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LUCIANO MARTINS LEITE DE OLIVEIRA

AVANÇOS EM GALVANOPLASTIA: PREVISÃO INTELIGENTE DA ESPESSURA DO REVESTIMENTO DE ZINCO EM AÇOS SAE 1008

CAXIAS DO SUL

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Dissertação apresentada ao Programa de Pós-Graduação em Tecnologia e Engenharia de Materiais para obtenção do grau de Mestre Profissional em Tecnologia e Engenharia de Materiais.

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RESUMO

Avanços em inteligência artificial (IA) possibilitam reduzir tempos de análise, custos e melhorar processos industriais. Este trabalho integra uma revisão da literatura e uma abordagem experimental sobre a aplicação de IA na eletrodeposição de zinco em aços de baixo carbono. A revisão, realizada na base Web of Science, revelou estudos ainda incipientes, indicando espaço para pesquisas que explorem o aprendizado de máquina (ML) na otimização do processo de galvanização. Experimentalmente, modelos preditivos de espessura de revestimento, essencial para resistência à corrosão conforme a norma NBR 10476 (ABNT,2016), foram desenvolvidos utilizando regressão multivariada, random forest e xgboost. O modelo xgboost destacou-se, com R^2 de 0,95 e MSE de 0,815, mostrando-se eficaz na previsão de resultados. Os modelos de IA permitem otimizar parâmetros do processo (tempo de processo, concentrações de ZnO/NaOH, material do ânodo e aditivos), melhorando a qualidade e reduzindo custos. Conclui-se que a IA oferece um caminho promissor para avanços na galvanização de aços de baixo carbono.

Palavras-chave: Inteligência artificial; revestimento de zinco eletrodepositado; galvanoplastia, XGBoost; eletrodeposição; previsão de espessura.

ABSTRACT

Advances in artificial intelligence (AI) make it possible to reduce analysis times, costs and improve industrial processes. This work integrates a literature review and an experimental approach to the application of AI in the electrodeposition of zinc in low carbon steels. The review, carried out on the Web of Science database, revealed studies that are still incipient, indicating room for research that explores machine learning (ML) in the optimisation of the galvanising process. Experimentally, predictive models for coating thickness, essential for corrosion resistance according to standard NBR 10476 (ABNT,2016), were developed using multivariate regression, random forest and xgboost. The xgboost model stood out, with an R^2 of 0.95 and an MSE of 0.815, proving effective in predicting results. AI models make it possible to optimise process parameters (process time, ZnO/NaOH concentrations, anode material, and additives), improving quality and reducing costs. It is concluded that AI offers a promising way forward for galvanising low carbon steels.

Keywords: Artificial intelligence; electrodeposited zinc coating; electroplating, XGBoost; electrodeposition; thickness prediction.

SUMÁRIO

1 INTRODUÇÃO

O aço e suas ligas são amplamente utilizados em setores como a indústria automotiva, construção civil e defesa, devido à sua versatilidade, resistência mecânica e baixo custo. Contudo, esses materiais apresentam baixa resistência à corrosão ambiental, o que compromete sua durabilidade em diversas aplicações (KATIRCI *et al*., 2021). Para mitigar esse problema, técnicas como a galvanização vêm sendo aplicadas, criando revestimentos metálicos permanentes que protegem os metais. A galvanização, também conhecida como eletrodeposição, consiste na imersão do aço em um banho eletrolítico contendo o sal do metal desejado, como zinco ou ligas metálicas, com a aplicação de um potencial catódico constante (MATLAKHOV *et al*, 2021; ABNT,2016). A eficácia do revestimento de zinco na proteção contra corrosão está diretamente relacionada à espessura depositada, tornando o controle rigoroso dos parâmetros do processo essencial para garantir a qualidade e a durabilidade do produto (MATLAKHOV *et al*, 2021; ABNT,2016).

Tradicionalmente, a determinação da composição ideal do banho eletrolítico e a otimização dos parâmetros de galvanização são realizadas por experimentos univariados. Contudo, essa abordagem consome tempo e recursos, além de apresentar limitações para aplicações em escala industrial (KATIRCI *et al*, 2021). Métodos baseados em aprendizado de máquina (ML), uma subárea da inteligência artificial (IA), surgem como alternativas promissoras. Esses métodos utilizam algoritmos capazes de processar grandes volumes de dados, identificar padrões ocultos e prever variáveis de saída complexas com alta precisão. Os algoritmos aplicados foram a regressão linear, o Random Forest (RF) e o XGBoost, sendo este último altamente eficaz em conjuntos de dados complexos devido à sua capacidade de evitar sobreajustes e modelar interações não lineares (COELHO *et al*, 2022; PIERSON, 2019; AGHAAMINIHA *et al*, 2021; JAYASINGHE *et al*, 2023).

Esta dissertação foi estruturada com base na elaboração de dois artigos científicos que refletem as principais etapas do estudo. O primeiro artigo, intitulado "Artificial intelligence applied to the electroplating process for low carbon steels: a literature review", apresenta uma revisão abrangente da literatura sobre a aplicação de IA no processo de eletrodeposição em aços de baixo carbono. O segundo artigo, "Technological advances in electroplating: artificial intelligence to predict zinc coating thickness on SAE 1008 low carbon steels", aborda o desenvolvimento experimental de modelos preditivos para a espessura do revestimento de zinco, utilizando algoritmos de aprendizado de máquina. A sequência dos artigos foi organizada de forma a primeiro apresentar o panorama teórico do tema, estabelecendo uma base sólida, e, em seguida, detalhar os resultados experimentais obtidos. Essa estrutura visa proporcionar uma compreensão progressiva e lógica das contribuições deste trabalho.

1.1 Justificativa e problema

A aplicação de revestimentos metálicos eficazes é fundamental para prolongar a vida útil de componentes metálicos e melhorar sua resistência em ambientes corrosivos. A criação de formulações ideais para o banho eletrolítico e a identificação de parâmetros que garantam a qualidade do revestimento ainda representam desafios significativos. Os métodos tradicionais, como experimentos univariados e o design fatorial fracionado, são limitados por seu custo, tempo elevado e redução na confiabilidade dos resultados (KATIRCI *et al*., 2021; COELHO *et al*, 2022).

O aprendizado de máquina (ML) emerge como uma alternativa inovadora, permitindo a análise de grandes conjuntos de dados para modelar relações complexas entre variáveis. No entanto, apesar dos avanços em Big Data e IA, a aplicação dessas tecnologias no campo da galvanização ainda é incipiente. (KATIRCI *et al*., 2021; COELHO *et al*, 2022, PIERSON, 2019)

Embora a galvanoplastia seja amplamente utilizada na indústria para melhorar as propriedades de superfícies metálicas, há uma lacuna tecnológica evidente na integração de IA nesse setor. A maioria dos processos ainda depende de técnicas empíricas e ajustadas manualmente, resultando em ineficiências e alto consumo eventual de recursos. Além disso, há uma escassez de pesquisas que exploram a aplicação da IA a estudos na área de métodos de proteção contra corrosão, e menos ainda na área de galvanoplastia de zinco, conforme OLIVEIRA *et al*. (2024). Isso reforça a necessidade de investigação sobre como os modelos preditivos podem aprimorar esse processo, proporcionando um avanço tecnológico e contribuindo para a modernização do setor. Essa lacuna tecnológica representa uma oportunidade de integrar métodos avançados de IA à galvanização, otimizando processos industriais e elevando a qualidade dos produtos galvanizados (KATIRCI *et al*., 2021; COELHO *et al*, 2022).

1.2 Objetivos

O objetivo geral deste trabalho é explorar a aplicação de inteligência artificial (IA) no processo de eletrodeposição de zinco em aços de baixo carbono.

1.2.1 Objetivos específicos

Realizar uma revisão da literatura sobre a interseção entre galvanização, aprendizado de máquina e aços de baixo carbono, identificando avanços e lacunas de pesquisa;

Desenvolver modelos preditivos para a espessura da camada de zinco galvanizado, utilizando dados experimentais oriundos de variações nos parâmetros do processo de eletrodeposição;

Avaliar o desempenho de diferentes algoritmos de aprendizado de máquina, como regressão linear, Random Forest e XGBoost, para prever a espessura do revestimento e sua relação com a resistência à corrosão;

Contribuir para a aplicação prática de métodos de IA na galvanização, otimizando processos industriais e promovendo melhorias na qualidade e durabilidade dos produtos galvanizados;

1.3 METODOLOGIA

A metodologia adotada para o experimento, tema do artigo 2 incluso neste trabalho, inclui o uso de planejamento fatorial fracionado para delinear o experimento e definir os valores dos parâmetros do processo de galvanoplastia. Os dados da variável de resposta (espessura de camada do revestimento de zinco) foram coletados por meio do experimento pelo método da célula de Hull.

O método da célula de Hull é um teste simples para avaliar o desempenho de banhos de eletrodeposição. Ele usa um dispositivo chamado célula de Hull, que possui um formato trapezoidal com um painel catódico inclinado. Ao aplicar uma corrente elétrica na célula, diferentes áreas do painel catódico são expostas a diferentes densidades de corrente. Isso permite avaliar como o depósito varia em função da densidade de corrente A figura 01 mostra uma ilustração da célula de Hull . (GABE, 1993)

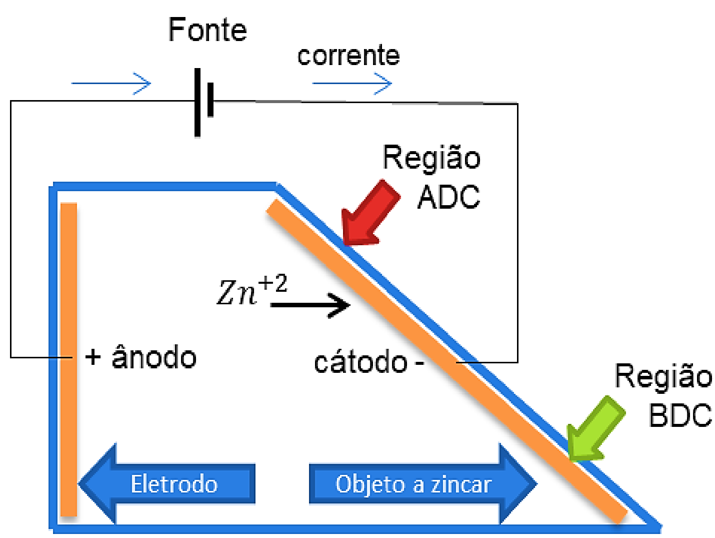

Figura 01. Ilustração da célula de Hull.

ADC: Altadensidade de corrente; BCD: Baixa densidade de corrente;

Após o experimento, com os dados de entrada (tempo de processo, concentrações de ZnO/NaOH, material do ânodo e aditivos) e dados de saída (espessura de camada do revestimento de zinco), foram gerados modelos preditivos utilizando três algoritmos de *machine learning*: regressão linear, Random Forest e XGBoost.

O XGBoost foi escolhido devido à sua capacidade de lidar com grandes volumes de dados e modelar relações complexas entre variáveis, superando modelos tradicionais em precisão. Além disso, sua eficiência computacional permite a aplicação em ambientes industriais sem comprometer a velocidade de processamento. (JAYASINGHE, 2023; AGHAAMINIHA , 2021; PIERSON,2019;)

2 ARTIGO 1: ARTIFICIAL INTELLIGENCE APPLIED TO THE ELECTROPLATING PROCESS FOR LOW CARBON STEELS: A LITERATURE REVIEW

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ARTIFICIAL INTELLIGENCE APPLIED TO THE ELECTROPLATING PROCESS FOR LOW CARBON STEELS: A LITERATURE REVIEW

INTELIGÊNCIA ARTIFICIAL APLICADA AO PROCESSO DE GALVANOPLASTIA PARA AÇOS DE BAIXO CARBONO: UMA REVISÃO DA LITERATURA

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ABSTRACT

Technological advances in computing, specifically in the area of artificial intelligence (AI), have made it possible to apply methods that seek to reduce the response times of analyses in order to reduce costs and improve the quality and safety of operations. This work aims to carry out a literature review, on three axes and their interactions: electroplating, AI and low carbon steels seeking to identify what has been developed in relation to ML methods applied to the electroplating of carbon steels, optimising industrial processes and improving the final quality of galvanised products. The search was carried out on the Web of Science - Main Collection (Clarivate Analytics) database. This review found that studies in these areas are incipient and we therefore conclude that there is space for further research into the application of AI in the development of models for determining corrosion resistance in low carbon steel subjected to electroplating.

Keywords: Artificial intelligence; Electrodeposited zinc coating; Electroplating, XGBoost; Electrodeposition; thickness prediction.

RESUMO

Os avanços tecnológicos na área de computação, especificamente na área de inteligência artificial (IA), possibilitaram a aplicação de métodos que buscam reduzir o tempo de resposta das análises, a fim de reduzir custos e melhorar a qualidade e a segurança das operações. Este trabalho tem como objetivo realizar uma revisão da literatura, em três eixos e suas interações: galvanoplastia, IA e aços de baixo carbono, buscando identificar o que tem sido desenvolvido em relação aos métodos de ML aplicados à galvanoplastia de aços carbono, otimizando os processos industriais e melhorando a qualidade final dos produtos galvanizados. A pesquisa foi realizada no banco de dados Web of Science - Main Collection (Clarivate Analytics). Esta revisão constatou que os estudos nessas áreas são incipientes e, portanto, concluímos que há espaço para mais pesquisas sobre a aplicação da IA no desenvolvimento de modelos para determinar a resistência à corrosão em aço de baixo carbono submetido à galvanoplastia.

Palavras-chave: Inteligência artificial; Revestimento de zinco eletrodepositado; Galvanoplastia, XGBoost; Eletrodeposição; Previsão de espessura.

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INTRODUCTION

Steel and its alloys are widely used in the automotive, construction and defence/military industries. However, their resistance to environmental corrosion is very low. Many methods have therefore emerged to increase corrosion resistance (KATIRCI, 2021). Although we generally think of corrosion as something harmful, it can be used to deposit metallic coatings on products through a process known as galvanisation. Low-carbon steels contain between 0.04% and 0.15% carbon and are used to make vehicle bodies and many other components. In the selected articles, some deal with alloy steel (ASKELAND , 2019).

Permanent coatings are applied to metals to prevent corrosion. The application of metallic coatings to the metal to be protected can be carried out by various mechanisms, one of which is the process of electroplating (galvanisation). Electroplating consists of immersing the metal to be protected (e.g. steel) in an electrolytic bath containing a salt of the metal (e.g. zinc or ZiNi alloy) that is to be deposited and applying a cathodic potential from a continuous voltage source to this metal (MATLAKHOV,2021). The protective power of a zinc layer in a specific environment is directly proportional to its deposited thickness (except for any porosity). For this reason, the need to control process parameters is fundamental to the quality of the part in terms of its resistance to corrosion (ABNT,2016).

Justification and Problem

To electrodeposit a ZnNi alloy (for example) in an alkaline bath, various bath formulations are available. Creating the best formulation (which gives adequate deposition and coating) using traditional one-factor-at-a-time experiments can be time-consuming. The fractional factorial experimental design method can be used to reduce the number of experiments. However, when this method is used, the reliability of the results decreases. In addition, it is very difficult to use these methods on an industrial scale due to the cost and time consumption. Machine learning is a promising method for detecting the effect of parameters on bath operation (KATIRCI,2021). Machine learning (ML) is the specific area of artificial intelligence (AI) that allows computers to learn from solving the data of a given task. ML aims to acquire knowledge from (very) large data sets, continuously improving its own performance. Although ML has gradually been applied to corrosion research, the corrosion community has benefited much less from the progress of Big Data Technologies (COELHO,2022).

In terms of maturity in the application of technologies, Brazilian industry is more digital than it was five years ago. In 2021, 69 per cent of industrial companies already used at least one digital technology from a list of 18 different applications. In 2016, 48 per cent of companies used some kind of digital technology, from a list of 10 options. However, the majority of companies use a low number of digital technologies, indicating that they are at an early stage in the digitalisation process. More than half of industrial companies don't use any digital technologies (31%) or use between 1 and 3 digital technologies (26%). Companies using 10 or more digital technologies account for just 7 per cent. Among the 18 different applications on the list of digital technologies presented, the application of artificial intelligence for solutions in the factory is applied by 9% of the companies surveyed (CNI,2022).

Objective

To carry out a literature review, based on three axes and their interactions: electroplating, AI and low carbon steels, seeking to identify what has been developed in relation to ML methods applied to the electroplating of carbon steels, as a way of optimising industrial processes and improving the final quality of galvanised products, through the prediction of process effects and consequent resistance to corrosion.

LITERATURE REVIEW

Galvanoplasty

Electroplating, also known as electrolytic galvanising or zinc plating, is a corrosion protection process in which zinc is electrolytically deposited on the base metal to form a homogeneous, thin and highly adherent layer, which does not affect the mechanical properties of the material, from a solution in which salts of the metal to be deposited are dissolved (ZEMPULSKI,2022).

As zinc (Zn) is more resistant to atmospheric corrosion than carbon steel, it is widely used to protect common steel products against the aggressive action of various atmospheres. When zinc is exposed to clean, near-dry atmospheres (RH<30%), it produces, through its chemical reaction with oxygen, a thin oxide film that constitutes an excellent protective barrier. When the relative humidity is above the critical RH, zinc produces insoluble hydroxide, due to the reaction with hydroxyls present in the aerated condensate, which also constitutes an excellent protective barrier. Permanent coatings are applied to metals to be protected in order to prevent corrosion in various corrosive media over a long period of time (MATLAKHOV,2021).

In the electroplating process, the surface is previously prepared to receive the electrodeposited layer of zinc. Once the first stages of surface preparation have been carried out, the galvanising phase begins, which consists of immersing the part in a vat of zinc salts, where the electric current acts to promote an oxidation-reduction reaction that will form the protective coating. The process variables are controlled so that the desired layer of zinc is deposited on the steel. The low initial cost and durability make galvanisation the most versatile and economical way to protect steel and cast iron from atmospheric corrosion for long periods, eliminating intermediate maintenance (ZEMPULSKI,2022). Zinc is widely used for cathodic protection of steel parts. Its price is low compared to other protection methods. It is mainly used on screws, nuts, nails and other parts in general. Checking that the temperature, current density and concentrations of the bath components are within the correct working parameters for zinc baths in electroplating processes is the basic control (SILLOS,2009).

In Brazil, the standard that specifies electrodeposited zinc coatings on iron or steel is ABNT NBR 10476:2016, Electrodeposited zinc coatings on iron or steel - Specification, (ABNT,2016), the purpose of which is to provide guidelines for the ordering, manufacture and supply of electrodeposited zinc coatings on the base metal, iron or steel, for corrosion protection purposes.

Machine learning

Recently, a set of advanced digital technologies known as Industry 4.0 has emerged offering new approaches to dealing with complexity and improving productivity. By deploying the right combination of technologies, manufacturers can increase speed, efficiency and coordination, and even facilitate self-managing factory operations. Manufacturers can apply these benefits to achieve the broader goals of producing high-quality goods and reducing costs. Industry 4.0 is characterised by a ubiquitous and mobile internet, smaller and more powerful sensors that have become cheaper, and artificial intelligence (AI) and machine learning (SCHWAB,2019).

Machine learning is the practice of applying algorithmic models to data in an interactive way, so that your computer discovers hidden patterns or trends that you can use to make predictions (PIERSON,2019). Machine learning (ML) shows enormous potential for increasing process efficiency. Unlike basic rule-based automation - which is typically used for standardised and predictable processes - ML can handle more complex processes and learn over time, leading to greater improvements in accuracy and efficiency. By applying ML to processes, leading organisations are increasing process efficiency by 30% or more, while increasing revenues by 5% to 10% (MCKINSEY,2022). ML methods are suitable for developing predictive models in cases where a large data set is available, the outcome to be predicted depends on several variables, and when a mechanistic model of the relationship between the input variables and the outcome is not well established (AGHAAMINIHA,2021).

The main types of machine learning are supervised and unsupervised. These are behind almost all ML applications. Supervised learning algorithms require the input data to have labelled results (have a result value). These algorithms read the already known characteristics of this data to produce an output model that successfully predicts those of new, unlabelled input data points. Unsupervised learning algorithms receive unlabelled data and attempt to group observations into categories based on underlying similarities in the input features (PIERSON,2019).

Also, based on the literature review, Industry 4.0 and its related technologies are ways of making factories smarter. This means that through technologies such as machine learning, more complex relationships between a variety of input variables and their effects can be predicted. This data-orientation and anticipation of likely outcomes can improve industrial performance in relation to the dimensions of costs, quality or flexibility (BCG,2022) (MCKINSEY,2022).

SYSTEMATIC REVIEW

A procedure developed by Medeiros et al. (MEDEIROS,2015), which proposes a systematic review method, based on an adaptation and simplification of the ProKnow-C method, with 10 stages and key questions, was used to investigate works related to the topic of this research. Based on this, the process of carrying out the literature review began, as shown below.

Stages of the systematic review

Step 1. Determine your objectives

What do you want to research? Integrated research areas: electroplating, low carbon steel and artificial intelligence.

Step 2. Determine a search descriptor

"Corrosion" OR "corrosion resistance" OR "Corrosion Prediction" OR "Atmospheric Corrosion" OR "Corrosion Rate" OR "Corrosion Risk" OR "oxidation" OR "Corrosion data") AND (("Galvaniz*" OR "Galvanis*" OR "galvanic current" OR "electrodepositation" OR "electrodepositation of zinc" OR "zinc electrodepositation" OR "galvanic protecition" OR galvan*

OR "electrochemical corrosion") OR ("Steel" OR "lowalloy steel" OR "low carbon" OR "Carbon steel" OR "SAE 1020" OR "SAE 1010" OR "SAE steel")) AND ("machine learning" OR "Image Processing" OR "Predicti*" OR "artificial intelligence" OR "Predictio* Mode*" OR "Orange data mining" OR "data mining".

Step 3. Choose the relevant databases

For this study, the Web of Science (WoS) database was chosen because, according to Cauchick,5 it is one of the most prominent databases, is multidisciplinary and indexes a variety of peer-reviewed journals. Available on the CAPES Journal Portal.

Step 4. Carry out the search using the descriptor WoS database search carried out.

Step 5. Filter the search by pre-selected criteria Apply filters to the searches made in Step 4.

Filter 1: Direct to the WoS base. Time frame: We searched for papers from the last five years and the current year, from 2017 to 2022, in order to understand the latest studies relating the three focal axes. Language cut-off: Only articles in English were filtered. Within the selections defined above, the result was 622 selected documents. The WoS spreadsheet file containing the data from all the articles was downloaded.

Filter 2: Keyword search using spreadsheet.

Criterion 1. Articles with the keyword "electroplating" in the title. Only 1 article out of 622 was selected.

Criterion 2. Articles with the keyword "artificial intelligence" in the title. There was only one article in the database of 622 papers, and it was not selected.

Criterion 3. Articles with the following keywords in the title: ("steel" AND "machine learning") OR ("steel" AND "prediction") OR ("corrosion" AND "machine learning") OR ("corrosion" AND "prediction"). Using these keywords and descriptors, 94 articles were selected from a pool of 622 papers.

In this screening (filter 2), using the three criteria presented, 94 articles were selected from a pool of 622 papers.

Filter 3: Reading the titles using a spreadsheet.

All 94 titles were read, and through an analytical screening of these, the researchers were left with 39 articles to analyse the abstracts.

Filter 4: Reading the summaries using a spreadsheet.

From the 39 articles screened, the abstracts were read to find the articles with the closest links to the axes of this study. By analysing the researchers, this selection resulted in the final choice of 8 articles, taking into account their objectives as described in section 3.2 Objectives of the articles. The articles chosen are shown in Table 1.

Step 6. Use software or spreadsheets to tabulate the information Data was tabulated using an electronic spreadsheet.

Step 7. Systematise the bibliography

Analysing abstracts, organising articles by author, year of publication, title, source, etc. Results presented in the Results section.

Step 8. Show the bibliometric indicators for each article

Publication by country: China published the most papers, with seven. In terms of keyword frequency, machine learning had the highest frequency with six hits, followed by atmospheric corrosion and random forest, both with five hits.

Step 9. Create graphs to present the results Report format in Step 10.

Step 10. Write a report

With regard to the selected portfolio, observations were made on the following points: Objectives of the papers, methodologies in relation to the data sources used by the authors, materials studied in the papers, environments to which the samples were exposed, input and output parameters of the machine learning models and the main results presented in the papers.

Objectives of the articles (Criteria for the final selection of articles)

With regard to the objectives of the papers, the proposal to use a machine learning model to predict the corrosion behaviour of steels predominates. In articles 1, 2, 4, 6 and 8, the proposal is to use modelling based on machine learning to simulate the corrosion behaviour of low-alloy steels. In article 5, the author mentions that his objective is to develop a method to differentiate local microstructures in low carbon steel based on multiple physical properties at the nanoscale combined with machine learning techniques to understand corrosion behaviour. In article 7, the proposal is to compare ZnNi layer thickness values in steel predicted by machine learning algorithms with realised experiments. As for article 3, since it is a review document, the authors mention that their proposal is to determine which ML models have been applied and how well they performed, depending on the corrosion topic considered.

Results

Based on the procedures described in section 3.1 Stages of the systematic review, the 8 most relevant documents were identified, according to the researchers perspective, and these are shown in table 1.

Table 1. Selected articles

N°	Article title	Authors' names	Year of publication	Total citations
1	Corrosion rate prediction and influencing factors evaluation of low-alloy steels in marine atmosphere using machine learning approach	Yan et al	2020	15
2	Improvement of the machine learning-based corrosion rate prediction model through the optimisation of input features	Diao et al	2021	14
3	Reviewing machine learning of corrosion prediction in a data- oriented perspective	Coelho et al	2022	8
4	Improving atmospheric corrosion prediction through key environmental factor identification by random forest-based modelling	Zhi et al	2021	8
5	Visualisation of electrochemical behaviour in carbon steel assisted by machine learning	Sun et al	2021	5
6	Machine learning modelling of time-dependent corrosion rates of carbon steel in presence of corrosion inhibitors	Aghaaminiha et al	2021	4
7	The prediction of the ZnNi thickness and Ni % of ZnNi alloy electroplating using a machine learning method	Katirci et al	2021	3
8	Analysis of Environmental Factors Affecting the Atmospheric Corrosion Rate of Low-Alloy Steel Using Random Forest-Based Models	Yan et al	2020	2

Source: Prepared by the author

Quantitative and qualitative analysis of the content of the papers

An analysis was made of the words that recurred most often in the abstracts of these articles, using the Orange Data Mining software. The word cloud is shown in figure 1.

Figure 1. Word cloud based on the abstracts of the articles. Generated in Orange Data Mining

With regard to the ML algorithms used in the papers, we can see that six articles use rf (randon forest). Other algorithms, such as k-means, SVD, GP, PR, ANN, SVM, Rlog, Rlin, GBDT, are used, as shown in figure 2.

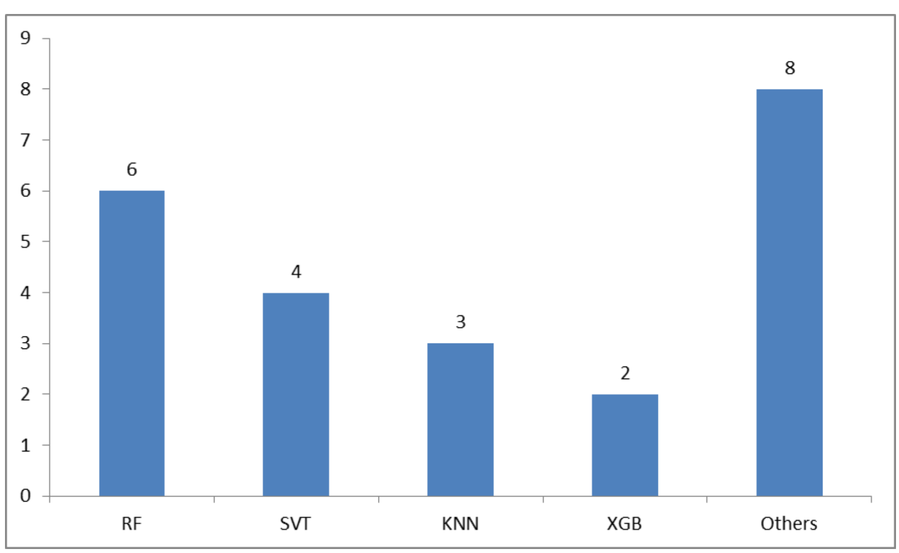

Figure 2. Number of articles per algorithm used

Materials and methodologies used in the work

With regard to the material used in the studies, all the articles used steel. Articles 1, 2, 4, 5, 6 and 8 specify low-alloy steel or carbon steel, while article 7 refers only to steel, and article 3, being a review document, indicates steel as the material used in some of the articles analysed.

With regard to the methodologies used, articles 1 and 2 used corrosion databases for input parameters. Articles 4, 5, 6, 7 and 8 used experimental data to carry out their research. As for article 3, since it is a review document, the authors mention that an extensive review of corrosion articles was carried out. Articles 1, 2, 4 and 5 carry out analyses in marine or saline environments. Article 1 notes that low-alloy steels are widely used in marine environments. Article 4 also uses urban environments to analyse the effects of corrosion, as do articles 6 and 7.

A count of articles quantifying the application of materials and methodologies is illustrated in figure 3 below.

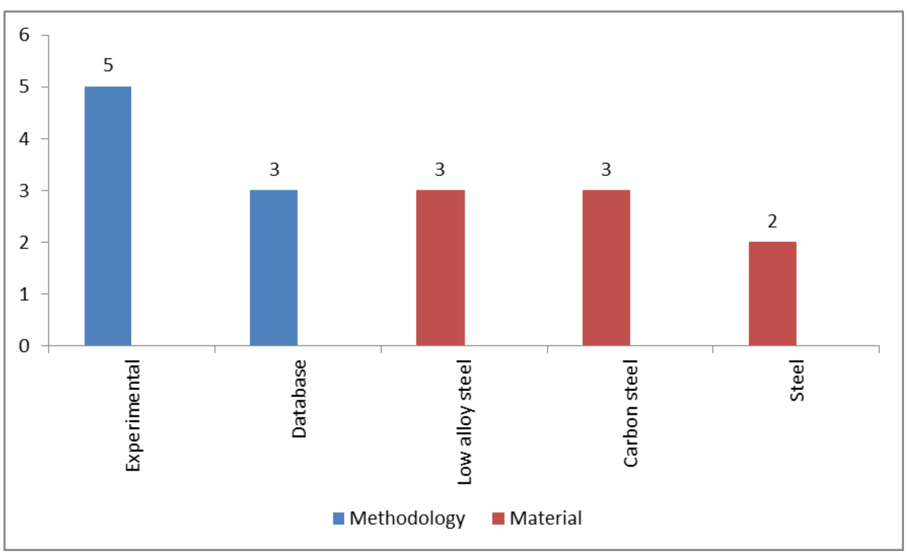

Figure 3. Number of articles analysed by material and methodology

Model input and output parameters

The chemical composition of the steels as an input parameter for the machine learning models is used in articles 1, 2 and 8. Environmental and environmental factors are used as input parameters in articles 1, 2, 4 and 8. Other input parameters distinct from the above are: 1. atomic force microscopy images, used in article 5; 2. variations in applied doses of corrosion inhibitors, used in article 6; and bath composition for electroplating protection, as used in article 7.

In the related articles, the predominant output parameter analysed is the corrosion rate, as indicated by articles 1, 2, 4, 6 and 8. Articles 3 and 5 also analyse parameters related to corrosion behaviour. Article 7 analyses the thickness of the electrodeposited coating used to protect the material (steel).

The number of articles per input and output variable used in the models is illustrated in figure 4 below.

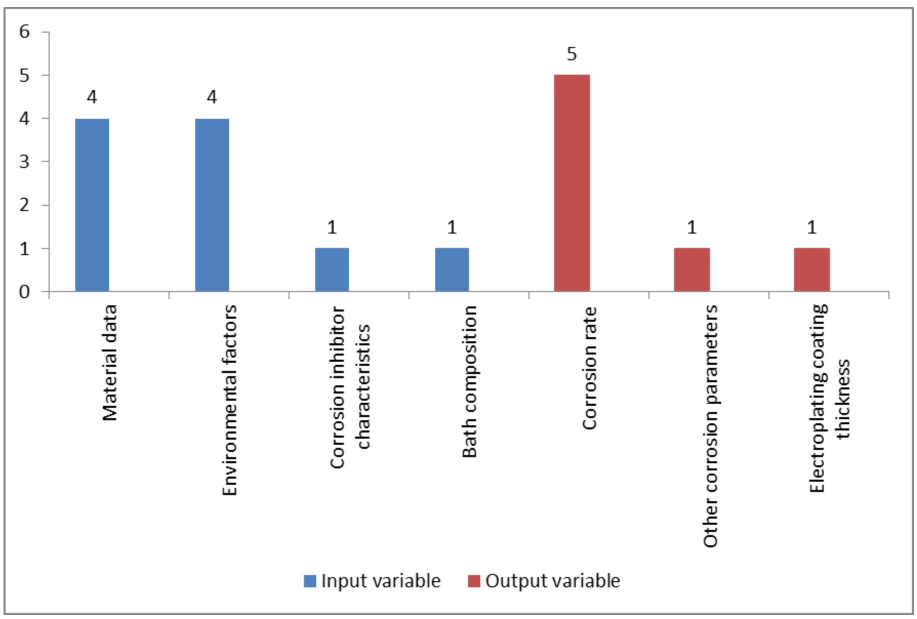

Figure 4. Quantities of articles by input and output variables used in the models

Results of the articles

Regarding the results, the documents report the following conclusions: In article 1, the authors mention that the results show that machine learning was efficient in analysing corrosion behaviour. In article 2, the authors state that machine learning is viable for assessing corrosion resistance.

In article 4, which compares different machine learning algorithms, the authors report that the SVR model was more accurate than others that use different technical characteristics.

In article 5, the studies carried out using atomic force microscopy images, the authors indicate that this provides a powerful tool for identifying and visualising corrosion-related features with data analysis. In article 6, the authors mention that they found that the random forest machine learning model was the best algorithm that predicted the entire corrosion time profile. In addition, the authors also state in their conclusion that the sensitivity of corrosion rates to changes in environmental variables is well predicted by the trained random forest model.

In article 7, the authors cite that the machine learning algorithm is a promising method for predicting the thickness of the coating referred to. In article 8, the authors conclude that machine learning provides a useful tool for analysing atmospheric corrosion mechanisms and assessing corrosion resistance. And to finalise the analysis of results, in article 3, as this is a review document, the authors mention that this work discusses possible research gaps and recommendations and provides a broad perspective for future research paths. The number of articles per conclusion is illustrated in figure 5 below.

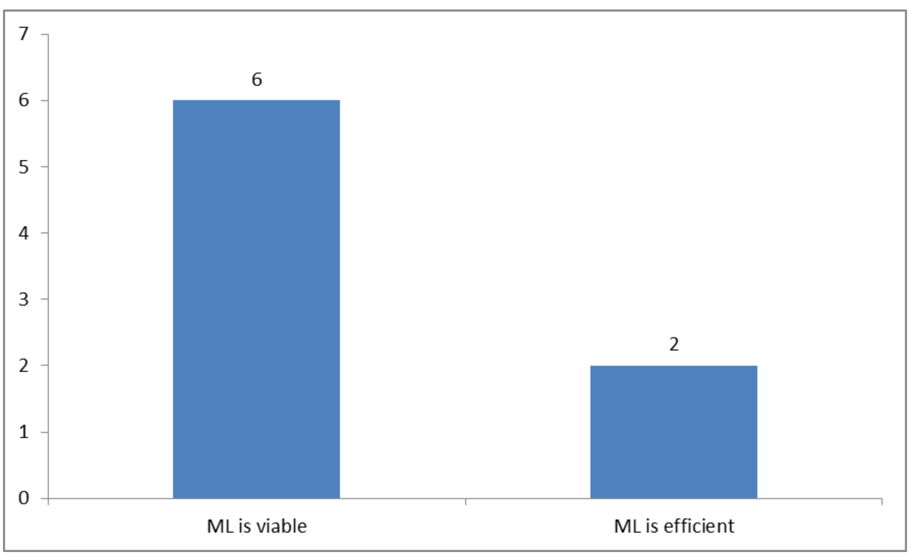

Figure 5. Number of articles per conclusion

CONCLUSION

Of the eight final articles researched, only one deals specifically with the application of machine learning to the ZnNi alloy electroplating process and its effects as a form of corrosion protection. The other articles mainly analyse corrosion behaviour in steels (corrosion rate), based on the input of data on the chemical composition of the material and environmental variables of the environment where the material is exposed to the models developed with machine learning. Therefore, based on the systematic literature review, it was possible to see that even though the scope was limited to the last five years plus the current year, 2022, studies with these integrated axes, using the research method presented in the paper, are very recent, starting with one publication in 2019 and having two publications in 2022.

With regard to the content of the papers, it was found that the most frequent machine learning algorithm was random forest (RF), which appeared in six of the eight papers analysed. It is interesting to note that three papers used data obtained from corrosion databases and five used experimental data. Therefore, for initial investigations into methodologies and the application of machine learning, it is possible to use databases to validate the proposed model and then, once it has been developed, check it against laboratory experiments until it reaches a level of development for applications in industrial environments.

In relation to the results of the studies, we found that six studies indicated that machine learning was viable and two indicated that it was efficient. We can therefore conclude that machine learning is a promising method for application in industry, as a way of predicting the corrosion resistance behaviour of galvanised materials, as well as carrying out analyses geared to the input data, which can thus provide greater speed, flexibility and quality in industrial processes.

The literature review points to the potential of applying machine learning as a way of predicting the behaviour and corrosion resistance of carbon steels. Through the key words chosen, a portfolio of 622 documents was identified and a final portfolio of eight documents, with scientific recognition and partially aligned with the researchers' perspective. As a result of this analysis and the reduction in the number of articles to eight, and given the concentration of articles from 2019 onwards on these integrated axes, the topic appears to be somewhat incipient. It was noted that there are references to AI applications in the area of corrosion, but without relevant integration with electroplating. Thus, there is space for new research using AI to develop models for determining corrosion resistance in low carbon steel subjected to electroplating.

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3 ARTIGO 2: TECHNOLOGICAL ADVANCES IN ELECTROPLATING: ARTIFICIAL INTELLIGENCE TO PREDICT ZINC COATING THICKNESS ON SAE 1008 LOW CARBON STEELS

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Article

TECHNOLOGICAL ADVANCES IN ELECTROPLATING: ARTIFICIAL INTELLIGENCE TO PREDICT ZINC COATING THICKNESS ON SAE 1008 LOW CARBON STEELS

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This study presents an artificial intelligence (AI)-based approach for predicting the thickness of electrodeposited zinc coatings on low carbon steel. The thickness of the coating is directly related to the corrosion resistance of the steel, according to the ABNT NBR 10476. The study investigates the influence of process time, ZnO/NaOH concentrations, anode material, and additives on coating thickness measured by X-ray fluorescence, employing the Hull cell method and a fractional factorial design. Statistical analysis and supervised machine learning algorithms, including multivariate regression, random forest, and extreme gradient boosting (XGBoost), were employed to develop prediction models. Among these models, XGBoost demonstrated superior performance with a coefficient of determination (R^2) of 0.95 and a mean squared error (MSE) of 0.815, highlighting the effectiveness of AI in comparison to traditional regression methods. The AI models developed provide a valuable tool for the electroplating industry. They allow for the optimization of input parameters to achieve desired coating thicknesses and improve corrosion resistance. This ultimately reduces costs and improves product quality.

Keywords: artificial intelligence; electrodeposited zinc coating; electroplating; XGBoost; electrodeposition; thickness prediction.

INTRODUCTION

To prevent corrosion, permanent coatings are applied to metals. Electroplating, also known as galvanizing, is one of the methods used to apply metallic coatings to the metal to be protected. This process involves immersing the metal to be protected, such as steel, in an electrolyte containing the salt of the desired metal, such as zinc or a metal alloy, and applying a constant cathodic potential to this metal from a direct voltage source. The effectiveness of a zinc coating in protecting the metal in a specific environment is directly related to its deposited thickness. It is therefore essential to control the process parameters to guarantee the quality of the part in terms of corrosion resistance.[1,2]

Various electrolyte formulations are available for electroplating. However, creating the best composition, which guarantees an adequate deposition and layer, through traditional experiments, carrying out one factor at a time, can be very time-consuming. A promising alternative for detecting the effect of parameters on process operation is the machine learning (ML) method.[3] Machine learning is a subfield of artificial intelligence (AI) that allows computers to learn from data to perform specific tasks. The practice of machine learning consists of applying algorithmic models to data interactively, allowing the computer to identify hidden patterns or trends, which in turn can be used to make predictions.[4] ML methods are suitable for developing predictive models in cases where a large data set is available, the outcome to be predicted depends on several variables, and when a mechanistic model of the relationship between the input variables and the outcome is not well established.[5] Although machine learning has gradually been applied to corrosion research, the corrosion community has still benefited little from the progress of Big Data technologies.[6]

The ML (AI) algorithms used in this work were linear regression, random forest (RF) and extreme gradient boosting (XGBoost).

Linear regression is a basic method in machine learning and statistics. It models the relationship between a dependent variable and one or more independent variables using a linear equation. Although useful for identifying basic trends and simple relationships (e.g., impact of current density (CD) on coating thickness), its lesser ability to model non-linear interactions limits its application in complex electroplating processes involving multiple factors, compared to the other models considered in the work.[4,5,7,8]

Random forest is a cluster learning method based on decision trees. It uses a mechanism to combine the predictions of multiple decision trees, each trained on a random subset of the data. RF is a solid choice for scenarios that require a balance between accuracy and interpretability. It effectively models non-linear interactions between variables such as current density, time and additive concentration, but can struggle with very high dimensional data.[4,5,7,8]

XGBoost is an advanced clustering algorithm designed for classification and regression. It builds decision trees iteratively (boosting) to minimize prediction errors. XGBoost is a highly advanced boosting algorithm with regularization, designed for maximum predictive power. It performs exceptionally well in complex, noisy datasets and offers built-in mechanisms to reduce overfitting. Nevertheless, it comes with high computational demands and reduced interpretability compared to the other models. Overall, linear regression is ideal for simpler, more interpretable tasks, random forest provides a balance of flexibility and robustness, and XGBoost delivers superior accuracy for demanding prediction problems, albeit at the cost of complexity and computational requirements.[4,5,7,8]

In the study of electroplating, XGBoost, with its regularization and advanced tree-based learning, is ideal for achieving high predictive accuracy. Its ability to deal with non-linearity, avoid overfitting and model complex interactions makes it suitable for the nature of the data analyzed.[4,5,7,8]

The aim of this work was to create a prediction model using artificial intelligence to predict the thickness of the electrodeposited zinc surface layer on low carbon steel substrates, based on variations in the parameters of the zinc electroplating process. The characterization of the material in relation to the thickness of the electrodeposited zinc coating is directly related to its resistance to corrosion in accordance with the ABNT NBR 10476.[1] For this characterization, a test was carried out to measure the thickness of the layer using X-ray fluorescence.[9]

The innovation of this work is related to the application of known AI algorithms to the traditional zinc electroplating process to predict the main output variable of this process (thickness of the galvanized zinc layer) based on the seven main input variables: electroplating time, concentrations in the electrolyte of ZnO, NaOH, additives (Purifier, Base 250 and Brightener) and anode material, in order to bring together two known methods for this parameterization of the electroplating process that is not yet present in the Brazilian industry.

As depicted in the Figure 1, this visual representation outlines the principal steps and key aspects of the proposed prediction model utilizing AI for the electrodeposition of zinc on low carbon steel substrates.

EXPERIMENTAL

Material

For the samples, in this work referred to as substrate, the alloy used as the base material (substrate) for electroplating was SAE 1008 low carbon steel, specifications shown in Table 1. The 0.9 mm thick sheet was laser cut to 100 mm × 70 mm.
Two types of anodes were used in the experiments. Anode 1, made of SAE 1008 steel, dimension 70 mm × 50 mm, same material as the substrate, according to the literature,[10] in the Hull cell test procedure. Anode 2, 99.92% pure zinc, according to energy dispersive X-ray (EDX) spectroscopic analysis, dimension 80 mm × 50 mm × 4 mm.

The use of a soluble anode (zinc) and an insoluble anode (steel) in the process was trialed in the laboratory to see if this variable had any significance on the electrodeposited thickness. In industry, steel is used as the anode because it is insoluble. The zinc for electrodeposition is entirely in the electrolyte.[10]

Table 1. Specifications of the substrate SAE 1008 steel[11]

Volume	Steel/coil	C / %	Mn / %	P / %	S / %
Specified	SAE 1008	max 0.1	max 0.5	max 0.04	max 0.05
Found	lot C562270401	0.044	0.288	0.016	0.009

The chemical substances used to prepare electrolyte solutions for electroplating were zinc oxide (ZnO, 80.7% pure), sodium hydroxide (NaOH, 97.5% pure), and commercial solutions, as leveling additives so called Base 250, commercial purifiers so called Purifier 1 and Purifier 2, and a brightener solution so called Brightener 250, purchased from a company that manufactures chemical products for surface treatment in Caxias do Sul, RS, Brazil.

The working electrolyte chosen was alkaline, based on sodium hydroxide (NaOH), because it is used commercially in the industry (a galvanic plant in the city of Caxias do Sul, RS, Brazil) where we would check the efficiency of the model applied in electrolyte production. The average pH of the solutions measured experimentally in the laboratory was 14.15.

Acid zinc electroplating processes, based on chlorides and sulfates, are highly sensitive to impurities, corrosive and require a more complex infrastructure than alkaline processes.12

Methods

Planning the experiment

The fractional factorial design method was used to carry out the experiments. 2k-p was used for the study, where k is the number of factors that vary between 2 established levels.13 According to Grömping,14 the 7 factor experiment with 16 iterations has IV resolution. This type of design is useful in factor selection experiments because it provides good information about the main effects and some information about all the second-order interactions.13 The experimental design was carried out using the FrF2 package written in the R programming language, in software RStudio,15 of the 1/16 fractional factorial type, with IV resolution, totalling 2(7-4) 16 iterations. Substrates were taken in duplicate, totaling 32 for the experiment.

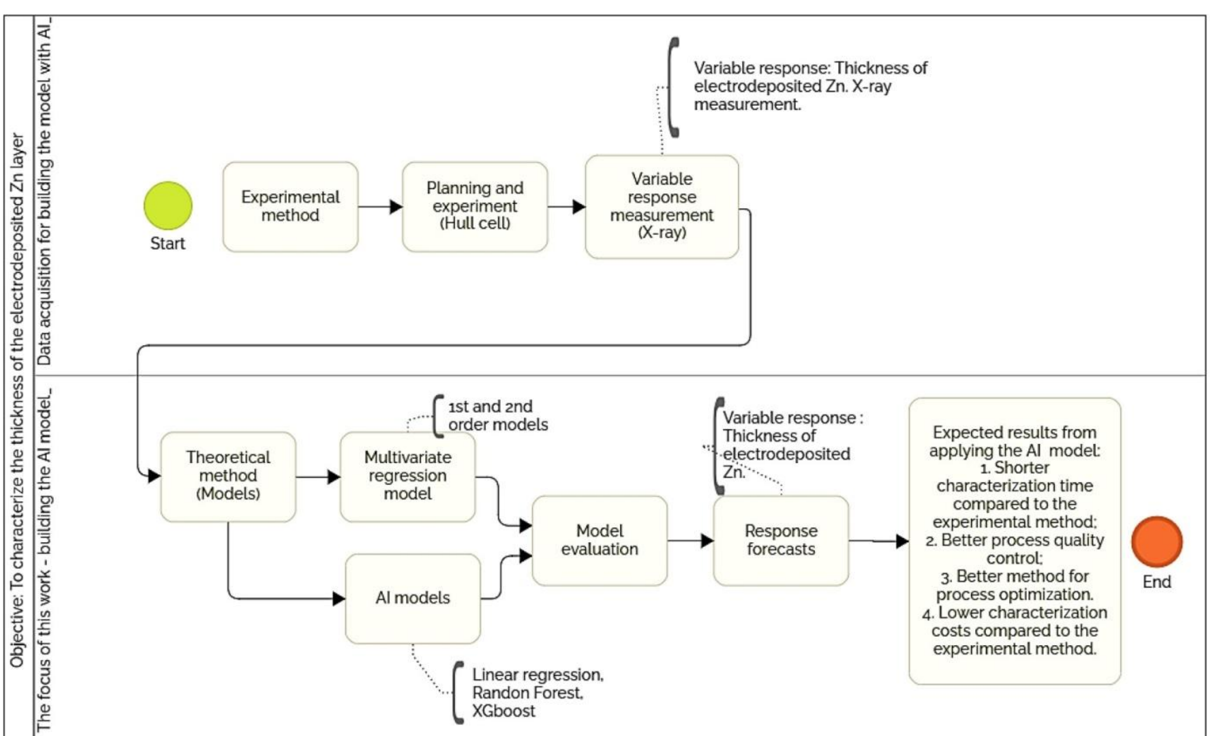

Figure 1. *AI-based prediction model for zinc electrodeposition on low-carbon steel substrates*

Electroplating experiment

The experiment was carried out using the Hull cell method, with a volume of 250 mL. This is a bench-top cell capable of producing a wide range of current densities in a cathode panel.[16] According to the diagram of the Hull cell shown in Figure 2, the indicated region of high current density (HCD) and low current density (LCD) can be observed.

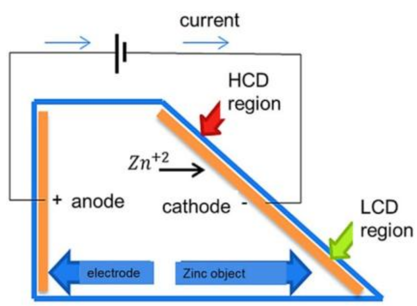

Figure 2. *Schematic diagram of the Hull cell*

It was used the basic procedure for carrying out a Hull cell test described by Sillos.10 The input variables used for electrodeposition experiments were selected based on technical bulletin from the manufacturer of the chemical products and are described in Table 2.

Table 2. Selected factor values

Variable	Factor	Unit	Low level	High level
1	time	min	15	30
2	ZnO	g L^{-1}	7	14
3	NaOH	g L^{-1}	105	140
4	purifier	mL L^{-1}	5.5	11
5	base 250	mL L^{-1}	6	12
6	brightener	mL L^{-1}	0.75	1.5
7	anode material	–	Fe	Zn

The process steps were carried out at room temperature (20 ± 2 °C). The experiments were executed according to the steps described in Table 3.

Table 3. Sequence of the experiment

Stage	Product	Concentration (v/v) / %	Time / min
1. Chemical degreasing	NaOH	50	10
2. Washing	deionized water		
3. Acid pickling	HCl	50	10
4. Washing	deionized water		
5. Hull cell	experimental solutions		15 or 30
6. Acid activation	HNO_3	0.5	0.1
7. Washing	deionized water		
8. Drying	air blower		

In the electrodeposit stage, the substrate was immersed in the electrolytic process in the Hull cell. For electroplating, a rectifier current source was used to supply electricity. In order to optimize the iterations, three Hull cells were used in parallel. Figure 3 shows the experiment. The iterations were randomized, and the same solutions did not occur simultaneously or successively.

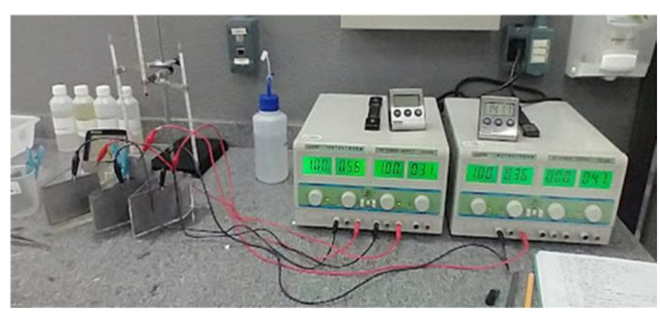

Figure 3. *Hull cell experimental iterations*

Figure 4 illustrates a substrate after the electroplating process, with the lower part electroplated with zinc and the upper part, the substrate without a layer.

In this work, a benchtop digital power supply, model FA-3030, manufactured by Instrutherm was used. This power supply has two independent channels that allow precise and continuous adjustment of both the output voltage and current, with accuracy of ±1 and ±2%, respectively. Voltage and current stability is guaranteed by line and load regulation circuits, with extremely low ripple and noise.[17]

The thickness of the zinc coating was measured using a Fischerscope® XRAY XAN 215 X-ray apparatus at two points on the electrodeposited substrate, in the HCD and LCD regions.

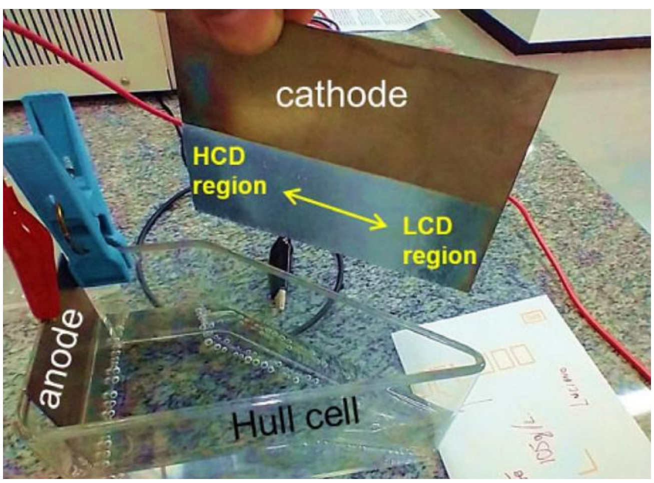

Figure 4. *Substrate after electrodeposition in a Hull cell*

Obtaining the values of the input and response variables

The experiment allowed to measure the thickness of the electrodeposited zinc coating at two points on each of the 32 substrates. One point in the LCD region and the other in the HCD region, totaling 32 measurements for each region or 64 total measurements. The data was tabulated and used to generate the zinc coating thickness prediction models. Table 4 illustrates the first 2 iterations (substrates) of the experiment. The last two columns are the response variables.

Forecasting models and performance evaluation methods

Experimental data from the laboratory was used and five regression models were employed, including two analytical models (first- and second-order multivariate regression) and three machine learning models (linear regression, random forest and XGBoost) to predict the thickness of the zinc coating. The results of the models were compared with experimental measurements to assess the accuracy of the predictions. Given the knowledge of the input and output variables in our experimental system, supervised machine learning algorithms were applied.

Initially, first- and second-order multivariate regression analytical methods were used as approximations, since the true functional relationship between Y and the variables x1, x2, ..., x_k was unknown.

To check whether there was a linear relationship between Y and the independent variables, the regression significance test was applied using analysis of variance (ANOVA) to assess the significant contribution of each independent variable to the model.[13]

After creating the analytical models, as proposed in this work, AI methods were used with the linear regression, random forest and XGBoost (XGB) algorithms. To compare the performance of the models, the coefficient of determination (R2) was used as a global statistic to assess the fit of the model. The R2 ranges from 0 to 1, with 1 being the perfect fit of the model, representing 100% of the variability in the response.13 The mean squared error (MSE) was also used to compare the AI models. MSE reflects the mean square difference between experimental and predicted values, with a low MSE indicating a low error rate.18 The flowchart of the work steps is shown in Figure 5.

Table 4. Input and response variables in the experiment

Run	Input variable							Response variable	
	Anode	Time / min	Purifier / (mL L^{-1})	Base 250 / (mL L^{-1})	Brightener / (mL L^{-1})	NaOH / (g L^{-1})	ZnO / (g L^{-1})	Thickness HCD / μm	Thickness LCD / μm
1	Zn	30	11	12	1.5	140	14	13	5.7
2	Fe	30	5.5	6	1.5	105	14	19.1	5.59
3	Fe	15	5.5	12	1.5	140	7	2.48	2.22
4	Zn	15	11	12	0.75	140	7	2.93	2.08
5	Fe	15	11	6	0.75	140	14	6.58	2.47
6	Zn	15	5.5	12	0.75	105	14	8.42	2.4
7	Fe	30	11	6	1.5	140	7	5.32	4.46
8	Fe	30	11	12	0.75	105	7	6.78	4.23
9	Zn	30	5.5	12	1.5	105	7	9.33	4.45
10	Fe	30	5.5	12	0.75	140	14	9.7	6.19
11	Fe	15	11	12	1.5	105	14	6.77	2.49
12	Zn	30	11	6	0.75	105	14	18.9	3.51
13	Zn	30	5.5	6	0.75	140	7	6.14	4.05
14	Fe	15	5.5	6	0.75	105	7	3.51	2.84
15	Zn	15	11	6	1.5	105	7	3.77	2.31
16	Zn	15	5.5	6	1.5	140	14	9.67	1.43
17	Fe	15	11	6	0.75	140	14	8.31	2.36
18	Zn	30	5.5	6	0.75	140	7	6.2	4.77
19	Zn	15	11	6	1.5	105	7	3.77	1.94
20	Fe	30	11	12	0.75	105	7	6.14	5.6
21	Zn	30	5.5	12	1.5	105	7	7.35	4.99
22	Fe	15	5.5	6	0.75	105	7	3.6	3.26
23	Zn	30	11	12	1.5	140	14	10.3	4.76
24	Fe	15	11	12	1.5	105	14	6.63	3.14
25	Fe	30	11	6	1.5	140	7	5.09	4.07
26	Fe	30	5.5	12	0.75	140	14	10.8	5.42
27	Zn	15	5.5	6	1.5	140	14	9.08	1.13
28	Zn	30	11	6	0.75	105	14	17.1	3.77
29	Zn	15	11	12	0.75	140	7	2.99	2.32
30	Zn	15	5.5	12	0.75	105	14	7.27	1.46
31	Fe	30	5.5	6	1.5	105	14	17.2	4.2
32	Fe	15	5.5	12	1.5	140	7	2.56	2.11

HCD: high current density; LCD: low current density.

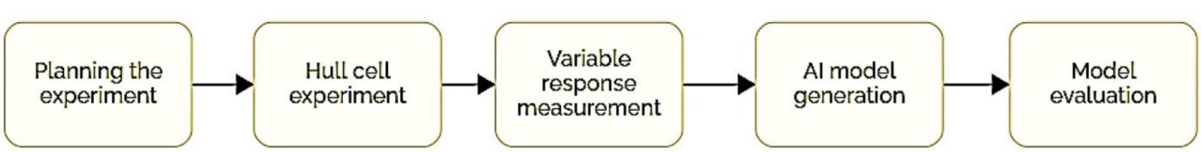

Figure 5. *Flow of work stages*

RESULTS AND DISCUSSION

The aim of this work was to develop a model using AI to predict the thickness of the electrodeposited zinc coating. Different prediction methods were used to compare their performance and choose which of these models best fitted the experimental data. As a result, one of the AI models was found to have the best fit to the experimental data.

Considering that in the industry some process parameters are known, and others do not have a practical quantitative analysis, as is the case of additives, an analysis was carried out to identify which ones have the greatest influence on the response variable, the thickness of the electrodeposited layer, through analysis of variance in multiple regression models. It can be seen that most of the process parameters that influence the thickness of the zinc coating can be measured and known.

The experiments were carried out with a variation of seven factors at two levels. This was important in order to provide various electrolyte configurations as input data for generating the models. In practical terms, it would be difficult to set up such configurations in industrial production tanks. According to the ABNT NBR 10476,1 the thickness of the zinc layer is decisive for the corrosion resistance of steel, so its measurement indicates the efficiency of industrial process control. Therefore, predicting this response variable can anticipate corrections and adjustments in the process to meet technical specifications for layer thickness, avoiding rework or quality problems in the field, which can have a severe impact on costs.

Multivariate regression models

Multivariate regression models were employed as a pre-analysis step to evaluate their predictive performance and compare them against AI-based methods. Additionally, these models facilitated statistical observations. First- and second-order regression models were constructed using the lm( ) function in the R programming language.[15] In this analysis, the response variable Y represented the thickness of zinc coatings electrodeposited on both the HCD and LCD (totaling 64 data points). The X input variables were the factors and their respective level values derived from the experimental design.

Model validation was carried out using ANOVA, with the *F*-test verifying the significance of the variables in influencing the regression estimates.

Figure 6 illustrates the linear regression between the predicted and experimental zinc layer thicknesses for the first-order regression model. The input variables from the design of the experiment were used to generate this model, which serves to establish how accurately the predictions align with the experimental results. The regression equation is represented as:

$$y = 1.7259 + 0.6944x \qquad (1)$$

The R2 = 0.6944 indicates a moderate correlation between the predicted and experimental thicknesses. The results demonstrate that the first-order regression model provides a reasonable approximation but leaves room for improvement in capturing the experimental trends. Figure 7 displays the linear regression for the second-order regression model. This model demonstrates an improved alignment between predicted and experimental values, with the regression equation:

$$y = 0.3253 + 0.9424x \qquad (2)$$

(2)

The $R^2 = 0.9424$ indicates a strong correlation, highlighting the superior predictive capability of the second-order model compared to the first-order model. The incorporation of higher-order terms clearly enhances the accuracy of the model, as reflected by the closer clustering of data points around the regression line.

Figures 6 and 7 provide a comparative insight into the performance of the first- and second-order multivariate regression models. The progression from the first- to the second-order model highlights the benefits of incorporating interaction effects, resulting in a substantially improved fit to the experimental data.

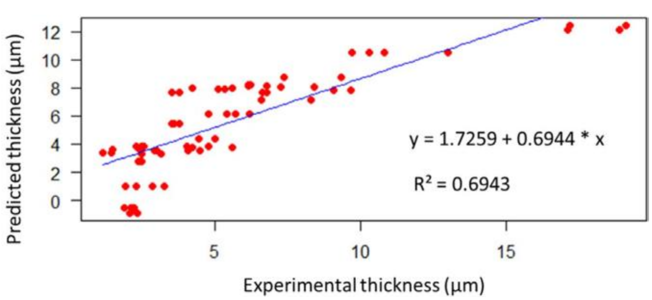

Figure 6. *Linear regression and first-order model between predicted (Y-axis) and experimental layer thickness (X-axis), generated in RStudio*[15]

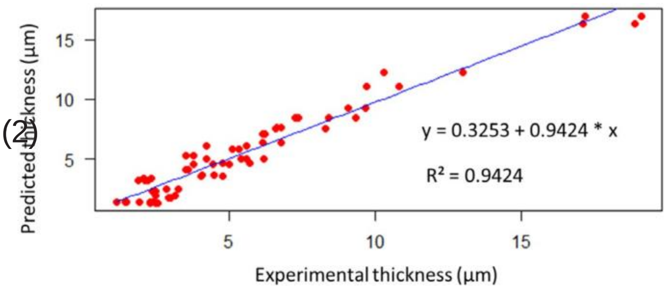

Figure 7. *Linear regression and second-order model between predicted (Y-axis) and experimental layer thickness (X-axis), generated in RStudio*[15]

Variables with a significant influence on the response of the model

The *F*-test, carried out in the FrF2 package, showed which variables in the regression had a significant influence on the estimate. For the first-order regression the parameters of time, ZnO and CD were the ones that most influenced the zinc coating thickness. For the second-order regression, the parameters of time, ZnO, NaOH, current density (DC), as well as the interactions time/DC, Base 250/DC, NaOH/DC and ZnO/DC, had the greatest influence on zinc coating thickness.

Machine learning models (AI)

Orange Data Mining[19] software was used to generate the AI models. Figure 8 shows the flowchart in the software.

The first FILE step is to import the data. Next, the models generated by each of the chosen algorithms are evaluated and compared using the R^2 and MSE metrics in TEST and SCORE. The algorithms chosen were: linear regression, as it is the one found in the FrF2 package, random forest, and gradient boosting.[7,20-22] Figure 9 shows the method chosen for the XRB algorithm. This method was chosen because Katirci *et al*.[7] pointed out in his conclusion that this was the best method verified in his work.

Table 5 shows through comparative metrics that XGB was the algorithm that generated the best model.

As XGB was the best algorithm, its generated model was used to make predictions using PREDICTIONS. Next, we plotted the XY dispersion, shown in Figure 10, which relates the experimental layer thickness to the layer thickness predicted using the model created by XGB, with the SCATTER PLOT step.

Table 5. Metrics of the chosen artificial intelligence algorithms, generated in Orange Data Mining[19]

Model	MSE	RMSE	MAE	R^2
Random forest	2.140	1.463	1.044	0.871
Linear regression	6.322	2.514	2.039	0.619
Gradient boosting	0.815	0.903	0.676	0.951

MSE: mean squared error; RMSE: root mean square error; MAE: mean absolute error; R^2: coefficient of determination.

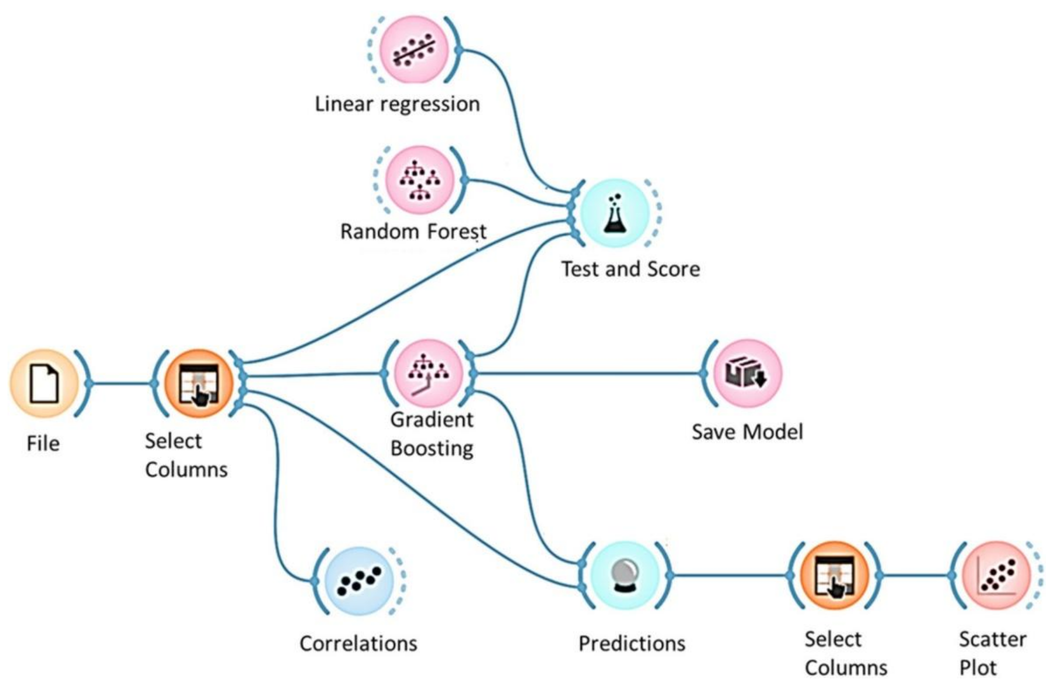

Figure 8. *Flowchart for choosing the artificial intelligence algorithm (generated in Orange Data Mining)*[19]

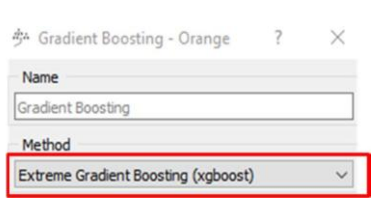

Figure 9*. Method chosen for the gradient boosting algorithm (generated in Orange Data Mining)19*

Evaluation of AI-generated models

Through the comparative metrics between the three proposed AI algorithms, XGB had the highest R2 = 0.95. This means that the model explains 95 per cent of the variability in the data. The MSE = 0.815 means that there is a low dispersion of error between the prediction and the experimental response. These analyses indicate that the model is valid for predicting the thickness of the electrodeposited zinc coating under the conditions outlined in the experiment.

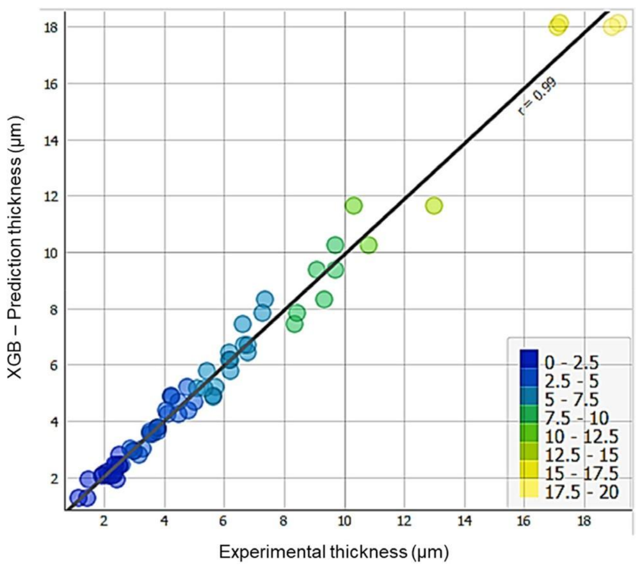

Figure 10. *Linear regression of the layer thickness predicted with the XGB algorithm in relation to the experimental one (generated in Orange Data Mining)*[19]

Comparison between the analytical (multiple regression) and AI (XGBoost) models

Considering the results of layer thickness predicted in the HCD and LCD regions, for the second-order linear regression model, whose performance was better than the first-order model, verified by the higher R2, generated by the FrF2 package in R language,15 with a coefficient of determination equal to 0.94, when compared with the AI model generated by the XGB algorithm in the Orange Data Mining software,19 it can be seen in Figure 11, its better performance with a R2 = 0.95. The results showed that the AI algorithm XGB stood out from the rest, providing the highest R2 values and the lowest MSE values for predicting the thickness of the zinc coating. This superior performance of XGB reinforces the ability of AI techniques to tackle complex problems such as electroplating low carbon steel.

Relationship between thickness in the HCD and LCD regions

This ratio is a parameter, calculated from the Hull cell experiment, which can indicate the quality of the electrolyte. The ratio between layer thickness measurements in the HCD and LCD regions can indicate excess (ratio below 1.8), lack (ratio above 2.2) or adequate quantity (ratio between 1.8 and 2.2) of the layer levelling additive (Base additive 250).10

Using the data from the experiment, and placing the relationship between HCD and LCD thickness as the response variable, Pearson's correlation was analyzed using the Orange Data Mining software.19 The correlation coefficient, also called Pearson's correlation coefficient, is a quantitative measure of the strength of the linear relationship between two random variables X and Y. If the two variables are perfectly linearly related with a positive slope, r = +1, and if they are perfectly linearly related with a negative slope, r = –1. If no relationship exists between the variables, r = 0.13

Based on the experiment, the variable with the highest correlation with the HCD/LCD ratio was the concentration of ZnO in the solution, with a Pearson coefficient = +0.684, a moderately strong correlation. The levelling additive (Base 250) is the second variable with the highest correlation with the HCD/LCD ratio, with Pearson coefficient = –0.324, a moderately weak correlation. This analysis indicated that for the conditions outlined in the experiment, this ratio not only qualitatively indicates the suitability of the levelling additive in the solution, but can also indicate the suitability of ZnO. In order to confirm this finding, experiments in a Hull cell, with different factor values, and in larger quantities are required. A larger number of experiments is also needed to check whether the correlation between the levelling additive (Base 250) and the HCD/LCD ratio will increase, or remain with a moderately weak correlation. Table 6 shows the result of the correlation between these variables.

Table 6. Pearson's correlation *versus* thickness in HCD/LCD, generated in Orange Data Mining[19]

Pearson's correlation	Variable 1	Variable 2
+0.684	R HCD/LCD	zinc (g L^{-1})
–0.324	Base 250 (ml L^{-1})	R HCD/LCD

HCD: high current density; LCD: low current density; R: relation.

Using the predictive model, the thickness can also be predicted in the Hull cell experiment and this relationship between the layer thickness in the HCD and LCD region can be calculated to check the adequacy of the amount of levelling additive (Base 250) in the solution.

Main effects of factors on the thickness of the electrodeposited zinc layer

Pearson's correlation analysis was carried out using the Orange Data Mining software19 to check the correlation between the input factors and the layer thickness response variable. Table 7 shows the correlation between the factors and the response. Three factors were found to have moderate correlations with the response (layer thickness). The highest correlation is with the CD factor (A dm-2), with a moderately strong correlation coefficient = +0.541. The correlations of the time and zinc (ZnO) factors show a moderately weak correlation. It was observed that the factor with the greatest influence on the electrodeposited layer, under the conditions outlined in the experiment, is the CD factor, followed by the time factor and the zinc factor. Sillos10 shows a direct relationship between the output variable, the thickness of the electrodeposited layer, and the factors (input variables) time and current density, indicating that the relationships found in this work are consistent with the literature.

Table 7. Pearson's correlation versus layer thickness, generated in Orange Data Mining19

Pearson's correlation	Variable 1	Variable 2
+0.541	thickness / μm	CD / (A dm^{-2})
+0.473	thickness / μm	time / min
+0.403	thickness / μm	zinc / (g L^{-1})
–0.157	thickness / μm	NaOH / (g L^{-1})
+0.049	anode (2)	thickness / μm

CD: current density.

Aspects of the visual characterization of the electroplated substrates

Due to the variation in factors, different combinations of electrolytes were created, making it possible to observe different visual aspects of the electroplated substrates. Figure 11 compares two electroplated substrates. Sillos10 relates the condition of the electrolyte to the visual appearance of the panel tested in the Hull cell, indicating that for an ideal electrolyte condition, the surface of the panel should be shiny and uniform. Figure 11a shows a galvanized substrate with a non-uniform visual appearance of the electrodeposited layer, with a matt appearance and the formation of a coarse deposit in the high current density zone, which according to Sillos,10 may be characteristic of the combination of high levels of the current density, time and electrolyte factors with an imbalance of brighteners. Figure 11b shows a visually uniform appearance of the electrodeposited layer and a more open shine, characteristic of the optimum experimental conditions and the ideal electrolyte condition. In the zinc electroplating process, the desired pattern should be visually similar to that in Figure 11b, with an open sheen, visually uniform deposition of the layer and no apparent defects (burnt surfaces, orange peel appearance, matt surface).

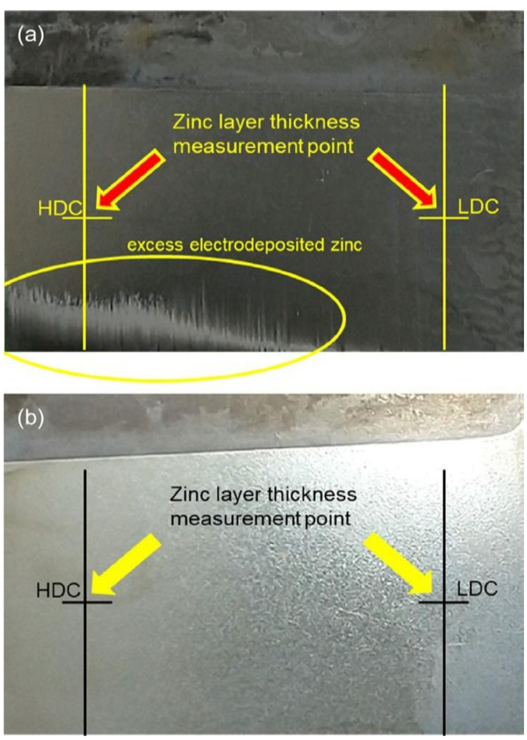

Figure 11. *Macroscopic visual characterization of two electroplated substra- tes from the experiment. (a) Galvanized substrate with a non-uniform visual appearance of the electrodeposited layer, with a matte appearance and the formation of a coarse deposit in the high current density zone, characteristic of problems in the experimental conditions related to the variables and the electrolyte. (b) Galvanized substrate with a uniform visual appearance of the electrodeposited layer and a more open shine, characteristic of the optimal experimental conditions and the ideal condition of the electrolyte*

Influence of current density on zinc deposition and thickness

The thickness of the deposits varied directly with the current density, being greater in the regions of higher current density. A difference in thickness was observed in the electrodeposited substrates, with higher values in the HCD regions, closer to the anode, and lower values in the LCD regions, further away from the anode. This variation is attributed to the non-uniform distribution of current density resulting from the geometry of the electrolytic cell, which causes a gradual increase in the electrical resistance of the solution with the distance between the electrodes. The literature[10,12] corroborates this observation, reporting that HCD promote intense gas evolution, as part of the applied current is used for metal deposition and part reduces other elements, mainly hydrogen. This phenomenon defines current efficiency. These changes lead to the formation of thicker deposits and a greater number of defects, such as pores and inclusions. On the other hand, in conditions of LCD, gas evolution is less intense, favoring the formation of more uniform deposits with fewer defects. These effects can be clearly seen visually in Figure 11a, where in the region of HCD there is an excessive deposit of zinc in the bottom left-hand corner that is not uniform in relation to the right-hand side (LCD).

Application of the model to an industrial electrolyte

To confirm the applicability of the model generated by the XGB algorithm, we carried out a new set of experiments using an electrolyte with an industrial composition. These experiments were carried out using electrolyte extracted directly from a real production tank at a galvanic plant in the city of Caxias do Sul, RS, Brazil. The input parameters and resulting coating thicknesses were recorded according to the methodology described in section Electroplating experiment.

The data from the experiment with the industrial electrolyte is presented in Table 8, showing the input variables and experimentally measured layer thicknesses.

The input variables include the type of anode, the electrodeposition time, the NaOH concentration and the ZnO concentration.

Model application process

The XGB model was applied using Orange Data Mining software.[19] Figure 12 shows the workflow used to load the data, select the variables, apply the model and generate the predictions, as well as visualizing the results in a scatter plot. The workflow consisted of the following steps:

(i) load data (file): load the experimental data;
(ii) select rows: filter the data as required;
(iii) select columns: select the relevant input and output variables;
(iv) load model: load the previously trained XGB model;
(v) generate predictions: apply the model to the experimental data to predict the coating thicknesses;
(vi) scatter plot: visualize the correlation between the values predicted by the model and the experimental values.

Model validation

Figure 13 shows a scatter plot relating the layer thickness predicted by the XGB model to the thickness measured experimentally. The linear correlation shown in the graph, with a correlation coefficient of r = 0.95, indicates a strong agreement between the predicted values and the experimental values. The colors of the points on the graph represent different thickness intervals, making it easier to see the distribution of the data.

Table 8. Input and response variables in the experiment

Run	Input variable				Response variable	
	Anode	Time / min	NaOH / (g L^{-1})	ZnO / (g L^{-1})	HCD thickness / µm	LCD thickness / µm
1	Zn	15	128	11	1.83	4.16
2	Fe	15	128	11	1.87	3.75
3	Fe	30	128	11	3.54	7.45
4	Zn	30	128	11	3.66	8.11
5	Zn	30	128	11	3.43	6.95
6	Zn	15	128	11	1.69	4.0
7	Fe	30	128	11	3.48	6.71
8	Fe	15	128	11	1.77	4.22
9	Zn	30	128	11	3.31	7.5
10	Fe	15	128	11	1.59	3.74
11	Fe	30	128	11	3.38	6.7
12	Zn	15	128	11	1.5	3.58
13	Zn	15	128	11	1.51	3.6
14	Zn	15	128	11	1.53	4.25

HCD: high current density; LCD: low current density.

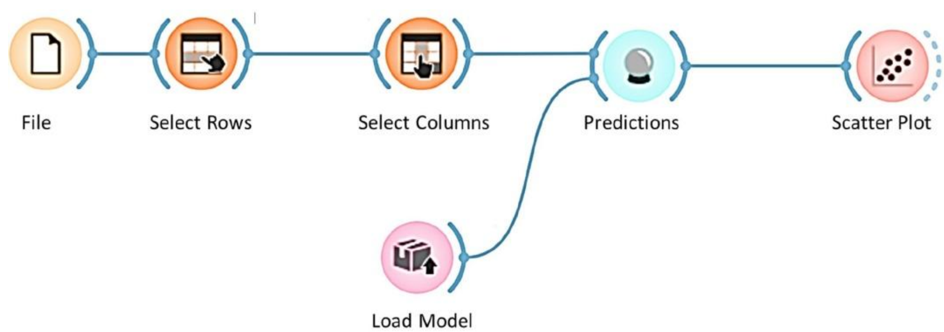

Figure 12. *Flowchart for choosing the artificial intelligence algorithm (generated in Orange Data Mining)*[19]

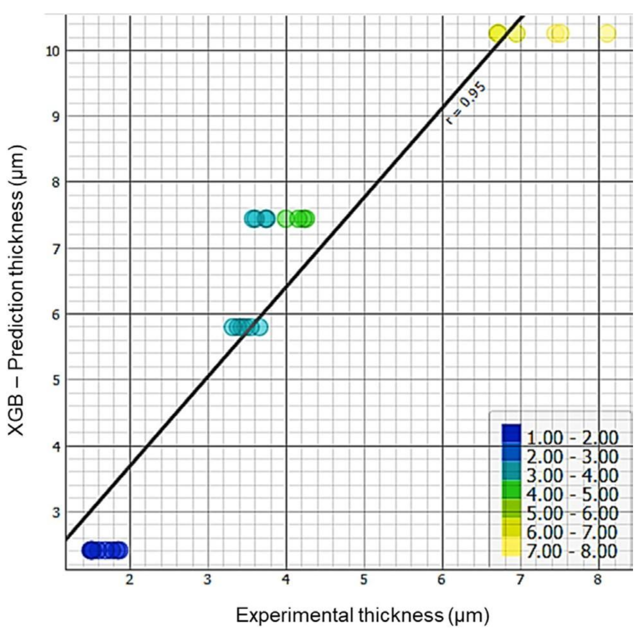

Figure 13. *Linear regression of the layer thickness predicted with the XGB algorithm in relation to the experimental one (generated in Orange Data Mining)*[19]

The high correlation observed between the experimental data and the model predictions confirms the robustness and applicability of the XGB model in industrial conditions. This experimental validation demonstrates that the model can be used reliably to predict zinc coating thickness in galvanizing processes using industrial electrolytes.

The results presented corroborate the effectiveness of the XGB model in predicting zinc coating thickness with high accuracy, even when applied to electrolytes taken from a real industrial environment. This experimental confirmation validates the use of the model in practical applications, providing an effective tool for optimizing and controlling the zinc electroplating process.

Correlation between expected coating thickness and process parameters

In this study, the correlation between the expected zinc coating thickness and the process parameters was analyzed using the XGBoost (XGB) algorithm. The main objective was to verify the strength of the relationship between the input parameters (current density and time) and the layer thickness obtained, both experimentally and predicted by the model.

Experimental correlation table

To assess the correlation between the input factors and the coating thickness, Pearson's correlation was used. Table 9 shows the correlation coefficients for the experimentally measured thickness versus CD and time. The values indicate the strength of the linear relationship between these variables.

Table 9. Pearson's correlation between factors and experimental coating thickness, generated in Orange Data Mining[19]

Pearson's correlation	Variable 1	Variable 2
+0.950	experimental thickness / μm	XGB thickness / μm
+0.731	experimental thickness / μm	CD / (A dm^{-2})
+0.639	experimental thickness / μm	time / min

CD: current density; XGB: extreme gradient boosting.

The results show an extremely high correlation (+0.950) between the experimental thickness and the thickness predicted by the XGB model, demonstrating the accuracy of the model in replicating the experimental data. CD showed a positive correlation (+0.731), indicating a strong relationship with coating thickness. The deposition time also showed a positive correlation (+0.639), although smaller, still significant.

Correlation table predicted by the XGB model

Table 10 details the correlation between the input parameters and the coating thickness predicted by the XGB model. These values were generated for the substrates tested with industrial electrolyte under real production conditions.

Table 10. Pearson's correlation between the factors and the coating thickness predicted by the XGB model, generated in Orange Data Mining[19]

Pearson's correlation	Variable 1	Variable 2
+0.841	XGB thickness / μm	CD / (A dm^{-2})
+0.539	XGB thickness / μm	time / min

CD: current density; XGB: extreme gradient boosting.

The data in Table 10 reveals that CD continues to be a determining factor in predicting layer thickness, with a positive correlation of +0.841. This reinforces the importance of precise control of CD in the electrodeposition process in order to achieve the desired coating thickness. The correlation between deposition time and the thickness of the layer predicted by the model is positive (+0.539), demonstrating that, although less influential than current density, time still has a significant impact on the thickness of the coating.

Discussion of the correlations

The correlations presented clearly indicate that the process parameters, specifically CD and time, have a significant relationship with the thickness of the zinc coating. The strong correlation between the experimental thickness and the thickness predicted by the XGB model (+0.950) validates the ability of the model to capture the influences of the process parameters on the coating thickness.

CD proved to be the most influential factor, with correlations of +0.731 and +0.841 for the experimental and predicted data, respectively. Deposition time, although with lower correlations (+0.639 and +0.539), still proved to be a relevant parameter in determining coating thickness.

These results confirm that there is a significant correlation between process parameters and coating thickness, corroborating the theoretical basis that process parameters are determinant in the formation of the coating layer. These correlations are fundamental for predictive modelling and for optimizing the zinc electroplating process in industrial environments.

Challenges, limitations and industrial applications of the model

It is important to emphasize the limitations of the model, with points to consider:

(i) as for the substrates, although they are statistically representative and allow for satisfactory analyses, more data could improve the learning of the model and confirm the correlation between the thicknesses in the HCD/LCD and the concentration of zinc (ZnO) in the solution;

(ii) the model used two time levels (15 and 30 min) based on the Hull cell test,10 but in industrial processes, the time can be longer, limiting the application of the model to longer periods;

(iii) the lack of industrial process data with different factor values for comparison with the predictions of the model is a limitation.

In addition to the points mentioned above, other factors (which remained at fixed levels) that could be influence the electroplating process, include the temperature and agitation of the electrolyte.

The result of this study suggests a starting point for process control based on predictive analysis. Companies already have extensive control data, such as ZnO, NaOH, temperature, time and current density. However, the relationship between these parameters and the characteristics of the parts in production batches has not yet been explored in order to build predictive models. This work proposes integrating existing data on these parameters with the characteristics of the parts, such as layer thickness, composition (ZnNi, ZnFe, etc.), accelerated corrosion tests, peeling, visual analysis and surface defects. The method presented is easy to apply and open source, allowing models to be created to predict other characteristics based on the layer thickness measurement presented here. Implementation on an industrial scale is feasible with production tools for machine learning models. The model can be made available online for other companies to use, but it is important to consider the limitations mentioned in this work and the need for more data and validation in varied industrial conditions to improve the model.

CONCLUSIONS

The aim of this study was to develop a model using AI to predict the thickness of the surface layer of zinc electrodeposited on low carbon steels using the electroplating process, taking into account variations in the parameters of the electroplating process. As a result, the best model using AI was generated by the XGBoost algorithm, which had the best performance among the models analyzed, obtaining R2 = 0.95 and MSE = 0.815.

The results of this study are consistent with the publication by Katirci et al.,7 where the authors conclude that the results of the analysis show that the XGB algorithm provides the best estimate for the thickness of ZnNi and Ni%. Specifically, the XGB machine learning technique had the highest R2 values and the lowest MSE values for the prediction of coating thickness. Furthermore, the XGB method was found to be the most effective AI model generator among the models tested, based on the same metrics used in the literature.

This is an important result, as it shows the scientific and methodological alignment with the work published by Katirci et al.,7 in the area of AI applied to electroplating processes for predicting the thickness of the electrodeposited layer on low carbon steel substrates.

The predictive models generated in

this work have the potential to optimize costs by improving the quality of parts, reducing the time between possible problems and the detection of effects, as well as providing predictive capacity for the process, providing the ability to know what is going to happen, before it happens, in terms of responses. Thus, for the variable chosen, the thickness of the electrodeposited zinc coating, due to its importance and direct relationship with the corrosion resistance capacity of the substrate, according to ABNT NBR 10476,1 the application of the predictive model is viable for this process.

The possibility of predicting the thickness of the electrodeposited layer on low carbon steel substrates is a significant contribution to improving industrial processes, since this prediction relationship is currently non-existent in many electroplating companies, according to field visits carried out. The data and models from this study can be made available online for those interested to analyze and work with. It is worth emphasizing that although this study focused on the SAE 1008 steel alloy, the concepts and methodologies presented here can serve as a basis for future investigations involving other low carbon steel alloys. In short, this work contributes to the advancement of the application of artificial intelligence in electroplating processes, offering an innovative and accurate approach to predict the thickness of the electrodeposited zinc coating on low carbon steel substrates, with the potential to boost the anticorrosive coatings industry.

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4 RESULTADOS E DISCUSSÃO

4.1 INTRODUÇÃO AOS RESULTADOS

Neste capítulo, são apresentados e discutidos os principais resultados dos estudos realizados sobre Inteligência artificial para prever a espessura do revestimento de zinco em aços de baixo carbono SAE 1008. Os resultados dos dois artigos científicos abordam a aplicação de inteligência artificial (IA) e aprendizado de máquina (ML) no processo de eletrodeposição de zinco em aços de baixo carbono, com foco na otimização de parâmetros e na previsão de variáveis críticas, como a espessura do revestimento. O primeiro artigo enfatiza a eficiência do aprendizado de máquina na análise do comportamento à corrosão, destacando lacunas na literatura e recomendando caminhos para futuras pesquisas. Já o segundo artigo apresenta uma abordagem experimental para o desenvolvimento de modelos preditivos, utilizando algoritmos como regressão multivariada e XGBoost, que demonstraram ser ferramentas poderosas para previsão e controle do processo industrial.

4.2 RESULTADOS SINTETIZADOS DOS ARTIGOS

A tabela 01 sintetiza as principais diferenças e contribuições dos dois artigos analisados. O primeiro artigo foca na revisão de literatura, identificando lacunas e destacando o aprendizado de máquina como ferramenta promissora, especialmente com algoritmos como Random Forest e SVR, para a análise de corrosão e otimização de processos. Por outro lado, o segundo artigo apresenta um estudo experimental que valida o uso de IA, destacando o XGBoost como o modelo mais eficaz na previsão da espessura do revestimento de zinco, com resultados superiores aos métodos tradicionais. Enquanto o primeiro artigo estabelece uma base teórica para avanços futuros, o segundo valida a aplicação prática em cenários industriais, mostrando como parâmetros críticos, como densidade de corrente e tempo, podem ser usados para otimizar o processo de galvanização. Essa comparação evidencia a complementaridade dos artigos, onde a teoria e a experimentação se alinham para promover avanços no campo da eletrodeposição.

Tabela 01: Comparação dos Resultados

Aspecto	Artigo 1	Artigo 2
Foco Principal	Revisão de literatura e identificação de lacunas.	Desenvolvimento de modelo preditivo experimental.
Algoritmos Destacados	Random Forest, SVR.	XGBoost (R^2 = 0,95, MSE = 0,815).
Parâmetros Críticos	Variáveis ambientais e comportamentos de corrosão.	Tempo, ZnO, densidade de corrente.
Aplicação	Base teórica para avanços futuros.	Validação experimental e aplicação industrial.

Fonte: Elaborado pelo autor (2025).

4.3 ANÁLISE DOS RESULTADOS

Resultados do Artigo 1: Revisão da Literatura

- A literatura aponta o aprendizado de máquina como uma ferramenta eficiente para analisar o comportamento de corrosão e prever características importantes como espessura de revestimentos.
- Modelos como Random Forest e SVR destacaram-se em diferentes estudos por preverem com precisão perfis de corrosão e efeitos de variáveis ambientais.
- A revisão destacou a importância de algoritmos avançados na análise de imagens de microscopia de força atômica para identificar características relacionadas à corrosão.
- O trabalho conclui que, embora incipiente, a aplicação de IA e ML na galvanização de aços de baixo carbono é promissora, especialmente no desenvolvimento de modelos preditivos que correlacionem parâmetros do processo à resistência à corrosão.

Resultados do Artigo 2: Estudo Experimental

- O modelo baseado em XGBoost apresentou o melhor desempenho na previsão da espessura do revestimento de zinco, com $R^2 = 0,95$ e MSE = 0,815, superior aos modelos de regressão linear e Random Forest.
- A análise de variância indicou que os parâmetros tempo, concentração de ZnO e densidade de corrente têm maior influência sobre a espessura do revestimento.
- A validação experimental demonstrou uma forte correlação ($r = 0,95$) entre os valores previstos pelo modelo e os dados experimentais, confirmando a robustez da abordagem baseada em IA.
- O estudo também destacou a aplicabilidade prática do modelo em condições industriais, utilizando eletrolíticos reais de produção.

O objetivo deste estudo foi desenvolver um modelo baseado em Inteligência Artificial (IA) para prever a espessura do revestimento de zinco eletrodepositado, comparando diferentes métodos de previsão para identificar o mais eficaz. Os resultados indicaram que o modelo de IA, utilizando o algoritmo XGBoost (XGB), teve o melhor ajuste aos dados experimentais, destacando-se por explicar 95% da variabilidade dos dados, com um erro médio quadrático (MSE) de 0.815.

Para avaliar o desempenho dos modelos, também foram utilizados modelos de regressão multivariada. A regressão de segundo grau mostrou uma correlação de $R^2 = 0.9424$, superando a regressão de primeiro grau, com $R^2 = 0.6944$. No entanto, o modelo XGB obteve desempenho superior com $R^2 = 0.951$, indicando sua maior precisão na previsão da espessura do revestimento.

A dispersão XY, apresentada na Figura 02, relaciona a espessura da camada experimental com a espessura da camada prevista utilizando o modelo criado pelo XGB, com o eletrólito delineado para a geração do modelo. Os dados da experiência com o eletrólito industrial são apresentados na Tabela 4, do artigo 2, que mostra as variáveis de entrada e as espessuras de camada medidas experimentalmente.

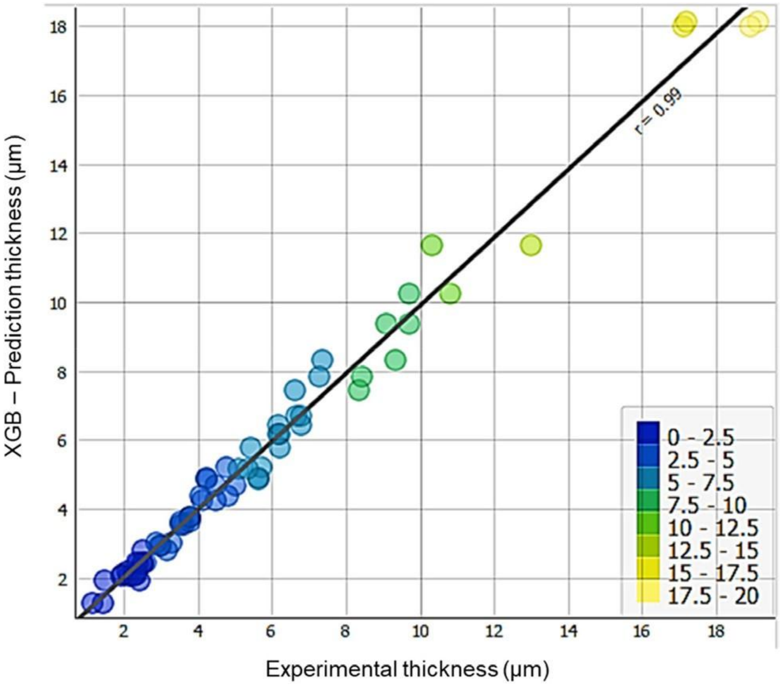

Figura 02. Regressão linear da espessura da camada prevista com o algoritmo XGB em relação à experimental (OLIVEIRA et al., 2025)

A análise da correlação de Pearson revelou que a densidade de corrente teve a maior correlação positiva com a espessura da camada (r = +0.841), seguida pelo tempo de deposição (r = +0.539). Esses resultados confirmaram que a densidade de corrente e o tempo de deposição são fatores cruciais para a obtenção de espessuras de revestimento adequadas.

A comparação entre os modelos de regressão e IA mostrou que o modelo XGB foi mais eficaz, oferecendo previsões mais precisas e menores margens de erro, o que evidencia a viabilidade do uso de IA para otimizar processos industriais de galvanoplastia.

Além disso, a aplicação do modelo a uma composição de eletrólito industrial em condições reais de produção validou a robustez do modelo, com uma correlação forte entre os valores experimentais e os previstos (r = 0.950), confirmando sua aplicabilidade para otimizar e controlar o processo de eletrodeposição de zinco na indústria.

Os dados da experiência com o eletrólito industrial são apresentados na Tabela 8, do artigo 2, que mostra as variáveis de entrada e as espessuras de camada medidas experimentalmente.

As variáveis de entrada incluem o tipo de ânodo, o tempo de eletrodeposição, a concentração de NaOH e a concentração de ZnO.

A figura 03 mostra um gráfico de dispersão que relaciona a espessura da camada prevista pelo modelo XGB com a espessura medida experimentalmente. A correlação linear apresentada no gráfico, com um coeficiente de correlação de r = 0,95, indica uma forte concordância entre os valores previstos e os valores experimentais. As cores dos pontos no gráfico representam diferentes intervalos de espessura, facilitando a visualização da distribuição dos dados.

A elevada correlação observada entre os dados experimentais e as previsões do modelo confirma a robustez e a aplicabilidade do modelo XGB em condições industriais. Esta validação experimental demonstra que o modelo pode ser utilizado de forma fiável para prever a espessura do revestimento de zinco em processos de galvanização que utilizam electrólitos industriais.

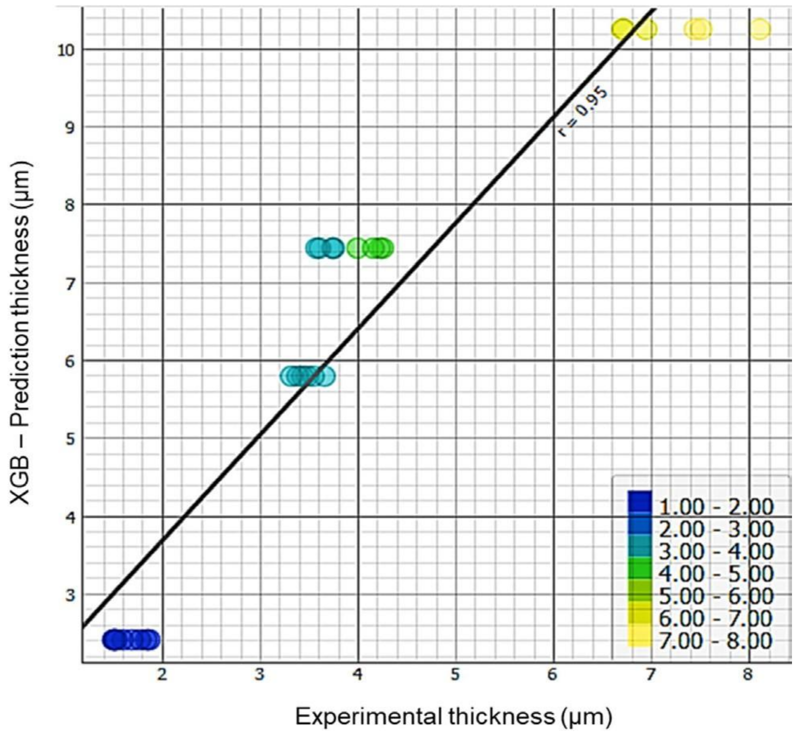

Figura 03. Regressão linear da espessura da camada prevista com o algoritmo XGB em relação à experimental (OLIVEIRA et al., 2025)

Análise dos Resultados

Precisão dos Modelos: O modelo XGBoost destacou-se como o mais preciso em prever a espessura do revestimento, superando técnicas tradicionais de regressão multivariada.

Correlação de Variáveis: Parâmetros como densidade de corrente e tempo mostraram forte correlação com a espessura do revestimento em ambos os estudos, validando as bases teóricas do processo de galvanização.

Contribuição Industrial: Os resultados do segundo artigo mostram que os modelos de IA podem ser integrados ao controle industrial, permitindo ajustes em tempo real e redução de custos operacionais.

Limitações do XGBoost

Apesar do excelente desempenho, o modelo pode apresentar limitações tanto do algoritmo XGBoost, quanto no modelo treinado com os dados experimentais. Do ponto de vista do algoritmo, o XGBoost requer um ajuste refinado de hiperparâmetros para melhoria da previsão, o que pode demandar tempo de processamento e experimentação. No caso do experimento apresentado, estes ajustes de hiperparâmetros foram simplificados, por se tratar de um experimento controlado. Isto favoreceu a manutenção ajustada pelo *software Orange Data Mining*. Outra razão da superação desta limitação ao trabalho foi a utilização do *software Orange Data Mining*, que aborda a aplicação dos algoritmos de forma simplificada, para explorações neste contexto aplicado, experimental.

Além disso, o modelo é sensível à qualidade e volume dos dados, sendo menos eficaz quando há poucos dados disponíveis ou quando os dados possuem alto ruído. No caso específico do estudo experimental, o modelo em escala industrial pode demandar ajustes ou necessidade de maior quantidade de corridas experimentais para melhoria das previsões.

Outra possível limitação prática está relacionada à demanda computacional do XGBoost, que pode ser um desafio para indústrias que não possuem infraestrutura adequada (computadores, bancos de dados estruturados, sensoriamento adequado) para processamento de grandes volumes de dados.

4.4 SUGESTÕES FUTURAS

Com base nos resultados obtidos, pode-se testar o modelo para outras ligas de aço com baixo teor de carbono. Também pode-se testar o modelo para galvanoplastia com outros materiais metálicos de revestimento, além de pesquisar quais outros materiais de substrato ou de revestimento, poderiam aplicar o modelo desenvolvido e verificar qual seria a qualidade do modelo, mensurados pelas métricas R^2 e MSE.

Outras caracterizações podem fazer parte de novos estudos preditivos. Percentual de elemento de liga em camadas (ZnNi, ZnFe,...,etc.), corrosão acelerada em névoa salina, desplacamento, dureza de camada, são caracterizações quantitativas que podem gerar novos modelos preditivos. Também pode-se identificar as correlações entre as variáveis de resposta.

Análises visuais de brilho ou de defeitos superficiais podem abrir espaço para visão computacional utilizando-se IA. Essa abordagem é especialmente relevante, pois permite a caracterização automática das amostras a partir de imagens, correlacionando-as com os parâmetros de entrada do processo. Um estudo futuro poderia avaliar a viabilidade de complementar a inspeção visual de um operador treinado com modelos de IA baseados em visão computacional, analisando se a combinação das duas abordagens aumenta a precisão e confiabilidade da avaliação, quando comparada à inspeção exclusivamente humana.

Além de outras caracterizações, analisar as principais variáveis de entrada que influenciam cada variável de resposta, pode auxiliar ainda mais o controle de processo e consequentemente melhoria de qualidade e controle de custos operacionais. Estudar quais variáveis de entrada mais influenciam as respostas para diferentes caracterizações, poderia abrir uma nova análise.

Avaliação dos Impactos Reais da IA nos Custos e na Eficiência Produtiva

Recomenda-se a validação e aplicação do modelo em escala industrial como um próximo passo essencial para demonstrar sua viabilidade prática. A implementação do modelo em processos produtivos pode ser aprofundada por meio da inserção de parâmetros operacionais, mensurados por métodos analíticos convencionais, permitindo a análise preditiva da espessura da camada e a verificação do atendimento às especificações de qualidade. Além disso, pesquisas futuras podem explorar a incorporação de sensores baseados em Internet das Coisas (IoT – Internet of Things) para o monitoramento contínuo dos parâmetros do processo, viabilizando ajustes automatizados que otimizem a deposição do revestimento.

Outra perspectiva relevante para estudos futuros envolve a ampliação da aplicabilidade do modelo, testando-o em diferentes condições operacionais e tipos de banho eletrolítico, a fim de validar sua robustez e adaptar sua utilização a uma gama mais ampla de cenários industriais. Dessa forma, será possível consolidar a relevância da abordagem proposta e fortalecer seu potencial de adoção no setor industrial, particularmente na galvanização e em outras áreas que dependem de processos de revestimento.

Além dos ganhos em qualidade e eficiência produtiva, a integração da Inteligência Artificial ao controle do processo de eletrodeposição pode trazer impactos econômicos significativos. Estudos futuros podem se concentrar na análise detalhada de custo-benefício, quantificando a redução de desperdícios de matéria-prima, a minimização da necessidade de retrabalho e a otimização do consumo energético. Essa abordagem permitiria demonstrar de forma objetiva como a aplicação do modelo pode gerar retorno financeiro e aumentar a competitividade da indústria, incentivando sua adoção em larga escala.

Adicionalmente, sugere-se investigar o potencial da IA para aprimorar o processo produtivo, com foco na redução do consumo de energia, água e produtos químicos. A utilização da IA pode permitir a otimização automática de parâmetros, como corrente elétrica e temperatura, garantindo a qualidade do depósito com menor consumo energético. Do mesmo modo, a IA pode contribuir para um uso mais eficiente da água, monitorando sua qualidade e ajustando os tratamentos necessários para reduzir desperdícios.

Outra possibilidade é a implementação de modelos avançados para controle da composição do banho eletrolítico, incluindo a dosagem precisa de aditivos e a previsão da vida útil do banho. Isso possibilitaria um planejamento mais eficiente da reposição química, reduzindo descartes prematuros e aumentando a sustentabilidade do processo.

Por fim, a aplicação da IA no monitoramento da qualidade do banho em tempo real poderia proporcionar ajustes automáticos que evitam degradação prematura e garantem a estabilidade do processo. Essas melhorias reforçam o potencial da IA na eletrodeposição de zinco, incentivando novos estudos que explorem sua viabilidade em ambientes industriais e sua aplicação em diferentes setores produtivos.

Avaliação dos desafios potenciais na implementação de IA na produção

Diante dos potenciais desafios na implementação da IA na indústria de eletrodeposição de zinco, conforme discutido nos artigos FIEMG LAB (2025), EMBRAPII (2025), TRACTIAN (2025) e PWC BRASIL (2025), futuras pesquisas podem explorar soluções para mitigar essas barreiras e otimizar a aplicação da tecnologia no setor.

Baixa qualidade e falta de integração de dados: Estudos podem investigar metodologias para aprimorar a integração de sensores inteligentes e sistemas legados, garantindo maior precisão na coleta e análise de variáveis químicas e elétricas em tempo real.

Falta de transparência: Pesquisas voltadas para o desenvolvimento de modelos de IA explicáveis podem contribuir para maior confiabilidade e compreensão dos processos automatizados, reduzindo a resistência à adoção da tecnologia.

Impacto no Emprego e Capacitação: Avaliar estratégias de requalificação profissional e treinamento técnico pode facilitar a adaptação da mão de obra aos novos modelos produtivos baseados em IA.

Riscos Operacionais e Técnicos: A criação de modelos mais robustos, capazes de lidar com variações ambientais e de matéria-prima, pode aumentar a confiabilidade dos modelos preditivos no controle da qualidade do revestimento.

Viabilidade Econômica: A análise de modelos de investimento e incentivos para pequenas e médias empresas pode viabilizar a implementação da IA de forma mais acessível, promovendo a digitalização do setor sem comprometer sua sustentabilidade financeira.

4.5 APLICABILIDADE PRÁTICA

No cenário atual das indústrias, muitos processos de galvanoplastia dependem de medições esporádicas para monitorar parâmetros críticos, como a espessura da camada de zinco eletrodepositado. Essas medições muitas vezes são realizadas por fornecedores especializados, o que torna o processo mais dependente de fatores externos. Essa abordagem pode ser eficaz, mas apresenta limitações significativas, especialmente no que diz respeito à agilidade e à autonomia do controle do processo. Ainda, há casos de empresas que monitoram periodicamente os parâmetros de processo (concentrações de NaOH, ZnO, tempo, densidade de corrente), mas não correlacionam com a espessura de camada de zinco obtida.

A implementação de um modelo preditivo para prever a espessura da camada de zinco, mesmo que utilizando técnicas de medição mais tradicionais, oferece uma série de vantagens comparativas para a indústria, tornando o processo mais eficiente, autônomo e com melhor controle de custos.

Vantagens de aplicar o modelo preditivo

Autonomia no controle do processo:

Com o modelo preditivo, a indústria pode monitorar e ajustar os parâmetros de processo em tempo real, sem depender de laboratórios externos ou do envio de amostras para análise. Isso elimina o tempo de espera por resultados de fornecedores e garante decisões mais rápidas e precisas.

O modelo fornece a previsão da espessura da camada de zinco com base em parâmetros de processo como corrente elétrica, temperatura e pH, permitindo ajustes imediatos para garantir a qualidade do produto final.

Redução de custos operacionais:

A dependência de fornecedores para análise de amostras pode ser cara e envolver custos com transporte e análise laboratorial. O modelo preditivo permite a redução desses custos, já que os dados podem ser analisados internamente.

Além disso, como o modelo ajuda a otimizar os parâmetros de galvanização (tempo, corrente, concentração do eletrólito), pode reduzir a necessidade de retrabalho em peças que não atendem aos requisitos de qualidade, resultando em economias significativas.

Gerenciamento de dados em tempo real:

A integração de sensores IoT para monitoramento contínuo de parâmetros de processo, combinada com o modelo preditivo, oferece uma visão em tempo real do processo de galvanização. A capacidade de gerenciar e analisar dados continuamente ajuda a prevenir problemas antes que eles ocorram, melhorando o desempenho geral da linha de produção.

Exemplos de aplicação do modelo preditivo em sistemas industriais existentes

Realizar a medição dos parâmetros de processo de forma tradicional, ou seja, usando métodos químicos convencionais, como análises de laboratório para medir os parâmetros de concentração do eletrólito, densidade de corrente elétrica, entre outros. Após a medição, os dados obtidos são inseridos manualmente no modelo preditivo gerado com o XGBoost. O modelo irá fornecer uma previsão para a espessura da camada de zinco.

Monitoramento em tempo real: Implementar sensores IoT acoplados aos tanques de galvanoplastia para coleta de dados contínua, permitindo ajustes automatizados e minimizando erros humanos.

Automação da linha de produção: Desenvolver um sistema integrado que acione mudanças automáticas nos parâmetros do processo (como tempo de deposição e corrente elétrica) conforme os dados preditivos indicam necessidade de otimização.

Feedback em tempo real para operadores: Criar painéis de controle interativos que alertem operadores sobre variações críticas e recomendem ajustes, evitando falhas e desperdícios de materiais.

Possibilidades para análises de custos e benefícios na implantação de modelos preditivos

Testes industriais controlados: Implementar o modelo XGBoost em um ambiente piloto de produção, analisando métricas de economia de insumos, aumento da eficiência e qualidade da deposição metálica

Redução de desperdícios: Estimar o impacto econômico da implementação do modelo IA ao reduzir desperdício de metais e produtos químicos, através da previsão mais precisa do consumo ideal.

Otimização de tempo de produção: Analisar como a aplicação do XGBoost pode reduzir o tempo de ciclos produtivos, minimizando tempos ociosos e aumentando a capacidade produtiva da linha de galvanoplastia.

Retorno sobre investimento (ROI): Desenvolver projeções financeiras comparando custos de implementação da IA com os ganhos financeiros resultantes da melhoria da eficiência produtiva, eficiência energética e redução de perdas.

4.6 CONSIDERAÇÕES FINAIS

Esta subseção apresenta tópicos distintos, abordando alternativas no uso de aprendizado de máquina, métodos de correlação e a disponibilização dos dados experimentais.

Aprendizado por reforço como alternativa promissora

Além dos métodos supervisionados empregados no estudo, como o XGBoost, o aprendizado por reforço (Reinforcement Learning - RL) se destaca como abordagem promissora para otimização de processos industriais. Segundo PIERSON (2019), o RL ajusta a tomada de decisão com base em recompensas, similar ao aprendizado humano. Esse modelo pode otimizar a galvanização, ajustando parâmetros em tempo real para maximizar a qualidade do revestimento, reduzir desperdícios e melhorar a eficiência energética.

Correlação de Pearson e alternativa com Spearman

A análise de correlação foi realizada utilizando o coeficiente de Pearson, que pressupõe relações lineares entre variáveis. Essa abordagem permitiu identificar fatores críticos, como a densidade de corrente e o tempo de deposição. No entanto, a correlação de Spearman pode ser explorada em trabalhos futuros, sendo útil quando as relações não são estritamente lineares. Ao converter valores numéricos em rankings, Spearman permite detectar padrões de associação mesmo em distribuições não normais, complementando a análise realizada. (PIERSON 2019)

Treinamento do Modelo de *Machine Learning*

O modelo preditivo foi construído utilizando o algoritmo XGBoost. Os hiperparâmetros principais foram ajustados conforme segue:

Número de árvores: 100;

Taxa de aprendizado: 0,3;

Regularização: Lambda = 1;

Profundidade máxima das árvores: 6;

Divisão dos dados: 70% para treinamento e 30% para teste;

Disponibilização dos Dados

Os dados do trabalho experimental foram disponibilizados no GitHub. O acesso pode ser feito através do link:
https://github.com/LucianoMLO/variables_in_the_experiment. (MLO, 2025).

Essa iniciativa permite que outros pesquisadores utilizem os dados para validar ou expandir as análises apresentadas neste estudo.

5 CONCLUSÕES

Esta dissertação apresentou uma investigação e experimentação aplicada sobre inteligência artificial para prever a espessura do revestimento de zinco em aços de baixo carbono SAE 1008, estruturando os resultados em dois artigos científicos que refletem as principais etapas do estudo.

No primeiro artigo, "*Artificial intelligence applied to the electroplating process for low carbon steels: a literature review*", revelou que a aplicação de ML no estudo da corrosão e galvanização ainda é incipiente, com poucos trabalhos publicados desde 2019. Entre os algoritmos mais utilizados, o Random Forest destacou-se em seis dos oito estudos analisados, demonstrando viabilidade e eficiência na análise de dados experimentais e de bancos de dados. Constatou-se que a integração de IA e eletrodeposição ainda apresenta lacunas significativas, sugerindo espaço para futuras pesquisas que desenvolvam modelos mais robustos para prever a resistência à corrosão de aços galvanizados. Assim, o artigo estabelece um panorama teórico que fundamenta o avanço no uso de IA em processos de galvanização.

No segundo artigo, "*Technological advances in electroplating: Artificial intelligence to predict zinc coating thickness on SAE 1008 low carbon steels*" desenvolveu e validou um modelo preditivo utilizando o algoritmo XGBoost, que apresentou o melhor desempenho entre os analisados, com $R^2 = 0,95$ e MSE = 0,815. A aplicação prática do modelo mostrou-se viável, permitindo a previsão da espessura do revestimento em condições industriais e otimizando parâmetros críticos, como densidade de corrente e tempo. O estudo demonstrou a capacidade de IA de prever variáveis essenciais para a qualidade do produto, reduzindo custos operacionais e melhorando o controle do processo. Além disso, o trabalho destaca o potencial de ampliar a aplicação da metodologia para outras ligas de aço de baixo carbono, contribuindo para a modernização do setor.

Os trabalhos apresentados nesta dissertação oferecem contribuições significativas no campo científico e industrial. Cientificamente, o estudo amplia a compreensão sobre o uso de IA na galvanização, abordando lacunas na literatura e validando modelos preditivos com elevada precisão. Praticamente, demonstra como a integração de IA pode elevar a eficiência e a competitividade da indústria de revestimentos anticorrosivos, proporcionando maior controle sobre o processo e redução de custos. A aplicação de IA em processos industriais, como a galvanização, também alinha-se às tendências de digitalização e automação, fortalecendo a posição da indústria no cenário global. Assim, esta dissertação representa um avanço significativo na modernização do setor e estabelece um marco para futuras investigações e implementações tecnológicas.

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