy logic systems, as well as developing a formal experimental design to expand the prototype dataset and support industrial applications aimed at reducing penetration-related defects.

KEYWORDS: Type-1 fuzzy logic; Ceramic coating; Iron casting; Process modeling; Membership functions.

Introduction

The preparation of the ceramic coating applied to sand cores is a critical stage in iron casting, as it governs the interaction between molten metal and the sand surface and strongly influences the occurrence of defects such as metal penetration, surface porosity, and dimensional protrusions. In the industrial operation examined, these defects generate between 3% and 8% scrap, resulting in rework, material waste, and significant economic losses.

The complete process flow is depicted in Figure 1 [1], which illustrates the sequence from sand-core fabrication and ceramic-coating application, through oven drying to stabilize the coating, to the assembly of core packages in the mold and the subsequent pouring of molten iron, culminating in the production of the V8 monoblock. The behavior of these coatings is inherently complex due to their sensitivity to sedimentation, batch-to-batch variability of raw materials, and the influence of resting time.

The *Foseco Ferrous Foundryman's Handbook* reports that coating viscosity may change within seconds under shear forces, recommending continuous agitation and frequent verification of density and consistency to avoid coating-related failures during pouring [2]. Such characteristics lead to dynamics that linear models struggle to capture, making the process strongly dependent on operator judgement.

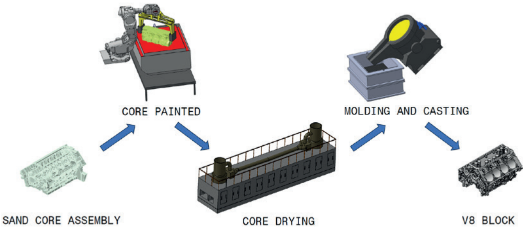

Figure 1. Monobloc production.

Linear regression is commonly employed for modeling industrial processes; however, several studies indicate that its performance deteriorates when relationships among variables are not strictly linear or when the data contain uncertainty or imprecision [3, 4]. In modern manufacturing, structural variability, decision-making based on tacit knowledge, and the scarcity of deterministic relations often result in modest fits and limited predictive capability for classical statistical tools [5]. These limitations have motivated the adoption of artificial-intelligence methods to model complex processes where human expertise plays a central role.

Among such methods, Type-1 Fuzzy Logic Systems (T1 FLS) hold a prominent position because they integrate quantitative information with linguistic knowledge, making them suitable for representing processes with transitional zones and nonlinear behavior. Their theoretical foundation traces back to Zadeh's seminal 1965 work introducing fuzzy sets as a means to model vague concepts in real systems [6]. Since then, fuzzy logic has proven effective in process control, uncertainty modeling, and decision-making when deterministic methods fall short [7]. Recent applications confirm its value in industrial contexts characterized by substantial variability, such as robotic manipulators with nonlinear friction [8], efficiency assessment in industrial washing processes [9], and dynamic warehouse evaluation using hybrid expert-sensor data [10]. Similarly, in physicochemical processes with complex interactions, fuzzy systems have been shown to outperform response-surface models and neural networks in terms of stability and representation capability [11].

In the context of ceramic coatings for sand cores, understanding how operational parameters influence the "Final density" is essential, because this property directly affects coating performance during pouring. The *Initial amount* of coating available in the tank, the volumes of paste and water added, and the *Initial density* collectively form a set of closely related variables whose combined effect cannot always be adequately described using conventional linear models.

Against this background, the present work develops and analyzes 58 Type-1 fuzzy logic models, all formulated with four input variables and one output, using five membership functions per variable and different combinations of triangular, trapezoidal, and Gaussian shapes. Various strategies for rule definition and interval partitioning were also explored. These models are compared with a multiple linear regression model built using the same experimental dataset. The objective is to determine which approach more accurately represents the behavior of the ceramic coating under operational conditions characterized by variability, imprecision, and decisions supported by operator experience.

Methodology

The methodological approach was designed to compare the capability of a multiple linear regression model and several Type-1 Fuzzy Logic Systems (T1 FLS) to represent the behavior of the "Final Densi-

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ty" of the ceramic coating used in sand-core packages. The comparison is based on experimental data obtained from a prototype that reproduces the real industrial process, and on the systematic evaluation of different arrangements of membership functions and rule bases.

Experimental data

The data used in this study were obtained from a prototype that emulates the operation of preparing and adjusting the ceramic coating. The operating procedure follows the logic of the actual industrial process: an initial volume of coating is available in a working tank, its "Initial Density" is measured, and based on this measurement, "Paste" or "Water" is added to adjust the formulation until an acceptable "Final Density" is reached.

Four input variables and one output variable were considered to describe the behavior of the coating during the adjustment stage. The input variables represent the operating conditions at the moment the correction is performed, whereas the output variable corresponds to the density obtained after adjustment, which is directly related to the thickness of the coating film applied to the cores and therefore to its performance during molten metal pouring.

The input variables are:

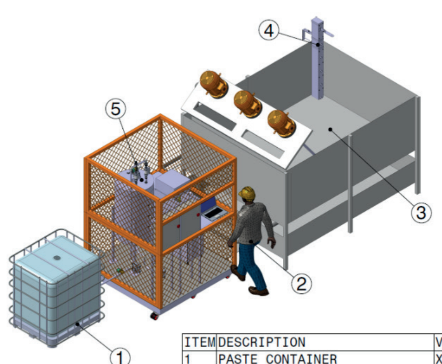
- "**Initial amount**": volume of coating available in the tank before any correction (L).
- "**Paste**": volume of ceramic paste added during adjustment (L).
- "**Water**": volume of water added during adjustment (L).
- "**Initial Density**": density of the coating measured before adding paste or water (g/cm^3).

The output variable is:

- "**Final Density**": density measured after adjustment and homogenization of the mixture (g/cm^3). This is the variable modeled, as it is associated with the film thickness applied to the cores and the coating's ability to prevent defects during pouring.

The experimental data used in this study, including "Initial amount", "Paste", "Water", "Initial Density", and "Final Density", are shown in Table 1.

From these data, minimum, maximum, mean, and range values were computed for each variable. These statistics were used to define the universes of discourse and to design the membership functions employed in the fuzzy models. In particular, the range-divided-by-five relationship was used to propose five linguistic levels per variable, corresponding to *very low*, *low*, *medium*, *high*, and *very high*. Figure 2 shows the prototype used to collect the data.



ITEM	DESCRIPTION	VARIABLE
1	PASTE CONTAINER	X2
2	WORKER	NA
3	PAINT VAT	X1
4	DENSITY MEASUREMENT SENSORS	X5, X4
5	WATER CONTAINER	X3

Figure 2. Ceramic-coating preparation process.

Input					Output
Sample	Initial amount (L (L)	Paste (L)	Water (L)	Initial Density (g/cm³)	Final Density (g/cm³)
1	160.9113	0	1.3711	1.2303	1.2215
2	167.2923	0	0.2562	1.189	1.1865
3	170.4489	0	0.565	1.1926	1.188
4	172.355	0	3.3751	1.1967	1.1891
5	174.6753	0	0.4294	1.1958	1.1923
6	187.7538	0	0.2712	1.1968	1.1961
7	172.581	8.1213	0	1.1372	1.1754
8	184.0472	2.1396	0	1.1758	1.1895
9	169.4018	0	1.4163	1.1926	1.1873
10	172.1666	0	0.5424	1.1896	1.1894
11	177.6361	0	0.1959	1.1992	1.1911
12	186.8573	0	1.1301	1.2005	1.176
13	187.7387	0	2.8327	1.2056	1.2025
14	190.2399	0	1.1602	1.2075	1.205
15	196.0107	0	0.226	1.2008	1.1915
16	172.1742	19.1129	0	1.1785	1.1797
17	189.2982	0	1.228	1.1944	1.1698

Table 1. Experimental input and output data used for modeling

Multiple linear regression model

To establish a statistical reference, a multiple linear regression model was fitted relating the four input variables to "Final Density". The general form of the model is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 \quad (1)$$

Where:

X_1 is "Initial amount" (L)

X_2 is "Paste" (L)

X_3 is "Water" (L)

X_4 is "Initial Density" (g/cm³)

Y is "Final Density" (g/cm³).

The parameters were estimated using the least-squares criterion. In matrix notation:

$$\hat{\beta} = (X^T X)^{-1} X^T Y \quad (2)$$

The model's performance was evaluated using the coefficient of determination:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n} (Y_i - \bar{Y})^2} \quad (3)$$

where $\hat{Y}_i$ is the predicted "Final Density" for observation i and $\bar{Y}$ is the mean "Final Density". The adjusted R^2 was also computed to account for the number of explanatory variables relative to sample size.

For the data in Table 1, the fitted model is:

$$\hat{Y} = 0.691505624 - 0.000255545X_1 - 5.89044 \times 10^{-5}X_2 - 0.000649009X_3 + 0.456609268X_4 \quad (4)$$

where X_1, X_2, X_3, and X_4 correspond to “Initial amount”, “Paste”, “Water”, and “Initial Density”, respectively. Table 2 summarizes the analysis of variance (ANOVA), while Table 3 presents the estimated coefficients together with their standard errors and significance values.

From these results, the coefficient of determination was $R^2 \approx 0.4984$, with an adjusted $R^2 \approx 0.3312$, indicating that the model explains roughly half of the variability observed in “Final Density”. The F-value of 2.98 with $p \approx 0.0635$ suggests that, as a whole, the model is not statistically significant at the 95% confidence level. However, examination of the individual coefficients in Table 3 shows that only “Initial Density” exhibits a significant effect on “Final Density”, with $p \approx 0.017$, whereas “Initial amount”, “Paste”, and “Water” do not show clear linear effects within the operational range considered.

Overall, the ANOVA and significance tests confirm that the adjustment process of the coating exhibits a structure more complex than what can be captured through a linear combination of the input variables. Figure 3 illustrates the regression fit and shows that, although a general trend exists, the model does not accurately reproduce the full dispersion of the experimental data.

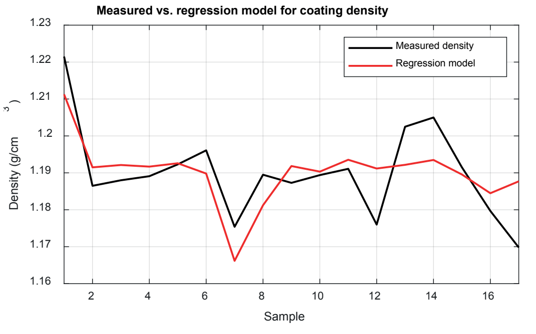


Figure 3. Fit graph: experimental data and multiple linear regression model.

Construction of the T1 FLS models

To address the limitations of the regression model, a family of Type-1 fuzzy logic models was developed to more faithfully represent the uncertainty and nonlinearity inherent to the process. The starting point is the definition of a fuzzy set. For a universe of discourse X and a fuzzy set A, the membership function is defined as:

$$\mu_A(x): X \to [0,1] \quad (5)$$

where $\mu_A^{(x)}$ indicates the degree to which x belongs to the linguistic term .

In the analyzed family of models, five linguistic labels were primarily used for each variable: *very low*, *low*, *medium*, *high*, and *very high*. Additionally, configurations with three labels were evaluated for comparison. These labels were assigned to membership functions covering the ranges observed in Table 1, using triangular (6), trapezoidal (7), and Gaussian (8) functions.

Source	DF	Sum of Squares	Mean Square	F	p-value
Regression	4	0.0011822	0.00029555	2.9814	0.0635
Residual	12	0.00118958	9.91313×10^{-5}	–	–
Total	16	0.00237178	–	–	–

Table 2. ANOVA of the multiple linear regression model

Parameter	Coefficient	Standard Error	t	p
Intercept	0.69150562	0.20201089	3.4231	0.005
Quantity (X_1)	–0.000255545	0.00025565	–0.9996	0.3372
Paste (X_2)	-5.89044×10^{-5}	0.00061306	–0.0961	0.925
Water (X_3)	–0.000649009	0.0028653	–0.2265	0.8246
Initial Density (X_4)	0.45660927	0.16490277	2.769	0.017

Table 3. Estimated coefficients of the regression model

$$f(x;a,b,c) = \max\left(min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \tag{6}$$

$$f(x;a,b,c,d) = \max\left(min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \tag{7}$$

$$f(x;\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{8}$$

The parameters of the triangular and trapezoidal membership functions were defined from the minimum, maximum, and range of each variable. The range-divided-by-five strategy was applied to generate five approximately equidistant intervals, assigning the extremes to *very low* and *very high*, and the intermediate points to *low*, *medium*, and *high*. This ensures complete coverage of the universe of discourse and sufficient overlap between adjacent labels to represent smooth transitions. Figure 4 illustrates the contrast between a configuration using three membership functions and another using five functions for the "Initial amount" variable.

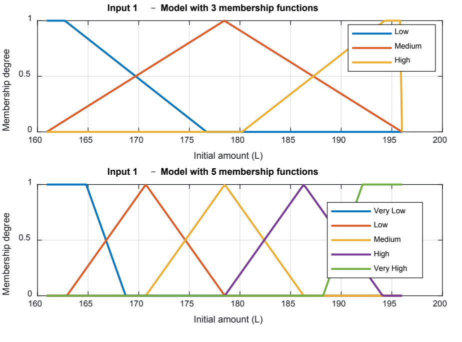


Figure 4. Contrast between schemes with three and five membership functions for the Initial amount variable.

As an alternative, label boundaries were defined using the 20th, 40th, 60th, and 80th percentiles. This approach proved less robust because the data distribution is non-uniform, resulting in narrow or unrepresentative intervals. A rule base derived solely from expert knowledge was also explored; although this incorporated process expertise, it required greater tuning effort and did not yield clear improvements in the coefficient of determination compared with the uniform-division strategy.

An important finding was the influence of the extreme membership functions. Models that used open functions for *very low* and *very high* achieved higher R^2 values than those with closed extremes, suggesting that the process can generate values near the bounds of the operating range and that outer labels should extend their influence. This comparison is shown in Figure 5.

The rule base was constructed using rules of the form:

If "Initial amount" is *low*, "Paste" is *low*, "Water" is *medium*, and "Initial Density" is *very high*, then "Final Density" is *very high*.

Using these structures, fifty-eight fuzzy models were generated by varying the type of membership functions, the openness of the extremes, and the criteria for partitioning the ranges. Each model was evaluated using the same dataset in Table 1, and its performance was assessed using the coefficient of determination.

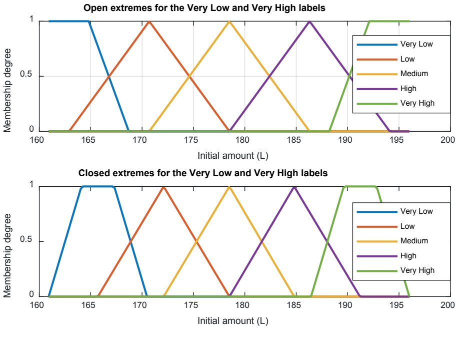


Figure 5. Comparison between membership functions with open and closed extremes for the Initial amount variable.

Table 4 summarizes the most representative models and their performance. Among all configurations, those using five membership functions per variable, triangular–trapezoidal combinations with open extremes, and rule bases derived from uniform-range division achieved the best results. In particular, model PX-8 reached $R^2 = 0.765$, clearly outperforming the linear regression model. Figure 6 shows the membership functions defined for the "Initial amount" variable in model PX-8, which are representative of the other input variables since they share the same linguistic partitioning.

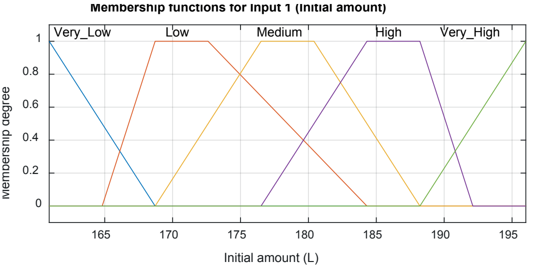


Figure 6. Membership functions of the Initial amount input in the PX-8 fuzzy model.

Results and discussion

Performance of the regression model

The multiple linear regression model presented in Section 2.2 provided an initial approximation of the behavior of "Final Density" as a function of "Initial amount", "Paste", "Water", and "Initial Density". The coefficient of determination obtained, $R^2 \approx 0.4984$, indicates that the model explains roughly half of the variability observed in "Final Density". The adjusted coefficient of determination, $R^2_{adj} \approx 0.3312$, reinforces the notion that the explanatory power of the model is limited when the number of variables is considered relative to the sample size.

The analysis of variance yielded an F-value of 2.98 with $p \approx 0.0635$. Although this p-value is relatively close to the conventional 0.05 threshold, it does not support

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Model	No. of MFs per variable	Type of membership functions	Extremes (very low / very high)	R^2
PX-6	5	Triangular + trapezoidal	Open	0.691
PX-7	5	Triangular + trapezoidal	Open	0.709
PX-8	5	Triangular + trapezoidal	Open	0.765

Table 4. Best T1 FLS models and their coefficient of determination R^2

the conclusion that the overall model is statistically significant at the 95% confidence level. Examination of the individual coefficients shows that only "Initial Density" has a statistically significant effect on "Final Density" ($p \approx 0.017$), whereas "Initial amount", "Paste", and "Water" do not exhibit clear linear contributions within the operating range considered.

From a practical standpoint, these results indicate that "Initial Density" is the dominant variable in the system, while the effects of "Paste" and "Water", together with their nonlinear interactions, are not adequately captured by the linear model. Figure 3 shows that, although there is a general alignment trend, the dispersion around the regression line remains considerable. Overall, the performance of the regression model confirms that the process is more complex than what a linear model can represent, which justifies the exploration of alternative approaches such as Type-1 fuzzy logic systems.

Performance of the T1 FLS models

A total of 58 T1 FLS models were constructed, all of them using five linguistic labels per variable. In addition, a few models with three labels (for example, PA-1) were tested and are used here as comparative references.

Figure 4 shows the comparison between a configuration with three trapezoidal membership functions (test PA-1) and another with five membership functions (test PB-1). Test PA-1 achieved $R^2 \approx 0.086$, whereas PB-1 reached $R^2 \approx 0.63$. Similar comparisons were carried out for several additional models, and the same trend was observed. In general, partitioning the universe of discourse into five linguistic labels tends to improve the quality of fit compared with using only three labels. In this work, PA-1 and PB-1 are presented as representative examples of that behavior.

Figure 5 illustrates the effect of open versus closed membership functions at the extremes. In test PB-1, the *very low* and *very high* labels were defined using open-ended functions, and an $R^2 \approx 0.63$ was obtained. In test PB-2, which has closed extremes and the same general structure, the coefficient of determination dropped practically to zero. This pattern was also confirmed in other configurations, indicating that, for this particular process, the shape of the membership functions at the boundaries of the operating range is a critical factor for representing the system adequately. Nevertheless, these findings do not imply that five labels and open extremes are always the best option in any application, but rather that they constituted the most suitable configuration for the coating preparation process studied in this work.

Table 4 summarizes the three best models obtained. Model PX-8 reached $R^2 \approx 0.765$, followed by PX-7 with $R^2 \approx 0.7094$ and PX-6 with $R^2 \approx 0.691$. Figure 6 shows the membership functions of model PX-8, where a combination of triangular and trapezoidal functions with five well-overlapped labels and open extremes can be observed. These configurations correspond to models in which the rules were defined based on the uniform division of each variable's range, resulting in a balanced structure consistent with the experimental data.

Overall comparison between regression and T1 FLS

The direct comparison between the models allows a clear synthesis. The linear regression model achieved $R^2 \approx 0.4984$, whereas the best T1 FLS model (PX-8) obtained $R^2 \approx 0.765$, and models PX-7 and PX-6 remained above 0.69. Although some poorly tuned fuzzy models exhibited low R^2 values, the overall set of results shows that, when the membership functions and rule base are properly designed, it is possible to consistently outperform the regression model using the same dataset.

In relative terms, the increase from $R^2 \approx 0.4984$ in the regression model to $R^2 \approx 0.765$ in model PX-8 represents a substantial improvement in explanatory capability. Both approaches agree on the relevance of "Initial Density" as a key variable, but the fuzzy system is able to combine it with linguistic states of "Initial amount", "Paste", and "Water", providing a representation that more closely reflects the way plant operators reason about and adjust the coating.

Figure 7 presents the comparison of "Final Density" values predicted by the regression model and by the PX-8 T1 FLS against the experimental data. The figure shows that the fuzzy model follows the data trend more closely in different regions of the operating range, whereas the regression model exhibits more pronounced deviations. This reinforces the idea that Type-1 fuzzy logic systems are a suitable alternative for modeling coating preparation processes characterized by high variability and a strong empirical component, and that they can serve as a basis for future decision-support tools or process control strategies.

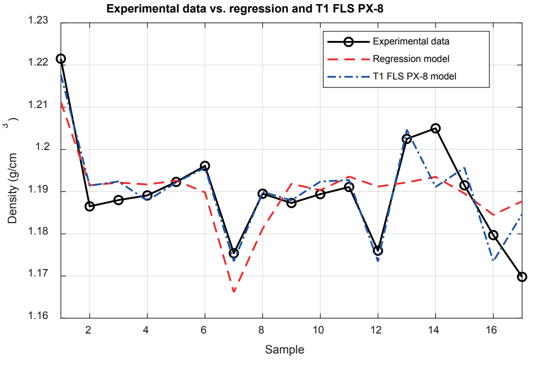

Figure 7. Comparison of the fit between the linear regression model, the T1 FLS PX-8 model and the experimental data.

Conclusions

This work compared the performance of a multiple linear regression model and several Type-1 fuzzy logic systems (T1 FLS) for predicting the "Final Density" of a ceramic coating applied to sand core packages. Using the experimental data obtained from the prototype, the regression model achieved a coefficient of determination of $R^2 \approx 0.4984$ and an adjusted R^2 of approximately 0.33. The full model was not statistically significant at the 95% confidence level, and only “Initial Density” showed a significant effect, confirming that the process is more complex than what a linear model can represent.

The fifty-eight T1 FLS models constructed with the same input and output variables demonstrated that, when properly designed, fuzzy systems better represent the process behavior. Model PX-8 reached $R^2 \approx 0.765$, outperforming the regression model. It was observed that using five membership functions per variable—combining triangular and trapezoidal shapes with open extremes—and a rule base defined through the uniform partition of each variable's range yields more stable fits than configurations with fewer labels, closed extremes, or percentile-based rules. These findings position Type-1 fuzzy logic as a more suitable alternative for capturing the relationship between “Initial amount”, “Paste”, “Water”, “Initial Density”, and “Final Density” in the coating preparation process.

Future work will focus on exploring alternative modeling methods, particularly neural networks and Type-2 fuzzy logic systems, as well as designing a formal experiment to expand the prototype's database. This would enable a more rigorous comparison of these approaches under controlled conditions and support progress toward plant-level applications aimed at reducing rejection caused by penetration defects.

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