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Application of AI in environmental protection: corrosion and biosorption

Primena VI u zaštiti životne sredine: korozija i biosorpcija

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Abstract: Artificial intelligence (AI) plays an important role in the field of scientific research. This paper aims to review the application of AI in corrosion and biosorption. The use of AI can advance the research process in terms of prediction, environmental and cost management, optimization and determination of the influence of parameters. Corrosion is a highly complex process that depends on many factors. Studying the interaction of these factors using AI enables better corrosion control. By applying AI, it is possible to determine the diverse influence of factors under real conditions using the database of numerous researches. In addition to the prevention and monitoring of corrosion and biosorption processes, it is important to focus the application of AI on environmentally friendly methods and chemicals. In this way, it is possible to identify compounds and materials of natural origin that can serve as substitutes for toxic compounds for corrosion protection or heavy metal removal. The importance of using non-destructive methods and monitoring data in real time is particularly emphasized, in order to avoid statistical errors. Optimization with the RSM method for corrosion and biosorption processes is widely used, determining process parameters where the best effect of corrosion protection and biosorption is achieved.

Keywords: AI, corrosion, biosorption, optimization.

Sažetak: Veštačka inteligencija (VI) ima važnu ulogu u oblasti naučnih istraživanja. Cilj ovog rada je pregled primene VI u oblasti korozije i biosorpcije. Primena VI može unaprediti proces istraživanja u smislu predviđanja, upravljanja životnom sredinom i troškovima, optimizacije i određivanja uticaja parametara. Korozija je veoma složen proces koji zavisi od mnogo faktora, ispitivanje interakcije ovih faktora primenom VI omogućava bolju korozionu kontrolu. Primenom VI je moguće utvrditi višestruki uticaj faktora u realnim uslovima prema bazi podataka mnogobrojnih istraživanja. Pored prevencije i praćenja procesa korozije i biosorpcije, važno je usmeriti primenu VI na ekološki prihvatljive metode i hemikalije. Na ovaj način je moguće identifikovati jedinjenja i materijale prirodnog porekla, koja mogu biti zamena za toksična jedinjenja koja se koriste za zaštitu od korozije ili za uklanjanje teških metala. Posebno je naglašen značaj primene nedestruktivnih metoda i praćenja podataka u realnom vremenu, kako bi se izbegle statističke greške. Optimizacija primenom RSM metode za procese korozije i biosorpcije se često koristi, pri čemu se određuju parametri procesa u kojima se postiže najbolji efekat zaštite od korozije i biosorpcije.

Ključne reči: VI, korozija, biosorpcija, optimizacija.

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INTRODUCTION

The possibility of using artificial intelligence in science facilitates the work of researchers (Zawacki-Richter et al., 2019). In the field of research, two types of studies are conducted: analytical and experimental. Experiments are becoming more expensive because they require more time, material and energy to achieve adequate results. Soft computing techniques are helpful to reduce the cost (Sharma et al., 2022). Machine learning, deep learning and artificial intelligence are in a relation. Machine learning focuses on enabling computers to perform tasks without explicit programming. Deep learning is based on artificial neural networks (ANN) as a subset of machine learning. By applying artificial intelligence, machines are taught to think and act like humans (Rajendran et al., 2022). Other AI applications such as pattern recognition, evolutionary computation, neural networks, expert systems, discriminant analysis, metaheuristic optimization, swarm optimization, image processing, and computer vision, are also used (LeCun et al., 2015). RSM is similar to adaptive neuro-fuzzy inference systems (ANFIS), which represent an AI modeling tool integrated with neural networks for data prediction (Onu et al., 2022; Onu et al., 2021). Studies related to the comparison of different methodologies used for prediction of complex nonlinear systems, including RSM and ANFIS, show that none is superior to the other (Okwu et al., 2021; Onu et al., 2022; Emembolu et al., 2022). The response surface methodology (RSM) is widely used in engineering, such as materials engineering, food engineering, chemical engineering, bioprocess engineering and pharmaceutical engineering, to evaluate the impact of individual factors or their interactive effects (Goh et al., 2008). The statistical tools used to design experiments in RSM enable the prediction and optimization of the processes studied (Veza et al., 2023). The application of artificial intelligence for environmental protection is of great importance and has great potential. It can be applied towards environmental health protection and sustainability (Nti et al., 2023). Recent scientific research has focused on the application of artificial intelligence in the field of corrosion protection and biosorption (Anadebe et al., 2023; Lin et al., 2023).

A very important application of AI in the field of corrosion detection can be divided into predictive maintenance (PdM) approaches for corrosion detection and computed vision and image processing techniques. PdM can be done with a knowledge-based model, a physic-based model, a data-based model and with a hybrid model. Computer vision and image processing approaches for corrosion detection can be divided into infrared thermography, texture analysis and non-destructive methods (Imran et al., 2023). Many researches focus on the protection of materials from corrosion by using environmentally friendly chemicals (Nazeer, Madkour, 2018; Rani, Basu, 2012). Natural materials and plant waste are often the starting components for obtaining environmentally friendly additives in coating applications, corrosion inhibitors and biosorbents (Ong et al., 2021; ElShami et al., 2020; Khaled et al., 2025; Falade et al., 2025; Rasheed et al., 2025; Marković et al., 2023; Zdravković et al., 2023). The application of environmentally friendly materials in corrosion protection and biosorption can be a circular process, in which the waste from the process of obtaining the plant corrosion inhibitor can be used as a biosorbent (Zdravković et al., 2024).

Environmental pollution is a serious problem in the modern world. Heavy metal pollution is reaching dangerous levels, with these metals being major pollutants in lakes, oceans, rivers, marines, industrial and even treated wastewater (Ghorbani et al., 2007). Biosorption, i.e. sorption using biological, low-cost adsorbents derived from plant waste, has emerged as a promising alternative to conventional methods to combat this problem. Multivariant statistical methods have gained attention in recent years and are used to identify the optimal combinations of factors as well as their interaction. These tools are also useful in reducing the cost and time of these studies. An experimental design consists of estimating the coefficients in a mathematical model used to predict the response and testing the adequacy of the model. Factorial experimental designs are the most commonly used experimental designs to determine response surfaces and the more complex RSM (Bingol et al., 2012). RSM is a collection of mathematical and statistical techniques that can be used to analyze the effects of different independent variables on system response (Amini et al., 2008). RSM has been applied in recent years to optimize many heavy metal removal processes using low-cost materials as biosorbents, including the removal of Cu^{2+} ions using raw chicken eggshell (Marković et al., 2023), calcined chicken eggshell (Marković et al., 2025) and bean shells (Marković et al., 2023). ANN are considered a promising tool because of the simplicity towards simulation, predict and model. ANN models are able to describe adsorption systems better than general rate models (Prakash et al., 2008). Recently, response surface methodology has been constantly compared with ANN in terms of their predictive capabilities for various processes. ANN use learning algorithms to evaluate the relationships between the input and output variables and can also be used to model the water management processes (Enyoh et al., 2023).

The aim of this article is to demonstrate the possibilities of applying AI in the field of corrosion protection and biosorption by identifying risks and methods of corrosion control and biosorption.

1. CORROSION PROTECTION

The degradation and destruction of materials caused by environmental influences is known as corrosion. The combined effects of chemical, electrochemical, mechanical, and/or biological variables can cause corrosion (Hoang et al., 2020, Kumari, Lavanya, 2024). The oil and gas industry is directly related to corrosion under insulation. The lack of adequate inspection technologies contributes to this well-known industrial challenge. However, an AI-enhanced inspection tool can provide better corrosion control under these conditions (Amer et al., 2020). Corrosion prevention and protection methods are crucial for sustainability, cost efficiency and safety. Various corrosion control techniques are used: environmental control, material selection, protective coatings, surface treatments, alloying, cathodic protection, design optimization and corrosion inhibitors (Kumari, Lavanya, 2024). The corrosion management system encompasses design, construction and operation and remains the main focus in ensuring the integrity and safe operation of the asset. The application of AI to predict corrosion rate offers advantages where real high-frequency data streams from sensors using machine learning algorithms, enabling predictions based on historical experience with specific assets (Alias et al., 2024).

A corrosion inhibitor is a chemical compound that is introduced in trace amounts to a corrosive medium. Corrosion inhibitors work by interfering with the electrochemical reactions that drive the corrosion processes on metal surfaces (Lavanya et al., 2024; de Souza Morais et al., 2023). Industrial corrosion is a challenge due to material wear and high maintenance costs, which is why effective corrosion inhibitors are very important. Identifying the most efficient compounds in corrosion inhibitors can be time-consuming (Putra et al., 2025). Some inhibitors are specific for certain metals. One example is the corrosion inhibition of copper by tannins, so the identification of plant extracts or expired pharmaceutical products containing these compounds is of great importance (Shah et al., 2013; Kusmierek, Chrzescijanska, 2015). However, tannins also act as corrosion inhibitors for other metals such as steel, iron and aluminum (Rahim, Kassim, 2008; Proença et al., 2022; Zelinka, Stone, 2011). The application of AI can facilitate the identification of the corrosion inhibitor that acts best on the corresponding metal (Lin et al., 2023). Another environmentally friendly way of corrosion protection is the use of plant extracts (natural additives), which have the same functions as synthetic additives (Ong et al., 2021). AI can be used to predict costs, workforce and other variables to be considered for protective coating management (Correa, Mariano, 2022). Prevention is also important to protect the environment from corrosion damage. An example is the application of AI for crack detection in nuclear power plants (Allah et al., 2024). Stress corrosion cracking (SCC) poses a significant challenge to the integrity and longevity of conventional and advanced alloys used in aerospace, marine and nuclear energy applications. Conventional alloys (steel, aluminium, and titanium) and advanced materials (additive-manufactured and high-entropy alloys) exhibit unique SCC behaviour that is affected by corrosive environments, mechanical stress, and temperature variations. Using extensive data sets from experiments and field studies, AI can identify patterns and correlations that traditional methods may miss (Mathew, Adu-Gyamfi, 2024). In addition to the application of AI for the corrosion of metals and metal alloys, AI methods have also been used to predict the corrosion of cement and sulphur concrete in sewage systems. AI-based techniques: adaptive neuro-fuzzy inference system (ANFIS), genetic programming (GP) and multi-expression programming (MEP) were used. Two sets of chemical experiments in acidic solutions and biological tests with *Thiobacillus thiooxidans* were conducted to investigate corrosion in concrete samples. The results show that machine learning-based models can help engineers to estimate the corrosion of concrete pipes in sewer systems (Sabour et al., 2021).

Corrosion protection in marine conditions is very important (Lawal et al., 2024). Adequate choice of corrosion protection can reduce the corrosion rate of metals and protect the environment (Bardal, 2004). The application of AI can be very useful in the prediction and detection of marine corrosion (Imran et al., 2023). Pattern recognition (PR) is one of the AL techniques applied for the prediction of marine corrosion (Imran et al., 2023). This method has also been used to detect corrosion under the coating (Ali et al., 2016). The electrochemical method (electrochemical noise, EN) was used to detect the corrosion and passivation of 304 steel. The results show that the PR accuracy was higher than using only statistical parameters and parameters selected by principal component analysis (Legat, Dolecek, 1995).

The predictive maintenance approaches can provide a mechanism to prevent external corrosion for effective corrosion control (Jimenez et al., 2020). An example is the PdM with a data-based model where the mathematical model from the real-time data was applied to predict corrosion damage to the ship structure (Makridis et al., 2020). The most appropriate mathematical model was proposed for long-term corrosion in physical infrastructure and ship corrosion using the PdM with physic-based model (Bouzaffour et al., 2021). The PdM with hybrid model was used for structural health monitoring, for hull structure maintenance and corrosion detection (Jimenez et al., 2020).

RSM can be used to determine the conditions under which the corrosion inhibitor slows down the corrosion process the most (Ahmadi, Khormali, 2024). Using the RSM results optimization of corrosion process can be performed. By optimizing the corrosion process, it can be determined at which parameters the highest inhibition efficiency is achieved with the minimum dose of corrosion inhibitor, which is investigated when several parameters are changed simultaneously (Emembolu et al., 2022). The most common combination of parameters for the optimization of the corrosion process using corrosion inhibitors are the temperature, the immersion time of the metal in the electrolyte and the concentration of the inhibitor (Ahmadi, Khormali, 2024). Inhibitor concentration, electrolyte concentration and metal immersion time can also be used as variables (Edoziuno et al., 2020; Udunwa et al., 2022; Gu et al., 2015). AI enables to quickly discover and optimize new corrosion inhibitors (Lin et al., 2023).

However, in addition to the numerous advantages of applying AI, it also has its limitations. AI methods are compared to black boxes that merely attempt to map a relationship between output and input variables based on a training dataset. This raises concerns regarding the ability of the tool to generalize to situations that were not well represented in the dataset. The solution may lie in combining or integrating multiple AI paradigms in a hybrid solution or coupling AI paradigms with more traditional solution techniques. Another limitation of using AI-based search methods to solve a problem is that it is often difficult to gain true insight into the problem and the nature of the solution, as is possible when using mathematical programming methods, for example (Chowdhury, Sadek, 2012).

2. BIOSORPTION

Heavy metal pollution associated with wastewater originating from industrial activity, is a serious environmental problem. The growing demand for clean water around the world demonstrates the importance of water purification, i.e. the removal of hazardous heavy metals. The problem of pollution will worsen in the coming years, which will lead to an increase in demand for clean water and thus increase pressure on wastewater treatment (Babu et al., 2023; Jendia et al., 2020). At the industrial level, many conventional methods are used for wastewater treatment, including precipitation, reduction, oxidation, ion exchange and sorption (Bingol et al., 2012). Biosorption is a method that offers itself as a possible alternative for the removal of heavy metals. It is a user-friendly process, so to speak, as it offers many advantages, including a simple design, a specific affinity for certain pollutants and low cost. Industrial and agricultural by-products are used as biosorbents as they are very practical due to their favorable physical, chemical and surface properties, abundant availability and low cost (Marković et al., 2023).

RSM consists of statistical and mathematical techniques that can be used to develop an adequate functional relationship between a response and a number of input (or control) variables. Two major groups of models are commonly used in RSM, namely first-degree and second-degree models. First-order experimental designs include the 2^k factorial experimental design, the Plackett-Burman experimental design, and the simplex experimental design. Second-order designs include the 3^k factorial design, the central composite design (CCD) and the Box-Behnken design (BBD) (Khuri, Mukhopadhyay, 2010). The RSM coupled with the BBD and the CCD has been used as a tool to optimize biosorption processes in a large number of papers in recent years. These statistical models are used to optimize the biosorption processes considering the operational variables that affect the metal uptake efficiency, such as the pH of the aqueous phase, initial sorbate concentration, biosorbent dose, contact time, and others. The modeling coupled with ANOVA statistical analysis to evaluate the significance of the model and to show the influence of the individual variables and their interactions (Choinska-Pulit et al., 2018; Fawzy, 2020).

ANN is a mathematical model that attempts to simulate the structure and functionalities of a biological neural network. ANN are build of blocks, each of which represents an artificial neuron, that is, simply put, a simple mathematical function (model). By combining two or more artificial neurons, an artificial neural network is created. Artificial neural networks are capable of solving complex problems by processing the input information in their basic artificial neurons in a parallel, distributed, non-linear and local way (Suzuki, 2017). The application of

ANN in modeling biosorption processes has increased significantly in recent years. Artificial network models have been used to correlate and predict isotherms, kinetics, breakthrough curves and other responses of many adsorbents, biosorbents and adsorbates, in the field of water treatment, including biosorption. A variety of models are used to analyze, correlate and predict biosorption processes. However, these models are usually based on restrictive theories and assumptions, which limits their applications. ANN help overcome the disadvantages of traditional models by providing better predictions at various operating conditions. In mathematical terms, the performance of a biosorption system is described as a nonlinear function that depends on the properties of the biosorbent, the chemistry of the adsorbate(s), the fluid properties, the operating conditions and the equipment configuration. This nonlinear function can be modeled using an artificial neural network, as there are no limitations to incorporate all independent variables affecting the analyzed system. Environmental factors, such as the pH of the aqueous phase, the initial sorbate concentration, the contact time, the biosorbent dosage and others, have a significant impact on the efficiency of the biosorption process. In order to achieve the highest removal, optimal conditions must be met, and the influencing factors mentioned must be optimized using suitable modeling and simulation methods. ANN can be used to understand the complex interactions between the experimental factors and the uptake of metal ions. Artificial neural networks can also predict the performance of multicomponent biosorption systems by including performance metrics, such as adsorption capacity, as output variables. Moreover, ANN has significant potential over traditional models for the analysis of real fluids in which multiple adsorbates are present, leading to different removal behavior (Reynel-Avila et al., 2022; Fawzy et al., 2018).

Recently, RSM and ANN methods have been jointly applied by researchers to predict the biosorption processes. By applying both techniques, the results can be compared to gain a better understanding of the process. The combination of RSM and ANN, where the experimental RSM data is used to train and validate the ANN, provides more accurate results (Dulla et al., 2018; Ghosh et al., 2015).

CONCLUSION

The application of AI in the field of corrosion and biosorption has proven to be an effective and fast way to analyze results and optimize processes to make them less expensive and time-consuming. Numerous AI techniques allow researchers to adapt their research to achieve the most realistic results possible. By applying AI, it is possible to predict corrosion processes, improve the process of corrosion protection and identify new environmentally friendly compounds that have not yet been tested as corrosion inhibitors. The use of non-destructive methods is another advantage of AI. AI techniques are also used to optimize the biosorption process by analyzing the response of the system to different environmental conditions. The influence of many different variables on the efficiency of the process and their interactions can be studied using AI. However, AI also comes with certain disadvantages in the form of errors that can occur when experimentally obtained data is used for modeling. Process optimization has proven to be one of the most important applications of AI for both corrosion and biosorption.

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