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Prediction and optimization models for electrodeposition of different materials: A review

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ABSTRACT

Electrodeposition, a fundamental technique in materials science, has been developed to produce nanostructured coatings with improved mechanical, chemical, and physical properties. This study encompasses a systematic review of approaches based on prediction and optimization models at electrodeposition processes applicable to various materials. It discusses the theoretical background, such as mechanisms of nucleation and growth, and the key factors influencing the characteristics of coatings. The paper reviews traditional thermodynamic models as well as advanced data-driven techniques, with a special focus on machine learning methods, such as artificial neural networks (ANNs), dynamic ANNs (DANNs), and support vector machines (SVMs). The models are validated by the prediction of properties such as hardness, adhesion, and corrosion resistance. We also compare optimization strategies, such as genetic algorithms, particle swarm optimization, and their hybrids, to analyze their capability to improve both coating quality and process efficiency. The development discussed in this research is representative of the increased usage of AI and computational approaches, which allow for process control in real time, decreasing experimental costs and designing performance coatings. At the same time, new trends like sustainable electrodeposition, electrochemical 3D printing, or intersection with additive manufacturing are highlighted as well. This study highlights that predictive and optimization models have the potential to significantly impact the development of electrodeposition technologies targeted for industrial uses.

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1. Introduction

Electrodeposition is a prominent process in materials science, where metal ions or conductive polymers are reduced from an electrolyte solution to form a thin metal coating on a substrate. This process is helpful in improving the surface properties of materials, such as corrosion resistance, wear resistance, and mechanical properties. This is usually accompanied by applying an electric current to the electrolyte, causing negative charged particles to deposit on the substrate. Electrodeposited nanostructured coatings have attracted increased attention in recent years, especially concerning their improved physical and mechanical properties relative to conventional coatings. A suitable illustration of this type of behavior is the chromatophoric coatings of chromium nanoparticles (CrNPs), which have noted improvements in hardness, adhesion, and corrosion resistance properties, offering application perspectives in different industrial fields (Chakraborty et al., 2025; Nasirpouri, 2017; Okonkwo et al., 2022; Bedolla-Hernández et al., 2022; Lin & Dahan, 2015).

Electrodeposition is not only one of the most used techniques for surface engineering, but also one of the most important techniques used in materials science. Establishing and ensuring ideal surface properties are fundamental in many industrial sectors, ranging from aerospace (Weston et al., 2010), automotive (Nakano et al., 2011; Nakano et al., 2010; Streitberger, 2008; Wasekar et al., 2020) and electronics (Lincot, 2005; Christie & Cameron, 1994), to high-performance metal systems, to both workpiece and tool surfaces. Tailoring these properties via controlled electrodeposition possesses some unique advantages to enhance component durability and functionality. As illustrated in **Fig. 1**, the selection of a customized coating

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is guided by the specific protective or functional requirements of the industrial setting. Gaining insight into the mechanisms driving these processes, including nucleation, growth, and formation of structures that are resultant of both, is crucial for the optimization of these coatings. The electrodeposition process plays a significant role in surface energy interactions, adhesion forces, and mechanical strength, all of which are key properties of these technologies. Furthermore, since electrodeposition frequently concerns nanomaterials, the dimensions, morphology, and distribution of nanoparticles in the coatings inherently dictate their thermodynamic and mechanical responses (Lincot, 2005; Christie & Cameron, 1994; Nakano et al., 2011; Nakano et al., 2010; Streitberger, 2008; Weston et al., 2010).

The main goal of this work is to compare the prediction and optimization models used for electrochemically deposited nanostructured coatings to predict their physical-mechanical properties. This comparative study explores the efficacy of these models, trained on data collected in controlled experimental conditions, in predicting the performance of coatings deposited on various substrates. By doing so, the study contrasts classical electrodeposition predictions with those predictions made using machine learning algorithms to highlight the advantages and disadvantages of each based on the operating conditions and properties of interest to be predicted for the coatings.

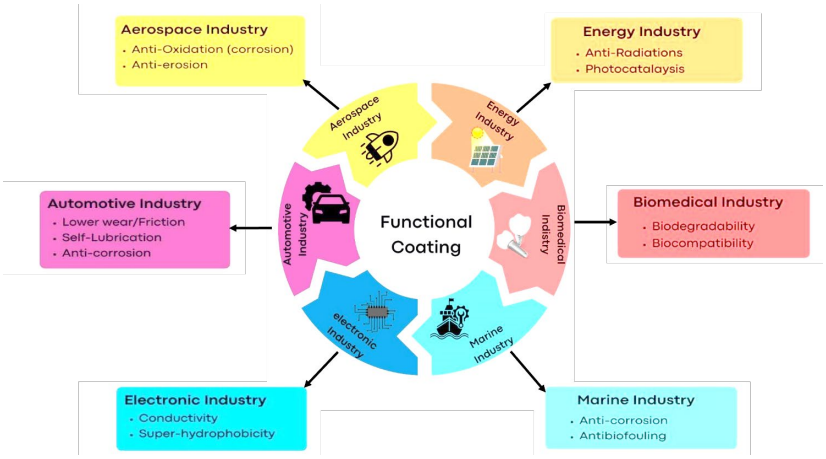

Fig. 1. Specific protection or function needs of functional coatings in versatile industrial applications.

2. Theoretical Background

2.1. Fundamentals of Electrodeposition

Electrodeposition processes involve the deposition of conductive ions from an electrolyte solution onto a substrate to produce a thin coating layer. This requires an external electric current to be applied in order for the reduction reaction to occur at the cathode, and for the coating to be deposited. In most systems, the approach utilizes an aqueous electrolyte solution with metal salts, leading to reduction of metal ions onto the surface of the substrate. It leads to the development of an electrochemical environment, wherein a metal coating is formed, with its properties being dependent on the exact parameters of the electrochemical environment. This layer is formed based on the applied current, voltage and temperature of the electrolyte (Nasirpouri, 2016; Paunovic & Schlesinger, 2006; Xu et al., 2024).

One practical reason behind the popularity of electrodeposition is that it is a well-controlled method of pouring a material that can be useful in industries that require specific thickness, uniformity, and surface properties. Since properties of the coatings, like hardness, corrosion-, and wear-resistance, are directly related to deposition parameters, knowledge of the fundamentals of electrodeposition is key for optimization of the process and prediction of performance (Xu et al., 2024; Lincot, 2005; Streitberger, 2008).

2.2. Key Materials Used in Electrodeposition

Electrodeposition, which enables any conductive material to be plated (even though in varying thicknesses), offers a diverse array of unique properties depending on the substrate selected. Electrodeposited coatings typically comprising metals including chromium (Cr), copper (Cu), gold (Au), nickel (Ni) and silver (Ag) and conductive polymers as mix of paste and binder are some of the most used materials. Such materials are selected for their beneficial physical and chemical characteristics, such as electrical conductivity, corrosion resistance, and mechanical strength. For example, chromium can be utilized mostly in chromium oxides (Cr_2O_3) coatings because of its resilience and hardness against corrosion which are great advantages for industrial companies (Chaudhuri & Maurer, 2025).

Electrodeposition can also be employed to develop composite coatings containing non-metallic particles (e.g., diamond nanoparticles) in a metal matrix, thus improving the mechanical and tribological behavior of the coating (Łosiewicz, 2015). One of the main advantages of this process is that the composition and morphology of the electrodeposited coatings can be controlled, allowing for the fabrication of tailored materials for a given application.

2.3. Mechanisms of Electrodeposition

Electrodeposition is based on multiple complex mechanisms that control the formation of the coatings as shown in **Fig. 2.** Those are nucleation, growth and evolution of the coating structure. The first stage of deposition: nucleation, is when metal ions from the electrolyte solution start to cluster at some preferential sites of the substrate surface. When a certain number of metal atoms are adsorbed at these sites, they will cluster and serve as nuclei for further growth. The next stage is the growth stage, in which the deposited material grows into the coating layer (Nasirpouri, 2016; Gurrappa & Binder, 2008).

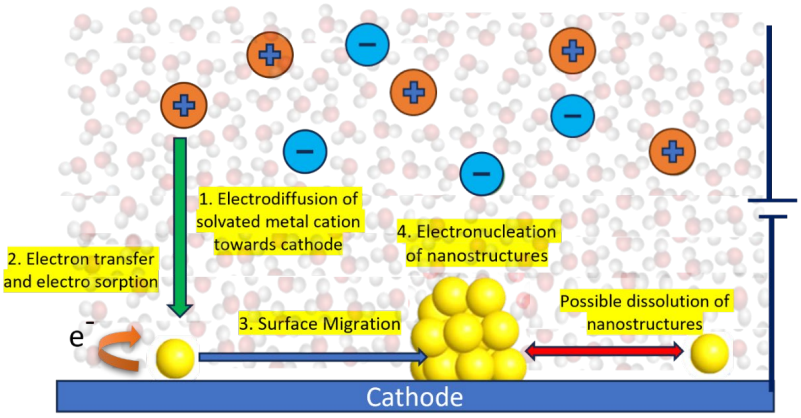

Fig. 2. A simplified diagram of metal electrodeposition onto a cathode. 1.Diffusion – Metal cations move through the solvent (water) toward the cathode. 2.Reduction & Adsorption – Near the cathode,
electrons reduce the metal cations, causing them to attach to the surface. 3.Migration – The metal atoms move along the cathode surface. 4.Nucleation – Atoms settle either as isolated sites or cluster together, forming nanostructures. The process competes with dissolution, which may lead to further migration.
Solvated cations (+) and anions (-) are shown, with hydrogen (white) and oxygen (red) atoms.

The thermodynamics and kinetics (energy of coating formation and deposition rate) dictate the structure of the coating. These are crucially important in regard to basic understanding of processes, and Gibbs free energy theory is essential for understanding the interaction of the surface of the substrate and the deposited matter, thus predicting the stability and morphology of the coating. Besides these basic mechanisms, the electrodeposition process is additionally governed by the interfacial energy at the coating/substrate interface and the potential distribution throughout the electrolyte solution, which also have a direct impact on the morphology and quality of the deposit (Li et al., 2021).

2.4. Key Factors Affecting Electrodeposition

There are many factors that affect the results of the electrodeposition process, and, consequently, the properties of the resulting coating. These include, but are not limited to, the following:

1. **Current Density**: The Higher applied current density causes higher deposition rate. Lower current densities result in slower deposition rates which leads to the formation of poor-quality coatings with rough surfaces or lack of uniform thickness. At lower current densities, coatings tend to be smoother, although this can also lead to reduced deposition speed and inefficient electrolyte utilization (Li, 2023; Brito et al., 2022; Yang et al., 2023; Zhang et al., 2022).

2. **Electrolyte Composition**: The composition of the electrolyte, the types of conductive ions and any additives (such as surfactants or complexing agents) are key factors in the control of shape and properties of the deposited coating. Certain additives, for example, can determine the crystallinity, the roughness, the adhesion strength of the coating, etc (Yang et al., 2023).

3. **Temperature**: The electrolyte temperature impacts the electrodeposition process kinetics highly. Normal temperatures facilitate the elimination of conductive ions, but very high temperatures can be detrimental, leading to undesirable reactions such as more hydrogen being evolved at the cathode or more porous coatings (Zhang et al., 2022).

4. **pH of the Solution**: The pH of an electrolyte influences electrolyte efficiency and deposition speed. Indeed, the pH is a significant parameter that permits to regulate several phenomena since its variation will change the ions metal concentration and the electrochemical potential of the system (Zhang et al., 2022).

5. **Substrate Preparation**: In addition to cleanliness, the roughness of the substrate surface can also have a significant impact on these early nucleation and growth steps of electrodeposition. This is important for ensuring proper adhesion and uniform coating deposition (Oliveira et al., 2021).

6. **Deposition Potential**: An applied potential between the anode and the cathode determines the reduction reaction, as well as the topography of the deposited material. This allows various deposition rates, coating thicknesses, and surface features (Streitberger, 2008).

These parameters can be tuned to tailor the properties of electrodeposited coatings for the application at hand. Thus, there are some important aspects in the research of electrodeposition processes, such as optimization of the variables involved and development of predictive models, for example the machine learning approaches which can predict the influence of these variables on the quality of the coatings.

3. Prediction Models in Electrodeposition

*3.1. Types of Prediction Model*s

One of the important applications of prediction models is their use in facilitating the electrodeposition process optimization by predicting different characteristics of coatings at different process conditions.

1. **Classical Models**: These models are based on the principles of elementary thermodynamics and kinetics. It usually employs those equations of electrochemical principles (e.g. the Nernst equation, Butler-Volmer equation) to model the growth rate of the deposit and coating development. Classical-modelling approaches can yield valuable insights into the electrochemical determinants that lead to electrodeposition but typically fail to account for full detail in the complex nonlinear interactions of the system (Zubar et al., 2022; Li et al., 2022). Methodology for modeling and analysis of physical processes is shown in **Fig. 3.**

2. **Data-Driven Models**: On the other hand, data-driven models establish relationships between process parameters and coating properties from experimental data. These models tend to be more flexible, generalizable, and adaptable. These integrated complex systems are influenced by different components and in addition, predict the outcome without performing heavy thermodynamic computations. This has become increasingly common in recent years (Bedolla-Hernández et al., 2022; Zheng & Wang, 2022) due to its capacity to predict coating properties with good results, even for systems that do not behave linearly or have not been fully characterized.

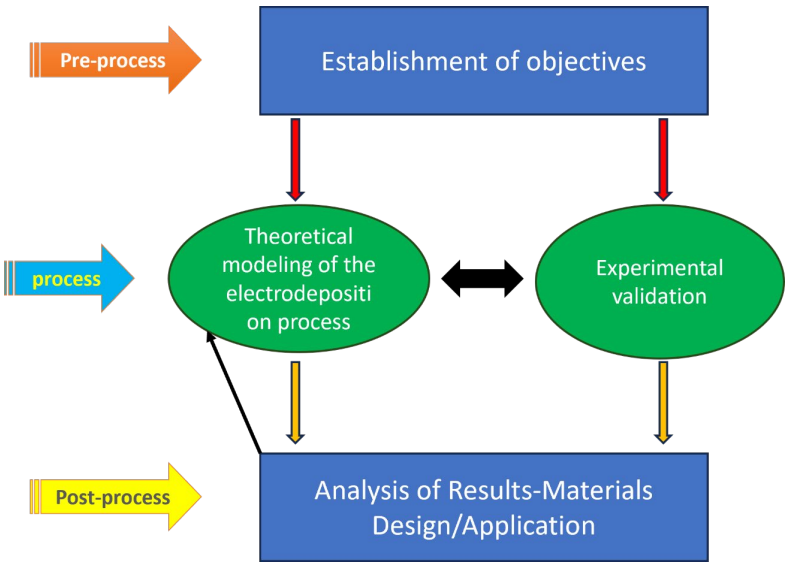

Fig. 3. Methodology for modeling and analysis of physical processes.

3.2. Computational Methods

The simulations also provide a way of improving the process in general or predicting the behavior of electrodeposition. With all the information generated, can we truly grasp electrodeposition processes in a timely and cost-effective manner? Their goal in these various approaches is to streamline the process as well as to measure the output of the electrodeposition process generally through some mixture of experimental measurement with or without numerical simulation (Tamura et al., 2024; Zhu et al., 2023; Yazdani et al., 2023; Aribou et al., 2023; Ataalite et al., 2023).

1. **Finite Element Method (FEM):** The Finite Element Method (FEM) is used to describe mechanisms that occur during electrochemical reactions taking place during the electrodeposition process. Since the deposition dynamics strongly affect the coating quality, this auditory estimation plays a key role in simulating electric fields, computing current density distribution and modeling ionic transport in the electrolyte among other things. They obtained kinetic information via finite element method (FEM) to predict metal ions spatial deposition and then proceeded to model nanostructured coatings (Tamura et al., 2024).

2. **Molecular Dynamics (MD)**: MD simulations allow us to understand the atomic-level interactions, both in the electrolyte as well as in the substrate, which provides information on nucleation and growth of the coating. At the same time, these types of simulations also allow for an extremely detailed probe of not necessarily the interactions of just the deposited atoms on top of the surface of the substrate, but also between them in the course of electro-deposition itself (Zhu et al., 2023; Yazdani et al., 2023).

3. **Monte Carlo Simulations**: This approach is used in many applications that have evidence of the stochastic nature of electrodeposition processes. Monte Carlo simulations, for example, sample by simulating many random events — such as how ions will diffuse in to and interact within the electrolyte to determine average system properties such as the coating morphology or thickness (Aribou et al., 2023; Ataalite et al., 2023).

The working principle of KMC–EAM method for simulating electrodeposition is shown in **Fig. 4**. By including the embedded-atom method (EAM) potential, collective diffusion mechanisms, and electrodeposition dynamics, this kinetic Monte Carlo (KMC) approach can be used to simulate the galvanostatic growth of a metal on a single crystal surface. Using KMC, EAM, and collective diffusion, essential components of the method are combined into the KMC-EAM framework as shown in the diagram on the left. Right hand figure is the 3D structure obtained from the KMC-EAM simulation, showing the surface morphology of the deposited metal layers (Ataalite et al., 2022).

These give also a clear or supportive view of the class of electrodeposition process type but are quite exotic and cost effective with respect to computation level when we do large scale simulations with a high accurate prediction. Machine-learned approaches have also been adopted to augment the modeling of electrodeposition for super-accelerated screening and predictions in such electrodeposition behaviors.

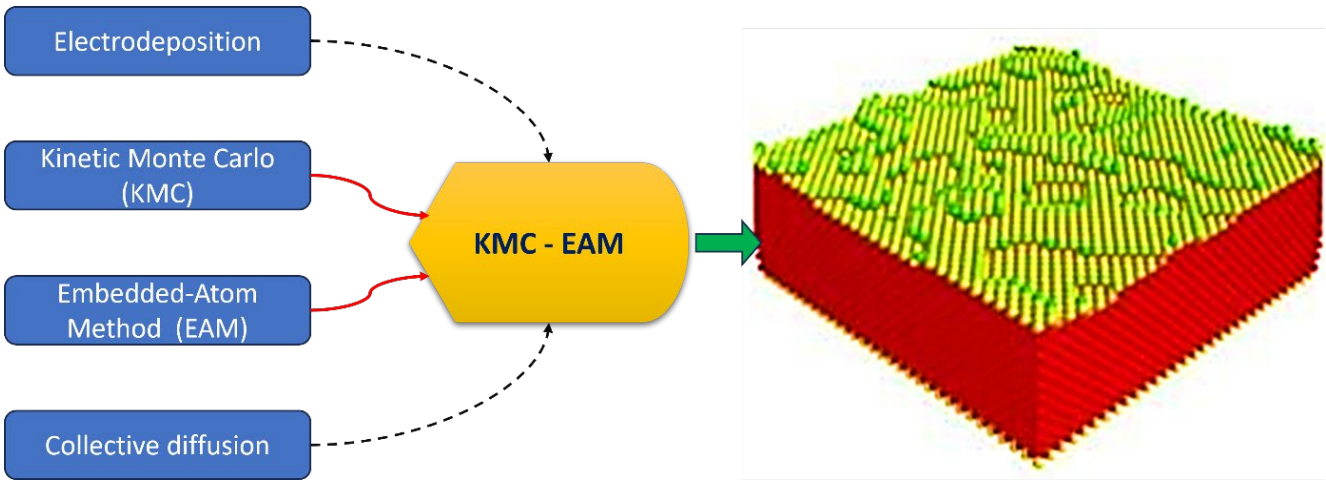

Fig. 4. Schematic representation of the KMC-EAM method for electrodeposition simulation. The kinetic Monte Carlo (KMC) approach incorporates the embedded-atom method (EAM) potential, collective diffusion processes, and electrodeposition dynamics to model metal growth on a single crystal surface. The resulting surface morphology, shown on the right, is obtained through the KMCEAM simulation under galvanostatic conditions.

3.3. Machine Learning Approaches

Machine learning (ML) methods as Data-driven approaches, are increasingly being applied for predicting the physical-mechanical properties of the electrodeposited coatings, with artificial neural networks (ANN) predominating among them. Huge datasets of experimental or simulation data can be analyzed to generate data-driven models from which predictions can be made about coating properties like hardness, adhesion, and corrosion resistance without needing detailed physical modeling (Treeratanaphitak et al., 2014; Katırcı & Tekin, 2022; Tamura et al., 2024).

1. **Artificial Neural Networks (ANNs)**: Artificial Neural Networks (ANNs) have been the most widely used machine learning approach for electrodeposition modeling. Artificial Neural Networks (ANNs) is a system of algorithms that work by being fed data and determining how it connects each layer of interconnected neurons by the weighted values which build a correlation (i.e. establishing the relationship between input variables like current density, temperature and electrolyte concentration against output properties like hardness and adhesion strength). The good generalizability of ANNs to predict nonlinear correlation of the electrodeposition process with high flexibility (Tamura et al., 2024; Ünal et al., 2023).

2. **Dynamic and Chaotic ANNs (DANNs and CANNs)**: In addition to classical Artificial Neural Network (ANN), more advance models like Dynamic ANNs (DANNs) and Chaotic ANNs (CANNs) are introduced to recreate the dynamic and chaotic response of the electrodeposition in experiments. These models take into account time-dependent variables and the many interactions that may happen within a system to allow for a more accurate prediction for coating properties under practical conditions (Sassi et al., 2021).

3. **Support Vector Machines (SVM)**: Support Vector Machines are another machine learning method for prediction of electrodeposition. Just to make a note, SVMs are a type of supervised algorithms to perform classification, and regression tasks by finding the max-margin hyperplane that can separate 2 classes. In electrodeposition, SVMs can be trained to classify different coatings or to predict system behavior with a switching together of different process parameters (Sánchez-Ruiz et al., 2023).

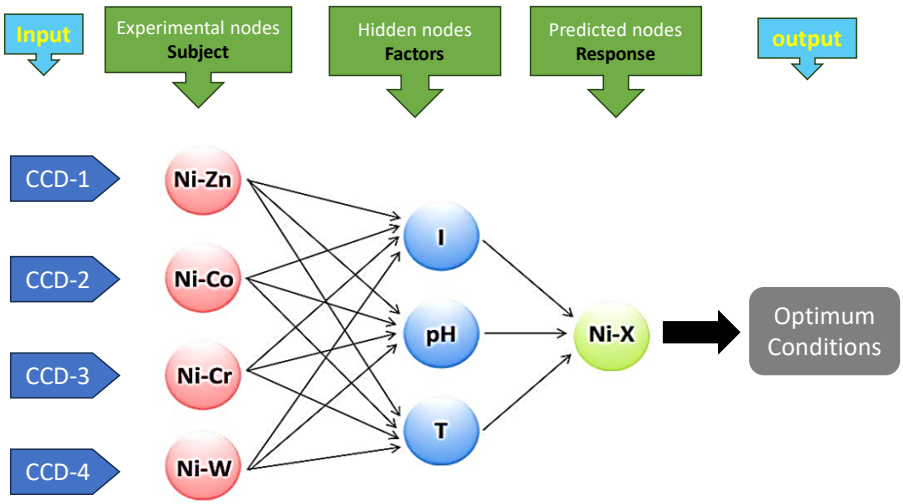

Fig. 5. Schematic representation of the optimization and prediction process for electroplated Ni based coatings using Central Composite Design (CCD) and Artificial Neural Network (ANN). The model incorporates key electroplating parameters—current density (I), bath pH, and temperature (T)—to optimize coating composition and thickness for various Ni-based alloys (Ni-Zn, Ni-Co, NiCr, Ni-W).

The rendering of the computational and experimental framework for electroplating optimization in Ni-based coatings tailor in **Fig. 5.** To this end, the left section of the figure emphasizes the major electrochemical parameters (current density, pH, and temperature) driving the deposition process. These factors become input for CCD and ANN that predict optimal conditions for electroplated Ni-alloys. Different optimized coating parameters of NiZn, Ni-Co, Ni-Cr, and Ni-W based alloys are shown in the right portion of **Fig. 5**. The study demonstrates the capability of ANN-based modeling in attaining accurate control overcoating thickness and composition, which subsequently contributes to better material properties in industrial applications (Ünal et al., 2023).

There are many limitations of classical methods in the context of data-driven modeling, such as: Scales with larger datasets; Excels in handling more complex phenomena with predicting performance over all operating conditions (particularly, combined with non-stationary and large datasets). But they need to be very carefully trained about the model and validated as they actually do.

3.4. Case Studies in Prediction Models

This has been demonstrated in multiple case studies that have been used to validate prediction models in the electrodeposition field. For example, one of our cases is the " Artificial intelligence-based model for physical-mechanical surface properties of nanostructured coatings". In this context, in this case, machine learning models, i.e., ANNs, DANNs, and CANNs were trained from empirical data of process parameters (applied potential, current intensity, electrolyte concentration). The models were then validated for their ability to predict the coating properties at other deposition conditions (Deshmukh et al., 2024).

1. **ANN-based Prediction**: This study investigates the ability of Artificial Neural Networks (ANNs) to estimate the hardness and adhesion strength of nanostructured metallic coatings. The developed models are three types of ANN considered as static (designated ANNS), dynamic (DANN) and chaotic (CANN) which are trained on the basis of the Gibbs free energy theory to model interfacial interactions in electrodeposited coatings. This model takes the input of the parameters of the electrodeposition process (i.e., applied potential, current intensity, ion concentration and residence time) and predicts the surface properties with a high accuracy. Of all the ANN tested, DANN had the best agreement between predictive ability and flexibility (Deshmukh et al., 2024).

2. DANN and CANN Models: Dynamic ANN (DANN) and Chaotic ANN (CANN) models outperformed the other distance metrics in the modelling of the complex electrodeposition process. The DANN-based model yielded superior prediction performance towards hardness and adhesion strength upon minimal overlearning, in contrast, CANN-based model on the contrary presented faster convergence ability but demonstrated more vulnerability to overfitting at relatively high electrodeposition potentials. The models captured the electro-diffusion behavior at the interface successfully and were validated with literature reported and experimental values. The results demonstrate that AI based models with the integration of thermodynamic principles can be a very useful tool for predicting the material property with a robust accuracy (~99%) (Deshmukh et al., 2024).

The potential of ML-models to predict and optimize electrodeposition processes and the ability of ML-models in other forms of domains are demonstrated as part of these case studies. Hence coupling machine learning with experimental data will significantly improve the ability to predict the characteristics of the coating, in addition to improving accuracy and reliability whilst contouring such predictions, which also increases the efficiency and quality of electrodeposition (Deshmukh et al., 2024).

4. Optimization Models in Electrodeposition

4.1. Optimization Techniques

Such optimization methods focus on the deposition process itself, the 2-step electrochemical deposition for better deposition efficiency and deposition property. Such approaches traditionally allow for the optimization of numerous coating performance metrics: current density, applied potential, electrolyte composition, temperature (Sánchez-Ruiz et al., 2023; Drews et al., 2001; Katırcı & Tekin, 2022; Tamilvanan et al., 2023; Dehestani et al., 2021). Below are some of the most common optimization methods:

1. **Gradient-Based Optimization**: A method when one iteratively modifies the process parameters based on the gradient of some properties of the objective function (e.g. hardness of coating, adhesion strength). If we want to create improvements to, or downplay a given property, we will let the algorithm adjust our parameters in the direction of the steepest descent (for minimization) or steepest ascent (for maximization) of the objective function (Sánchez-Ruiz et al., 2023) in an iterative manner.
2. **Genetic Algorithms (GA)**: Genetic Algorithms are empirical optimization algorithms that have been adopted from the natural selection process. These algorithms are inspired by the evolution cycle of a finite population, where we evolve to several generations, and we breed towards the most adapted candidates (a process called crossover). This cycle repeats over generations until a candidate solution is found to be superior. In electrodeposition, because GAs help optimize multiple process parameters simultaneously, it is possible to obtain the desirable coating properties (Drews et al., 2001; Katırcı & Tekin, 2022; Tamilvanan et al., 2023). GAs are sometimes called evolutionary computation and they emulate the processes of natural selection and reproduction to establish the best, or most “fit,” solutions. Like GA and GP, gene expression programming (GEP) also selects individuals in a population based on fitness values and applies genetic variation operators to determine the best correlation between input and output variables. The relationships are encoded with ETs (expression trees) or mathematical functions in GEP, which also provides precise predictions for the outputs under different circumstances. ETs are made up of different constants, functions, operators, and input variables, where nodes and terminals pass values, and mathematical functions connect elements between pipelines. In addition, AI techniques such as ANN and GEP have served as an indispensable process in increasing the popularity of research in physical, chemical, and mathematical sciences (**Fig. 6**) (Abbasi et al., 2012).

3. **Particle Swarm Optimization (PSO)**: It is an optimization algorithm inspired from social behavior, PSO uses a population of potential solutions known as particles. Individual particles include their own experiences, as well as experiences of neighboring particles, to update their position in parameter space to conclude the best solution. Clustering, a form of group classification, invests in a fast classification of large data sets, which stores them by similarity between data (Tamilvanan et al., 2023).

4. **Simulated Annealing (SA)**: Simulated annealing is a probabilistic optimization method modeled after the annealing process in metallurgy. It explores the parameter space by randomly propagating the process parameters, while new configurations are accepted with a probability function that decreases over time. This helps you to avoid local minimums and ensure a global optimal has been achieved (Dehestani et al., 2021).

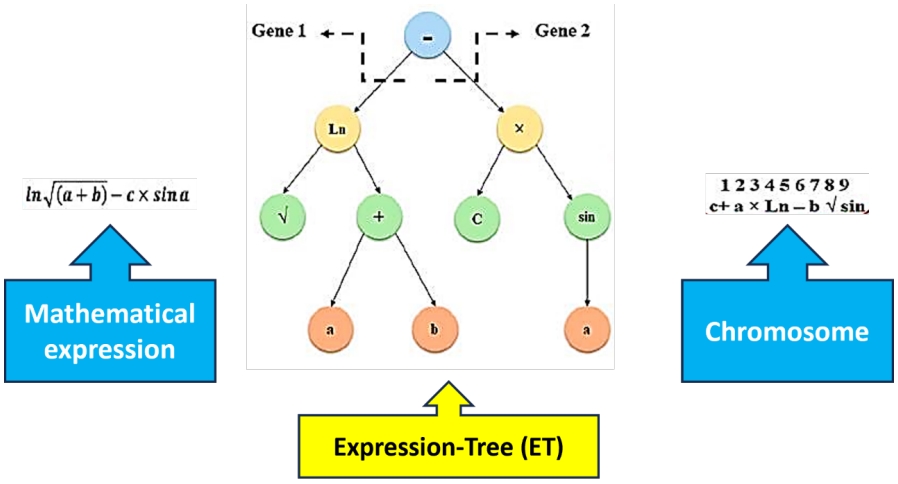

Fig. 6. Typical representation of linear string and their GEP model.

Process optimization strategies are essential to the field of electrodeposition since they can help define conditions that yield optimal coatings in terms of both performance and production.

4.2. Models for Efficiency and Quality

In the case of electrodeposition—optimization models mainly target two prominent areas: efficiency, and quality. Efficiency, meaning the capacity to create desired coating attributes with reduced energy and material expenditures, and quality in terms of physical and mechanical properties of the resulting coatings, including evenness, hardness, and interfacial tensile strength (Zeraati et al., 2022).

1. **Efficiency Models**: These models are focused on minimizing energy consumption and material waste during the process of electrodeposition. This is accomplished by selecting the deposition rate, current density, and electrolyte contents such that coatings are deposited in as little time as possible with the least possible resource consuming. This makes highly efficient models a critical component in minimizing the cost of production and increasing the sustainability of any process involving electrodeposition (Ciszewski et al., 2004).

2. **Quality Models**: These are focused on optimizing the quality of the coating, ensuring that it meets specific performance characteristics, such as uniformity, hardness, and adhesion strength, among others. Commonly, these models used a multi-objective optimization to target multiple coating properties at once, for example, minimizing surface roughness and maximizing hardness. Thus, predictive models, for example, those based on machine learning, can be combined with optimization methods to obtain high quality coatings by optimizing process parameters to be obtained according to the desired specifications (Pilone & Kelsall, 2006; Shukla, 2013).

3. **Integrated Efficiency and Quality Models**: Some optimization models integrate both efficiency and quality criteria. This ensures that the optimization of the process utilizes both the costs associated with producing coatings as well as the properties that need to be obtained. For example, based on machine learning models predicting coating properties, and optimization algorithms (genetic algorithms, or particle swarm optimization), it is feasible to identify the process parameters that provide the best trade-off with respect to optimal efficiency and quality (Zeraati et al., 2022).

4.3. Comparison with Traditional Methods

Electrodeposition is one of the most widely used methods for coating and fabricating metallic and semiconductor materials, yet traditional optimization is predominantly performed using trial-and-error approaches or experience-based heuristics. In these techniques, typically a single parameter is changed and an effect on coating properties is noted. Even though this

methodology can succeed, it is typically lengthy and often not efficient whatsoever, especially in the case of complex systems made up of multiple interdependent parameters (Granados et al., 2020).

Additionally, traditional optimization techniques were typically dependent on providing tuning settings and subjective knowledge to humans, which can be both time-consuming and inconsistent. These approaches enable the concurrent optimization of multiple process parameters and even predict how each variation will affect the final properties of the coating itself. As an example, based on ANNs, DANNs or even on CANNs it is possible to predict the covered properties for a wide range of input parameters, this approach generates a more precise but optimized process compared to the traditional methods (Deshmukh et al., 2024; Drews et al., 2001; Koochaksaraie et al., 2022).

Seungmin Oh (Rajabi et al., 2012) developed a dual neural network (DNN) model for the optimization of electroplating process parameters to improve thickness uniformity while reducing material cost and time. The study introduced two interconnected models: An energy density model that predicts energy density based on plating thickness and electrode spacing, and a uniformity model that determines optimal process parameters for minimal uniformity variation. Using 88,200 simulation data points from COMSOL, the model was trained and validated against a traditional fully connected neural network (FCNN). The model demonstrated superior performance through lower MSE and MAPE values, PCA analysis, and loss function evaluation. The DNN approach outperformed the FCNN in terms of accuracy and efficiency. It provides a novel AI-driven optimization method for electroplating. However, further validation of its practical applicability requires real-world electroplating experiments and comparisons with other machine learning techniques.

Machine-learning-based optimization model is one more that can learn on huge data sets and improve predictive accuracy over time. Since it can learn with new or unseen conditions, these models are typically more effective than static rules and will therefore result in more robust decisions (Treeratanaphitak et al., 2014; Katırcı & Tekin, 2022; Tamura et al., 2024; Deshmukh et al., 2024).

4.4. Case Studies in Optimization Models

Many application case studies have shown that the optimization models prove to be worth it in electrodeposition. An example of this can be observed in the optimization of the coating parameters in the chromium nanoparticle electrodeposition process in which machine learning models are being developed to predict properties of the coating before further optimization (hardness, adhesion strength, and nanoparticle density); most of the work aims to enhance the properties of resulting materials in wear applications. Therefore, in this study, a multiobjective optimization strategy was adopted to include competing objectives that work against each other, those being high hardness and strong adhesion that must be obtained at a minimum energy loss within the deposition process (Deshmukh et al., 2024; Koochaksaraie et al., 2022).

1. **Genetic Algorithm for Chromium Coatings**: Electrodeposition parameters of coatings (current density, potential and electrolyte concentration) were optimized by a genetic algorithm. The results showed that GA successfully detected the process conditions which enabled us to obtain harder and more adhesive coatings, with low energy cost. The optimization also identified an optimal set of parameters of high-quality chromium coatings (Koochaksaraie et al., 2022).

2. **Machine Learning-Based Optimization**: In a separate study, optimization of the electrodeposition of chromium nanoparticle coatings utilizing ANNs and DANNs was presented. The models were trained on experimental data, which were then applied to predict optimal process parameters for gaining desirable hardness and adhesion strength. These results revealed that min-max learning models performed better than conventional methods, providing users with more accurate predictions and better optimization results (Deshmukh et al., 2024).

3. **Comparative Analysis**: Synthetic optimization models were developed such as integrating physics-based data with ML algorithms to optimize the coatings process. The advantages of this accelerated exploration and optimization were demonstrated, with machine learning models identifying superior coating parameters in a quicker period and fewer experimental runs than traditional experimental techniques (Deshmukh et al., 2024; Koochaksaraie et al., 2022).

The optimization models presented in these case studies are crucial for the development of the circumstances of the electrodeposition process. This hybridization enables us to enhance the properties of coatings and to optimize materials, energy and time.

5. Comparative Study of Prediction and Optimization Models

5.1. Overview of Comparison Techniques

Researchers compared different prediction and optimization models in the study of electrodeposition to assess their performance and identify the most appropriate one for a specific process (오승민, 2024; Gan et al., 2021; Subramanian et al., 2009). As discussed above, two main aspects considered by comparative techniques are predictive accuracy and optimization efficiency. Predictive accuracy means that the model must be able to accurately predict the coating properties based on input

process parameters which include hardness and adhesive strength. In contrast, optimization efficiency measures the model's ability to optimize multiple process parameters to yield the desired coating characteristics with minimal energy and material waste (오승민, 2024; Deshmukh et al., 2024).

Common comparison techniques include:

1. **Cross-validation**: splitting the data into multiple training/testing sets to assess how well the model performs and generalizes to new data.

2. **Error analysis**: This involves determining error statistics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared values to verify that the model is predictively accurate.

3. **Multi-objective optimization**: Explore multi-objective optimization, where models are evaluated based on performance across multiple objective functions (e.g. maximizing coating hardness and minimizing surface roughness or energy consumption).

These methods then systematically compare the relative merits of each model through comparative approaches and characterize the relative degree in which each model is relevant to the case of the problem of electrodeposition and govern the decision making on their selection from models that activate optimized processes (Gan et al., 2021).

5.2. Performance Metrics

These are the common metrics that are used to evaluate the performance of various prediction and optimization models. These imply the efficiency indicators of the model in predicting and optimizing the coatings' properties, making the model even more useful in attaining the process goals (Sánchez-Ruiz et al., 2023).

1. **Predictive Accuracy**: One of the key metrics to be considered in comparative studies illustrates the accuracy of a model to predict coating properties like hardness, adhesion strength and surface topography. Here are some commonly used metrics for assessing predictive performance:

- **Root Mean Squared Error (RMSE)**: This is the mean error over predicted and real numbers in which larger errors will be given greater weight.
- **Mean Absolute Error (MAE)**: It provides a summary of absolute error between the predicted value and the actual value so that you can have the bigger picture of your model. ○ **R-squared (R^2)**: The proportion of variability of the dependent variable (a coating property) explained by the independent variables. (Closer to 1; the better predictor you have).

Referring to (Sánchez-Ruiz et al., 2023), the least RMSE of linear regression, SVM and GPR model were selected, after training. The GPR model on the validation set gives the lowest RMSE of 0.057658, whereas SVM and linear regression return RMSEs of 0.12295 and 0.16019, respectively. Statistical metrics such as RMSE, R^2, MSE, and MAE for GPR, SVM, and linear regression models are given in **Table 1**.

Table 1. Model statistics for GPR, SVM, and LR (Sánchez-Ruiz et al., 2023)

Statistic	Tips	GPR	SVM	LR
RMSE	Smaller value is better	0.057668	0.12295	0.16019
R^2	Value close to 1 is better	0.96	0.78	0.58
MSE	Smaller value is better	0.003243	0.016704	0.31695
MAE	Smaller value is better	0.045733	0.078151	0.12418

2. **Optimization Efficiency**: Optimization Efficiency is the criteria from the aspect of the decision-making basis of the model, specifically solving multiple parameters of the process within the premise of ensuring optimal coating properties and the best quality to trade off, which shows whether the correctness of the model (Katırcı & Tekin, 2022; Subramanian et al., 2009). Efficiency is basically measured along the following lines:

- **Energy Consumption**: Energy required delivering which fit for an application based on adhesion and erosion resistance characteristics of the coated during the application of electrodeposition. Sustainable and economic processes with less energy consumption are desirable.
- **Material Usage**: The overall consumption of raw material from the process. The optimization for the final model gets used should be to be as good as you can achieve, without putting too much matter, gaining high value paintings.

3. **Convergence Time**: Time required for the optimization model to reach the solution Faster convergence is very crucial to accelerate the electrodeposition process, thus saving the production time and cost (Subramanian et al., 2009; Wang et al., 2024).

These performance metrics are crucial for the comparison of different models that have been used for prediction and optimization of electrodeposition. This guide gives researchers insight into what models perform the best in terms of predicting and optimization power, which will be essential for the continued development of electrodeposition as a field.

5.3. Strengths and Limitations of Different Models

Each of the methods for electrodeposition has pros and cons, making them appropriate for systems of varying complexities, coating characteristics of interest, and data availability (Katırcı & Tekin, 2022; Wang et al., 2024). The advantages and disadvantages of each prediction and optimization model applied to electrodeposition are summarized in Table 2. It emphasizes their flexibility, precision, computational cost, and compatibility with various levels of process complexities, thus guiding the decision of the most relevant model selection.

Table 2. Comparison of Different Electrodeposition Models

Model	Strengths	Limitations
Artificial Neural Networks (ANNs)	- Flexible and capable of modeling complex, nonlinear relationships - Useful when process parameters and coating properties are unclear - Predictive accuracy improves with larger datasets	- Requires large datasets for training; poor performance with small data - Acts as a 'black-box' model; difficult to interpret physical principles
Dynamic and Chaotic ANNs (DANNs and CANNs)	- Can model time-dependent and chaotic behavior in electrodeposition - Better describes real-world dynamics with nonlinearities and time variations	- More complex and computationally expensive than standard ANNs - Requires more data and takes longer to converge
Traditional Computational Methods (e.g., finite element modeling, molecular dynamics)	- High accuracy in modeling underlying physical phenomena - Suitable for fine descriptions of electrochemical systems - Can model various deposition conditions and their effects	- Computationally expensive, requiring high power and time - Struggles with highly complex nonlinear systems without strong assumptions
Optimization Techniques (e.g., Genetic Algorithms, Particle Swarm Optimization)	- Solves complex multi-objective optimization problems - Optimizes multiple parameters concurrently - Resilient to local minima, useful for trade-offs (e.g., hardness vs. energy use)	- Can be computationally expensive for many optimization parameters - Needs careful tuning of algorithm parameters - Solution spaces can be too large to find truly optimal results

1. **Artificial Neural Networks (ANNs)**:

- **Strengths**: ANNs are extremely flexible and can model complex, nonlinear relationships between input and output variables without needing detailed physical models. Machine learning models are particularly useful when the relationship between process parameters and coating properties is not readily understood, or too complex for classical mathematical models to describe. ANNS have the ability to learn from large datasets and thus, as data on a given phenomenon becomes available, their predictive accuracy improves (Tamura et al., 2024; Ünal et al., 2023).

- **Limitations**: ANNs need an extensive amount of data for training, and if the dataset is small or not indicative of the process, performance will decrease. Also, they are usually seen as “black-box” models, as the underlying mechanisms leading to the predictions are not easily interpretable, which may be a drawback if it is important to understand the physical principles behind the process (Tamilvanan et al., 2023).

2. **Dynamic and Chaotic ANNs (DANNs and CANNs)**:

- **Strengths**: DANNs and CANNs can include time-dependent and chaotic behavior of the electrodeposition process compared to ordinary ANNs. The developments in modeling offer an advantage here as they better describe the true dynamics of the process, especially in cases where nonlinearities or time varying system characteristics can be seen, such as in real-world electrodeposition (Sassi et al., 2021).

- **Limitations**: These models are more complex and computationally expensive than traditional ANNs because they need more data to train themselves with a longer time to converge. They offer more accurate predictions but can be less simple to implement and cost more computationally to use (Sassi et al., 2021).

3. **Traditional Computational Methods** (e.g., finite element modeling, molecular dynamics):

- **Strengths**: Traditional approaches provide a very high level of accuracy in terms of modeling the underlying physical phenomena of the electrodeposition process. These techniques are well suited when a fine description of the electrochemical system is necessary. They can also be utilized to model different deposition conditions and the effect of physical parameters on coating formation (Shojaei & Khayati, 2023; Boutana et al., 2025).

- **Limitations**: These methods are computationally expensive. They can be computationally expensive, requiring substantial power and time, particularly for large-scale or highly complex systems. They can also have constraints on their capacity as regards systems characterized by complex nonlinear dynamics or more formally incomprehensible dynamics, unless subjected to radical assumptions (Nasirpouri, 2016; Chen et al., 2022).

4. **Optimization Techniques (e.g., Genetic Algorithms, Particle Swarm Optimization)**:

- **Strengths**: Such optimization methods are capable of seamlessly solutioning complex multi-objective optimization problems, like genetic algorithms and particle swarm optimization. These methods can concurrently optimize multiple process parameters and are resilient to local minima (traps), rendering them appropriate for electrodeposition processes involving trade-offs among conflicting objectives (i.e., maximizing hardness vs. minimizing energy consumption) (Katırcı & Tekin, 2022).

- **Limitations**: The methods can be computationally expensive, especially for many parameters to be optimized. Moreover, they might need delicate adjustment of algorithm parameters in order to get the best out of them. In others, however, the solution spaces are so large that it is practically not possible to find a truly optimal result.

Model selection also relies on the demands of the electrodeposition process. To tackle these challenges, machine learning approaches such as artificial neural networks (ANNs) or optimization approaches, such as genetic algorithms, provide a flexible and efficient way to explore the parameter space, while more classical computational methods provide detailed understanding of the underlying physical mechanisms. In practice, a hybrid of these models tends to work best, leveraging their strengths and minimizing their weaknesses (Katırcı & Tekin, 2022; Wang et al., 2024).

6. Advancements and Emerging Trends

6.1. Recent Developments in Prediction and Optimization

Now, novel prediction and optimization models for electrodeposition are emerging that greatly improve the capacity to customize coatings for specialized industrial applications. With the adoption of these machine learning advancements and data, more effective and precise models can be developed and used to determine complex relationships between parameters of the process and properties of the respective coating, such as hardness, adhesion strength, and wear resistance.

First is the employment of artificial neutral networks (ANNs) in the prediction of physicalmechanical properties of electrodeposited coatings, which has helped this prediction move forward. The obtained models can predict the characteristics of the coatings from input parameters used in the deposition process such as applied potential, current intensity and concentration of the electrolyte. Nevertheless, with regard to the sagacity of artificial neural networks (ANNs), extensions can be applied using dynamic (DANNs) and chaotic (CANNs) neural networks (NNs) in response to recent cutting-edge developments, which enables estimation of time-dependent and nonlinear behaviors in electrodeposition (Tamura et al., 2024; Zhu et al., 2023; Sassi et al., 2021).

Along with machine learning models, work has been done to integrate computational methods with data-driven techniques. More recently, finite element modeling (FEM) and molecular dynamics (MD) have been integrated with machine learning algorithms to more accurately simulate the electrochemical processes taking place during electrodeposition. This hybrid approach permits the modeling of coating formation on an atomic scale, a requirement for elucidating how surface interactions, mass transfer, and electrochemical kinetics influence coating quality (Nasirpouri, 2016; Shojaei & Khayati, 2023; Chen et al., 2022; Phillips et al., 2020).

6.2. Integration of AI and Machine Learning

The machine-learning-enabled electrodeposition processes have revolutionized the ways in which electrodeposition processes are predicted, optimized, and controlled. Among these technologies, AI-driven models, especially based on machine learning algorithms, have been progressively used for analyzing large datasets resulting from experimental studies or simulations. Unlike traditional predictors, which are often based on mechanistic approaches that require rigorous mathematical

equations, these models learn directly from data to capture the intricate relationships between input variables (e.g., process parameters) and target properties (e.g., hardness, adhesion, and corrosion resistance) (Phillips et al., 2020).

Especially, machine learning methods like supervised learning (regression and classification) or unsupervised learning (clustering and dimensionality reduction) are very suitable for handling problems caused by the high complexity along with nonlinear interaction in the electrodeposition system. These models can learn from experimental data directly and, in the long term, keep improving their predictive accuracy, supporting real-time predictions aimed at optimizing process parameters (Oliveira & Toniolo, 2024).

Furthermore, the combination of AI with simulation methods like finite element analysis (FEA) and molecular dynamics simulations is leading to a more holistic approach to understanding the electrodeposition process. Integrating these methodologies allows researchers to achieve high fidelity predictions of coating properties while simultaneously optimizing process parameters in real time, enabling enhancements in both quality and efficiency of electrodeposited coatings (Hiran et al., 2021).

6.3. Novel Materials and Techniques in Electrodeposition

Compared to the improvements identified in predictive and optimal models, there are said to be advancements in the materials and techniques of electrodeposition as well. As a result, new coatings technologies are evolving to scale while addressing the increasing client requirements for advanced performance, long-lasting durability, and greater functionality in an extensive range of applications.

1. **Nanostructured Coatings**: The incorporation of nanoparticles into electrodeposited coatings has been a focus of interest, as these materials have displayed considerable enhancements in mechanical and thermal properties. Chromium nanoparticles (CrNPs), for instance, are widely utilized for the synthesis of coatings that show improved hardness, abrasion resistance, and anti-corrosion property. These coatings are commonly used in high-performance scenarios including the aerospace and automotive sectors. Especially by controlling the deposition process, the size, shape and even the distribution of the nanoparticles in the coating can be optimized, which in turn acts in the function required for a specific application (Bedolla-Hernández et al., 2022).

2. **Composite Coatings**: Another trend on the rise is composite coatings, used for the formation of non-metallic materials such as ceramics, polymers, and carbon nanotubes into the metal matrix during the electrodeposition process. By combining the properties of metal and non-metallic correlating or coating, these coatings give better mechanical strength, thermal stability, corrosion resistance, and abrasion resistance. An illustrative example includes diamond nanoparticle composites that are increasingly utilized because of their extreme hardness and resistance to wear, which makes them suitable for use in cutting tools, engine components and industrial machinery (Huang et al., 2021; Walsh et al., 2020).

3. **Green Electrodeposition**: There has been increasing demand for the development of more environmentally friendly processes in electrodeposition. Electrodeposition and similar processes are often based on toxic chemicals and heavy metals as well, which poses a high risk for the environment and health. This has warranted research into multiple green electrodeposition methods that utilize eco-friendly, non-toxic electrolytes. For example, ionic liquids are a promising replacement for traditional solvents in the realm of electrodeposition. Not only do these solvents lower the environmental impact, but they also allow for the deposition of a broader array of materials that are difficult to deposit through traditional means (Low et al., 2006; Kang et al., 2022; Costa et al., 2022).

4. **Electrodeposition for Energy Storage**: One of the most exciting areas of innovation in electrodeposition is its use in energy storage devices, such as batteries and supercapacitors. Electrodeposition techniques are being used to fabricate high-performance electrodes for lithium-ion batteries, supercapacitors, and fuel cells. Intercalating new materials in a precise manner during deposition of the electrodes makes it possible to improve energy storage capacity, energy efficiency and cycle stability (Maniam & Paul, 2021; Eh et al., 2021; Eh et al., 2021).

5. **3D Printing and Additive Manufacturing**: Advancements in 3D printing and additive manufacturing technologies are significant in the electrodeposition sector as well. This enables the development of highly customized coatings for complex geometries by merging electrodeposition and 3D printing techniques. Such integration enables deposition of coatings on complex parts with precise accuracy, thereby paving way for new manufacturing opportunities in the fields of aircraft, medical instrumentation and electronics (Zheng et al., 2021; Wei et al., 2022).

Critical parameters responsible for deposition process as shown in **Fig. 7**, can be divided into four main pieces across field—Electrode, Electrolyte, Current, Particle, enclosed by corresponding material properties, electrode process and solution properties, electrochemical conditions and particle properties. The interplay of these parameters is crucial for controlling the electrodeposition process and obtaining high-performing composite coatings in the various application sectors (Ayalew et al., 2023).

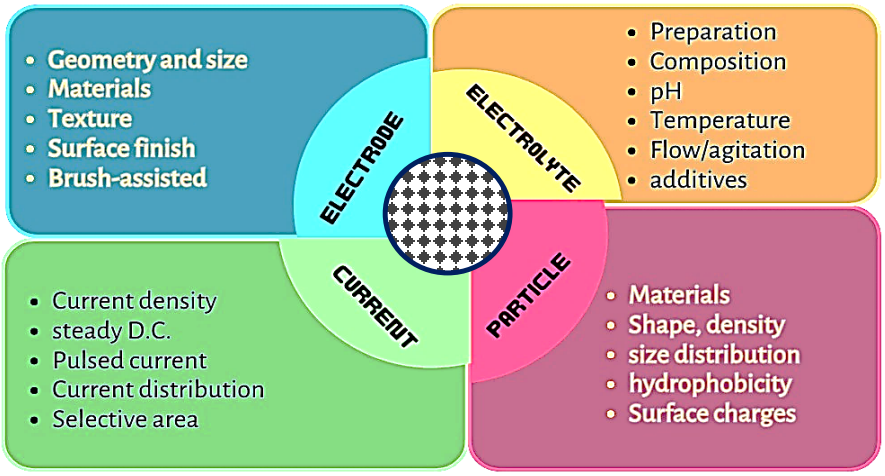

Fig. 7. Key factors influencing the electrodeposition of composite coatings

7. Conclusion

This review article has reviewed the current developments in the prediction and optimization of electrodeposition processes and highlighted its effectiveness in machine learning techniques and computational models to predict and optimize the coating properties. The following are the key findings of this review:

1. **Machine Learning for Prediction and Optimization**: The use of predictive models that incorporate machine learning techniques, including Artificial Neural Networks (ANNs), Dynamic ANNs (DANNs), and Chaotic ANNs (CANNs), have demonstrated significant success in predicting the physical-mechanical properties of the coatings obtained by electrodeposition, for example, hardness and the adhesion strength. These models provide enhanced predictive accuracy compared to the traditional methods for processes with complex and nonlinear connections between the parameters of the process and the properties of the coating.

2. **Hybrid Approaches**: The fusion of classical computational techniques (FEM, MD) with machine learning has led to a greater sense of the mechanistic underpinnings of the electrodeposition process. These hybrid models capture the fundamental electrochemical behavior on the atomic scale while taking advantage of the flexibility and generalizability of machine learning to enhance predictive capability.

3. **Optimization Techniques**: Genetic algorithms (GAs) and particle swarm optimization (PSO) are some of the optimization techniques used for electrodeposition process optimization to satisfy competing objectives, such as high-quality deposition, energy and material conservation. It is one step further to advance the process of electrodeposition with a hybridization of AI-based optimization models.

4. **Emerging Trends**: A few new materials and processes in electrodeposition have been developed, such as nanostructured coatings, composite coatings and environmentally friendly electrodeposition processes. These developments are meeting the increasing need for better performing coatings, including hardness, durability, and sustainability. Finally, the role of electrodeposition in energy harvesting devices along with the combination with 3D printing technologies shows huge potential for future studies and industrial use.

Future Directions for Research

The field of electrodeposition is poised for further advancements, particularly with the increasing integration of **AI** and **machine learning**. Future research should focus on the following areas:

1. **Advanced Machine Learning Models**: Explore deeper use of machine learning techniques such as deep learning and reinforcement learning that can improve quality of both segmentation and prediction of electrodeposition Control over more complex data and the concurrent optimization of more parameters would then lead to improved process control and better coating properties.

2. **Real-Time Process Monitoring and Control**: Nevertheless, an approach to data interpretation in-process control via machine learning (ML) would then allow for real time screening of the system in an adaptive system for process control (e.g. electrodeposition). Real-time monitoring of the deposition process using sensors and AI algorithms can minimize energy use and improve the uniformity of coating quality.

3. **Sustainable and Green Electrodeposition**: As environmental awareness becomes ubiquitous, requiring more environmentally friendly electrodeposition. Future work should also explore more environmentally friendly alternatives for electrodeposition, including less toxic chemical species and non-toxic solvents. Chinese researchers are also attempting to investigate ionic liquids and other non-aqueous and green electrolytes.

4. **Novel Coating Materials**: It is time to continue the research on new materials such as composite coatings and nanostructured coatings. Discovering how these materials behave under various electrochemical settings can be used to create coatings with improved mechanical properties, including higher hardness, wear resistance, and corrosion protection. Their commercial viability will significantly rely on the employment of these coatings across high-performance industries like aerospace, automotive, and electronics.

5. **Integration with Additive Manufacturing**: Integrating electrodeposition with additive manufacturing (3D printing) is an innovative avenue and area of future research. The integration of 3D printing into coating processes would allow for coatings to be deposited on complex shapes down to the micron scale and enable end-user designed components in other methods.

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