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.3 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 Mining8

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.

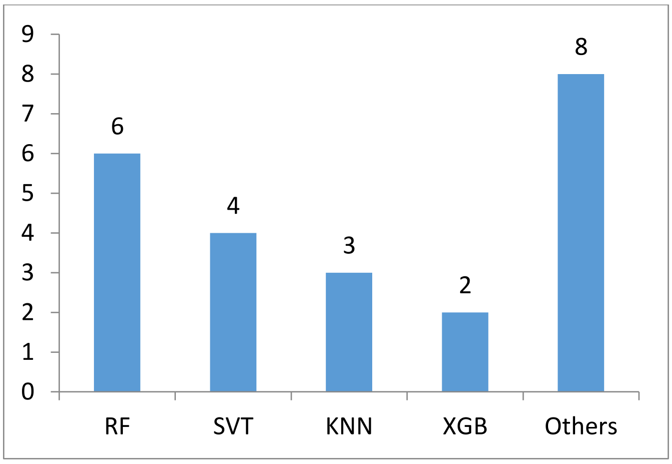

Figure 2. Number of articles per algorithm used

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.

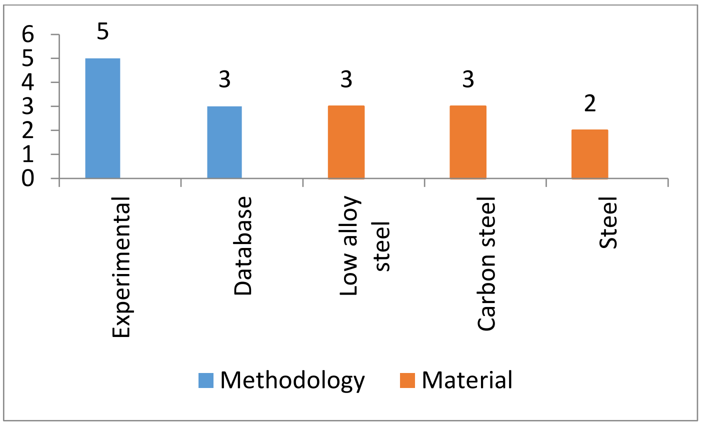

Figure 3. Number of articles analysed by material and methodology

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.

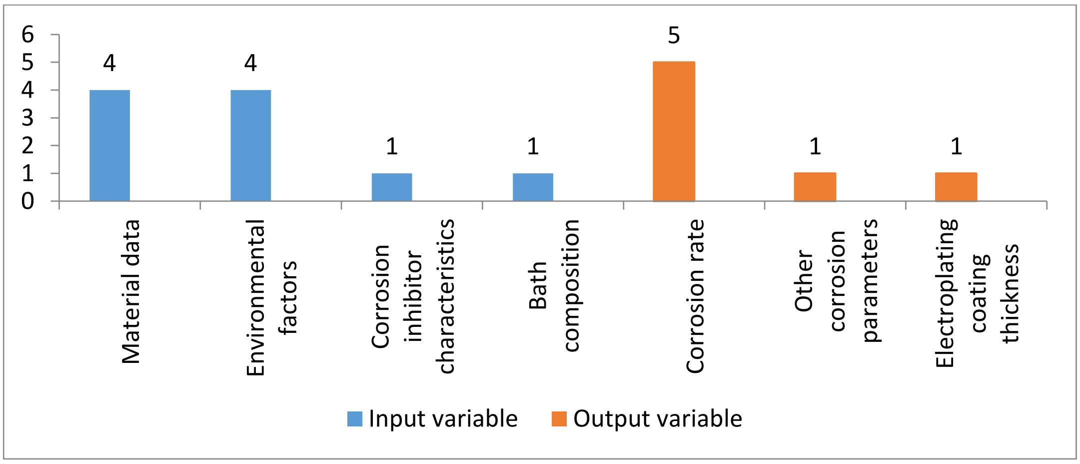

Figure 4. Quantities of articles by input and output variables used in the models

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.

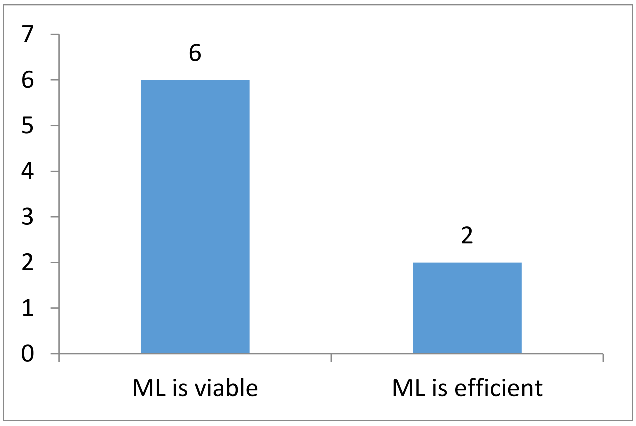

Figure 5. Number of articles per conclusion

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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