Application of artificial neural networks in predicting and optimising electroplating parameters: a systematic review

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Abstract. Optimising electroplating parameters is crucial for enhancing coating performance, but traditional methods are often time consuming and resource intensive. This review evaluates the application of Artificial Neural Networks in electroplating optimisation, highlighting their predictive accuracy and efficiency. A VOSviewer analysis explores how the application of artificial neural networks in electroplating has evolved, from advancements driven by the Fourth Industrial Revolution to emerging uses aimed at mitigating climate change. Findings show that hybrid and ensemble ANN approaches with Statistical Regression, Random Forest, and Support Vector Machine achieve R^2 values above 0.92, outperforming traditional techniques. However, data scarcity, model interpretability, and computational demands remain a challenge. Addressing these limitations through improved data availability and AI integration can enhance ANN adoption in industrial workflows, promoting more efficient and sustainable electroplating processes.

1 Introduction

Corrosion is a costly global challenge estimated to cost 3-4% of the global Gross Domestic Product (GDP) [1]. It leads to surface degradation, equipment failure, and increased maintenance, causing plant shutdowns, resource waste, product contamination, reduced efficiency, and safety risks [2]. This creates numerous challenges in the daily operations of various industries, leading to significant financial loss. Although corrosion is inevitable, corrosion management and prevention techniques can significantly extend the life of metal equipment.

Surface protection strategies are essential in extending the service life of metallic components and structures. Among the various protective techniques, electroplating is a well-established and widely adopted method due to its effectiveness, versatility, and relative simplicity. During electroplating, a thin metal layer is deposited onto a metal substrate to improve corrosion resistance, hardness, and aesthetics [3]. Achieving optimal electroplating is dependent on the control of various parameters including current density, bath composition, temperature, and deposition time.

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Electroplating optimisation has traditionally been based on empirical methods, where trial-and-error methods dominated. The use of statistics and empirical models has improved process understanding for a long time, but they remain resource-intensive and unable to provide reliable predictions. The emergence of computational modelling such as Density Functional Theory, Finite Element Methods provided a theoretical foundation, however, these methods exhibit limitations when it comes to complex, multivariable interactions [4], [5]. Currently, the integration of Artificial Neural Networks (ANNs) represents a shift from the Edisonian trial and error, towards data-driven optimisation, aligning with the broader transition in materials science [5].

Machine Learning (ML) has emerged as a transformative approach for tackling multivariate optimisation problems [6]. ML, a branch of Artificial Intelligence (AI), has gained growing research interest in the design and optimisation of materials and material processes. ANNs have gained attention due to their ability to predict and optimise complex, nonlinear, multivariable processes such as electroplating [4]. Their adaptability and generalisation capabilities make them particularly suitable for electroplating applications. They can predict coating characteristics such as corrosion resistance and coating thickness, and optimise process parameters including temperature, bath composition, and current density [7].

The integration ANNs into electroplating processes plays a critical role in enhancing efficiency, precision, and sustainability within manufacturing. This leads to improved coating quality, minimised material waste, and reduced energy consumption. The use of ANN also facilitates real-time monitoring, fault detection, and predictive maintenance, enhancing productivity while lowering operational risks [8].

In this way, ANN-based electroplating contributes to a more sustainable and future-ready manufacturing ecosystem. This paper presents a systematic review of the application of ANNs in predicting coating characteristics including corrosion resistance, corrosion rate, and coating thickness, and optimising electroplating parameters such as current density, bath composition, deposition time, and temperature. The discussion also considers ANN architectures, modelling strategies, and performance indicators used to evaluate predictive accuracy and optimisation efficiency. The review aims to consolidate current knowledge, highlight key developments, thereby providing a foundation for future work at the intersection of computational intelligence and electrochemical materials processing.

2 Method

This review was conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines [9]. The framework provided a structured approach that ensured comprehensive reporting, transparency, and reproducibility. The primary objective is to identify, appraise, and synthesise the available evidence on the application of Artificial Neural Networks (ANNs) in predicting and optimising electroplating parameters. To complement the systematic approach, a partial bibliometric analysis was integrated to capture broader intellectual structures and research trends. The systematic review adheres to the following PRISMA steps, formulation of the research question, definition of eligibility criteria, identification of information sources, development of the search strategy, screening of records, retrieval of full texts, assessment of eligibility, selection of studies, data extraction, and synthesis and reporting of findings.

2.1 Review questions

The guiding question for this review is: “How effective are ANNs in predicting and optimising electroplating parameters?” The question was developed using the PerSPECTiF framework, which defined the perspective (metal electroplating processes), setting (industrial and experimental electroplating), phenomenon of interest (effectiveness of ANN), environment (published research), comparison (traditional optimisation approaches), timeframe (the last 20 years), and findings (accuracy, efficiency, feasibility).

2.2 Search strategy and information sources

In line with PRISMA's emphasis on transparency in literature identification, the second and third steps were the definition of eligibility criteria and the identification of information sources. A comprehensive search strategy was developed to retrieve relevant studies from Scopus, Web of Science, ScienceDirect and SpringerLink. These databases were selected for their breadth of peer-reviewed literature in engineering, computational modelling, and artificial intelligence. The search covered the period from 2005 to 2025 to ensure that recent developments in ANN applications were captured.

Keywords relating to electroplating, ANNs, and optimisation were combined using Boolean operators (AND, OR) and wildcards. The search string included electroplating concepts: "electroplating" OR "electro-deposition" OR "metal plating" OR "surface coating" OR "thin film deposition", ANN concepts: "artificial neural networks" OR "ANN" OR "neural networks" OR "machine learning" OR "deep learning" and process focus: "optimisation" OR "predict*" OR "process optimisation" OR "parameter optimisation" OR "model optimisation". Search strings were tailored to each database to account for indexing variations.

2.3 Eligibility criteria

Eligibility criteria were defined prior to screening. Studies were considered eligible if they investigated electroplating processes for metals or alloys and employed ANNs to predict or optimise parameters such as bath composition, current density, plating time, or temperature. Only publications in English, including peer-reviewed articles, conference proceedings, theses, and technical reports, were included. Exclusions applied to studies on non-metal coatings, research that used other machine learning methods without ANN, review articles without original analysis, purely theoretical models, or studies limited to corrosion monitoring without optimisation focus.

2.4 Selection and screening process

The initial database search identified 5,851 records. After removing duplicates (n = 17), excluding records through automated tools (n = 4,835), and discarding non-English publications (n = 157), a total of 842 records remained. Title and abstract screening led to the exclusion of 765 records that were unrelated to metal electroplating. Full texts were sought for 77 articles; however, seven could not be accessed. The remaining 70 full-text studies were assessed against the eligibility criteria. Of these, 18 were excluded for focusing solely on corrosion monitoring, 24 for applying other machine learning methods without ANN, and 6 for investigating non-metal coatings. The eighth step of PRISMA, study selection, resulted in the inclusion of 22 studies. The screening process is illustrated in the PRISMA 2020 flow diagram in Fig. ***1***.

The limited application of artificial ANN to predict and optimise electroplating parameters can be attributed to several factors including data scarcity, competition with established models and limited ANN expertise. Data generated during the electroplating process is highly variable and process specific. This kind of data is generally costly to generate. As a result, there are few large, standardised datasets available to train robust ANN models [10] [11]. Well-established statistical methods such as Response Surface Methodology and Design of Experiments remain the default for many practitioners, due to their interpretability and low barriers to implementation. Developing effective ANN models requires interdisciplinary expertise and poses "black box" interpretability concerns [12]. This can limit adoption in process-critical environments where understanding parameter influences is essential.

2.5 Data extraction

Data from the included studies was extracted using a pre-designed, standardised template. This template facilitated the capture of essential information, including study characteristics, methodological details and key findings. Study characteristics encompassed authorship, publication year, source, and study context such as metal-substrate system, experimental or industrial setting. Methodological details covered electroplating parameters investigated, ANN architecture, training methods, input-output variables, and performance metrics. Key findings focused on comparative analysis with traditional optimisation methods, reported outcomes such as prediction accuracy, optimisation success, process efficiency, as well as identified challenges or limitations.

2.6 Data synthesis

The included studies differed greatly in their designs, experimental conditions, and ANN methods; thus it was not possible to conduct a quantitative meta-analysis. Instead, a narrative synthesis was used to analyse the extracted data. Alongside the systematic review, a bibliometric analysis was carried out to provide a quantitative overview of the intellectual landscape of the field. This analysis was done using VOSviewer and the data collected prior screening. The data was cleaned and prepared using OpenRefine. The bibliometric approach addressed one primary aspect: keyword Co-occurrence Analysis. This technique helps to identify the main research themes and their interconnections. By examining the frequency and co-occurrence of keywords across the studies, clusters of related research topics are identified, giving insights into the thematic structure and development of the field. By integrating systematic review with bibliometric analysis, this study provides both a qualitative synthesis of evidence and a quantitative mapping of the research landscape, offering a robust and multidimensional understanding of the application of ANNs in electroplating optimisation.

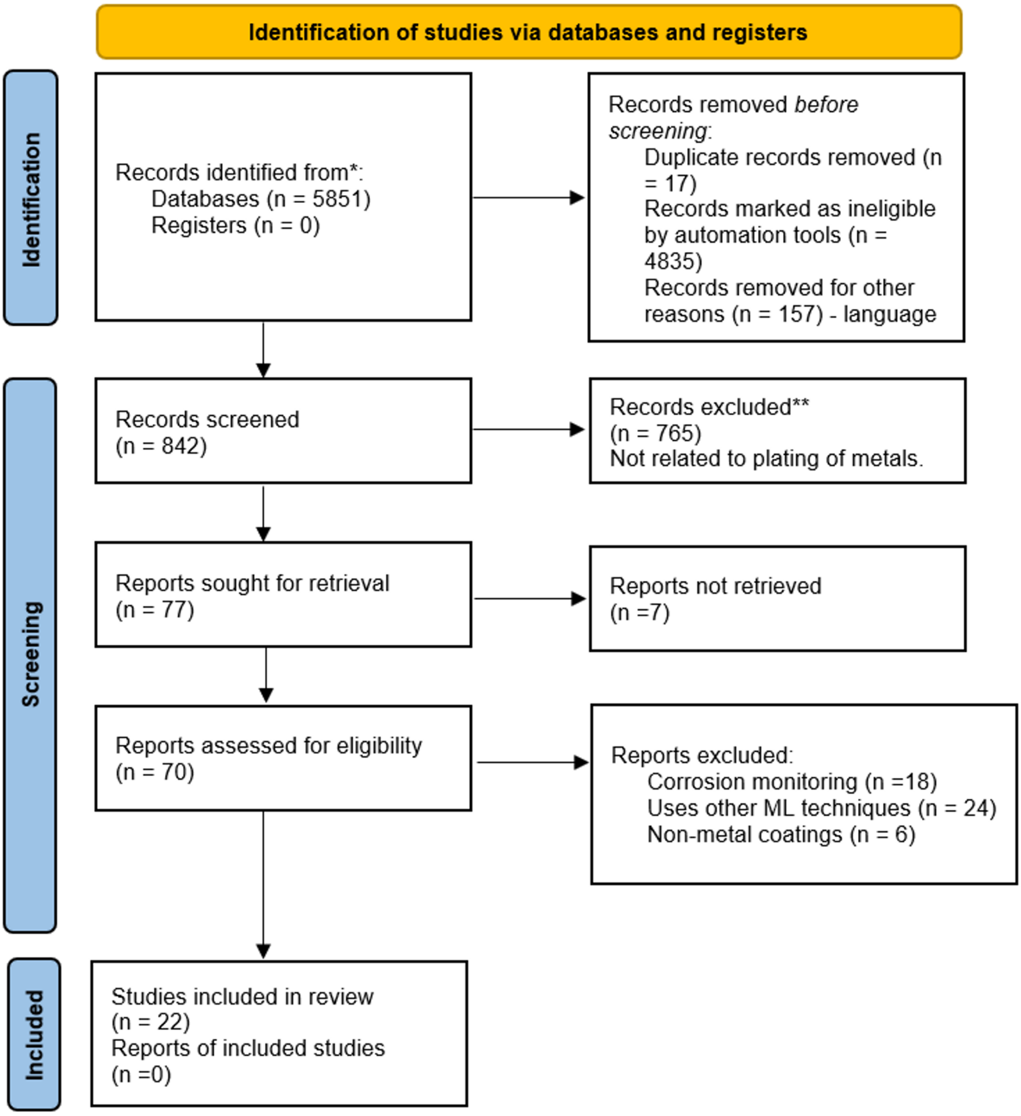

Fig. 1:The research screening process with exclusion criteria [9]

3 Analysis and interpretation

3.1 Thematic analysis

Keyword co-occurrence analysis provides valuable insight into the thematic structure and research focus. Fig. *2* presents a network map generated using VOSviewer. The network map illustrates the relationships between frequently occurring terms and reveals distinct clusters corresponding to major research themes. The size of the node corresponds to the number of co-occurrences.

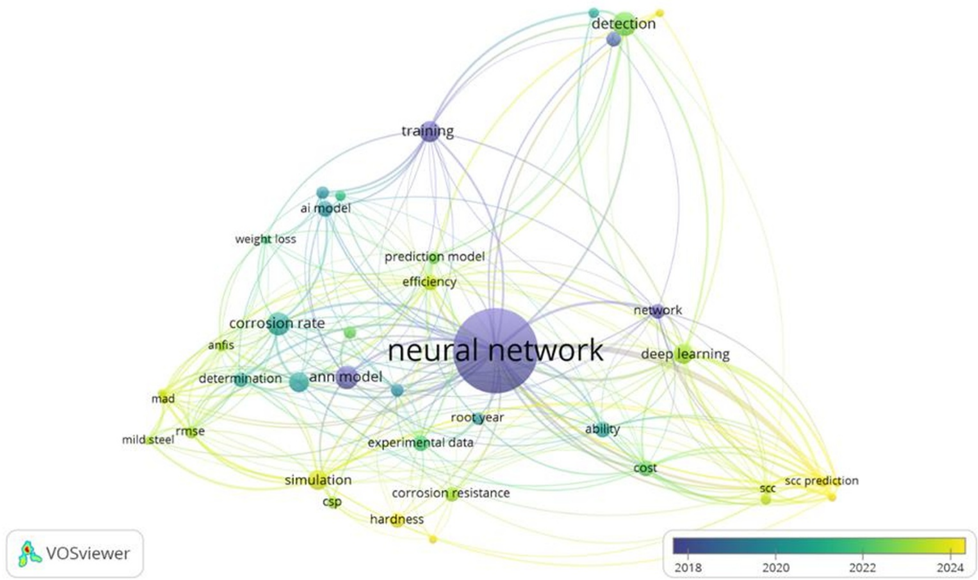

Fig. 2: Network diagram of ANN trends

3.1.1 2018 to 2020

Between 2018 and 2020, research on the application of ANN in electroplating focused primarily on the foundational development and training of neural network models. This is indicated by frequent keywords such as "training," "neural network," and "network." Simultaneously, the appearance of terms like "ANN model," "simulation," and "corrosion rate" suggests efforts to apply neural networks to experimental corrosion data [13], [14].

3.1.2 2020 - 2022

Research shifted from foundational development to practical applications between 2020 and 2022. Keywords such as "efficiency," "cost," "deep learning," and "prediction model" reflect increased use of neural networks for predictive analytics and process optimisation (Katirci and Danaci, 2023b). The appearance of terms like "ANFIS" (Adaptive Neuro-Fuzzy Inference System) [14] and "AI model" also indicates growing interest in hybrid and alternative AI frameworks logic or statistical inference, enhancing prediction accuracy and interpretability [7].

3.1.3 2022 - 2024

From 2022 to 2024, research has focused on specialised applications of neural networks. Keywords such as "detection," "SCC prediction," (Stress Corrosion Cracking) and "corrosion resistance" highlight efforts to address specific challenges like corrosion resistance. Increased use of performance metrics, including "MSE" (Mean Squared Error) and "MAD," (Mean Absolute Deviation) indicates growing attention to model evaluation [12]. The emergence terms like "weight loss," "hardness," and "mild steel" indicate a shift toward material-specific optimisation and analysis.

By 2022, AI tools had progressed beyond generic modelling, enabling targeted applications like SCC detection, corrosion resistance analysis, and materials property prediction [16]. Researchers increasingly applied domain-specific architectures and fine-tuned models for tasks such as predicting hardness, weight loss, and electrochemical behaviour in materials like mild steel, stainless steel, and coatings. As AI models moved closer to deployment in critical infrastructure and safety-sensitive industries, there was a stronger push for quantitative performance evaluation. This led to more widespread reporting of metrics like MSE, MAD and cross-validation procedures [17]. The adoption of rigorous benchmarking aligned with broader scientific calls for transparency and reproducibility in AI-driven research. Global infrastructure challenges exacerbated by climate change, aging pipelines, and frequent extreme weather events, placed stress corrosion cracking and localised corrosion at the forefront of materials science. Governments and industries prioritised predictive maintenance and materials degradation forecasting in sectors like oil & gas, nuclear, and transportation.

Growth in materials informatics and open data platforms such as Citrine and the Materials Project enabled the development of accurate, materials-specific AI models for corrosion resistance, mechanical properties, and degradation prediction. Integration of lab data with Finite Element Models (FEM) and other Multiphysics simulations provided richer inputs for training deep learning systems [18]. Research funding bodies increasingly emphasised sustainable infrastructure and corrosion resistant materials, prompting targeted investigations using AI to evaluate and design alloys and coatings tailored for harsh environments.

3.2 Application of ANNs in electroplating

3.2.1 Electroplating parameters

During the electroplating process, the input parameters can be classified into two categories, process parameters and plating bath parameters as shown in Fig. ***3***. Process parameters include current density, coating time and duty cycle, while plating bath parameters include concentration, pH, and temperature. The output parameters such as coating thickness, corrosion rate and corrosion resistance provide insight into how well the material will perform under specific environmental conditions.

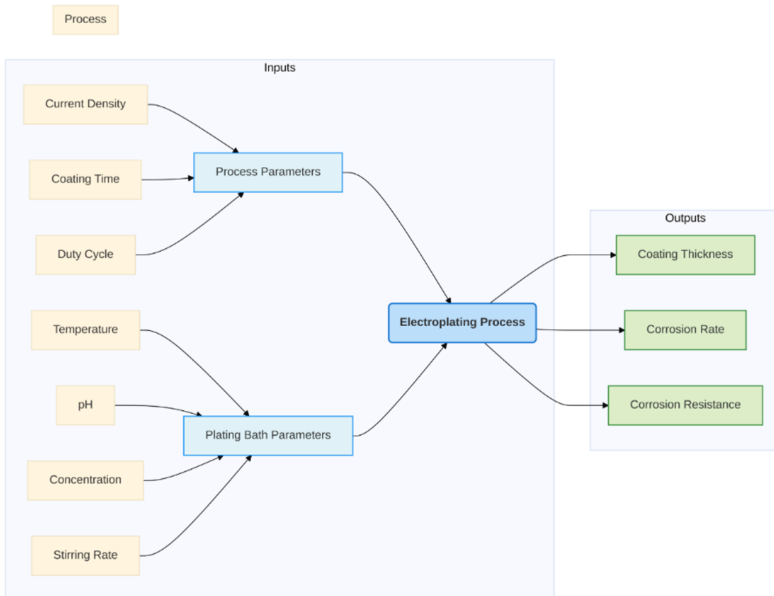

Fig. 3: Electroplating parameters

3.2.2 Prediction and optimisation of electroplating parameters using ANNs

Recent advancements in AI have led to the development and application of diverse machine learning strategies. These strategies are employed to improve the accuracy and efficiency of prediction, control, and optimisation in electroplating processes. Among these are ensemble models, hybrid models, and hybrid ensemble models. Ensemble models are machine learning methods that combine multiple base learners into a single more accurate and robust model compared to the individual models [19]. Hybrid models bridge data driven approaches with domain specific knowledge by integrating ANNs with optimisation algorithms such as Genetic Algorithms (GA) or Particle Swarm Optimisation (PSO), as well as with physically grounded methods like Molecular Dynamics (MD), Density Functional Theory (DFT), and the Finite Element Method (FEM) [4].

Hybrid ensemble models integrate techniques from both hybrid and ensemble modelling approaches. This technique combines the strengths of ensemble and hybrid strategies by integrating multiple hybrid learners within an ensemble framework, alongside thermodynamic modelling. For instance, an architecture might include ANN-GA models, ANN based learners, and interpretable AI techniques such as SHAP analysis [7, 12], and [4]. Optimisation is frequently achieved through hybrid approaches such as ANN-GA [16] or ANN-RSM [17], allowing multi-objective optimisation to improve coating performance and process efficiency. The aim of these models is to accurately predict and optimise input parameters to obtain optimal output parameters, ensuring superior coating performance.

Table 1 summarises recent studies that have applied hybrid and hybrid-ensemble modelling approaches to electroplating systems across various substrate/coating combinations. A diverse range of machine learning techniques were employed, often in combination with statistical or design-of-experiment framework. In most studies, the parameters studied were also the parameters optimised. The unique insights derived from each study are also summarised on the Table 1.

Table 1. Summary of hybrid ensemble models used in electroplating processes

Reference	Hybrid Ensemble methods	Materials (Substrate/ coating)	Evaluation metrics & validation methods	Parameters studied	Insight gleaned
[15]	Mask RCNN, RF, F1 scores, NSGA-II, MLP, SVC, GP, XGBoost	Brass/Nickel	F1 score, accuracy, precision, and recall, Intersection over union (IoU) , SEM	I, t, pH, c	Deep learning detects patterns in complex data; ensemble models refine predictions. Automates and optimises selection of bath additives and process time, enhancing coating uniformity and efficiency.
[21]	BPNNN, remnmx, Momentum BNNN	Aluminium alloy matrix/Nickel & Tungsten graded coating	R, Microhardness, EDSSEM, XRD,	T, I, Duty cycle	Focuses on mechanical and thermal stability, suitable for aerospace or automotive; ANN helps model nonlinear thermo-mechanical behaviour.
[22]	ANN, BPNN, RMSE, OED, Sigmoid, GD	Copper & carbon steel/Nickel-Phosphorus	RMSE, XRD	pH, T, c	OED structures efficient experimental datasets: GD enhances training accuracy. Enables precise control over plating rate and phosphorus content by fine-tuning bath temperature and pH with fewer experiments.
[17]	ANN, RSM, ANOVA	Mg alloy /Tungsten & Copper	RSM, R^2, R, MSE,	Pulse time, Compaction load	Combines ANN's nonlinear modelling with RSM's statistical optimization and sensitivity analysis. Identifies key input parameters (e.g., pulse time, compaction load) and optimizes them to maximise deposition rate and minimize surface roughness.
[23]	ANN, RF, MLR, SVR, XGBoost, FC	Magnesium Alloys/ Al, Zn, Mn, Si, Fe, Cu, Ca, Sr, Sn	R^2, MAE, XRD, EIS	E_{corr}, I_{corr}, c	Ensemble models improve prediction robustness and feature ranking. Helps isolate dominant factors affecting corrosion resistance, guiding parameter adjustments (e.g., bath composition) for improved performance.
[10]	ANN, BPNN, LMA, OTD, LPR, PREMNMX, POSTMNMX,	Aluminium/ Titanium carbide	R, Microhardness, EIS, XRD, SEM-EDX, R	I, Duty cycle, F, Stirring rate, c	LMA improves training efficiency; SEM/XRD provide physical validation. Achieves high accuracy in predicting wear and microhardness, allowing precise adjustment of stirring rate, current density, and duty cycle.
[7]	ANN, CNN, SVR, PSO, GA, SHAP	Magnesium/ Aluminium	Hardness, Thermal expansion coefficients, Yield Strength	pH, c, T, t	Metaheuristics (GA/PSO) explore wide parameter space; SHAP explains ANN output. Enables multi-objective optimization (e.g., hardness vs. corrosion rate) and provides interpretable paths to optimal parameter settings.
[22]	ANN, RF, R, FR	Low-alloy steel /copper	XRD, XPS, SEM, EIS, XRD, XPS	R_{corr}, T, pH, I	Experimental tools verify ANN predictions; RF reduces overfitting. Enhances trust in AI-predicted coating behaviours under varying temperatures and pH, enabling better fine-tuning of process conditions.
[22]	SVM(GK), R, ANN, RF	Cr-alloyed steel /LDH-NO_2 corrosion inhibitor	R^2, MAE, RMSE, 100 - fold cross validation, EIS	c, pH, R_{corr}	Combines diverse ML strengths with electrochemical validation. Optimizes corrosion resistance by aligning model predictions with real-world EIS data across various pH and composition levels

Reference	Hybrid Ensemble methods	Materials (Substrate/ coating)	Evaluation metrics & validation methods	Parameters studied	Insight gleaned
[14]	BBD, ANN, ANOVA	Copper/ Nickel-Phosphorus alloy coating	R^2, BBD, SEM, OM, EDX, EIS	T, c, R_{corr}	DoE ensures efficient sampling; SEM/EDX correlate physical outcomes with model trends. Reduces experimentation load while optimizing bath temperature and composition for minimum corrosion rate.

Abbreviations: Artificial Neural Networks (ANNs), Fuzzy Logic (FL), Backpropagation Algorithm, Correlation Coefficient (R), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Support Vector Machine (SVM), Random Forest (RF), Genetic Algorithm (GA), Gradient Boosted Decision Trees (GBDT), Radial Basis Function (RBF), Support Vector Regression (SVR), XGBoost, K-Nearest Neighbors (KNN), Monte Carlo Simulations (MCS), Back Propagation Neural Networks (BPNN), Cascade Forest (cForest), Pearson Correlation Coefficient (PCC), Molecular Dynamics (MD), Finite Element Method (FEM), Phase Field Method (PFM), Artificial Intelligence (AI), Density Functional Theory (DFT), EDS (Energy Disperse Spectroscopy), SEM (Scanning Electron Microscope), XRD (X-ray Diffraction), Convolutional Neural Network (CNN), Box-Behnken Design (BBD), Analysis of Variance (ANOVA), bath temperature (T), frequency (F), concentration (c), current density (I), time (t), Corrosion potential (E_{corr}), Corrion current (I_{corr}), Corrosion resistance (R_{corr})

During model development, model accuracy and reliability must be evaluated. Studies often report metrics such as R^2 (coefficient of determination), RMSE, MAE, and cross-validation scores to evaluate predictive performance. Classification metrics like accuracy, F1 score, and intersection over union (IoU) are commonly applied in surface analysis. For instance, [24] accurately predicted copper deposition efficiency with a $R^2 = 0.965$. Table 2 summarises how different ANN models have performed in predicting electroplating outcomes, highlighting their accuracy and reliability.

Table 2. Evaluation metrics

Reference	Specific Finding	Quantitative Metric(s)
[24]	Accurately predicted copper deposition efficiency	$R^2 = 0.965$
[17]	Showed high prediction ability of ANN compared to RSM	Correlation coefficient (R) > 0.99
[15]	Classified coating surfaces with high accuracy	IoU values between 89% and 98%
[16]	Accurately predicted coating properties using ANN	$R^2 > 0.92$

Furthermore, traditional surface evaluation techniques such as Electrical Impedance Spectroscopy (EIS), Scanning Electron Microscope (SEM), and X-ray Diffraction (XRD) further validated improved coating performance. EIS is used for corrosion testing, providing measurements such as corrosion rate amongst others. SEM enables detailed morphological and microstructural analysis of surfaces, revealing deposition uniformity, porosity, and defect structures, parameters that are essential for understanding and correlating material performance. XRD remains a cornerstone for phase identification and crystallographic analysis, particularly in evaluating coating crystallinity. [14] used SEM, optical microscopy, and EDX to confirm that the predicted coatings had a compact coating structure with minimal porosity. The evaluation metrics, together with experimental validation methods demonstrate the importance of integrating computational and experimental approaches to ensure model reliability.

These combined methodologies allow ANNs to go beyond being black-box predictors. With the support of interpretable models, optimisation algorithms, ensemble learners, and real-world validation techniques, ANNs become powerful decision-making tools. They help materials scientists not only predict properties like corrosion resistance or plating rate with high accuracy, but also optimise processing conditions for desired outcomes, accelerating coating development cycles and enabling more reliable and efficient material design. Collectively, the studies highlight that hybrid ensemble methods provide both predictive accuracy and practical interpretability, ultimately guiding parameter prediction and optimisation for superior coating performance in complex electrochemical systems.

4 Discussion

This review demonstrates a consistent trend in the adoption and success of hybrid ensemble and ML models for the prediction and optimisation of electroplating parameters. These models significantly outperform traditional empirical approaches, which rely on sequential experimentation and post-process surface analysis. For example, Mask RCNN, as used by [15], achieved high classification accuracy in identifying coating quality, enabling rapid surface defect detection without manual inspection. Similarly, backpropagation-based neural networks, such as those used by [21], successfully determined optimal electrodeposition conditions with minimal deviation from experimental results. In another study, [22] demonstrated that a properly tuned ANN could replicate electroless nickel plating outcomes with high precision, validated using orthogonal experimental design. ANN-RSM models optimised pulse time and compaction load to maximise deposition rate while minimising surface roughness [17]. ANN-SHAP-GA frameworks enabled multi-objective optimisation, such as balancing hardness versus corrosion resistance, while providing interpretable guidance for parameter selection [7].

Evaluation metrics such as RMSE, MAE, R^2, and MAPE were commonly reported to quantify prediction accuracy. These consistently indicate that ML models offer superior generalisability and lower error margins compared to traditional statistical or empirical methods. Furthermore, the integration of optimisation algorithms with learning models enhanced the ability to navigate complex, multivariate parameter spaces typical of electroplating processes. Hybrid and ensemble models, in particular, allowed researchers to optimise multiple process parameters simultaneously, including bath composition, temperature, current density, and deposition time, while maintaining high prediction accuracy for coating characteristics such as hardness, corrosion resistance, and surface morphology.

The combination of predictive and optimisation capabilities highlights a key advancement in computational materials engineering. Not only do these models reduce experimental overhead, but they also enable more precise and adaptive control over electroplating processes. The synergy between traditional experimental techniques (e.g., EIS, SEM, XRD) and ANN-based models ensures robust validation, interpretable insights, and accelerated innovation in surface engineering. Overall, these findings reinforce the value of data-driven approaches in supporting efficient, reliable, and sustainable electroplating processes.

5 Conclusion

Artificial intelligence (AI), particularly machine learning and deep learning techniques, is reshaping surface engineering and electroplating. Data-driven approaches have significantly enhanced the prediction of coating properties and the optimisation of process parameters, including current density, bath composition, temperature, and deposition time, with unprecedented accuracy [25 - 27]. This reduces reliance on time-consuming experimental trial-and-error, improving the consistency, quality, and efficiency of electroplating processes through the accurate prediction and optimisation of the electroplating parameters.

Beyond prediction and optimisation, AI facilitates real-time monitoring and adaptive control of electrochemical processes, enabling intelligent manufacturing environments [28]. Furthermore, the integration of explainable AI and image processing tools allows for automated defect detection and quality assessment at the microstructural level [7]. As a result, AI is not only accelerating discovery and optimisation in materials processing but also contributing to the development of smarter, more sustainable, and future ready electroplating technologies.

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