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COMPATIBILITY ANALYSIS BETWEEN PAINT AND PRIMER FOR CORROSION PROTECTION OF METAL STRUCTURES: A Data Analysis-Based Approach with Python

ANÁLISE DE COMPATIBILIDADE ENTRE TINTA E PRIMER PARA PROTEÇÃO CONTRA CORROSÃO DE ESTRUTURAS METÁLICAS: Uma Abordagem Baseada em Análise de Dados com Python

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RESUMO – A corrosão de estruturas de aço é um desafio relevante na construção civil, comprometendo a durabilidade e elevando os custos de manutenção. Prolongar a vida útil de superfícies metálicas reduz a necessidade de substituições e reparos, contribuindo para a diminuição do consumo de materiais e dos impactos ambientais. Nesse cenário, a escolha adequada dos sistemas de revestimento, especialmente quanto à compatibilidade entre tinta e primer, é fundamental para aumentar a durabilidade estrutural e reduzir desperdícios. Este estudo aplica técnicas de análise de dados com Python para avaliar a eficiência de diferentes combinações de tinta e primer na proteção anticorrosiva. Foram utilizados algoritmos de classificação para prever o desempenho dessas combinações e métodos de agrupamento com base em normas técnicas, como a ISO 12944. Os resultados indicam que o modelo K-NN apresentou acurácia de 52%, evidenciando limitações na distinção entre classes. Em contrapartida, os métodos de agrupamento (K-Means e hierárquico) mostraram maior consistência, identificando padrões entre espessura, durabilidade e ambiente. Sistemas em ambientes industriais e marítimos apresentam maior espessura e durabilidade, enquanto urbanos e rurais demandam soluções menos robustas. Esses achados reforçam o potencial das técnicas de análise de dados na tomada de decisão para seleção de sistemas anticorrosivos.
Palavras-chave: Proteção anticorrosiva; análise de dados; Python; compatibilidade tinta-primer.

ABSTRACT – Corrosion of steel structures represents a significant challenge in civil construction, compromising durability and increasing maintenance costs. Extending the service life of metallic surfaces reduces the need for replacements and repairs, contributing to lower material consumption and environmental impacts. In this context, the appropriate selection of coating systems—particularly regarding paint–primer compatibility—is essential to enhance structural durability and minimize waste. This study applies Python-based data analysis techniques to evaluate the effectiveness of different paint and primer combinations in anticorrosive protection. Classification algorithms were used to predict the performance of these combinations, while clustering methods were employed based on technical standards such as ISO 12944. The results indicate that the K-NN model achieved an accuracy of 52%, revealing limitations in distinguishing between classes. In contrast, clustering methods (K-Means and hierarchical) demonstrated greater consistency, identifying patterns related to thickness, durability, and exposure environment. Systems used in industrial and marine environments exhibited greater thickness and durability, whereas urban and rural

environments required less robust solutions. These findings highlight the potential of data-driven approaches to support decision-making in the selection of anticorrosive systems.

Keywords: Corrosion protection; data analysis; Python; paint-primer compatibility.

1. INTRODUCTION

Even when properly designed to withstand permanent and variable loads, steel structures are subject to deterioration over time, especially when preventive or corrective maintenance is not properly carried out. This degradation can significantly compromise the load-bearing capacity of the structure throughout its service life. According to ASTM E632-82, service life is defined as the time interval after the beginning of a building or construction element's use, during which its essential properties remain within minimum acceptable levels, provided that regular and appropriate maintenance is performed. Among the main degradation mechanisms affecting metal structures, corrosion stands out as a phenomenon that negatively impacts various sectors of technological society, generating significant costs. According to Pannoni (2017), in industrialized countries, economic losses related to corrosion are estimated to account for approximately 3.5% of the Gross Domestic Product (GDP). The author also highlights that 30% to 50% of these losses could be avoided through the use of well-known and readily available corrosion control techniques. In this context, painting is one of the primary techniques used to protect steel structures from deterioration.

The proper assessment of the integrity of steel structures in service, especially those showing signs of failure or degradation, plays a key role in the technical and economic management of such systems. When well executed, this practice allows for a balance between operational safety and cost reduction, contributing decisively to the decision-making process between repairing or replacing elements affected by corrosion (Inoue; Pinto; Ribas, 2024). Among the available alternatives for corrosion protection of steel structures and equipment, painting stands out as the most economical and widely adopted method. Its viability stems mainly from ease of application and maintenance, along with its ability to create effective barriers against aggressive atmospheric agents. However, the effectiveness of this method directly depends on the correct selection of products and compatibility between layers, such as primer and topcoat (Gnecco; Mariano; Fernandes, 2006).

The objective of this article is to evaluate the efficiency of different paint and primer combinations in the anticorrosive protection of steel structures, through the application of data analysis techniques developed in Python. To this end, the K-Nearest Neighbors (K-NN) classification algorithm was employed to predict the performance of the combinations, as well as the accuracy of the model to validate its predictive effectiveness. In addition, clustering methods — specifically K-Means and hierarchical clustering — were applied based on technical standards such as ISO 12944 (2018), to investigate the relationship between the characteristics of the coating systems - type of primer, type of paint; layer thickness and number of coats; cost - and their suitability for different exposure environments (rural, urban, industrial and maritime). In this way, the aim is to contribute to the more efficient selection of coating systems, aligning technical performance, durability and sustainability.

The article is structured into sections, beginning with the Introduction. Section 2 presents the theoretical framework, addressing the types of protection systems applied to steel structures as well as the use of data analysis. Section 3 describes the research methodology adopted. Section 4 presents and discusses the results obtained. Finally, Section 5 brings together the main conclusions of the study.

2. THEORETICAL FRAMEWORK

Corrosion significantly compromises the durability of steel structures, particularly in aggressive environments, where exposure to moisture, pollutants, and saline conditions accelerates degradation processes. To mitigate these effects, protective coating systems—especially paint systems composed of primers and topcoats—are widely employed as effective barriers against corrosive agents. In this context, the proper specification of painting systems plays a crucial role in ensuring long-term performance and structural integrity. Furthermore, advances in machine learning have introduced new possibilities for predicting and optimizing anticorrosive solutions, supporting more efficient and data-driven decision-making in the selection of these systems.

2.1. Painting systems for protecting steel structures against corrosion

Technological advancements in civil engineering have been driven by the analysis of structural failures and premature deterioration in buildings. Understanding the inadequate behaviors of structures has revealed the need to deepen knowledge about materials and construction systems. Unsatisfactory performance, often linked to the use of incompatible or low-quality materials due to economic decisions,

contributes to early degradation. This led to the emergence of the field of building pathology, focused on investigating the causes of failures and improving structural performance (Weimer; Thomas; Dresch, 2018).

As established by ABNT NBR 15575-1:2013, building performance refers to its behavior during use, meeting safety, habitability, and sustainability requirements. Ensuring minimum performance involves both the integration of building systems and the proper selection of materials. In this context, it is important to differentiate durability — the material's resistance to degradation influenced by environmental factors — from service life, which is the period a building maintains adequate performance with proper maintenance. Corrosion, a well-documented degradation process, especially in metals, results from chemical or electrochemical reactions with the environment. In steel, it leads to the formation of rust — a brittle compound that expands significantly, compromising structural integrity (Weimer; Thomas; Dresch, 2018; Gentil, 2022).

According to Gentil (2022), four main strategies are used to mitigate corrosion in metallic materials: process modification (proper design, surface preparation, cathodic protection), changing the corrosive environment, modifying the metal, and applying protective coatings, which are effective in various environments. Among these, painting is widely used due to its versatility, ease of maintenance, and cost-efficiency. Paint systems typically consist of primer, with anticorrosive pigments and adhesion function; intermediate coating, which increases the total thickness and may act as a sealer; and finish coat, which provides chemical resistance and determines the final color. The selection of a coating system depends on environmental aggressiveness - classified as rural, urban, industrial, or marine per ISO 12944 (2018) - and considers both natural and anthropogenic factors. These systems function as both chemical and physical barriers and are defined based on steel type, exposure conditions, and desired service life (Gnecco; Mariano; Fernandes, 2006). The ISO 12944 (2018) provides technical guidelines for anticorrosive protection of steel structures using paint systems, classifying environments by atmospheric corrosivity based on material mass loss. Corrosivity categories range from C1 (very low) to C5 (very high), covering conditions from dry interiors to aggressive industrial or coastal zones, with additional classes for submerged or buried structures. The standard also outlines design recommendations to support coating application and maintenance. Durability is categorized as low (≤7 years), medium (7–15 years), high (15–25 years), or very high (>25 years), serving as planning references rather than performance guarantees. According to ISO 12944 (2018), the appropriate selection of anticorrosive paint systems depends on an accurate assessment of environmental corrosivity. Adhering to the standard's guidelines significantly enhances the durability of steel structures, lowers maintenance costs, and improves the technical performance of protective coatings.

2.1. Use of machine learning in materials science

The use of machine learning (ML) in materials science has been highlighted for providing significant advantages, such as reducing costs and time in the development of new materials, when compared to traditional methods. The ability to process large volumes of data allows for more efficient analysis, accelerating the discovery of materials with specific properties and optimizing selection and characterization steps. In addition, machine learning algorithms offer reasonable predictions for several properties, facilitating approaches such as structure-oriented design and prediction of molecular behavior. However, some challenges still need to be overcome, such as the need for robust and reliable databases, since data quality directly impacts the performance of models. Thus, although machine learning represents a promising tool for materials science, its effective application requires methodological care and continuous advances in the development of models and data infrastructure (Wei *et al*., 2019).

Traditional corrosion analysis relies on long-term exposure tests under representative conditions, but these methods face limitations such as small sample sizes and high data dimensionality, hindering short-term predictive decisions. In contrast, machine learning (ML) techniques enable the analysis of large, complex datasets, allowing for nonlinear modeling and improved prediction accuracy. In corrosion studies, ML has enhanced the reliability of forecasts by integrating multiple influencing variables into robust models. Ensemble methods, in particular, stand out for combining multiple models to boost predictive performance, often surpassing traditional approaches. The development and maintenance of structured databases are also crucial to support the effective application of ML in corrosion analysis (Coelho *et al*., 2022).

3. MATERIALS AND METHODS

The ML analysis was carried out in two distinct stages using data imported into the Google Colab platform via Python programming. The first stage involved a classification task aimed at identifying compatibility between different types of primers and topcoat paints. In the second stage, clustering algorithms were applied to associate painting systems with their respective steel exposure environments, with the objective of uncovering patterns that could inform the recommendation of suitable anticorrosive systems.

Castro (1999), as cited by Bessa (2019), developed a compatibility matrix between different types of paints (Table 1) to provide technical guidance in selecting appropriate coating systems. This matrix served as the foundation for the data analysis conducted in the first stage of the study, particularly in the classification process using machine learning algorithms.

Table 1. Compatibility matrix for primer and topcoat systems.

PRIMER / TOPCOAT	Acrylic	Alkyd	Silicone Alkyd	Chlorinated Rubber	Epoxy Coal Tar	Epoxy Polyamide	Epoxy Polyamine	Vinyl Epoxy Polyamine	Ethyl Silicate	Phenolic	Latex	Polyester	Polyurethane	Inorganic Silicate.	Silicone	Vinyl
Acrylic	B	C	C	B	B*	B	B	C	C	B	C	B	B	C	C	B
Alkyd	C	B	B	B	B*	B	B	B	NR	B	C	B	B	NR	C	B
Silicone Alkyd	C	B	B	B	B*	B	B	B	NR	B	C	B	B	NR	B	B
Chlorinated Rubber	C	B	B	B	B*	B	B	B	B	B	C	B	B	B	C	B
Epoxy Coal Tar	NR	NR	NR	NR	B	B	B	C	B	C	NR	B	NR	B	NR	NR
Epoxy Poly-amide	NR	NR	NR	NR	B*	B	B	C	B	C	NR	B	NR	B	NR	NR
Epoxy Poly-amine	NR	NR	NR	NR	B*	B	B	NR	B	C	NR	B	NR	B	NR	NR
Vinyl Epoxy Polyamine	NR	NR	NR	NR	B	B	B	B	B	C	NR	B	B	B	NR	B
Ethyl Silicate	NR	NR	NR	NR	C	C	C	C	B	C	C	C	C	C	NR	NR
Phenolic	NR	NR	NR	NR	C*	B	C	NR	C	B	NR	B	NR	B	NR	NR
Latex	C	C	C	C	C*	C	C	C	B	B	B	B	C	B	C	C
Polyester	NR	NR	NR	NR	C*	C	C	NR	NR	C	NR	B	NR	NR	NR	NR
Polyurethane	NR	NR	NR	NR	B*	B	B	B	B	B	NR	B	B	B	NR	NR
Silicone	B	C	C	B	B*	B	B	B	B	B	C	B	C	B	B	B
Vinyl	C	C	C	B	B*	B	B	C	B	B	C	B	C	B	C	B

SOURCE:
B – GOOD
C – CONDITIONING
NR – NOT RECOMMENDED (CONSULT THE MANUFACTURER)
* – INDICATES THAT THERE WILL BE BLEEDING
Source: (Castro, 1999).

A supervised learning classification model was developed using data imported in .csv format and preprocessed through label encoding. This numerical encoding of textual data was essential to enable the application of machine learning algorithms, which require numerical inputs. The dataset was then split into training and test subsets using the hold-out technique, with 80% of the samples allocated for training and 20% for testing. To standardize input variables, data normalization was performed using the Standard

method, adjusting the values to a distribution with zero mean and unit variance. This step is particularly relevant for the performance of the K-Nearest Neighbors (K-NN) classifier, which is sensitive to the scale of input features. The K-NN algorithm was selected for its simplicity and effectiveness in multi-class classification problems. The number of neighbors (k) was empirically set to 3, based on accuracy results from cross-validation. An error analysis was also conducted to identify specific primer and paint combinations with higher misclassification rates, allowing for a better understanding of model performance and confusion patterns.

In the second stage of the study, the focus shifted to analyzing coating systems used for the anticorrosive protection of metallic structures, emphasizing various primer and topcoat combinations and their expected durability, as recommended by CBCA (Brazilian Center for Steel Construction) (Pannoni, 2017). A total of 30 different coating systems were evaluated, as presented in Table 2 (only the first entries are shown). For analytical purposes, these systems were categorized according to their exposure environments - rural, urban, industrial, and marine - as defined by relevant technical guidelines and their respective levels of atmospheric corrosion aggressiveness.

Table 2. First Lines of the Table of Painting Systems for Steel (CBCA).

SYSTEM	PRIMER	PRIMER COATS	DRY FILM THICKNESS PER PRIMER COAT (µm)	FINISH TOPCOAT	FINISH COATS	DRY FILM THICKNESS PER FINISH COAT (µm)	TOTAL DRY FILM THICKNESS (µm)	MIN. DURABILITY (years)	MAX. DURABILITY (years)	STEEL TYPE	COST	ENVIRONMENT
CBCA-01	NONE	0	0	ALKYD DF	1	75	75	3	6	CARBON	LOW	RURAL
CBCA-02	ALKYD	1	40	ALKYD	2	40	120	4	7	CARBON	MEDIUM	RURAL
CBCA-03	EPOXY	1	40	ALKYD	2	40	120	5	8	CARBON	MEDIUM	RURAL
CBCA-04	EPOXY	1	40	EPOXY	2	40	120	6	9	CARBON	MEDIUM	RURAL

Source: (Adapted from Pannoni, 2017).

Initially, the data were imported from a .csv table, and the first rows of the DataFrame were inspected to understand the dataset structure. Text columns were also converted to numerical values using label encoding to enable clustering algorithms. With the data properly encoded, the independent variables (X) were defined to include all numerical columns, while the dependent variable (Y), representing the different exposure environments, was preserved for later comparative analysis.

To determine the optimal number of clusters in the K-Means model, the elbow method was applied, analyzing intra-cluster inertia relative to the number of clusters. Based on this analysis, the K-Means algorithm was implemented, and the results were visualized using scatter plots to illustrate data distribution and cluster centroid locations. For a more comprehensive analysis, a loop was developed to automatically generate plots exploring various combinations among the features in X. Additionally, hierarchical clustering was applied as an alternative data segmentation technique. The resulting clusters were visualized through a dendrogram, facilitating the evaluation of similarity relationships among the coating systems based on their technical and compositional characteristics. This combination of methods enabled a comparative and visually interpretable assessment of the performance of coating systems under different environmental conditions.

4. RESULTS AND DISCUSSION

The following section presents the main findings obtained from the computational analysis. The results are organized into two subsections: first, the application of the K-Nearest Neighbors (K-NN) classification algorithm to predict the compatibility and performance of primer and topcoat combinations; and second, the use of clustering algorithms - K-Means and hierarchical clustering - to group coating systems based on their technical characteristics and environmental suitability.

4.1. Classification algorithm: K-NN

The dataset used for the predictive model in the first stage of primer and topcoat combination compatibility consisted of 240 distinct combinations (Table 1). For validation purposes, the hold-out method was employed, in which 20% of the dataset (equivalent to 48 combinations) was reserved for testing the model. These samples were used to evaluate the predictive capability of the algorithm and to compare the predicted results with the actual, previously classified values. The comparative analysis between actual and predicted values revealed significant patterns of accuracy and error.

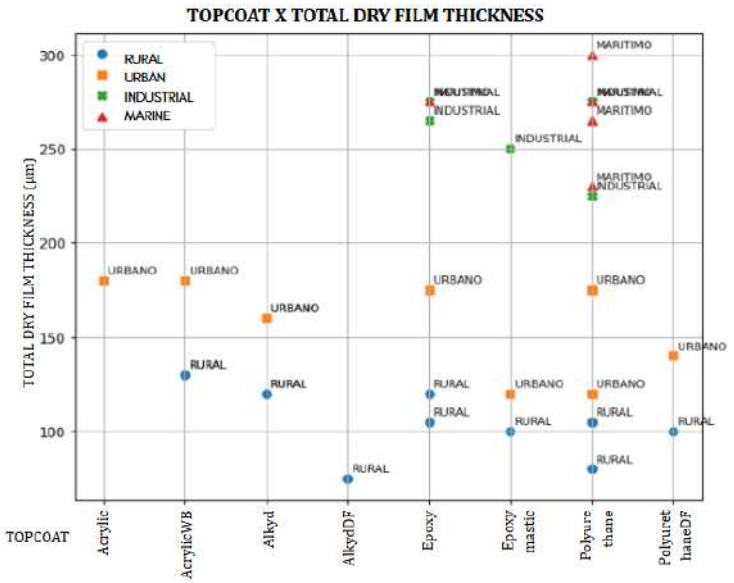
Presenting an accuracy of 0.52, the K-NN classification model exhibited significant limitations, particularly in differentiating between the "GOOD" and "CONDITIONED" classes—an error likely stemming from ambiguity in classification criteria, which can vary depending on technical standards or manufacturer guidelines. The "CONDITIONED" label, indicating acceptable performance under certain restrictions, may have introduced inconsistencies in labeling, affecting the model's learning process. Additionally, frequent confusion between the "GOOD" and "NOT RECOMMENDED" categories raises greater concern, as it implies the potential misclassification of technically inadequate systems as suitable, compromising the reliability of technical decisions. The model also tended to classify "GOOD WITH BLEEDING" systems simply as "GOOD", suggesting that the bleeding condition was underrepresented in the dataset or insufficiently weighted among the input variables. These recurring misclassifications highlight the model's current inadequacy for autonomous technical application and emphasize the need for refinement through class balancing, clearer labeling criteria, and inclusion of additional variables that improve the precision of primer and paint compatibility assessments.

4.2. Clustering algorithms: K-Means and hierarchical clustering

Clustering analysis using the K-Means algorithm was applied to 30 anticorrosive coating systems (Table 2) based on technical and environmental variables, with the 'ENVIRONMENT' attribute used to assess consistency. The elbow method indicated k = 2 or k = 4 as optimal, and k = 4 was chosen to better differentiate protection strategies across exposure environments. The model execution resulted in four cluster centers with distinct characteristics in terms of dry film thickness, number of coats, durability, and cost, reflecting different anticorrosive protection strategies for varied contexts. The comparison between predicted cluster labels and actual 'ENVIRONMENT' labels revealed partial overlap (urban, rural, industrial, and marine), which is expected due to the complexity of technical criteria and variability among manufacturers.

Based on the analysis of the clusters generated by the K-Means model with four clusters, several relevant patterns were identified in the relationship between technical variables and the steel exposure environment. Regarding the type of topcoat and total dry film thickness (Figure 1), it was observed that marine and industrial environments require higher thicknesses, indicating the need for enhanced protection. Polyurethane coatings were the most commonly used across all environments, followed by epoxy systems, with film thickness being the main differentiating factor. This result highlights the importance of adapting coating specifications according to environmental severity.

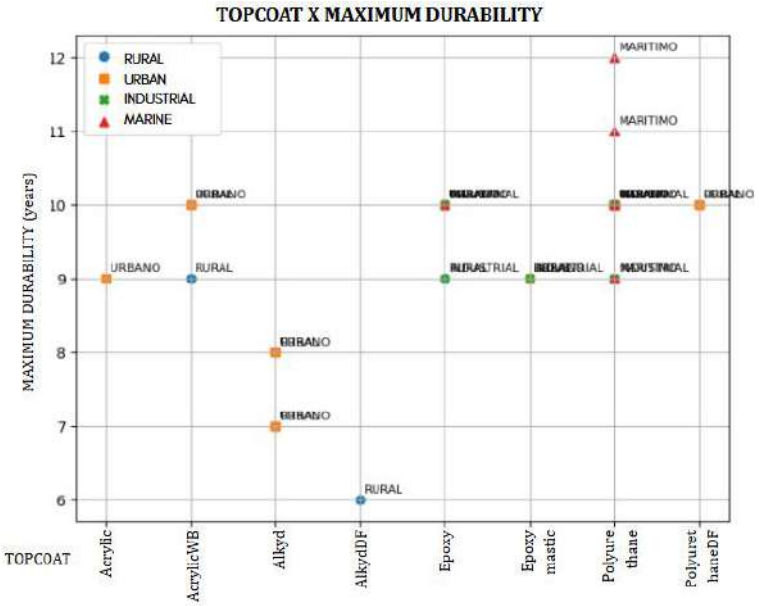
Figure 1. K-Means analysis: topcoat paint vs. total dry thickness.



Source: (Authors).

In the analysis of finish type versus maximum durability (Figure 2), it was found that, although urban and rural systems can achieve durability levels comparable to those found in industrial environments, coatings designed for marine exposure tend to exhibit greater durability. This behavior can be attributed to the more severe environmental conditions, which require more robust protection systems, as well as the difficulty of maintenance in these environments. The results reinforce the role of environmental exposure as a key factor in durability performance.

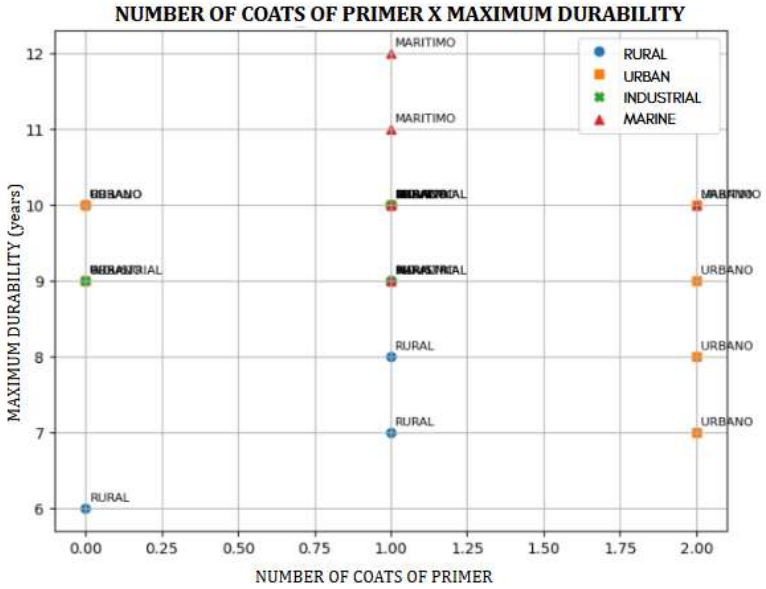
Figure 2. K-Means analysis: topcoat paint vs. maximum durability



Source: (Authors).

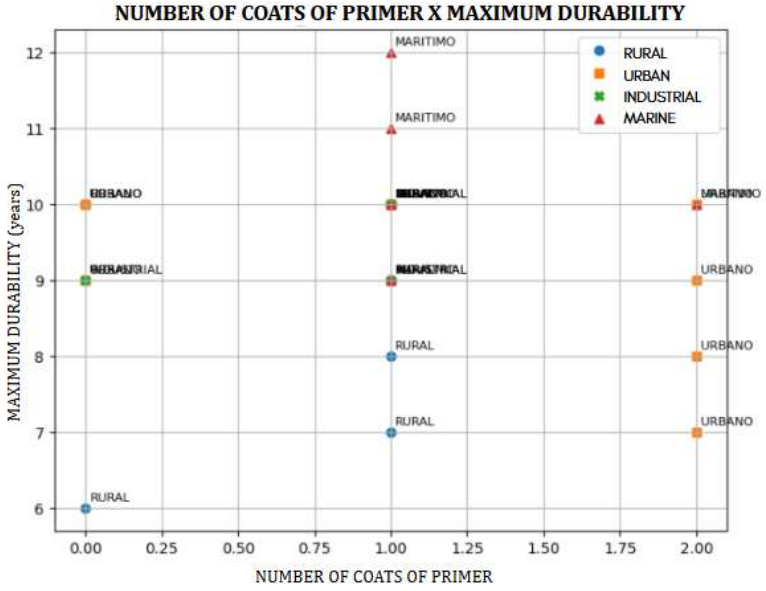
Figures 3 and 4 show the relationship between the number of primer and finishing paint coats and maximum durability. It can be observed that increasing the number of coats does not necessarily result in a proportional increase in durability. In more aggressive environments, such as industrial and marine settings, the strategy generally prioritizes coating thickness rather than the number of layers. This suggests that performance is more strongly influenced by the thickness of the overall protective barrier than by the number of applications in isolation.

Figure 3. K-Means analysis: number of base coats vs. maximum durability



Source: (Authors).

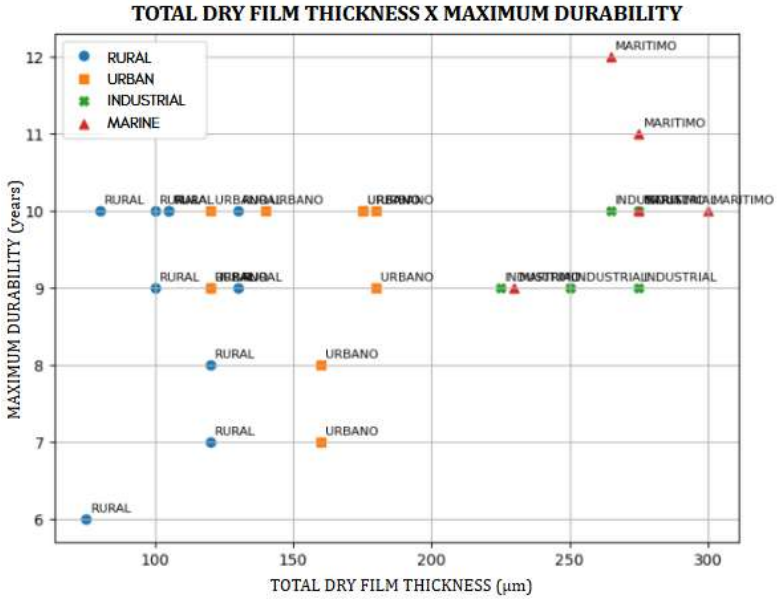
Figure 4. K-Means graph: number of coats of finishing paint vs. maximum durability



Source: (Authors).

In Figure 5, it is possible to see the correlation between the total dry film thickness and maximum durability. A clear positive relationship is observed, indicating that thicker coating systems tend to provide a longer service life. This trend confirms established technical principles in corrosion protection, where increased thickness improves the barrier effect against aggressive agents. However, the dispersion of some data points suggests that thickness alone is not the only determining factor, and other variables need to be considered.

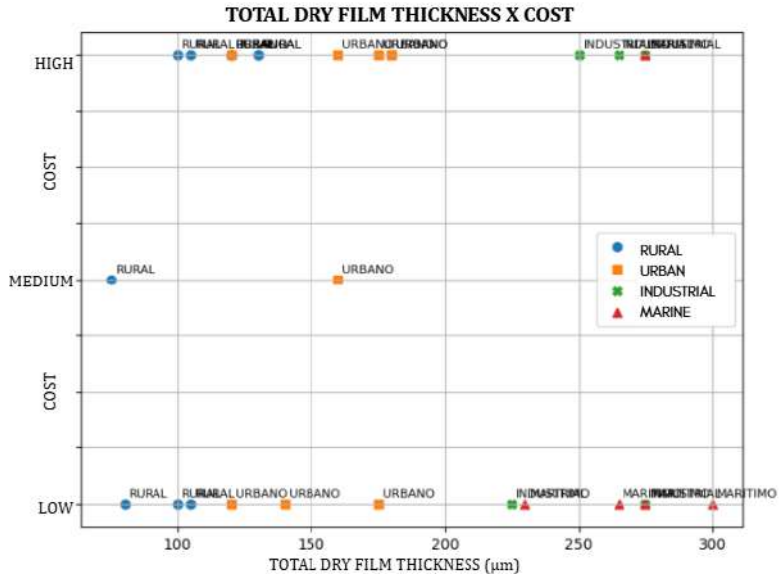
Figure 5. K-Means analysis: total dry thickness vs. maximum durability



Source: (Authors).

However, when analyzing total dry film thickness against cost (Figure 6), it was noted that increased thickness and durability do not necessarily result in higher system costs. Some systems applied in urban and rural environments, despite having lower thicknesses, exhibited higher costs -indicating that final pricing is also influenced by factors such as formulation technology, manufacturer brand, and specific regulatory requirements. This finding highlights the complexity of cost-performance relationships in coating system selection.

Figure 6. K-Means analysis: total dry thickness vs. cost.

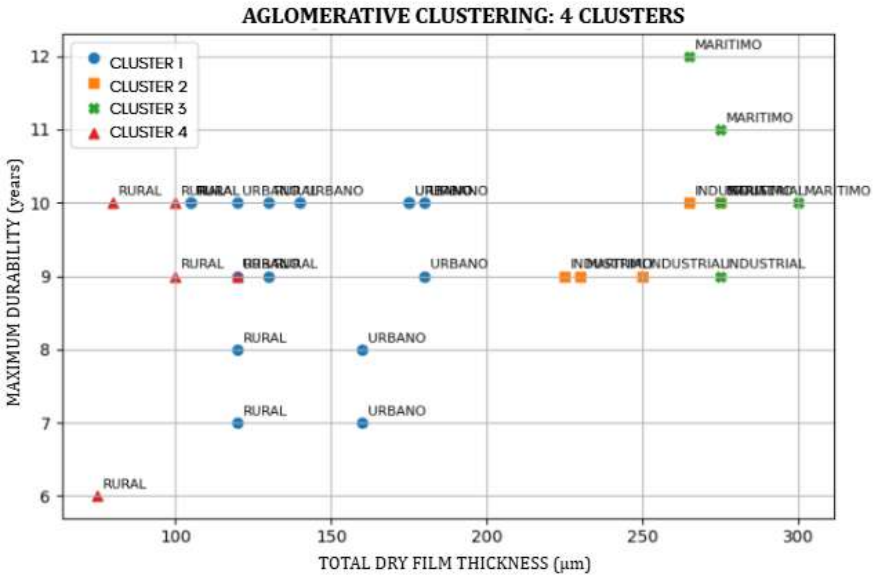


Source: (Authors).

These findings demonstrate that the clustering model was capable of identifying technical patterns which, although not perfectly aligned with the actual environments, exhibit practical coherence and can support more informed decisions regarding the selection and specification of coating systems based on operational and economic considerations.

The analysis using hierarchical clustering revealed two consistent interpretative possibilities regarding exposure environments. When divided into four clusters (Figure 7), the model was able to accurately reflect the actual environments — urban, rural, industrial, and marine — suggesting a more specific differentiation among the technical characteristics of the coating systems applied to each.

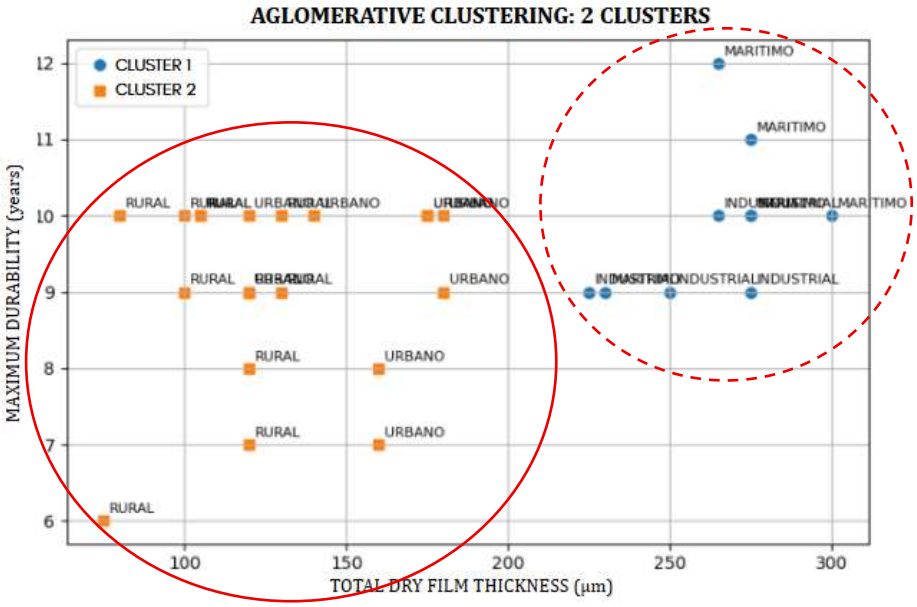
Figure 7. Hierarchical clustering graph with 4 clusters



Source: (Authors).

However, a structure with two main clusters (Figure 8) was also observed, in which urban and rural environments were grouped together (continuous line), while industrial and marine environments formed another cluster (dashed line). This division can be mainly explained by the differences in the thickness of the coating layers used, as systems designed for industrial and marine environments tend to be more robust, with greater thicknesses and protection requirements, whereas urban and rural systems require thinner layers, reflecting lower environmental aggressiveness.

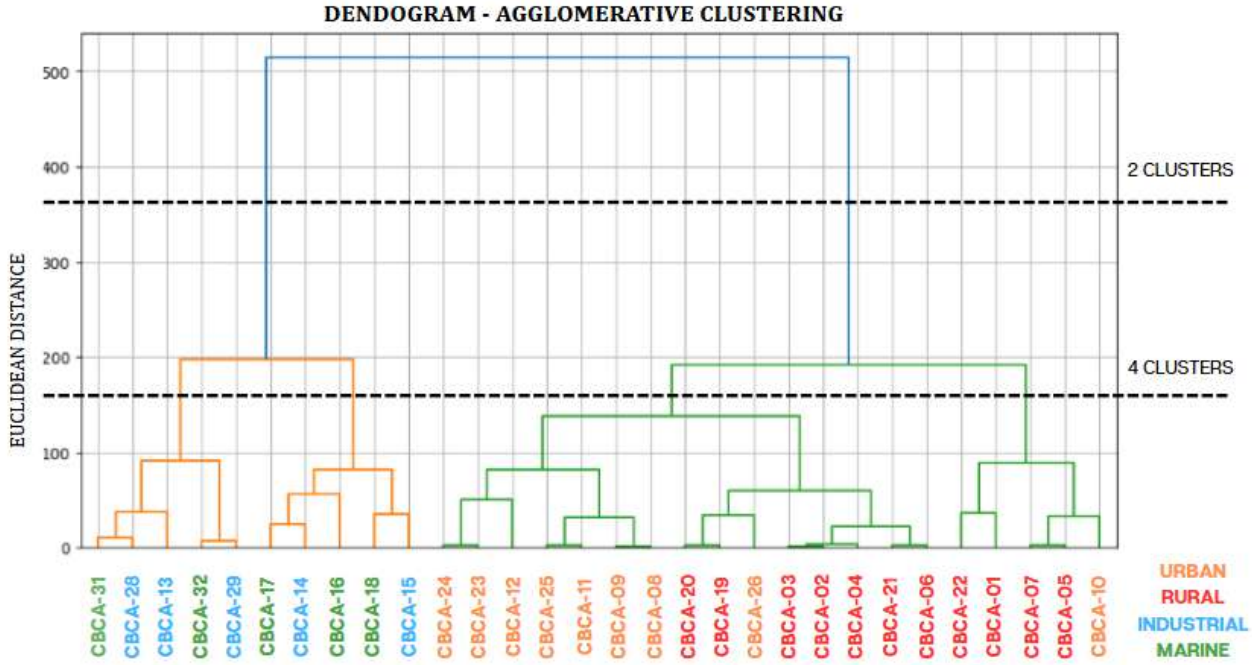
Figure 8. Hierarchical clustering graph with 2 clusters.



Source: (Authors).

The visual organization of the dendrogram (Figure 9) reinforces the coherence of the groupings suggested by the hierarchical clustering model, which proved effective in identifying patterns in the data based on technical attributes such as dry film thickness, number of coats, durability, and cost. The choice between 2 or 4 clusters depends on the objective of the analysis: a broad, simplified view favors grouping into 2 clusters, while a more detailed and specific analysis justifies the adoption of 4 clusters.

Figure 9. Dendrogram.



Source: (Authors).

5. CONCLUSION

The results obtained in this study reinforce the importance of proper design of the painting system to ensure the durability and performance of anticorrosive protection systems, especially across different exposure environments. It became evident that the environment significantly influences technical specifications — such as number of coats, dry film thickness, and type of finish — as also guided by ISO 12944, which classifies environments into corrosivity categories and recommends distinct protection systems for each condition. Regarding the computational methods applied, the K-NN algorithm showed limitations, with reduced accuracy in predicting performance, which partially compromises its effectiveness for this purpose. In contrast, the K-Means and hierarchical clustering methods demonstrated greater consistency in identifying patterns between the coating systems and their exposure environments, contributing more significantly to the exploratory analysis of the data. The approach used offers practical benefits such as reducing specification errors, lowering maintenance costs, and increasing the service life of metallic structures, in alignment with the best practices recommended by the ISO standard. For future work, it is suggested to expand the dataset with more real-world coating systems, include field performance variables, and apply supervised models with more robust metrics, in addition to exploring the implementation of these algorithms in digital tools to directly support engineers and designers.

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