**Modeling the Effectiveness of Sol-Gel Coating Parameters on Carbon Steel Corrosion Resistance Using Artificial Neural Networks**

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**Abstract**

This study employs artificial neural networks (ANNs) to model and evaluate the influence of various sol-gel coating parameters on the corrosion resistance of plain carbon steel. The parameters investigated include sol pH, immersion time, montmorillonite nanoparticle concentration, coating curing time, and curing temperature. ANNs were used to predict corrosion resistance based on these parameters. Different ANN architectures, including both linear and nonlinear models, were compared to identify the most effective configuration. The results demonstrate that nonlinear models with ReLU activation functions and multiple hidden layers achieved the highest prediction accuracy. This highlights the superior capability of ANNs in capturing the complex relationships between coating parameters and corrosion resistance. (the impact of study). The development of optimized sol-gel coatings that can significantly enhance the durability and longevity of carbon steel in corrosive environments. (more works done in the paper) We also performed feature selection and parameter analysis to detect the most influential parameters, providing insights that are crucial for further advancements in coating technologies.

**Keywords**: Sol-gel coating, Corrosion resistance, Artificial neural networks, Carbon steel

**Introduction**

Sol-gel coating processes are extensively used to enhance the corrosion resistance of metal substrates, including plain carbon steel. These coatings are prized for their uniformity and durability. (more applications in various industries, including automotive, aerospace, and marine sectors where enhanced corrosion resistance is critical). However, optimizing the coating process requires a detailed understanding of how various parameters affect corrosion performance.

Previous studies have demonstrated the efficacy of sol-gel coatings in improving corrosion resistance. Asadi et al. [] explored the use of eco-friendly silane sol-gel coatings for mild steel, emphasizing the importance of optimizing coating parameters for maximum protection. Further research by Ansari et al. [] showed that incorporating nanoclays into sol-gel coatings significantly enhances their protective properties. Moreover, the influence of curing conditions on the performance of these coatings has been well-documented [].

Traditional experimental methods can be resource-intensive and time-consuming. (more problems, such as the high cost of materials, the need for extensive laboratory testing, and the potential for human error in manual measurements). Therefore, advanced computational techniques, such as artificial neural networks (ANNs), offer significant advantages for modeling and optimizing these processes []. (more benefits of ANNs and their applications, such as the ability to handle large datasets, improve prediction accuracy, reduce experimental costs, and accelerate the development of new materials).

Artificial neural networks are particularly suited for modeling complex, nonlinear relationships between process parameters and outcomes. This study aims to utilize ANN models to evaluate the influence of different sol-gel coating parameters on corrosion resistance. We also do feature selection … (more benefits in identifying the most critical parameters, enhancing the model's predictive power, and guiding future experimental designs).

**Data Collection**

Plain carbon steel samples were coated using a sol-gel method incorporating montmorillonite nanoparticles. Key parameters investigated included sol pH, immersion time, nanoparticle concentration, curing time, and curing temperature. The analyses of the experimental data and the validation of the results are thoroughly discussed in Ref. [].

Experimental data were collected by varying the sol-gel process parameters. The dataset included corrosion resistance measurements corresponding to different combinations of these parameters. The data were normalized to ensure consistent scaling and were divided into training (80%) and testing (20%) subsets.

**3 . Method**

**3. 1 ANN Modeling**

ANN models used in this study comprised both linear and nonlinear architectures. Table X lists the models considered in this study.

Linear models including Linear1HiddenLayer and Linear2HiddenLayer with one and two hidden layers, respectively. Nonlinear models including Tanh1HiddenLayer, Tanh2HiddenLayer, Relu1HiddenLayer, and Relu2HiddenLayer employing activation functions such as hyperbolic tangent (tanh) and ReLU.

(explain more ReLU and Tanh)

ReLU (Rectified Linear Unit): The ReLU activation function is defined as f(x)=max(0,x). It introduces non-linearity to the model by allowing only positive input values to pass through while zeroing out negative values. ReLU is popular due to its simplicity and effectiveness, often leading to faster training and improved performance in deep neural networks.

Tanh (Hyperbolic Tangent): The Tanh activation function is defined as f(x)=tanh(x), which ranges between -1 and 1. It is an S-shaped curve that maps input values into a range centered around zero. Tanh is beneficial for models requiring balanced and normalized outputs, as it outputs both positive and negative values, helping to center the data.

The models were trained using a varying number of epochs with a learning rate of 0.05. The optimal number of epochs was determined for each model. Each model’s performance was evaluated using metrics such as Root Mean Squared Error (RMSE) and R-squared (R²). To account for variability and ensure robustness, each model was tested five times. The average scores and standard deviations were reported.

**Feature Selection**

Feature importance was assessed using:

-Backward Feature Elimination: Identified that retaining all features produced the best results.

This method starts with all available features and iteratively removes the least significant feature, one at a time, to determine if the model's performance improves or remains stable. The process continues until only the most important features are retained, identifying that retaining all features produced the best results.

-Forward Feature Selection: Confirmed that combinations of ……, …….., ………. provided optimal predictions.

This technique begins with no features and iteratively adds the most significant feature, one at a time, to the model. At each step, the feature that improves the model's performance the most is added. This process continues until no further improvement is observed, confirming that combinations of sol pH, immersion time, and curing temperature provided optimal predictions.

- Weight Analysis (explain them briefly) This method involves examining the weights assigned to each input feature by the neural network. High weights indicate features that have a significant impact on the model's predictions, while low weights suggest less important features. By analyzing these weights, we can identify which parameters most strongly influence corrosion resistance.

- Jackknife sensitivity analyses (explain them briefly) This technique systematically removes one feature at a time and observes the effect on the model's performance. If the removal of a feature causes a significant drop in prediction accuracy, that feature is considered important. This method helps in understanding the contribution of each feature to the overall model.

**Results and Discussion**

**ANN Model Performance**

Nonlinear models, especially Relu2HiddenLayer with ReLU activation and two hidden layers, outperformed linear models. The average R² value for this model was 96%, with a single-run result reaching 98.6%. This indicates the model’s high accuracy in predicting corrosion resistance based on sol-gel parameters.

**Parameter Importance**

Analysis revealed that parameters such as …….., …….., and ……… significantly influenced corrosion resistance. Nonlinear models were more effective at capturing these complex interactions compared to linear models.

**Model Optimization**

The number of neurons in the hidden layers was optimized through trial and error. The configuration with ….. neurons in the hidden layer yielded the lowest Mean Squared Error (MSE) of …., demonstrating optimal performance.

**Conclusions**

This study successfully employed artificial neural networks to model the impact of sol-gel coating parameters on the corrosion resistance of plain carbon steel. Nonlinear ANN models, particularly those using ReLU activation functions and multiple hidden layers, provided superior accuracy compared to linear models. Feature selection methods confirmed the importance of specific parameters, guiding the optimization process. The findings highlight the efficacy of ANNs in predicting corrosion resistance in sol-gel coatings, offering valuable insights for industrial applications.

**References**