

Review

Performance Prediction and Optimization of Electroless Nickel-Based Coating of Substrates: Review, Insights and Future Research Directions

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Abstract

Although previous reviews of electroless nickel-based coatings have focused separately on deposition, coating performance or prediction methods, a thorough review that concurrently discusses the input process variables, output performance variables, performance prediction techniques and optimization strategies remains unaddressed. This study aims to provide a comprehensive review of the available literature on the performance prediction and optimization of electroless nickel-based coating, focusing on substrate types, coating types, input process variables, output performance variables, prediction methods and optimization techniques, including their strengths and weaknesses. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was used for the screening and selection phases of the study. Considering 32 studies, the most commonly employed input process variable and output performance variable were reducing agent concentration (24 studies) and microhardness of the coatings (10 studies) respectively. Real-world problems generally involve multiple output variables, but most prediction models were single-output. The majority of previous studies (15 studies) employed Artificial Neural Network (ANN) prediction models, which are black-box methods, limiting optimization due to their inability to generate explicit mathematical equations. Despite requiring predefined experimental designs, Response Surface Methodology (RSM) was the most widely used optimization strategy, accounting for 11 reviewed studies. This review guides researchers in establishing their study objectives and future research directions by addressing research gaps in the reviewed articles.

Keywords: electroless coating; prediction; machine learning; optimization; nickel; substrates

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1. Introduction

Electroless plating is an autocatalytic deposition method of a metal layer onto a substrate without using an external electric current [1]. The target metal ions in the electroless plating bath are reduced by a strong reducing agent on the catalytic surface of substrates [2]. Electroless plating is applicable to different substrates such as metals, polymers and ceramics [3,4]. Electroless coating deposits either a metallic layer or a mixture of metallic and non-metallic layers onto a substrate to enhance surface performance, corrosion resistance and appearance [5]. Metal or non-metal substrates can be electroless-coated [6]. The terms “electroless coating” and “electroless plating” are often used interchangeably by many researchers [7–10]. While “electroless plating” indicates the deposition of metallic layers, the term “electroless coating” is more appropriate when describing the deposition of multi-component alloy coatings [11] or composite coatings [12].

The electroless plating process was invented by Riddell and Brenner [13] in 1946 when they found the proper conditions to achieve electroless plating. This process can produce a uniform thickness or composition of plating [14]. Wang et al. [15] claimed that electroless nickel plating is the most prevalent type used in surface finishing, outperforming electroplated nickel in wear resistance, thickness uniformity, lubricity and ductility. Nowadays, electroless nickel plating is widely used as a surface engineering method in industries such as mechanical, electronic, automobile, aerospace, chemical and textile [16].

The four main categories of electroless nickel coatings are pure nickel, alloy, nanomaterial and composite [17]. Alloy coatings can be classified as binary (Ni-B, Ni-P), ternary (Ni-W-P, Ni-Co-P, Ni-Cu-P), quaternary (Ni-W-Cu-P) or poly-alloy [18]. Titanium dioxide (TiO₂) is a common nanomaterial integrated into the Ni-P matrix for electroless coating due to its high corrosion resistance and microhardness properties [19]. Researchers tested different composite coatings by incorporating the hard ceramic second-phase particles (TiO₂, Al₂O₃, SiC, WC, ZrO₂, Si₃N₄ or diamond) into the Ni-P matrix for coating hardness enhancement [20]. Soft particles (PTFE, HBN, MoS₂ or graphite) are added to improve the coating's lubricity characteristic [20].

There is no proper review paper on electroless nickel-based coating of substrates involving input process variables, output performance variables, prediction techniques and optimization methods simultaneously. Some review papers have focused on electroless nickel-based coating and output performance variables aimed at enhancing substrate surface performance but did not discuss any input process variables, output prediction methods and optimization methods [21,22]. Other reviews have examined input process variables and electroless nickel-based coating of substrates but excluded output performance variables, performance prediction techniques and optimization approaches [23,24]. In addition, several review papers studied performance prediction methods in general but not specifically in the context of electroless nickel-based coating [25,26].

Paturi et al. [27] presented a review paper that examined the Artificial Neural Network (ANN) prediction method and output performance variables. However, the discussion of input process variables and optimization approaches was not emphasized in their study. Moreover, their research covered a wide range of coating materials in electroless plating and electroplating, rather than focusing on nickel-based materials. It has been around five years since the review study by Paturi et al. [27] was carried out. Hence, there is a need to conduct a specific and comprehensive review that assesses the existing literature on the performance prediction methods and optimization techniques specifically for electroless nickel-based coatings on substrates.

The objectives of this review study are stated as follows:

1. To review the existing research on performance prediction and optimization of electroless nickel-based coating of substrates.
2. To analyze the previous studies from different aspects, including the types of coating, types of substrates, input process variables, output performance variables, performance prediction methods, optimization methods, and their strengths and weaknesses.
3. To suggest future research directions that provide insights for enhancing electroless nickel-based coating.

Although the studies of machine learning for performance prediction in electroless nickel-based coating have become popular since 2020 [18,19,28–30], the review papers discussing machine learning prediction in this field are still limited. Therefore, this study presents the first holistic review of different machine learning and traditional prediction methods applied to the electroless nickel-based coating process, together with optimization techniques. It provides researchers with insights for conducting more detailed studies in this area.

The rest of the paper is structured as follows: Section 2 outlines the general concepts valuable to this study. Section 3 discusses the methodology used to conduct the review. Section 4 analyzes and reviews the previous studies. Analysis and discussion are provided in Section 5. Future research directions are identified in Section 6, while implications of this review are presented in Section 7. Lastly, Section 8 highlights the overall conclusions of the review.

2. Background and General Concepts

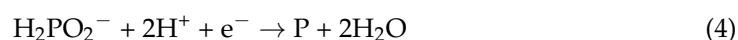
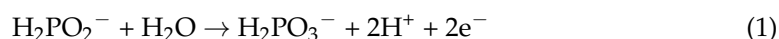
This section explains some background and general concepts on the topic. Section 2.1 elaborates on substrates and electroless nickel-based coating, while Sections 2.2–2.5 describe input process variables, output performance variables, prediction and optimization respectively.

2.1. Substrates and Electroless Nickel-Based Coating

A substrate is the material to which the coating is applied, and it can be made of different materials, such as metal, glass, textile, plastic or ceramic [1]. When a substrate is immersed in an electroless bath solution, potential is generated, which is then used in the electroless coating process [31]. Substrate surfaces are often polluted with other compounds or gasses [32]. Therefore, substrates should be coated to prevent direct contact with the surrounding environment, which helps to extend their lifespan and enhance their corrosion resistance [33,34]. Substrate coating is important for enhancing surface properties such as microhardness and abrasion resistance [35].

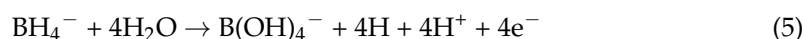
Instead of using electric current, the electroless coating method allows electron supply by a reducing agent [36,37]. The metal ions are reduced on the substrate surface when reducing agents lose electrons [38]. The electroless coatings are classified based on the application of reducing agents such as sodium hypophosphite for nickel–phosphorous (Ni-P) and sodium borohydride for nickel–boron (Ni-B) [39,40]. In addition to metal salts and reducing agents, the bath solution of electroless coating may comprise pH regulators, buffers, accelerators, stabilizers, complexing agents and wetting agents [22].

In recent decades, electroless plating, electroplating, sol–gel processes, anodizing and high-energy beam surface modification have been used to increase the hardness, wear resistance and corrosion resistance of surfaces [41]. Among these techniques, electroless nickel plating is well-recognized as an economical and efficient surface modification technique [41]. The anodic and cathodic reactions for electroless Ni-P plating using sodium hypophosphite reducing agent are shown below [42]:

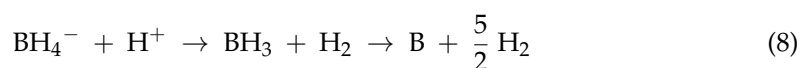


The following formulas supported by Das and Sahoo [43] are the chemical reactions that take place during electroless nickel plating with boron compounds:

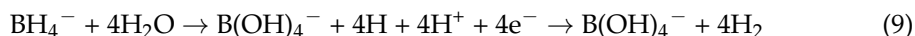
Nickel reduction:



Boron reduction:



Hydrolysis of borohydride:



2.2. Input Process Variables

Input process variables can be called independent variables or predictor variables [44]. The electroless coating process that involves multiple process variables is complex, as even a slight deviation in process parameters may lead to poor results [45]. Each input process variable performs a unique role in the electroless nickel-based coating process and can be altered to affect the output performance variables. Understanding predictor effects is vital if the predictive modeling aims to be informative or purely predictive [46]. If an independent variable's effect contradicts intuition, it could imply an unreliable fitted model or the discovery of a new occurrence [46]. Some common input process variables used are main salt concentration, reducing agent concentration, complexing agent concentration, stabilizer concentration, surfactant concentration, bath pH, bath temperature, etc.

2.3. Output Performance Variables

Output performance variables refer to response variables that researchers desire to explain or predict [47]. They are also known as dependent variables since they are dependent on independent variables. In electroless nickel-based coating, the output performance variables are typically related to the topological characteristics of substrates, such as micro-hardness, average surface roughness and phosphorus content of the coatings. The output performance variable can be any observable and quantifiable condition, scenario, factor or trait that can determine the influence of the independent variable [48]. For instance, plating rate and corrosion rate are quantifiable output performance variables in electroless nickel-based coating.

2.4. Prediction

Every scenario that needs a prediction has a distinct set of problems, and the feasible solutions to one situation are by no means applicable to another [49]. Prediction utilizes statistical techniques or machine learning to predict future outcomes using existing datasets [50]. Prediction models could provide essential information about a system's operation by fitting them to historical event behaviors [49]. Predictive modeling aims to develop approaches that accurately predict results or target values for new data [51]. Prediction helps nickel-based coating industries to predict the future behaviors of important output performance variables before making decisions in production. With the rapid development of computational technologies, machine learning has emerged as a powerful predictive tool owing to its ability to extract useful patterns from large datasets [52]. Implementing a machine learning prediction model such as ANN in electroless nickel-based coating can save processing time and expenditure [53]. This can increase the competitive edge of a company. Nevertheless, black-box models like ANNs generally exhibit limited interpretability due to the opaque connections between neurons and layers [54]. Furthermore, careful dataset size selection should be considered for machine learning models, as models trained on small datasets tend to overfit [55] and show poor generalization ability [56].

2.5. Optimization

Optimization is a process of identifying the optimal values of a set of input variables for achieving the targeted value of an output variable [57,58]. The optimized input process variables can be used to predict the optimal output performance values in electroless nickel-based coating. Metaheuristic methods such as Genetic Algorithm (GA) and traditional statistical approaches like Response Surface Methodology (RSM) are commonly used for electroless nickel-based coating optimization. Optimization is important to reduce costs and improve manufacturing quality in industries by fully utilizing and effectively allocating limited resources [59]. Precise control and optimization of process parameters can significantly reduce energy consumption, shorten production cycles and enhance the quality of finished products [60]. This can prevent unnecessary waste of resources and help in enhancing production efficiency in the electroless nickel-based coating industries.

3. Research Methodology

This study aims to review the previous research on performance prediction and optimization of electroless nickel-based coating of substrates. For this review study, no specific time frame was set to ensure a thorough search of relevant studies up to December 2025. This could foster a more in-depth understanding of the topic from its basis.

The article search keywords and strings used were “electroless coating” OR “electroless nickel coating” OR “ENi coating” OR “electroless nickel plating” OR “machine learning and electroless coating” OR “electroless nickel coating modeling” OR “electroless nickel plating prediction” OR “electroless plating prediction and optimization” OR “optimization of electroless coating” OR “parametric optimization of electroless coating” OR “multi-objective optimization of electroless coating”. An extensive literature search was conducted across different online databases including Springer, ScienceDirect, Emerald, IEEE Xplore, Taylor and Francis, Wiley, Sage, etc., as well as via the Google Scholar search engine. These databases were inspected to discover relevant journal articles, conference articles, book chapters, etc., as they support systematic, reproducible retrieval of literature and provide comprehensive coverage of the relevant research domain.

The research methodology followed the screening and selection steps in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology suggested by Moher et al. [61]. Figure 1 shows the PRISMA methodology from identification to screening, eligibility and inclusion before the review analysis. Firstly, 346 previous studies were identified by applying the search keywords via the online sources as mentioned before. Then, the duplicate articles from different online sources were removed, resulting in 324 articles. In the screening step, 76 published research documents in the English language were selected after excluding 248 irrelevant documents based on the titles. Subsequently, the abstracts and full texts of these articles were examined to assess their eligibility. There were 37 articles left eligible after removing 39 documents with unrelated abstracts and contents. At this stage, only Scopus-indexed articles were included in the analysis. Despite introducing a potential selection bias by excluding non-Scopus-indexed studies, this criterion prioritizes peer-reviewed, higher-quality literature and ensures broad multidisciplinary coverage. A total of five articles were eliminated after applying the Scopus-indexed exclusion criterion, leaving 32 of the most relevant articles as the final set of studies included in the review.

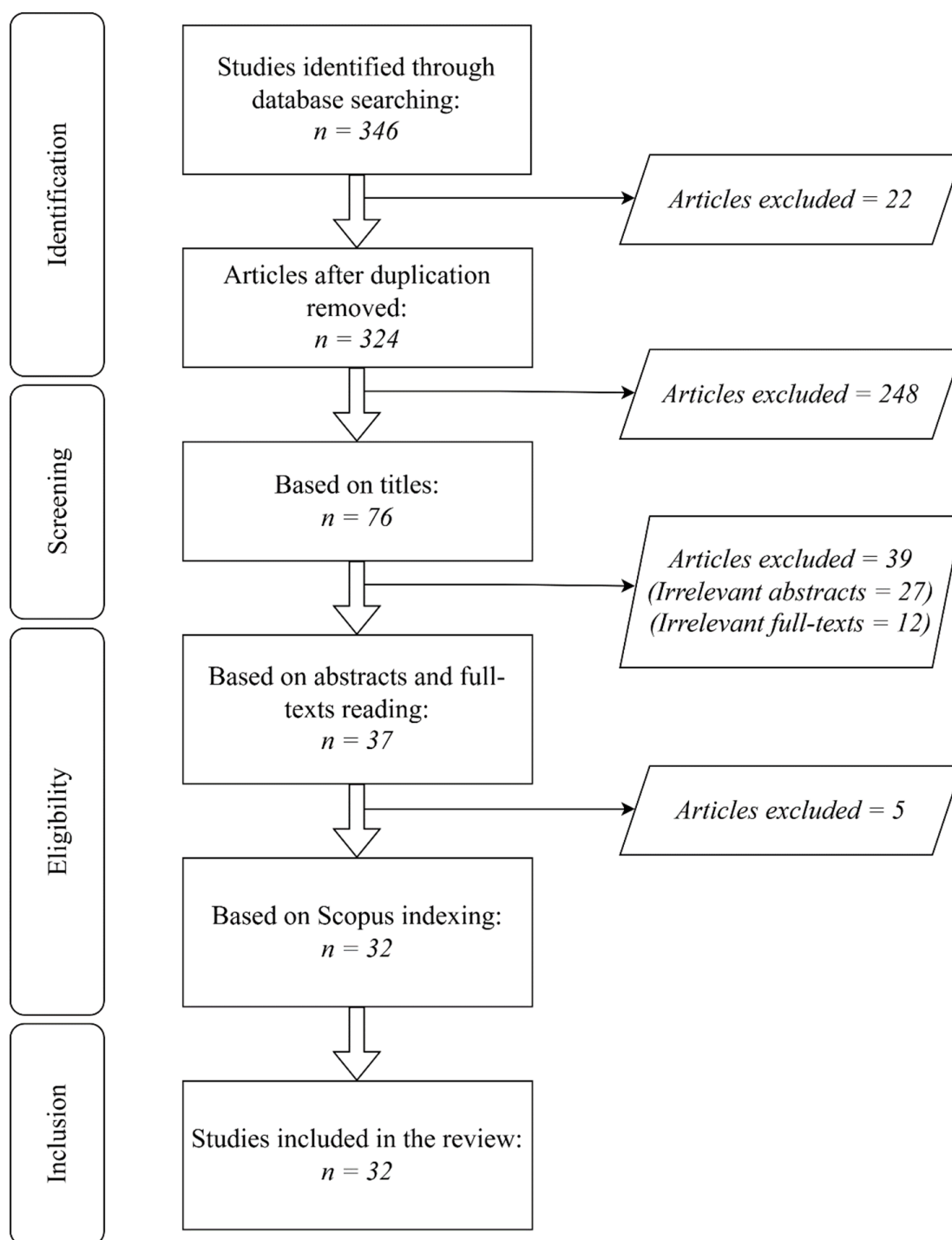


Figure 1. PRISMA methodology flow chart for article selection (authors' own work).

These 32 articles were analyzed in terms of substrate types, coating types, input process variables, output performance variables, performance prediction techniques and optimization methods. In addition, a bibliometric analysis of these studies was conducted to discover the most popular author keywords. The key results were discussed to identify future research directions based on the selected previous studies.

4. Review of Previous Studies

The reviewed studies are summarized in Tables 1–5 based on input process variables, output performance variables, prediction methods, performances of prediction methods

and optimization methods respectively. These studies are arranged in chronological order in these tables so that the connections between input process variables, output performance variables, prediction methods and optimization techniques can be mapped easily.

The reducing agent concentration (NaBH_4), nickel source concentration ($\text{NiCl}_2 \cdot 6\text{H}_2\text{O}$) and bath temperature significantly affected the deposited mass per unit area of electroless Ni-B plating on copper substrates in the study by Oraon et al. [31]. Similarly, Oraon et al. [62] conducted the electroless Ni-B plating using the same type of substrates, input process variables and output performance variable. In contrast, Yating et al. [63] studied a wider variety of input variables spanning bath composition and operating conditions for electroless Ni-P plating. These input variables included complexing agent concentration, stabilizer concentration, bath pH, bath temperature and molar concentration of $\text{Ni}^{2+}/\text{H}_2\text{PO}_2^-$, which were employed to predict the plating rate and phosphorus content (P%). In their study, Ni-P coatings were deposited on copper and carbon steel substrates.

Considering bath loading, metal turnover (MTO) and bath pH as the input process variables, Vaghefi and Vaghefi [64] investigated the phosphorus content of the electroless Ni-P coatings on low-carbon steel specimens as substrates. In 2012, Beygi et al. [42] studied electroless Ni-P plating rate using similar types of input process variables as those examined in previous studies, such as bath temperature, bath pH, main salt concentration ($\text{NiSO}_4 \cdot 2\text{H}_2\text{O}$), reducing agent concentration ($\text{NaH}_2\text{PO}_2 \cdot \text{H}_2\text{O}$) and complexing agent concentration ($\text{Na}_3\text{C}_6\text{H}_5\text{O}_7 \cdot \text{H}_2\text{O}$), while also including the less commonly used input process variable of plating time.

Besides using the bath pH and sodium hypophosphite concentration as the input process variables, Farzaneh et al. [7] also focused on the concentration and types of surfactants, namely sodium dodecyl sulfate (SDS), cetyltrimethylammonium bromide (CTAB) and polyvinylpyrrolidone (PVP). According to Farzaneh et al. [7], the addition of SDS to the bath changed the coating microstructure from crystalline to nano-crystalline/amorphous, thereby increasing the microhardness of the coatings. The cobalt sulfate concentration, sodium hypophosphite concentration and bath temperature were applied as the input process variables by Sarkar et al. [65] and Sarkar et al. [66] in their prediction models.

Among the reviewed studies, different types of prediction methods were applied to capture the intricate relationships between the input and output variables in electroless nickel-based coating. In 2006, Oraon et al. [31] predicted the deposited mass per unit area of electroless Ni-B plating on copper substrates using the Response Surface Methodology (RSM). The data collected using a full factorial design with six additional central points were used to fit a first-order response surface while data gathered using a central composite design (CCD) were utilized to accommodate the second-order response surface. Similarly, Oraon et al. [62] applied the same prediction technique. However, the steepest ascent method was used to approach the optimal region of the response surface after considering a first-order response surface model fitted by a full factorial experimental design. Then, the curvature around the optimal region was analyzed using a second-order response surface model with CCD. The predicting equations from both studies fit the observed data well, with F-values below 10.05 in Fisher's F-test.

Table 1. Input process variables used in previous studies.

Part 1											
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Input Process Variables								
			Bath Chemistry (Main Composition)				Bath Chemistry (Functional Additives)				
			Main Salt ^a Concentration	Reducing Agent ^b Concentration	Molar Concentration Ratio of the Main Salt Cation to the Reducing Agent Anion ^c	Phosphorus Concentration	Complexing Agent ^d Concentration	Stabilizer ^e Concentration	Surfactant ^f Concentration	Surfactant ^f Type	pH Regulator ^g Concentration
[31]	Copper	Ni-B	✓	✓							
[62]	Copper	Ni-B	✓	✓							
[67]	Copper	Ni-B	✓	✓							
[63]	Copper and carbon steel	Ni-P			✓		✓	✓			
[43]	AISI 1040 Mild steel	Ni-B	✓	✓							
[64]	Low-carbon steel	Ni-P									
[42]	Aluminium nanoparticle	Ni-P	✓	✓			✓				
[68]	Copper	Ni-Co-P		✓							
[16]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂	✓	✓							
[69]	6061 Aluminium alloy	Ni-P/nano-SiC				✓			✓		
[70]	Copper	Ni-Co-P		✓							
[71]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂	✓	✓							
[72]	ST 37-DIN 17100 Mild steel	Ni-B					✓				✓
[7]	AISI 1040 Mild steel	Ni-P		✓					✓	✓	
[65]	Copper	Ni-Co-P		✓							
[66]	Copper	Ni-Co-P		✓							
[28]	Cr12MoV Die steel	Ni-P		✓			✓				
[73]	AZ91D	Ni-W-P	✓	✓							
[19]	Magnesium alloy										
	Commercial aluminium alloy	Ni-P-nanoTiO ₂	✓	✓							
[8]	7075-T6 Aluminium alloy	Ni-B	✓	✓				✓			
[74]	7075-T6 Aluminium alloy	Ni-B							✓		
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P	✓	✓							
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂							✓		

Table 1. Cont.

Part 1											
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Input Process Variables								
			Bath Chemistry (Main Composition)				Bath Chemistry (Functional Additives)				
			Main Salt ^a Concentration	Reducing Agent ^b Concentration	Molar Concentration Ratio of the Main Salt Cation to the Reducing Agent Anion ^c	Phosphorus Concentration	Complexing Agent ^d Concentration	Stabilizer ^e Concentration	Surfactant ^f Concentration	Surfactant ^f Type	pH Regulator ^g Concentration
[76]	Copper	Ni-P-CNT	✓	✓							
[29]	Aluminium alloy 7075-T6	Ni-B	✓	✓				✓			
[77]	Aluminium alloy 7075-T6	Ni-B							✓		
[9]	Copper	Ni-W-P	✓	✓							
[18]	Copper	Ni-P	✓	✓							
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂		✓							
[78]	Copper	Ni-Cu-P	✓	✓							
[34]	Copper	Ni-Co-P		✓							
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃							✓		
Total			16	24	1	1	4	3	6	1	1
Part 2											
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Input Process Variables								
			Bath Chemistry (Reinforcement Additives)			Operating Parameters					Post-Treatment Parameter
			Ceramic Nanoparticle ^a Concentration	Carbon Nanotube Concentration	Other Metal Salt ^b Concentration	Bath pH	Bath Temperature	Plating Time	Metal Turnover	Bath Loading	Annealing Temperature
[31]	Copper	Ni-B					✓				
[62]	Copper	Ni-B					✓				
[67]	Copper	Ni-B					✓				
[63]	Copper and carbon steel	Ni-P				✓	✓				
[43]	AISI 1040 Mild steel	Ni-B					✓				✓
[64]	Low-carbon steel	Ni-P				✓			✓	✓	
[42]	Aluminium nanoparticle	Ni-P				✓	✓	✓			

Table 1. Cont.

Part 2											
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Input Process Variables								
			Bath Chemistry (Reinforcement Additives)			Operating Parameters					Post-Treatment Parameter
			Ceramic Nanoparticle ^a Concentration	Carbon Nanotube Concentration	Other Metal Salt ^b Concentration	Bath pH	Bath Temperature	Plating Time	Metal Turnover	Bath Loading	Annealing Temperature
[68]	Copper	Ni-Co-P			✓		✓				
[16]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂	✓								✓
[69]	6061 Aluminium alloy	Ni-P/nano-SiC	✓								
[70]	Copper	Ni-Co-P			✓		✓				
[71]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂	✓								✓
[72]	ST 37-DIN 17100 Mild steel	Ni-B									
[7]	AISI 1040 Mild steel	Ni-P				✓					
[65]	Copper	Ni-Co-P			✓		✓				
[66]	Copper	Ni-Co-P			✓		✓				
[28]	Cr12MoV Die steel	Ni-P				✓	✓				
[73]	AZ91D Magnesium alloy	Ni-W-P			✓	✓	✓				
[19]	Commercial aluminium alloy	Ni-P-nanoTiO ₂	✓				✓	✓			
[8]	7075-T6 Aluminium alloy	Ni-B									
[74]	7075-T6 Aluminium alloy	Ni-B									
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P			✓						
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂	✓			✓	✓				
[76]	Copper	Ni-P-CNT		✓							
[29]	7075-T6 Aluminium alloy	Ni-B									
[77]	7075-T6 Aluminium alloy	Ni-B									
[9]	Copper	Ni-W-P			✓						
[18]	Copper	Ni-P					✓				
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂	✓			✓	✓				

Table 1. Cont.

Part 2											
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Input Process Variables								
			Bath Chemistry (Reinforcement Additives)			Operating Parameters					Post-Treatment Parameter
			Ceramic Nanoparticle ^a Concentration	Carbon Nanotube Concentration	Other Metal Salt ^b Concentration	Bath pH	Bath Temperature	Plating Time	Metal Turnover	Bath Loading	Annealing Temperature
[78]	Copper	Ni-Cu-P			✓						
[34]	Copper	Ni-Co-P			✓		✓				
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃				✓					
Total			6	1	9	9	17	2	1	1	3

Part 1: ^a Main salt could be nickel chloride or nickel sulfate. ^b Reducing agent could be sodium hypophosphite or sodium borohydride. ^c Ratio of the main salt cation to the reducing agent anion could be Ni²⁺/H₂PO₂[−]. ^d Complexing agent could be sodium citrate, lactic acid or ethylenediamine. ^e Stabilizer could be trisodium citrate. ^f Surfactant could be sodium dodecyl sulfate (SDS), cetyltrimethylammonium bromide (CTAB), polyvinylpyrrolidone (PVP) or 3-(N, N-Dimethylmyristylammonio) propanesulfonate (3-DMAPS). ^g pH Regulator could be sodium hydroxide. Part 2: ^a Ceramic nanoparticle could be titanium dioxide (TiO₂) nanoparticle or silicon carbide (SiC) nanoparticle. ^b Other metal salt could be cobalt sulfate heptahydrate, zinc sulfate heptahydrate, sodium tungstate dihydrate or copper sulfate.

Table 2. Output performance variables used in previous studies.

Part 1										
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Output Performance Variables							
			Plating Rate	Phosphorus Content of the Coatings	Aluminium Content of the Coatings	Microhardness of the Coatings	Average Surface Roughness of the Coatings	Weight Percentage of Nickel in the Deposited Mass	Weight Percentage of Cobalt in the Deposited Mass	Wear Depth
[31]	Copper	Ni-B								
[62]	Copper	Ni-B								
[67]	Copper	Ni-B								
[63]	Copper and carbon steel	Ni-P	✓	✓						
[43]	AISI 1040 Mild steel	Ni-B								✓
[64]	Low-carbon steel	Ni-P		✓						
[42]	Aluminium nanoparticle	Ni-P	✓							
[68]	Copper	Ni-Co-P								
[16]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂				✓				
[69]	6061 Aluminium alloy	Ni-P/nano-SiC				✓				
[70]	Copper	Ni-Co-P						✓	✓	
[71]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂								✓
[72]	ST 37-DIN 17100 Mild steel	Ni-B					✓			
[7]	AISI 1040 Mild steel	Ni-P				✓				

Table 2. Cont.

Part 1										
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Output Performance Variables							
			Plating Rate	Phosphorus Content of the Coatings	Aluminium Content of the Coatings	Microhardness of the Coatings	Average Surface Roughness of the Coatings	Weight Percentage of Nickel in the Deposited Mass	Weight Percentage of Cobalt in the Deposited Mass	Wear Depth
[65]	Copper	Ni-Co-P				✓				
[66]	Copper	Ni-Co-P					✓			
[28]	Cr12MoV Die steel	Ni-P		✓						
[73]	AZ91D Magnesium alloy	Ni-W-P								
[19]	Commercial aluminium alloy	Ni-P-nanoTiO ₂				✓				
[8]	7075-T6 Aluminium alloy	Ni-B				✓				
[74]	7075-T6 Aluminium alloy	Ni-B					✓			
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P				✓				
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂				✓				
[76]	Copper	Ni-P-CNT	✓							
[29]	7075-T6 Aluminium alloy	Ni-B					✓			
[77]	7075-T6 Aluminium alloy	Ni-B				✓				
[9]	Copper	Ni-W-P				✓				
[18]	Copper	Ni-P								
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂	✓							
[78]	Copper	Ni-Cu-P					✓			
[34]	Copper	Ni-Co-P								
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃			✓					
Total			4	3	1	10	5	1	1	2
Part 2										
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Output Performance Variables							
			Deposited Mass per Unit Area	Corrosion Rate	Corrosion Resistance	Coating Thickness	Coating Failure Time	Incorporation of Silicon Carbide Nanoparticles	Coefficient of Friction of the Coatings	
[31]	Copper	Ni-B	✓							
[62]	Copper	Ni-B	✓							
[67]	Copper	Ni-B	✓							
[63]	Copper and carbon steel	Ni-P								
[43]	AISI 1040 Mild steel	Ni-B							✓	
[64]	Low-carbon steel	Ni-P								
[42]	Aluminium nanoparticle	Ni-P								
[68]	Copper	Ni-Co-P	✓							

Table 2. Cont.

Part 2									
Ref.	Type of Substrate	Type of Electroless Coating or Plating	Output Performance Variables						
			Deposited Mass per Unit Area	Corrosion Rate	Corrosion Resistance	Coating Thickness	Coating Failure Time	Incorporation of Silicon Carbide Nanoparticles	Coefficient of Friction of the Coatings
[16]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂							
[69]	6061 Aluminium alloy	Ni-P/nano-SiC			✓			✓	
[70]	Copper	Ni-Co-P							
[71]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂							
[72]	ST 37-DIN 17100 Mild steel	Ni-B				✓			
[7]	AISI 1040 Mild steel	Ni-P				✓			
[65]	Copper	Ni-Co-P							
[66]	Copper	Ni-Co-P							
[28]	Cr12MoV Die steel	Ni-P							
[73]	AZ91D Magnesium alloy	Ni-W-P					✓		
[19]	Commercial aluminium alloy	Ni-P-nanoTiO ₂							
[8]	7075-T6 Aluminium alloy	Ni-B							
[74]	7075-T6 Aluminium alloy	Ni-B							
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P							
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂							
[76]	Copper	Ni-P-CNT							
[29]	7075-T6 Aluminium alloy	Ni-B							
[77]	7075-T6 Aluminium alloy	Ni-B							
[9]	Copper	Ni-W-P							
[18]	Copper	Ni-P		✓					
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂							
[78]	Copper	Ni-Cu-P	✓						
[34]	Copper	Ni-Co-P		✓					
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃							
Total			5	2	1	2	1	1	1

Table 3. Prediction methods used in previous studies.

Ref.	Type of Substrate	Type of Electroless Coating or Plating	Prediction Methods						
			Artificial Neural Network (ANN)	Support Vector Machine (SVM)	Random Forest (RF)	Extra Trees (ET)	Taguchi Method	Response Surface Methodology (RSM)	Regression
[31]	Copper	Ni-B						✓	
[62]	Copper	Ni-B						✓	

Table 3. Cont.

Ref.	Type of Substrate	Type of Electroless Coating or Plating	Prediction Methods						Regression
			Artificial Neural Network (ANN)	Support Vector Machine (SVM)	Random Forest (RF)	Extra Trees (ET)	Taguchi Method	Response Surface Methodology (RSM)	
[63]	Copper and carbon steel	Ni-P	✓						
[64]	Low-carbon steel	Ni-P	✓						
[42]	Aluminium nanoparticle	Ni-P	✓						
[68]	Copper	Ni-Co-P						✓	
[69]	6061 Aluminium alloy	Ni-P/nano-SiC						✓	
[70]	Copper	Ni-Co-P						✓	
[72]	ST 37-DIN 17100 Mild steel	Ni-B							✓
[7]	AISI 1040 Mild steel	Ni-P						✓	
[65]	Copper	Ni-Co-P						✓	
[66]	Copper	Ni-Co-P						✓	
[28]	Cr12MoV Die steel	Ni-P	✓						
[73]	AZ91D Magnesium alloy	Ni-W-P						✓	
[19]	Commercial aluminium alloy	Ni-P-nanoTiO ₂	✓	✓	✓	✓		✓	
[8]	7075-T6 Aluminium alloy	Ni-B	✓					✓	
[74]	7075-T6 Aluminium alloy	Ni-B	✓						✓
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P	✓				✓		
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂	✓						
[76]	Copper	Ni-P-CNT						✓	
[29]	7075-T6 Aluminium alloy	Ni-B	✓						
[77]	7075-T6 Aluminium alloy	Ni-B	✓						✓
[9]	Copper	Ni-W-P	✓				✓		
[18]	Copper	Ni-P	✓					✓	
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂	✓						
[78]	Copper	Ni-Cu-P							✓
[34]	Copper	Ni-Co-P						✓	
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃	✓						
Total			15	1	1	1	2	14	4

Table 4. Performances of prediction models in previous studies.

Ref.	Performance
[31]	Estimated F-values < 10.05
[62]	Estimated F-values < 10.05
[63]	-
[64]	Training: root mean squared error (RMSE) = 0.071, maximum deviation = 0.15 Testing: RMSE = 0.074, maximum deviation = 0.18 Prediction probability = 0.79
[42]	ANN model 1: $R^2 = 0.847$ ANN model 2: $R^2 = 0.959$
[68]	Estimated F-values < 10.05
[69]	R^2 (SiC incorporation) = 0.9701 R^2 (Microhardness) = 0.9943 R^2 (Corrosion resistance) = 0.9817
[70]	R^2 (Weight percentage of nickel) = 0.859 R^2 (Weight percentage of cobalt) = 0.789
[72]	R^2 (Thickness) = 0.88 R^2 (Roughness) = 0.92
[7]	90% of total variations can be described
[65]	$R^2 = 0.9992$
[66]	$R^2 = 0.9478$
[28]	Mean squared error (MSE) = 0.0792, mean absolute error (MAE) = 0.2527
[73]	$R^2 = 0.9359$
[19]	ET model: $R^2 = 0.9447$, MSE = 75.384, MAE = 4.6794 RF model: $R^2 = 0.9145$, MSE = 117.1034, MAE = 7.5805 SVM model: $R^2 = 0.8929$, MSE = 182.2841, MAE = 6.337 ANN model: $R^2 = 0.842$, MSE = 210.4337, MAE = 11.8035 RSM model: $R^2 = 0.8539$, MSE = 269.084, MAE = 12.819
[8]	ANN model: $R^2 = 0.9852$, MSE = 34.18 RSM model: $R^2 = 0.9911$, MSE = 20.48
[74]	ANN model: $R^2 = 0.988$, MSE = 5.581×10^{-7} Quadratic regression model: $R^2 = 0.8801$
[17]	ANN model: $R^2 = 0.982$, root mean squared error (RMSE) = 8.84, MSE = 78.28, MAE = 4.88, mean absolute percentage error (MAPE) = 0.99 Taguchi method: $R^2 = 0.875$, RMSE = 23.1, MSE = 534, MAE = 19.42, MAPE = 3.836
[75]	ANN model: $R^2 = 0.959$, MSE = 34.5634, MAE = 4.45
[76]	Estimated F-values < 10.05
[29]	ANN model 1: $R^2 = 0.985$, MSE = 6.29×10^{-4} ANN model 2: $R^2 = 0.9998$, MSE = 6.32×10^{-5}
[77]	ANN model: $R^2 = 0.993$, MSE = 283.4 Quadratic regression model: $R^2 = 0.9876$ Linear regression model: $R^2 = 0.6394$ Exponential regression model: $R^2 = 0.5297$ Logarithmic regression model: $R^2 = 0.3575$ Power regression model: $R^2 = 0.2783$
[9]	ANN model: $R^2 = 0.896$ Taguchi method: $R^2 = 0.7923$
[18]	ANN model: $R^2 = 0.88$ RSM model: $R^2 = 0.87$
[39]	$R^2 = 0.982$, MSE = 0.075
[78]	Multi-linear model: R^2 (deposited mass per unit area) = 0.837 Multi-linear model: R^2 (surface roughness) = 0.71 Multivariate polynomial model: R^2 (deposited mass per unit area) = 0.881 Multivariate polynomial model: R^2 (surface roughness) = 0.9
[34]	$R^2 = 0.9673$
[30]	RMSE = 0.25517

Table 5. Optimization methods used in previous studies.

Ref.	Type of Substrate	Type of Electroless Coating or Plating	Optimization Methods								
			Genetic Algorithm (GA)	Non-Dominant Sorting Genetic Algorithm-II (NSGA-II)	Artificial Bee Colony (ABC)	Firefly Algorithm (FA)	Teaching-Learning-Based Optimization (TLBO)	Simulated Annealing (SA)	Response Surface Methodology (RSM)	Taguchi Method	Full Factorial Design
[31]	Copper	Ni-B									
[62]	Copper	Ni-B							✓		
[67]	Copper	Ni-B							✓		
[63]	Copper and carbon steel	Ni-P									
[43]	AISI 1040 Mild steel	Ni-B								✓	
[64]	Low-carbon steel	Ni-P									
[42]	Aluminium nanoparticle	Ni-P									
[68]	Copper	Ni-Co-P									
[16]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂								✓	
[69]	6061 Aluminium alloy	Ni-P/nano-SiC							✓		
[70]	Copper	Ni-Co-P		✓							
[71]	AISI 1040 Mild steel	Ni-P-nanoTiO ₂								✓	
[72]	ST 37-DIN 17100 Mild steel	Ni-B									✓
[7]	AISI 1040 Mild steel	Ni-P							✓		
[65]	Copper	Ni-Co-P							✓		
[66]	Copper	Ni-Co-P							✓		
[28]	Cr12MoV Die steel	Ni-P							✓		
[73]	AZ91D Magnesium alloy	Ni-W-P							✓		
[19]	Commercial aluminium alloy	Ni-P-nanoTiO ₂							✓		
[8]	7075-T6 Aluminium alloy	Ni-B	✓					✓	✓		
[74]	7075-T6 Aluminium alloy	Ni-B	✓								
[17]	AZ31 Magnesium alloy	Ni-Zn-Cu-P								✓	
[75]	Marine grade AH36 steel	Ni-P-nanoTiO ₂								✓	
[76]	Copper	Ni-P-CNT	✓								
[29]	7075-T6 Aluminium alloy	Ni-B									
[77]	7075-T6 Aluminium alloy	Ni-B	✓								
[9]	Copper	Ni-W-P								✓	
[18]	Copper	Ni-P							✓		
[39]	Low-carbon API X60 grade pipeline steel	Ni-W-P-nanoTiO ₂								✓	
[78]	Copper	Ni-Cu-P		✓							
[34]	Copper	Ni-Co-P			✓	✓	✓		✓		
[30]	GCr15 Steel	Ni-P-Al ₂ O ₃									
Total			4	2	1	1	1	1	11	7	1

Within the experimental range, the incorporation of SiC nanoparticles (%), microhardness (HV) and corrosion resistance ($\Omega \text{ cm}^2$) of the coatings on 6061 aluminium alloy substrates were predicted by Soleimani et al. [69] using RSM. The prediction accuracies of the models for SiC nanoparticle incorporation, microhardness and corrosion resistance of the coatings were $R^2 = 0.9701$, 0.9943 and 0.9817 respectively. A response surface model with CCD was developed by De et al. [70] to predict the weight percentages of nickel and cobalt in the deposited mass. Nevertheless, their prediction models achieved lower prediction accuracies than those reported by Soleimani et al. [69], with R^2 values of 0.859 and 0.789 for the weight percentages of nickel and cobalt respectively. Both studies validated the fitness of their models by using an F-test.

Farzaneh et al. [7] predicted the microhardness and coating thickness of electroless Ni-P plating of mild steel (AISI 1040) substrates using Box–Behnken design (BBD). Sarkar et al. [65] applied BBD as an RSM design to predict the microhardness of the electroless Ni-Co-P coatings on copper substrates. In the same year, Sarkar et al. [66] applied RSM in another study to predict the average surface roughness of electroless Ni-Co-P coatings.

Due to the rapid development of artificial intelligence, machine learning techniques have been utilized to seek more accurate predictions. The prediction of plating rate and phosphorus content (P%) was conducted by Yating et al. [63] using an Artificial Neural Network (ANN). Similarly, Vaghefi and Vaghefi [64] predicted the phosphorus content of the electroless Ni-P coatings with the use of ANN. The same prediction method was utilized by Beygi et al. [42] to predict the electroless Ni-P plating rate. The prediction models from these studies showed good agreement between the observed and predicted values. However, validation was not emphasized in these studies. The predictive performances of machine learning and traditional statistical prediction methods were compared in some previous studies in this field, as shown in Table 4. Vijayanand et al. [74] investigated the predictive performances of Back Propagation Neural Network (BPNN) and quadratic regression. The results demonstrated that the BPNN model attained a higher R^2 of 0.988 and a lower MSE of 5.581×10^{-7} compared to the quadratic regression model ($R^2 = 0.8801$). Shozib et al. [19] reported a lower predictive accuracy for both machine learning and statistical models but assessed a wider range of prediction methods compared to Vijayanand et al. [74]. The Extra Trees model in the study by Shozib et al. [19] exhibited the highest R^2 value of 0.9447 , followed by Random Forest (0.9145), Support Vector Machine (0.8929), Response Surface Methodology (0.8539) and Artificial Neural Network (0.842). These predictive performances are attributed to differences in dataset size and validation strategy, where a smaller dataset of 10 samples was trained, tested and validated by Vijayanand et al. [74] with a 70:15:15 ratio, while a larger dataset of 36 samples was trained and tested by Shozib et al. [19] using a 75:25 ratio. Basically, the machine learning methods applied are black-box models. None of the studies in this field focuses on the interpretability of machine learning prediction methods. A machine learning model that can provide an explicit explanation of the underlying correlations in electroless nickel coating enables more trustworthy decision-making. Further analysis and discussion on this are provided in Section 5.

With respect to optimization, the concentrations (gr/L) of surfactant, phosphorus and SiC nanoparticles in the electroless bath were optimized by Soleimani et al. [69] with the application of BBD to provide the best possible protection for the Ni-P/nano-SiC coating. Farzaneh et al. [7] also used BBD to optimize the microhardness and thickness of the electroless Ni-P coatings. Similarly, Sarkar et al. [65] and Sarkar et al. [66] employed RSM to identify the optimal cobalt sulfate concentration, sodium hypophosphite concentration and bath temperature for optimizing the microhardness and average surface roughness of the coatings respectively. Unlike these RSM-based studies, De et al. [70] utilized a Non-dominant Sorting Genetic Algorithm-II (NSGA-II) to enable concurrent multi-objective optimization

of responses. In their study, NSGA-II was used to obtain the optimal sodium hypophosphite concentration, cobalt sulfate heptahydrate concentration and bath temperature for multi-response maximization in the electroless Ni-Co-P coating of copper substrates.

Some studies, such as those by Das and Sahoo [43] and Gadhari and Sahoo [16], only employed the Taguchi method with an L_{27} orthogonal array, where optimization was conducted using signal-to-noise (S/N) ratio analysis and analysis of variance (ANOVA) to identify significant input variables and their optimal levels. However, these studies often report distinct significant input variables and optimal levels due to variations in experimental settings, response variables and environmental uncertainties. Although Taguchi methods can identify optimal factors under defined experimental conditions, they cannot predict system behavior beyond the tested ranges of the input variables.

5. Analysis and Discussion

This section presents and discusses the results of the studies reviewed in Section 4. A comprehensive analysis was conducted to assess the maturity of performance prediction and optimization methods for electroless nickel-based coating, considering the input process variables and output performance variables.

In Table 1, the input process variables used in the 32 previous studies were reviewed. The reducing agent concentration was the most widely used input process variable among the reviewed studies (24 out of 32), followed by the bath temperature (17 out of 32), main salt concentration (16 out of 32), bath pH (9 out of 32) and other metal salt concentration (9 out of 32). The reducing agent supplies electrons to reduce the metal ions in the electroless bath [8,79]. The reducing agent (sodium hypophosphite or sodium borohydride) is selected based on the type of electroless coating needed (Ni-P or Ni-B) [80]. It has been the most extensively studied input variable in predictive modeling of electroless nickel coatings, as small variations in reducing agent concentration can induce substantial changes in the deposition rate and coating microstructure. However, the reported relationships between input and output variables differed among the reviewed studies due to differences in bath compositions, experimental conditions and the variables monitored or varied.

Bath temperature triggers the reaction process that regulates ionization in the bath solution and the transfer of charges from source to substrate [31]. One way to control energy for deposition is through adjusting the bath temperature [22]. Nickel chloride or nickel sulfate can be used as a metal salt (ion source) in an electroless nickel solution [81]. The bath pH can be controlled using ammonia, ammonium chloride or sodium hydroxide [42]. The pH, as an accelerator, can reduce grain size to improve the coating's morphology [7]. Other additional metal salts in the bath such as cobalt sulfate heptahydrate, zinc sulfate heptahydrate and sodium tungstate dihydrate are important to enhance the surface coating's performance. All of the input process variables studied were quantitative variables except for the surfactant type studied by Farzaneh et al. [7].

As can be seen from Table 2, the microhardness of the coatings shows the highest count of 10 studies among all the reviewed output performance variables. Microhardness refers to the hardness of individual microstructure constituents [82]. The coating's microhardness will be considerably higher than that of the substrate as wear protection [65]. Its broad application in predictive modeling reflects its role as a direct indicator of wear resistance and mechanical strength, which are important in determining the performance of electroless nickel coatings. Moreover, it is easy to measure and highly sensitive to process variations of electroless nickel coating, allowing prediction models to evaluate coating performance effectively. The following widely used output performance variables were the average surface roughness and deposited mass per unit area of the coatings, each applied by five studies. The uneven surface texture formed by valleys and peaks is referred to as surface roughness [83]. Surface

roughness is significantly affected by the thickness of the coatings [84]. A low average surface roughness enhances the wear resistance of electroless nickel coatings [85].

An inspection of the data in Table 3 reveals that ANN was the most common prediction method applied in previous studies (15 studies). ANN is an artificial intelligence technique that simulates the biological processes in a human brain [86]. ANN can learn from input–output interactions in training data [19]. In contrast to traditional pattern analysis, it can handle non-linear and multi-dimensional problems [63]. The BPNN, a widely used algorithm in ANN [87], is made up of an input layer, one or more hidden layers and an output layer [88]. The number of neurons in the input and output layers can be specified by the number of input and output variables, while the number of hidden layers and the number of neurons in these hidden layers depend on the particular problem being addressed [89].

The ANN datasets can be organized into three sets: training, validation and testing [74]. The training dataset can adjust the errors and network weights for each iteration, the validation dataset involves the modification of the network architecture (training function, activation function and number of hidden layers), as well as regulating the number of neurons in the hidden layers, and the testing dataset assesses the efficiency and effectiveness of the trained network [42].

A total of 14 studies employed the RSM prediction method, indicating its popularity after ANN. Sarkar et al. [65] suggested that Box–Behnken design (BBD), as an RSM design, needed three levels to perform an experiment. The independent factor levels could be divided into low (−1), medium (0) and high (+1). It assists in establishing optimal process parameters. The Design Expert v25.0 software can be used to conduct experimental runs and generate a second-order quadratic equation to calculate the output performance variable [66].

Central composite design (CCD) was another widely used RSM [19] for prediction in electroless nickel-based coating. CCD can be divided into three parts: (i) a full or fractional factorial design with factor levels coded to low (−1) and high (+1) values; (ii) axial points located on each variable's axis at a distance from the designed center; and (iii) center points that can be reproduced for predicting the experimental error variance. Just like BBD, CCD could be used to develop a second-order response surface model [70].

It is apparent from Table 3 that very few studies (1 study) applied Support Vector Machine (SVM), Random Forest (RF) and Extra Trees (ET), owing to the limited recognition of these methods in the electroless plating field. Similarly, the infrequent application of the regression method (four studies) such as quadratic regression or non-linear regression, and the Taguchi approach (two studies) highlights that these methods have not received much attention in existing studies. ANN, SVM, RF and ET were categorized as machine learning prediction methods while the Taguchi method, RSM and regression were known as traditional statistical prediction methods.

Statistical models have relatively simple structures in explaining how a model's prediction is done. Experimental design such as CCD or BBD in RSM can reduce the volume of experiments [90]. However, the levels, factors and experimental designs are required to be defined beforehand in RSM [91], as in a Taguchi application [92]. The Taguchi method may oversimplify real-world complexity by assuming independent behavior for each factor [93,94]. In contrast, machine learning models can learn directly from raw and unstructured datasets [95] without the need for pre-set levels and data points. In addition, regression such as quadratic regression or non-linear regression requires a predefined functional form, assuming the relationship between inputs and outputs can be explained by the fixed function [96]. Machine learning prediction methods do not rely on predefined equations as some of them use data to generate prediction equations.

The Taguchi method and RSM were also utilized as statistical-based optimization approaches in previous studies. These two methods could inherently perform prediction and

optimization without the need for other optimization algorithms. They can identify the optimal values of input variables by examining multiple input variables at a time, making the explanation of a complex process effective [39,67]. However, likewise, experiments need to be conducted based on certain pre-determined data points before optimization can be done [9].

From the data in Table 5, it can be seen that RSM was the most popular optimization method among all the reviewed approaches (11 out of 32). The Taguchi method, Genetic Algorithm (GA) and Non-dominant Sorting Genetic Algorithm-II (NSGA-II) were used in seven studies, four studies and two studies, respectively, for optimizing the input variables. GA is known as an optimization technique that applies probabilistic search based on population [97,98]. Its working principle follows the natural selection and natural genetics theories in Darwin's principle [76]. Only one reviewed study suggested the use of a full factorial design. Likewise, Artificial Bee Colony (ABC), Firefly Algorithm (FA), Teaching–Learning–Based Optimization (TLBO) and Simulated Annealing (SA) were each applied in only one study. These metaheuristics help to obtain the optimal or near-optimal solutions [99,100] within a reasonable amount of computational time [101]. It should be noted that some studies such as those by Yating et al. [63], Vaghefi and Vaghefi [64], Beygi et al. [42] and Vijayanand et al. [29] performed prediction only in electroless nickel-based coating, leaving the optimization of variables unaddressed.

Figure 2 demonstrates a network visualization map from VOSviewer (version 1.6.20), showing author keywords applied in the reviewed studies. The map shows that the two most popular author keywords among the reviewed studies were “artificial neural network” and “response surface methodology”. This proves that ANN and RSM have been widely employed in the previous studies. Interestingly, Particle Swarm Optimization (PSO) was shown alongside “bp neural network” in the map. To date, PSO as a metaheuristic was utilized by Zou et al. [28] to optimize their ANN structure only, and it has not been used to optimize the input process variables of electroless nickel-based coating. This is because ANN is incapable of generating a mathematical model to elucidate the relationship between the input and output variables. Hence, having such a mathematical model is crucial so that PSO can be used to optimize the input process variables.

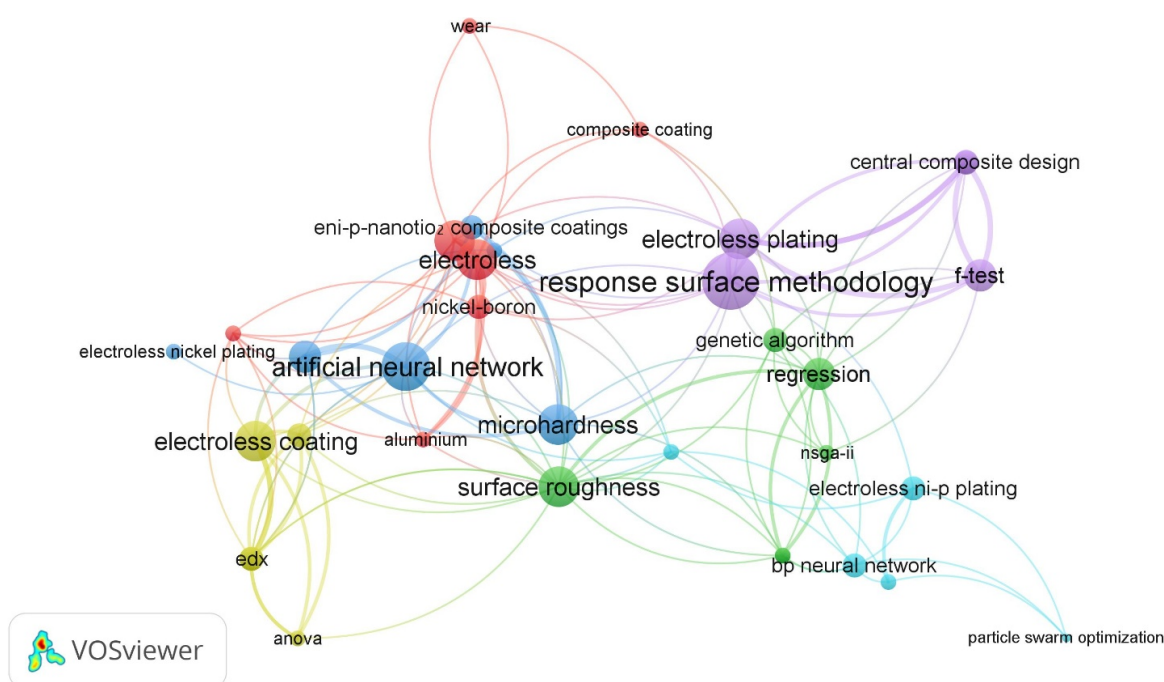


Figure 2. Network visualization map for author keywords used in the reviewed studies (authors' own work).

6. Future Research Directions

Several future research directions are proposed in this section based on the review, analysis and discussion conducted in the previous sections.

As mentioned earlier in Section 5, the Taguchi method and RSM need pre-set conditions and regression requires a predefined functional form for response prediction in electroless nickel-based coating. They were applied in many studies due to their simplicity in structure [102] and the small sample size condition [103]. The calculation process of a statistically defined model is easy to understand and straightforward [104]. However, to predict high-dimensional [105] and unstructured data [106] for future events, machine learning prediction methods will be better than these traditional statistical prediction methods. The patterns from input data can be learned to predict the outcomes [75] without requiring any pre-set data points, levels or experiments. Therefore, the research area can be broadened with the use of machine learning techniques, leading to better improvement in future research.

Based on all the reviewed studies, most of them used ANN to predict the performance of electroless nickel-based coating. However, the applications of ANN are found to have some shortcomings, which may be improved in future research. ANN itself could not perform input variables optimization. Similar to ANN, the SVM, RF and ET that were applied in the reviewed studies only provide a prediction role because they lack the capability to optimize the input process variables. Hence, many previous studies that used ANN in electroless nickel-based coating have stopped at the prediction phase without proceeding to the optimization stage. Optimization is crucial to obtain the optimal values of the input process variables in order to achieve the desired values of the output performance variables. It is highly recommended that future research in electroless nickel-based coating covers both prediction and optimization, and a better method that supports both of these tasks can be used.

Many researchers overlooked the fact that ANN, SVM, RF and ET prediction models are black-box approaches, whereas the Taguchi method, RSM and regression are recognized as white-box approaches. The application of black-box prediction models often results in opaque decision-making, and this lack of transparency makes it difficult for users to detect errors [107,108]. SVM and ANN are considered black-box machine learning prediction approaches due to the complex operations in SVM and multiple transformations of input data in ANN, which are difficult for machine learning specialists and experts to understand [109]. These approaches do not provide an explicit mathematical model that links the input variables to the output variables. An RF model lacks interpretability and clear model expression to show the relationship between the input and output variables [110]. As a result, errors and biases are hard to be identified and resolved [111]. Similar to RF, the output of ET is difficult to interpret due to its opaque internal structure [112,113]. Thus, it is important to assess the applications of other white-box prediction methods such as Genetic Programming (GP) in the electroless nickel plating field. GP is an evolutionary prediction technique [114] that can tackle the deficiencies of black-box prediction models [115] and is suitable for small-to-medium datasets. Moreover, white-box machine learning methods are recommended for complex, non-linear and high-dimensional problems owing to their ability to achieve higher precision and robustness than white-box statistical methods [116]. Table 6 shows the comparison of black-box and white-box prediction approaches used in previous studies.

As shown in Table 7, 30 out of 32 reviewed studies involved multiple input process variables. However, only seven reviewed studies predicted more than one output performance variable of electroless nickel-based coating. A model's capability to determine the optimal relevant links between inputs and outputs improves by increasing the number of

input variables because adding more characteristics to the model improves its ability to understand the underlying phenomena for the targeted responses [117]. Multi-output prediction models ensure a better representation and interpretability of real-world problems by considering the underlying relationships between features and targets, leading to more comprehensive, holistic and realistic prediction than single-output models [118]. To create a more useful prediction model for electroless nickel-based coating in the surface coating industry, multi-input and multi-output-based prediction models could be developed in the future. Furthermore, future research can explore hybrid physics-informed machine learning methods that integrate physical laws into learning architectures to improve model robustness, interpretability, generalization and transferability while reducing data dependence, particularly under noisy or limited data conditions [119]. It is also beneficial to create standardized benchmark datasets that incorporate diverse input and output variables to enable the objective evaluation and cross-validation of prediction models for electroless nickel-based coating.

Table 6. Comparison of black-box and white-box prediction approaches.

No.	Prediction Methods	Black-Box	White-Box
1.	ANN	✓	
2.	SVM	✓	
3.	RF	✓	
4.	ET	✓	
5.	RSM		✓
6.	Regression		✓
7.	Taguchi method		✓

Table 7. The number of input process variables and output performance variables used in previous studies.

No.	Ref.	Number of Input Process Variables Used	Number of Output Performance Variables Used
1.	[31]	3	1
2.	[62]	3	1
3.	[67]	3	1
4.	[63]	5	2
5.	[43]	4	2
6.	[64]	3	1
7.	[42]	6	1
8.	[68]	3	1
9.	[16]	4	1
10.	[69]	3	3
11.	[70]	3	2
12.	[71]	4	1
13.	[72]	2	2
14.	[7]	4	2
15.	[65]	3	1
16.	[66]	3	1
17.	[28]	4	1
18.	[73]	5	1
19.	[19]	5	1
20.	[8]	3	1
21.	[74]	1	1
22.	[17]	3	1
23.	[75]	4	1
24.	[76]	3	1

Table 7. *Cont.*

No.	Ref.	Number of Input Process Variables Used	Number of Output Performance Variables Used
25.	[29]	3	1
26.	[77]	1	1
27.	[9]	3	1
28.	[18]	3	1
29.	[39]	4	1
30.	[78]	3	2
31.	[34]	3	1
32.	[30]	2	1

7. Implications

This unique study exhibits several practical implications. It provides practitioners with insights to understand the strengths and weaknesses of the performance prediction and optimization techniques applied. This could guide industrial managers in selecting a suitable method to predict and optimize the performance of electroless nickel-based coating of substrates. Manufacturers in electroless coating industries can obtain insights to improve the quality of their products by using the best resource settings and parameter values to optimize coating surface performance. This leads to more sustainable production with reduced waste and defects over time.

In addition, this study has presented a thorough review and analysis of the prediction and optimization methods used in the electroless nickel-based coating field. This enables researchers to identify their research objectives and future research directions by addressing the research gaps in the reviewed studies. These efforts could further improve the application of prediction and optimization techniques in electroless coating industries. Moreover, this study highlighted the limitations of the performance prediction and optimization methods that were overlooked in the previous studies. Researchers could leverage the results of this study to develop or apply new prediction and optimization methods for electroless nickel-based coating.

8. Conclusions

Electroless nickel-based coating of substrates has not been properly reviewed in a study that concurrently discusses the input process variables, output performance variables, performance prediction approaches and optimization methods. Hence, the objectives of this study are to review the literature on performance prediction and optimization of electroless nickel-based coating of substrates, evaluate the previous studies from various aspects as mentioned earlier in Section 1 and recommend future research directions that offer valuable insights for improvement.

The three common input process variables used among all the reviewed studies were the reducing agent concentration (24 studies), bath temperature (17 studies) and main salt concentration (16 studies). Microhardness of the coatings was the most widely used output performance variable (10 out of 32), followed by average surface roughness (5 out of 32) and deposited mass per unit area of the coatings (5 out of 32). Previous studies mostly utilized the ANN black-box approach to predict the performance of electroless nickel-based coating. Some of these reviewed studies applied additional optimization techniques while some of them did not conduct any optimization. RSM, the most widely used optimization technique, was applied in 11 of the 32 studies, while the Taguchi method was adopted for optimization in seven of the reviewed studies. However, the Taguchi method and RSM require pre-set data points, levels and experimental designs, resulting in disadvan-

tages compared to machine learning-based prediction approaches and metaheuristic-based optimization approaches.

This study has presented a comprehensive review of the existing literature on performance prediction and optimization for electroless nickel-based coatings on substrates. Practitioners could gain insights on the strengths and weaknesses of the performance prediction and optimization techniques applied. This study serves as a guide for industrial managers to select suitable prediction and optimization methods and helps researchers to establish their research objectives and future research directions in this subject area. It is recommended that future review studies could explore other non-nickel-based types of coating such as copper coating, since this study primarily focused on nickel-based coating. Moreover, researchers may draw insights from this study and conduct new reviews in other fields or processes.

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