Tanzania Journal of Engineering and Technology 2025, **44**(1):153-168
Websites: https://ajol.org/tjet; https://tjet.udsm.ac.tz
ISSN 1821-536X (**print**); ISSN 2619-8789 (**electronic**)
https://doi.org/10.52339/tjet.v44i1.1050

*Regular Research Manuscript*


# Developing Predictive Mathematical Model for Optimizing Coating Weight Variation in Galvalume Production: A Case Study of a Metal Industry

**Christopher Abila Moris and Victoria Mahabi**†

Mechanical and Industrial Engineering Department, College of Engineering and Technology, University of Dar es Salaam, P.O. Box 35131, Dar es Salaam, Tanzania

†Corresponding Author: mahabi@udsm.ac.tz; ORCID: 0000-0002-0719-7411


**ABSTRACT**

*Variations in coating weight for galvanized steel sheets can result in notable differences between batches. Such variations may cause various issues, such as diminished corrosion resistance, lower mechanical strength, and visual defects, which can ultimately drive up costs, lead to customer dissatisfaction, and pose safety risks. Even with attempts to manage elements like air knife pressure and line speed, coating weight inconsistencies remain challenging. The research focuses on developing a predictive mathematical model designed to optimize variations in coating weight during Galvalume production. The critical parameters influencing coating weight variation were identified and analysed using a systematic literature review, primary data collection and process observation. The findings reveal that substrate thickness, air knife pressure, line speed, bath composition, bath temperature, nozzle-to-strip distance and immersion time significantly affect coating weight. By applying regression analysis and optimization techniques such as Response Surface Methodology (RSM), the study provides a comprehensive understanding and practical solutions for achieving consistent coating weights. As a result, a model that integrates these factors was developed to forecast coating weight, and the predictive model can be used by industry practitioners to optimize production processes, reduce material wastage and ensure high-quality outputs in hot dip galvanization operations.*


ARTICLE INFO

Submitted: **Aug. 31, 2024**

Revised: **Feb. 10, 2025**

Accepted: **Feb. 11, 2025**

Published: **Apr. 2025**

**Keywords:** Coating Weight Variation, Predictive Mathematical Model, Hot Dip Galvanization, Process Optimization, Galvalume Production


## INTRODUCTION

The characteristics of steel such as strength, toughness, ductility, easy manufacture, good formability, weldability, availability, ferromagnetic properties, recyclability and low cost make it widely used in different engineering applications. In order to utilizing these beneficial characteristics of steel, the protection against corrosion is usually required. Corrosion protection methods employed to protect steel include altering the metal by alloying, changing the environment by lowering its humidity or using inhibitors, controlling electrochemical potential by applying cathodic and anodic currents and applying organic and metallic coatings. The most popular steel protection method is metallic coatings with a continuous hot dip process.

This method involves continuously feeding the steel sheet through a bath of molten coating metal. The molten coating metal can be zinc only or 55% Al – Zn (Coni *et al*., 2009; James & Taifa, 2023).
Zinc-only coatings generally provide good corrosion resistance; however, their effectiveness can diminish in aggressive environments, such as those containing carbonates and chlorides (Elewa et al., 2019). However, a 55% Al - Zn alloy coated steel sheet, also known as Galvalume developed with an organic composite coating, helps prevent surface crack and corrosion. The organic composite coatings instinctively form a protective film that inhibits the steel's triggered corrosion mechanism under severe conditions such as acidic rain or the presence of dissolved salts (Elewa et al., 2019). The coating combines the durability of aluminium, and galvanic protection of zinc, resulting in a product that exhibits excellent corrosion resistance in marine and industrial environments, high-temperature oxidation resistance, heat reflectivity of the aluminium coatings and a pleasant and distinctive appearance. The chemical composition of the coating is 55% aluminium, 43.5% zinc and 1.5% silicon (Coni et al., 2009).
Among the common problems that can arise during the galvanization process, impacting the quality and consistency of the galvanized coating on steel sheets, is inconsistent coating weight, which can occur due to fluctuations in temperature, immersion time, or line speed as a results section of the sheet can be under- or over-galvanized (Verma et al., 2022). The problem of inconsistent coating weight in galvanized steel sheets can lead to significant batch-to-batch variations in order to check compliance with standards. The coating weight is usually measured after the production process. Also, these variations can lead to several problems, including compromised corrosion resistance, reduced mechanical strength and aesthetic defects, which can result in increased costs, customer dissatisfaction and potential safety hazards. Despite efforts to control factors such as air knife pressure and line speed, inconsistencies in coating weight persist. Therefore, it is essential to investigate and understand the production process of Galvalume steel sheets in order to solve the problem of inconsistency in coating weight. The study sought to address three major questions, and the first is, what factors affect coating weight variation in the hot-dip galvanization process? Secondly, how can the coating weight outcomes be predicted using mathematical model? lastly, what are the optimal setting for process parameters that minimizes coating weight variation in the hot-dip galvanization process?

## Production Process of Galvalume Steel Sheet

The manufacturing of Galvalume steel sheets, as shown in

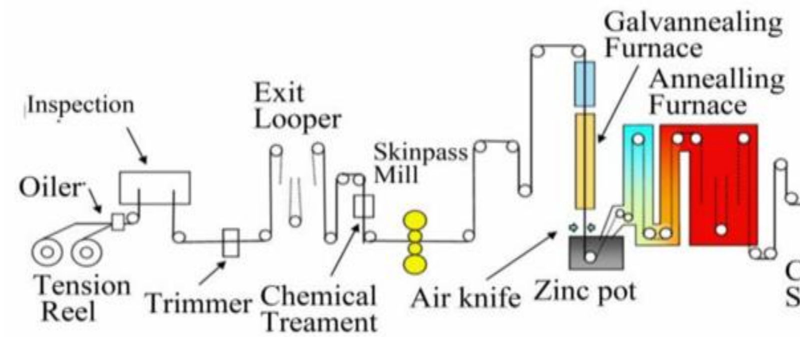


Figure **1**, involves a continuous hot-dip coating process, where molten aluminum-zinc is uniformly applied to the surface of the steel substrate. The steel, with thickness ranging between 0.12mm and 0.55mm and width up to 1830 mm, is passed through a bath of molten Al – Zn at speeds of about 600 feet per minute in the form of a continuous ribbon.
The process starts with welding the ends of sheared steel sheets to create a continuous strip. This strip is then straightened using a high-performance tension leveller to achieve excellent flatness. The steel is subsequently cleaned with an alkaline solution, rinsed, and dried. The cleaned

steel is then conveyed into the heating furnace to make it softer and impart formability and desired strength. The heating furnace operates in a low gas atmosphere composed of nitrogen and hydrogen to remove any oxide traces from the steel surface. A vacuum chamber, known as the 'Snout,' is connected to the furnace exit and to the molten aluminium-zinc (Al-Zn) coating bath to prevent re-oxidation of the heated steel by air. In the Al-Zn coating bath, the steel is conveyed around a submerged roll, allowing it to react with the molten mixture of 55% aluminium, 43.5% zinc, and 1.5% silicon. The coated steel is then withdrawn vertically from the bath. Excess molten Al-Zn is removed with an air knife (high-pressure air) to achieve a precisely controlled coating thickness. Finally, the steel is then cooled to solidify the Al-Zn coating on its surface. Proper solidification before contact with any other rolls is crucial to avoid damage or deformation of the coating. After solidification, the coated steel sheet undergoes chemical treatments tailored to its intended use, including phosphate treatment for enhanced paintability and a chrome-free special treatment for improved corrosion resistance (Xiong et al., 2022).

## Effect of Coating Weight Variation

Paints can be categorised into oil- and water-based (Gambi & Taifa, 2023). It is important to determine the effect of coating weight variation. The thickness of the coating is proportional to the coating weight. Hence, coating weight should be optimized by effectively monitoring the coating thickness. The degradation-resisting ability of galvanized steel sheets is a function of the coating thickness. The thicker galvanized coatings provide enhanced durability. For example, for any environmental condition, G90 coating will last longer than a G60, where G represent galvanized coating when factors such as painting, maintenance, and all are equal (Elewa et al., 2019). Despite the higher coating thickness of galvanized steel to provide better protection against corrosion, if it exceeds the required standard range, it can reduce the formability of the steel sheet. Therefore, it is necessary to control the coating thickness variation to the required standard range to achieve effective corrosion resistance and other steel sheet application examples in automotive applications (Gorain et al., 2012). The AL – ZN coating weight/mass can be measured in g/m$^2$ or microns, by the following methods: measuring stripped off from the steel substrate using a measuring gauge, weighing before and after galvanizing, magnetic thickness gauge and x-ray spectrometric method (Tanzania Bureau of Standards (TBS), 2017). The knife gap, knife gap pressure, and line speed are variables that affect the coating weight and thickness. Hence, to meet the standard requirement, the weight control should be applied at the knife strip, which must be between the upper and lower limit at any point on the strip (Elewa et al., 2019).

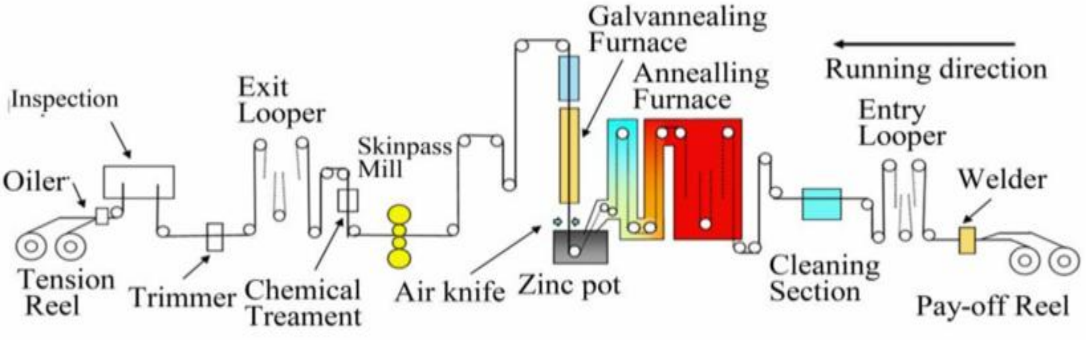


**Figure 1: Hot dip Continuous galvanizing line source (Xiong et al., 2022)**

## Factors affecting coating weight variation

Achieving precise and uniform coating weight (CW) is crucial in hot-dip galvanization. Both sides of the galvanized strip must receive a coating of specified weight, maintaining consistency both longitudinally and transversely. However, ensuring this consistency poses significant challenges due to the complex interactions among various factors affecting coating weight (Elewa et al., 2019). While primary operational variables such as strip speed, knife-to-strip distance, and air gas pressure are directly controllable, and their effects on coating weight are well understood, many other influencing factors are beyond the control of both the control system and the operator, impacting the weight and distribution of the zinc coating as it is applied to the strip (Deote et al., 2012).

Sumitomo (2018) has argued that the significance of the air knife in influencing the quality (beautiful surface appearance and uniform coating weight) has raised the demand for its enhancement. However, challenges such as edge splash and edge over coating hinder improvement efforts (Takeishi & Morino, 2000). An ordinary air knife discharges air flow even to areas with no steel strip, so the jets from the top and bottom side collide, disturbing the flow near the strip edge (Ahn & Chung, 2006). This turbulence results in zinc splash and operational instability. The introduction of edge baffle plates helps mitigate collisions, but the narrow clearance introduces complications, particularly during abrupt bends in the steel strip (So et al., 2011). In response to these operational stability concerns, the NSblade air knife has been developed to effectively address these issues and improve overall performance during high-speed operations

Adetunji (2015) has evaluated the effect of withdrawal speed on the overall quality of hot dip galvanized steel sheets. The results showed that linking withdrawal speed to steel sheet thickness has been shown to improve the quality of galvanized steel sheet products concerning their thickness. For this study the overall quality steel sheet galvanized at 450 ℃ for 1 minute immersion time was the best at withdrawal speeds of 3m/min, 4m/min and 5m/min for gauges 18,22 and 28, respectively (Yadav, 2021). However, the results obtained showed varying quality parameters for different thicknesses.

The research by Deote et al. (2012) demonstrates that factors such as line speed, jet pressure, nozzle-to-strip distance, zinc bath temperature and strip temperature consistently appear as critical factors affecting coating weight. These variables directly impact zinc flow and interaction with the steel substrate, ultimately determining the final coating thickness. Variations in these parameters can lead to uneven coating distribution and potential performance issues. Deote et al. (2012) observed that factors like jet height above the bath, bath composition, steel sheet thickness and roughness contribute less directly to coating weight, and cannot be entirely ignored. These uncontrollable factors can introduce complexities in coating weight control strategies. For example, variation in bath composition can affect zinc fluidity and surface tension, while steel sheet roughness can influence zinc adhesion. Including these factors in the controlling strategy often requires intricate analysis and data integration.

## Optimization and Mathematical model to predict coating weight

Unanticipated outcomes during galvanization pose significant financial and quality challenges for steel manufacturers. However, predicting steel's mechanical properties before or during the process offers substantial benefits. This predictive capability can provide operators with critical insights, allowing them to enhance product quality through early adjustments, minimize waste by reducing over-coating and scrap production, and decrease reprocessing costs by identifying potential issues before the final stages. Additionally, the ability to forecast steel properties enables better process control, optimizes resource utilization, and results in superior products at a lower cost, benefiting both the company and its customers (Garza, 2019).

Elsaadawy et al. (2007) developed an analytical model for predicting coating weight in the continuous hot-dip galvanizing process, particularly during the air knife wiping stage. This model enhances prediction accuracy by incorporating improved correlations for pressure and shear stress distributions within the air jet, based on a combined approach of experimental measurements and computational fluid dynamics (CFD) simulations. Compared to existing models, the innovative model offers significantly more precise predictions of coating weight, especially in the critical low Z/d region (knife-to-strip distance). Validation against industrial coil average coating weight data shows excellent agreement, particularly at lower coating weights (up to 75 g/m²), with a maximum deviation of 8%. However, studies have shown that linear models are somewhat limited when applied to complex situations (Ghoreishi et al., 2007; Marschik et al., 2020).

Design of Experiments (DOE) has been used to analyze the factors influencing zinc coating thickness in hot-dip galvanizing (HDG), focusing on variables such as dipping time (the duration the steel is immersed in the zinc bath), the nickel content in the zinc bath, and the silicon content in the steel. The analysis indicates that dipping time and nickel concentration are the most critical factors for controlling coating thickness. Also, results show that a zinc bath with 0.05% nickel and a dipping time of 3 minutes produced a thinner coating, potentially reducing zinc usage and costs while accommodating various silicon levels. These findings both support and differ from previous research, suggesting areas for future exploration (Verma et al., 2022).

Wang (2018) conducted a study on factors affecting zinc layer thickness; various optimization techniques were utilized, including Response Surface Methodology (RSM), the Taguchi method (Deshpande et al., 2021), and Genetic Algorithm (GA). RSM developed a robust model to analyze the complex interactions between air knife parameters and speed, while the Taguchi method highlighted air pressure as a crucial factor for stability and air knife range as the main determinant of average coating thickness. By integrating these findings, the Genetic Algorithm provided predictions for optimal settings to achieve target coating thickness. This multi-faceted approach enhanced both the precision of the coating process and the understanding of variable interactions, demonstrating the effectiveness of GA in achieving desired specifications.

Al-rubaiey et. al (2015) did a study on protecting steel poles from rusting using different coating thickness and soil type parameters. Regression analysis was used to create a model which explored the relationship between coating thickness and soil conditions. The findings indicated that thicker coatings slowed down rusting up to a certain point. However, going too thick caused tiny cracks, making the coating weaker. Predicting the thickness of the aluminium and zinc coating on steel during the galvanization process can be as challenging, and without a predictive model, operators are left to guess, which can lead to the waste of aluminium and zinc and result in uneven coating thicknesses (Mao et al., 2020). There is a clear need for a mathematical model that allows operators to make real-time adjustments, consistently achieve the desired coating thickness, and optimize resource usage for perfect galvanization.

## MATERIALS AND METHODS

### Research Design

The study employed a mixed-methods research design, concentrating on data collection and statistical analysis to develop a predictive model. The approach was selected to quantify the factors influencing coating weight variation systematically and to construct a mathematical predictive model based on statistical evidence.

## Data Collection Methods

### *Document review*

A document review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The review aimed at identifying key factors influencing coating weight variation and effective modelling techniques. This involved searching academic databases such as Google Scholar, ScienceDirect and Taylor and Francis Online using a comprehensive search string combining terms related to hot dip galvanization, coating weight variation, predictive modelling and process optimization. The search terms were combined using Boolean operators (such as AND, OR, NOT) to create a comprehensive search string. (Hot-dip galvanization OR HDG OR Galvalume production line) AND (coating weight variation) AND (predictive modelling OR mathematical modelling) AND (optimal settings for process parameters). The review included articles published in English within the past 10 years (2014-2024), Focusing on the hot dip galvanization process, factors affecting coating weight, predictive modelling techniques and optimization of process parameters. It excluded those studies published in languages other than English, studies with limited focus on coating weight variation and Conference proceedings, editorials or opinion pieces.

### *Document Analysis and Process Observation*

Data collection from the Galvalume production line was achieved through document analysis and direct observation of the production process. This method included examining detailed production records and observing the process to identify factors influencing coating weight variation. Additionally, the factors highlighted in the systematic literature review were thoroughly recorded.
A total of 60 data sets were collected from the metal industry, representing a comprehensive sample of the production line's operations. The sample size of 60 data points was chosen based on several important considerations. First, it was necessary to ensure sufficient statistical power to detect significant relationships between variables. Second, the sample needed to be representative of the production line's operations over one month to provide an accurate reflection of typical performance. Lastly, the sample size balanced the need for comprehensive data with practical constraints related to data collection and analysis, ensuring that the study could be conducted efficiently while yielding meaningful results.

## Data analysis techniques

Descriptive statistics were first employed to summarize the collected data, offering a clear overview of key factors and their distributions. This included calculating measures such as the mean, standard deviation, and range for continuous variables and frequency distributions for categorical variables. Following this, multiple regression analysis was conducted using Minitab Statistical Software to develop a predictive mathematical model for coating weight outcomes. This analysis aimed to identify the model that provided the best predictive accuracy. Once the optimal model was established, Response Surface Methodology (RSM) was utilized to refine the results further. RSM involves advanced optimization techniques to determine the most effective settings of the input variables to achieve the desired coating weight response

The study was based on several assumptions to facilitate the research design, data collection and analysis method. To start, it was essential to assume that the data collected from the Galvalume production line was consistent and reliable, with minimal discrepancies in the production records and process observations. Also, the systematic literature review was assumed to have comprehensively covered all relevant and recent studies within the specified inclusion criteria, providing a representative overview of the factors influencing coating weight variation and effective modelling techniques. Finally, the Minitab version 17 statistical software used for data analysis was assumed to be reliable and capable of handling the dataset effectively, providing accurate outputs for the regression analysis and response surface methodology (RSM).

## RESULTS AND DISCUSSION

Firstly, the study identified the factors affecting coating weight variation through the document review. The initial search identified a total of 53,221 articles across different databases and using multiple keywords, as suggested by Athuman et al. (2024) and Pamba and Taifa (2024) (refer to

Table **1**). A subsequent screening process, detailed in Figure 2, resulted in 30 articles being chosen for final analysis.

**Table 1: Number of studies found in selected digital libraries (databases) after a general term search**

| S/N | Term Search | Google Scholar | ScienceDirect | Taylor and Francis online | Total |
|---|---|---|---|---|---|
| 1 | Hot-dip galvanization process (HDG) | 1430 | 247 | 27 | 1704 |
| 2 | Key factors in Hot-dip galvanization | 16700 | 822 | 196 | 17718 |
| 3 | Coating weight variation | 16400 | 580 | 12 | 16992 |
| 4 | Predictive mathematical modelling | 2120 | 206 | 30 | 2356 |
| 5 | Optimal settings for process parameters | 14200 | 174 | 77 | 14451 |
| | Total | 50850 | 2029 | 342 | 53221 |

The review identified several key factors influencing coating weight variation in the Hot dip galvanization process. One of the factors is substrate characteristics, which includes the thickness, surface roughness, and chemical composition (e.g., silicon (Si), manganese (Mn)) of the substrate, which can significantly impact coating weight(Pokorny et al., 2016; Liu et al., 2024 and Elewa and Afolalu, 2019). Also, process parameters such as line speed, bath temperature, immersion time, air knife pressure, and nozzle-to-strip distance are crucial parameters affecting coating weight (Guelton, 2017; Shukla et al., 2017; Lekbir, 2017; Verma, Sharma, & Badar, 2022; Romero & Alabazares, Lara, 2014) and Bakhtiari, 2014). Furthermore, the review highlighted bath chemistry, the zinc bath's composition playing a role in coating weight control and formation (Bondareva et al., 2014; Rose et al., 2021). Additionally, it was observed that operational factors such as Shift changes (day/night) can introduce variations due to potential differences in operator practices (Parmar et al., 2022).

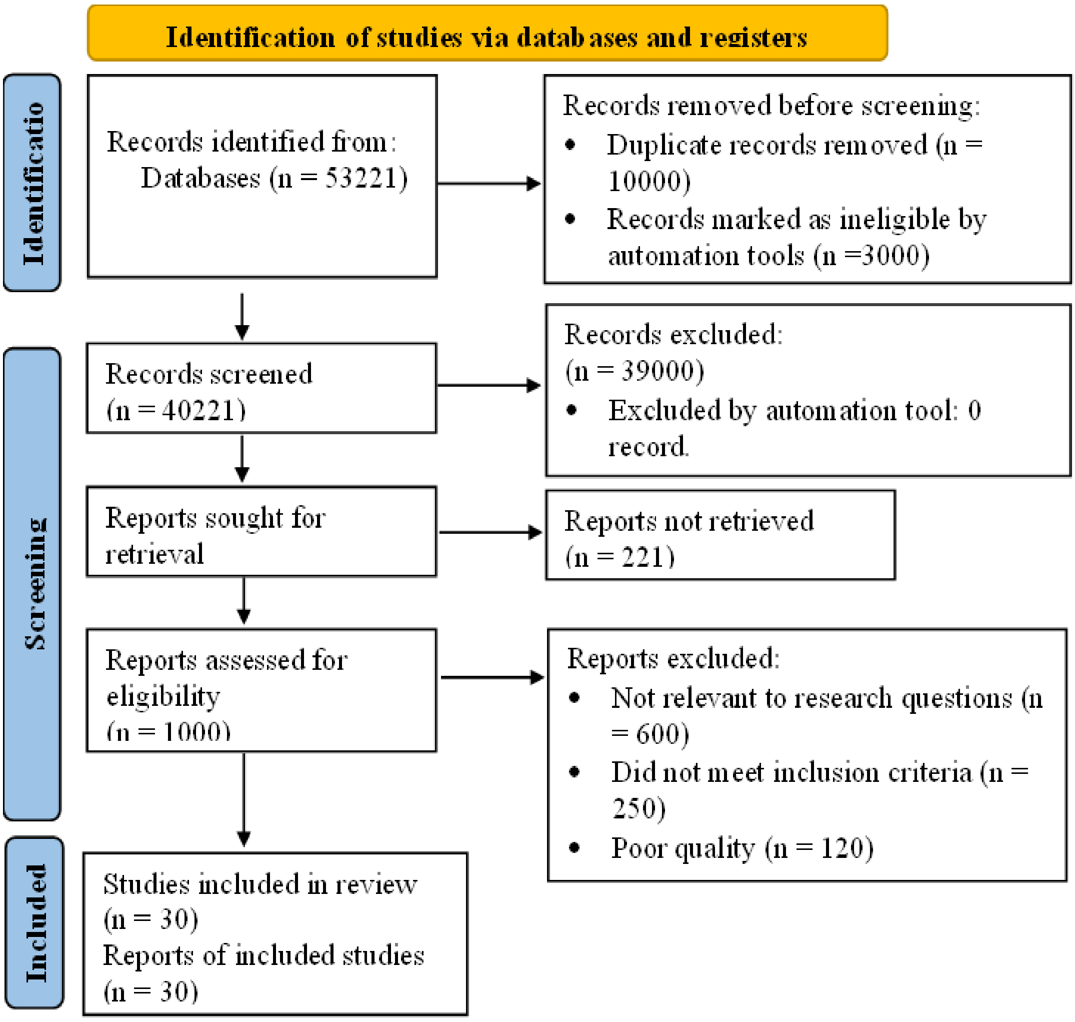


**Figure 2: PRISMA 2020 flow diagram for systematic reviews.**

## Predictive Modelling Techniques

A document review identified various techniques for predicting coating weight in hot dip galvanization (HDG). These techniques include Multiple linear regression (MLR), which establishes linear relationships between coating weight and process parameters (Cheddadi, 2017). Also, Verma et al. (2022) and (Oktavina, 2023) utilized Taguchi Method to optimize the hot dip galvanization process. Artificial Neural Networks (ANNs) were also employed to capture complex non-linear relationships (Shukla et al., 2017; Reséndiz-Flores et al., 2021; César García, 2020; and Fiorilla, 2022). Response Surface Methodology (RSM) was also used to optimize process parameters for achieving the desired coating weight. Soft computing techniques like fuzzy logic were explored in some studies to handle uncertainties and improve prediction accuracy (Mousavifard et al., 2019).

## Development of a Predictive Mathematical Model for Coating Weight

### Descriptive Analysis

Descriptive statistics were employed to summarize the data from the metal industry's Galvalume production line, offering a comprehensive overview of key factors and their distributions. This analysis, conducted using Minitab version

17 Statistical Software, is detailed in Table 2. It includes measures of the mean, standard deviation, range, and frequency distributions for continuous and categorical variables.

**Table 2: Descriptive statistics analysis for the metal industry's Galvalume production line**

| Variable | Shift | N | S1 | S2 | S3 | S4 | S5 | S5 | S6 | S7 |
|---|---|---|---|---|---|---|---|---|---|---|
| Coating Weight(g/m2) | Day | 30 | 69.8 | 1.24 | 6.77 | 56 | 65.75 | 69 | 74 | 87 |
| | Night | 30 | 69.63 | 1.06 | 5.82 | 57 | 66.75 | 69 | 72.25 | 85 |
| Substrate Thickness (mm) | Day | 30 | 0.2307 | 0.00849 | 0.0465 | 0.175 | 0.18 | 0.2245 | 0.288 | 0.295 |
| | Night | 30 | 0.2304 | 0.00873 | 0.0478 | 0.172 | 0.18 | 0.221 | 0.29 | 0.296 |
| Air Knife Pressure (bar) | Day | 30 | 1.1457 | 0.0513 | 0.2811 | 0.69 | 0.798 | 1.3 | 1.355 | 1.48 |
| | Night | 30 | 1.0847 | 0.0528 | 0.2892 | 0.71 | 0.77 | 1.26 | 1.35 | 1.45 |
| Line Speed (MPM) | Day | 30 | 125.3 | 2.23 | 12.19 | 106 | 117.5 | 122 | 138 | 150 |
| | Night | 30 | 124.43 | 1.77 | 9.7 | 110 | 117.5 | 121 | 130.5 | 147 |
| Bath Temperature (°C) | Day | 30 | 617.87 | 0.425 | 2.33 | 614 | 616 | 618 | 620 | 622 |
| | Night | 30 | 618.03 | 0.466 | 2.55 | 612 | 617 | 618 | 620 | 622 |
| Bath Composition (wt% Al) | Day | 30 | 55.097 | 0.0415 | 0.227 | 54.77 | 54.89 | 55.085 | 55.31 | 55.52 |
| | Night | 30 | 55.101 | 0.0411 | 0.225 | 54.78 | 54.91 | 55.065 | 55.31 | 55.54 |
| Nozzle to Strip distance (mm) | Day | 30 | 141.17 | 6.26 | 34.29 | 79 | 104.8 | 149 | 170.3 | 190 |
| | Night | 30 | 144.23 | 5.81 | 31.8 | 82 | 116.5 | 150 | 173 | 189 |
| Immersion Time (seconds) | Day | 30 | 8.927 | 0.154 | 0.844 | 7.63 | 8.18 | 8.975 | 9.775 | 10 |
| | Night | 30 | 8.81 | 0.129 | 0.707 | 7.79 | 8.223 | 8.665 | 9.435 | 10 |

**Notes:** S1 = Mean, S2 = Standard Error Mean, S3 = StDev Minimum, S4 = First Quartile (Q1), S5 = Median, S6 = Third Quartile (Q3), S7 = Maximum

## Multiple regression analysis

Several techniques can be applied to develop a mathematical model predicting the coating weight. Examples of such techniques include Response Surface Methodology (RSM), the Taguchi method (Deshpande et al., 2021), and the Genetic Algorithm (GA). Likewise, regression analysis is one of the recommended techniques as it can enable the quantification of the association between coating parameters such as pressure, temperature and spray angle together with the metal coating properties (Setiawan & Santosa, 2021). Therefore, this research deployed the multiple regression model to develop the optimized model for coating weight variation in Galvalume production.

The predictive mathematical model for the coating weight outcomes in a metal industry's galvalume production line was developed using regression analysis using Minitab version 17 Statistical Software. The response variables were the coating weight ($g/m^2$), and the predictors include substrate thickness (mm), Air knife pressure (bar), line speed (MPM), Bath temperature (°C), Bath composition (wt% Al), Nozzle to Strip distance (mm), immersion time (seconds) and shift (Day/Night).

## Evaluating Multiple Regression Models

By starting with the best subsets, regression was created; this included Coating Weight versus Substrate Thickness (mm), Air Knife Pressure (bar), Line Speed (MPM), Bath Temperature (°C), Bath Composition (wt% Al), Nozzle to Strip distance (mm), Immersion Time (seconds). **Error! Reference source not found.** provides alternatives for the selection of the best model. The aim was to determine the model that provides a good fit for better predicting coating weight outcomes. The last row (row number 7) was identified to fit the model well.

Give the value of R-sq (adj) that is 83.3 and the value of R-sq (pred) that is 79.5. This gives the difference between R-sq (adj) and R-sq (pred) of is 3.8, which low, indicating a small drop-off. A large drop-off indicates overfitting and too many variables in the model. The mallow Cp is 8, which is close to the number of predictors plus 1, indicating a good sign, and the standard error is relatively low, suggesting a good fit for the data. When looking at Mallow Cp. If Mallow Cp is greater than a number of predictors, indicating the model might have too many predictors, leading to overfitting; conversely, the lower Cp, indicating the model may be underfitting, suggesting too simple and does not capture the underlying pattern of data.

Equations (1) and (2) represent the regression model, indicating the dependent variable (Y) against the independent variables ($X_1$ to $X_9$).

Table **4** further explains the significance of the regression model coefficients.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \varepsilon \qquad (1)$$

Where, $X_1$ to $X_9$ = Substrate Thickness (mm), Air Knife Pressure (bar), Line Speed (MPM), Bath Temperature (°C), Bath Composition (wt% Al), Nozzle to Strip distance (mm), Immersion Time (seconds), Shift Day and Shift Night.

$$Y = -686 - 31.3X_1 + 0.36X_2 + 0.2120X_3 + 0.368X_4 + 9.30X_5 - 0.0123X_6 - 0.199X_7 + 0.0X_8 - 0.050\,X_9 + \varepsilon \qquad (2)$$

**Table 3: Response is Coating Weight (g/m$^2$)**

| Vars | R-sq | R-Sq (adj) | R-Sq (pred) | Mallows Cp | S | P1 | P2 | P3 | P4 | P5 | P6 | P7 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 78.4 | 78.0 | 76.3 | 20.5 | 2.9356 | | | X | | | | |
| 2 | 77.5 | 77.1 | 75.3 | 23.6 | 2.9942 | | | | | X | | |
| 3 | 83.3 | 82.7 | 81.1 | 5.0 | 2.6011 | | | X | | X | | |
| 4 | 81.5 | 80.9 | 79.1 | 11.3 | 2.7358 | | | X | | | X | |
| 5 | 84.6 | 83.8 | 81.9 | 2.3 | 2.5182 | X | | X | | X | | |
| 6 | 84.3 | 83.5 | 81.2 | 3.4 | 2.5422 | | X | X | | X | | |
| 7 | 85.2 | 84.1 | 82.0 | 2.3 | 2.4935 | X | | X | X | X | | |
| 8 | 84.7 | 83.6 | 81.2 | 4.2 | 2.5378 | X | X | X | | X | | |
| 9 | 85.3 | 83.9 | 81.2 | 4.1 | 2.5109 | X | | X | X | X | X | |
| 10 | 85.2 | 83.9 | 81.4 | 4.3 | 2.5151 | X | | X | X | X | | X |
| 11 | 85.3 | 83.6 | 80.6 | 6.0 | 2.5329 | X | | X | X | X | X | X |
| 12 | 85.3 | 83.6 | 80.2 | 6.1 | 2.5341 | X | X | X | X | X | X | |
| 13 | 85.3 | 83.3 | 79.5 | 8.0 | 2.5565 | X | X | X | X | X | X | X |

**Note(s):** P1 = Substrate Thickness (mm), P2 = Air Knife Pressure (bar), P3 = Line Speed (MPM), P4 = Bath Temperature (°C), P5 = Bath Composition (wt% Al), P6 = Nozzle to Strip distance (mm) and P7 = Immersion Time (seconds)

**Table 4: Description of the regression model coefficients**

| Predictor | Coefficient | P-Value | VIF Variance Inflation Factor | Interpretation |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| Substrate Thickness (mm) | -31.3 | 0.094 | 6.51 | Not statistically significant, negative relationship<br>High VIF (6.51) suggests some multicollinearity but not severe |
| Air Knife Pressure (bar) | 0.36 | 0.883 | 4.18 | Not statistically significant, minimal effect<br>The VIF (4.18) shows moderate collinearity |
| Line Speed (MPM) | 0.2120 | 0.004 | 5.14 | Statistically significant, positive relationship.<br>The VIF (5.14) suggests moderate collinearity. |
| Bath Temperature (℃) | 0.368 | 0.163 | 3.51 | Not statistically significant, positive relationship.<br>The VIF (3.51) is low, indicating minimal collinearity |
| Bath Composition (wt% Al) | 9.30 | 0.070 | 11.22 | Marginally significant, positive effect.<br>The high VIF (11.22) indicates a serious multicollinearity |
| Nozzle to Strip distance (mm) | -0.0123 | 0.643 | 6.62 | Not statistically significant.<br>The VIF (6.62) indicates moderate collinearity. |
| Immersion Time (seconds) | -0.199 | 0.784 | 2.77 | Not statistically significant.<br>The VIF (2.77) indicates low collinearity. |
| Shift (Night) | -0.050 | 0.943 | 1.08 | Not statistically significant, no impact.<br>The VIF (1.08) is very low, indicating no collinearity. |

Table 5 depicts the model summary, providing key statistics indicating the regression model's overall fit. The Standard Deviation of Residuals (S) is 2.58130, reflecting the average deviation of observed values from the regression line. While a lower value would indicate a better fit, this value suggests a moderate level of unexplained variability. The R-squared ($R^2$) value of 85.30% demonstrates that the predictors explain a substantial portion of the variance in coating weight, indicating a good model fit. The Adjusted R-squared ($R^2$(adj)) value of 83.00% accounts for the number of predictors, offering a more precise measure of model performance. Its slightly lower value than $R^2$ suggests that some predictors may contribute less significantly to the model. The Predicted R-squared ($R^2$(pred)) value of 78.80% shows how well the model predicts new data. Its proximity to the Adjusted $R^2$ suggests the model generalizes well to new data.

**Table 5: Model Summary**

| S | R-sq | R-sq(adj) | R-sq(pred) |
|---|---|---|---|
| 2.58130 | 85.30% | 83.00% | 78.80% |

Also, line speed (MPM) was found to be statistically significant, indicating a positive relationship with the coating weight. Also, bath composition (wt% Al) was marginally significant, suggesting a positive effect. Other predictors, such as substrate thickness, air knife pressure, bath temperature, nozzle-to-strip distance, immersion time, and shift (night), were not statistically significant individually. However, they still contribute to the model's accuracy due to potential interactions and real-world complexities. Therefore, further analysis was conducted to determine optimal process parameters that minimize coating weight variation, considering the combined effect of all factors within the developed model.

## Optimal settings for process parameters

After developing the regression model to predict coating weight, the study focused on finding the optimal process parameters to minimize variation within the 75 to 100 g/m² target range. To achieve this, Response Surface Methodology (RSM) was used. RSM is a statistical technique that employs designed experiments to optimize outcomes by examining the relationships between multiple input variables and the desired output. Through RSM, the study aimed to identify the specific combinations of process parameters that achieve the target coating weight while accounting for potential interactions among the variables. The optimal settings for the process parameters to achieve the target coating weight are shown in

Table **6**.

**Table 6: Optimal setting for the process parameters**

| Response Coating Weight ($g/m^2$) | VARIABLE SETTING | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Substrate Thickness (mm) | Air Knife Pressure (bar) | Line Speed (MPM) | Bath Temperature (°C) | Bath Composition (wt% Al) | Nozzle to Strip distance (mm) | Immersion Time (seconds) | Shift (Day/Night) |
| 75 | 0.295 | 1.48 | 106 | 612 | 55.53 | 129.82 | 10 | D/N |
| 76 | 0.296 | 0.79 | 150 | 612 | 54.77 | 190 | 8 | D/N |
| 77 | 0.296 | 0.76 | 150 | 612 | 54.77 | 190 | 8 | D/N |
| 78 | 0.295 | 1.48 | 106 | 612 | 55.53 | 121.88 | 10 | D/N |
| 79 | 0.234 | 1.09 | 128 | 617 | 55.16 | 115.8 | 8 | D/N |
| 80 | 0.173 | 0.70 | 149.7 | 612.4 | 55.06 | 190 | 8 | D/N |
| 81 | 0.234 | 1.09 | 128 | 617 | 55.16 | 134.5 | 10 | D/N |
| 82 | 0.296 | 0.69 | 149.9 | 622 | 55.54 | 190 | 10 | D/N |
| 83 | 0.295 | 1.48 | 106 | 612 | 55.53 | 109.3 | 10 | D/N |
| 84 | 0.234 | 1.09 | 128 | 617 | 55.16 | 144.7 | 10 | D/N |
| 85 | 0.295 | 1.48 | 106 | 612 | 55.53 | 104.4 | 10 | D/N |
| 86 | 0.294 | 1.46 | 106.6 | 621.8 | 55.51 | 79 | 10 | D/N |
| 87 | 0.234 | 1.09 | 128 | 617 | 55.16 | 168.2 | 10 | D/N |
| 88 | 0.234 | 1.09 | 128 | 617 | 55.16 | 174.6 | 10 | D/N |
| 89 | 0.234 | 1.09 | 128 | 617 | 55.16 | 180.6 | 10 | D/N |
| 90 | 0.234 | 1.09 | 128 | 617 | 55.16 | 186.2 | 10 | D/N |
| 91 | 0.234 | 1.09 | 128 | 617 | 55.18 | 190 | 10 | D/N |
| 92 | 0.234 | 1.09 | 142.8 | 622 | 54.77 | 190 | 10 | D/N |
| 93 | 0.234 | 1.09 | 143.7 | 622 | 54.77 | 190 | 10 | D/N |
| 94 | 0.234 | 1.09 | 144.5 | 622 | 54.77 | 190 | 10 | D/N |
| 95 | 0.234 | 1.09 | 145.3 | 622 | 54.77 | 190 | 10 | D/N |
| 96 | 0.234 | 1.09 | 146.2 | 622 | 54.77 | 190 | 10 | D/N |
| 97 | 0.234 | 1.09 | 147.0 | 622 | 54.77 | 190 | 10 | D/N |
| 98 | 0.234 | 1.09 | 147.8 | 622 | 54.77 | 190 | 10 | D/N |
| 99 | 0.234 | 1.09 | 148.7 | 622 | 54.77 | 190 | 10 | D/N |
| 100 | 0.234 | 1.09 | 149.5 | 622 | 54.77 | 190 | 10 | D/N |

The optimal settings represent the parameter combinations that minimize coating weight variation while achieving the desired target range. It is important to note that these settings are based on the data utilized in this study. Further validation under varying production conditions is recommended to ensure these results' robustness.

## CONCLUSION AND RECOMMENDATION

The study aimed to investigate the factors influencing coating weight variation in the Galvalume production process and to develop a predictive model for coating weight outcomes. A thorough analysis combined a systematic literature review with empirical data. The study identified several key factors affecting coating weight, including substrate characteristics (such as thickness, surface roughness, and chemical composition), process parameters (like line speed, bath temperature, immersion time, air knife pressure, and nozzle-to-strip distance), bath chemistry, and operational conditions. A regression model was developed, highlighting line speed and bath composition as significant predictors of coating weight. However, the model's explanatory power underscores the inherent complexity of the process. Using the multiple regression model, the study determined the optimal process parameters to minimize coating weight variation within the desired range. These findings lay the groundwork for enhancing the Galvalume production process and improving overall process efficiency.

## Recommendation

Based on the study's findings, several recommendations are proposed to optimize coating weight variation in the Galvalume production line. First, the plant should implement the developed predictive model to control significant parameters statistically, ensure consistent coating weights, reduce material waste, and enhance product quality. Regular monitoring and adjusting process parameters, in line with the model's recommendations, are crucial to maintaining optimal conditions and minimizing variations. Additionally, investing in training for technical staff on the use of the predictive model and the importance of maintaining optimal process parameters will help ensure effective implementation and management. Lastly, future research should consider integrating advanced techniques such as Artificial Neural Networks (ANNs) and fuzzy logic to further enhance the model's predictive capabilities, addressing complex relationships and uncertainties in the production process.

## Implications for practice

Implementing the developed predictive model for the Galvalume production line can significantly enhance operational efficiency. The production line can achieve more consistent coating weights by systematically controlling key parameters such as line speed, air knife pressure, bath temperature, bath composition, nozzle-to-strip distance, and immersion time. This approach reduces material waste and improves product quality. Transitioning from a trial-and-error method to a data-driven strategy marks a substantial advancement in process optimization.

## Limitations and Future Research

Despite the valuable insights gained, this study recognizes several limitations. The analysis was based on a sample size of 60 data points, which, while adequate for the current statistical methods, may not fully capture the variability inherent in the production process. Future research could benefit from larger datasets and the consideration of additional uncontrollable factors, such as environmental conditions and raw material variations. Exploring advanced modelling techniques, such as Artificial Neural Networks (ANNs) and integrating soft computing methods, could further enhance the model's predictive accuracy.

In summary, the study offers a preliminary understanding of controlling coating weight variation in hot dip galvanization processes. The developed predictive model is a basic practical tool for optimizing production parameters, leading to improved operational efficiency and product quality. Future research should aim to refine these models and investigate new methodologies to address the complexities of industrial production environments.

## REFERENCES

Adetunji, O. (2010). Optimizing Hot Dip Galvanizing Operations of Steel Sheets for better Quality. *Journal of Natural Sciences, Engineering and Technology*, ***9***(2), 99–105.

Ahn, K. J., & Chung, M. K. (2006). A noble gas wiping system to prevent the edge overcoating in continuous hot-dip galvanizing. *ISIJ International*, **46**(4), 573–578. doi:10.2355/isijinternational.46.573

Athuman, A. H., Mahabi, V., & Taifa, I. W. R. (2024). Conceptualising Management Practices for Mapping Mobile Phone Waste Through Scientometric, Bibliometric and Visual Analytic Tools. In C. Machado & J. P. Davim (Eds.), *Management for Digital Transformation* (pp. 183–211). Springer International Publishing, Springer, Cham. doi:10.1007/978-3-031-42060-3

Bakhtiari, A., Toroghinejad, M. R., & Ashrafizadeh, F. (2014). The Effect of Zinc Bath Temperature on The Morphology, Texture and Corrosion Behaviour of Industrially Produced Hot-Dip Galvanized Coatings. *Metallurgical and Materials Engineering*, **20**(1), 41–52.

Bondareva, O. S., Melnikov, A. A., & Amosov, A. P. (2014). Influence of Hot-Dip Galvanizing Temperature on Formation of Zinc Coating on a Steel with a High Silicon Content. *Advances in Environmental Biology*,**8**(June), 943–948.

César García, M. M. P. and J. D. (2020). *Prediction of Mechanical Properties for High Strength Low Alloyed Steels in a Commercial Hot Dip Galvanizing Line without Soaking Section*. *Metals*. 2020;**10**(5):561.doi:10.3390/met10050561

Cheddadi, B. I. and A. (2017). *Principal Component Regression Model Optimization of Steel in An Annealing Heating Furnace on Hot-Dip Galvanizing Line*. *2017*. https://cmm2017.sciencesconf.org/124950/paper_CHDL_EMI_MS.pdf

Coni, N., Gipiela, M. L., D'Oliveira, A. S. C. M., & Marcondes, P. V. P. (2009). *Study of the Mechanical Properties of the Hot Dip Galvanized Steel and Galvalume*. **31**(4), 319–326.

Deote, A. P., Gupta, M. M., & Zanwar, P. D. R. (2012). Process Parameter Optimization for Zinc Coating Weight Control in Continuous Galvanizing Line. In *International Journal of Scientific & Engineering Research* **3**(11), pp. 1–6).

Deshpande, V. A., Taifa, I. W. R., & Deresse, N. C. (2021). Deployment of the Taguchi technique for surface roughness optimisation. *International Journal of Industrial and Systems Engineering*, **39**(1), 1–30. doi:10.1504/ijise.2020.10028682

Elewa, Afolalu, F. (2019). *Overview Production Process And Properties Of Galvanized Roofing Sheets* . doi:10.1088/1742-6596/1378/2/022069

Elewa, R. E., Afolalu, S. A., & Fayomi, O. S. I. (2019). Overview Production Process and Properties of Galvanized Roofing Sheets. *Journal of Physics: Conference Series*, **1378**(2). doi:10.1088/1742-6596/1378/2/022069

Elsaadawy, E., Aramco, S., Mcdermid, J. R., Hrymak, A. N., & Forbes, J. F. (2007). *Coating Weight Model for the Continuous Hot-Dip Galvanizing Process Coating Weight Model for the Continuous Hot-Dip Galvanizing Process*. *November 2014*. doi:10.1007/s11663-007-9037-2

Fiorilla, S. (2022). *A Deep Learning Model for Controlling the Galvanizing Process in A Production Line*. [University of Bologna]. https://amslaurea.unibo.it/id/eprint/26923/1/thesis.pdf

Gambi, C. P., & Taifa, I. W. R. (2023). A Mathematical Algorithm Approach for Estimating Water-Based Paint Requirements for a Given Wall Costance. *Tanzania Journal of Engineering and Technology*, **42**(1), 213–227.

Garza, D. V. (2019). *Defect detection with predictive models in the galvanizing process*. [Instituto Tecnológico y de Estudios Superiores de Monterrey]. https://hdl.handle.net/11285/645037

Ghoreishi, S. R., Messager, T., Cartraud, P., & Davies, P. (2007). Validity and limitations of linear analytical models for steel wire strands under axial loading, using a 3D FE model. *International Journal of Mechanical Sciences*, **49**(11), 1251–1261. doi:10.1016/j.ijmecsci.2007.03.014

Gorain, N., Steel, T., Ganapathy, M., & Steel,

T. (2012). Effect of Coating on Formability of Steel Sheets. *International Deep Drawing Research Group (IDDRG) Conference*, *October*, 492–500.

Guelton, N., Lopès, C. & Sordini, H. (2017).Cross Coating Weight Control by Electromagnetic Strip Stabilization at the Continuous Galvanizing Line of ArcelorMittal Florange. *Metall Mater Trans B* **47**, 2666–2680 (2017). doi:10.1007/s11663-016-0672-3

James, J. M., & Taifa, I. W. R. (2023). Quality improvement of long oil alkyd (LOA) resin requirements in the formulation of Hi-gloss paints. *International Journal of Quality and Reliability Management*, **40**(7), 1753–1776. doi:10.1108/IJQRM-08-2022-0247

Lekbir, C. (2017). Effect of Immersion Time and Cooling Mode on the Electrochemical Behavior of Hot-Dip Galvanized Steel in Sulfuric Acid Medium. *Journal of Materials Engineering and Performance* **26**, 2502–2511 doi:10.1007/s11665-017-2696-5

Liu, Q., Cao, Y., Chen, S., Xu, X., Yao, M., Fang, J., & Lei, K. (2024). Hot-Dip Galvanizing Process and the Influence of Metallic Elements on Composite Coatings. *Journal of Composites Science*, **8**(5), doi:10.3390/jcs8050160

Mao, K., Yang, Y. L., Huang, Z., & Yang, D. Y. (2020). Coating Thickness Modeling and Prediction for Hot-dip Galvanized Steel Strip Based on GA-BP Neural Network. *Proceedings of the 32nd Chinese Control and Decision Conference*, *CCDC 2020*, 3484–3489. doi:10.1109/CCDC49329.2020.9164854

Marschik, C., Roland, W., Löw-Baselli, B., & Steinbichler, G. (2020). Application of hybrid modeling in polymer processing. *SPE ANTEC 2020*.

Neha Verma, Vinay Sharma, M.Affan Badar, N. C. (2022). Optimization of Zinc Coating Thickness by Unreplicated Factorial Design of Optimization of Zinc Coating Thickness by Unreplicated Factorial Design of Experiments in Hot Dip Galvanization Process. *International Journal of Precision Engineering and Manufacturing*, *December*. doi:10.1007/s12541-022-00695-2

Neha Verma, V. S. and M. A. B. (2022). Improving Sigma Level of Galvanization Process by Zinc Over-Coating Reduction Using an Integrated Six Sigma and Design-of-Experiments Improving Sigma Level of Galvanization Process by Zinc Over-Coating Reduction Using an Integrated Six Sigma and Design-of. *Arabian Journal for Science and Engineering*, **47**(7), 8535–8549. doi:10.1007/s13369-021-06341-9

Oktavina, R. (2023). Optimizing The Hot-dip Galvanizing Process Of Angle Bar Steel Product According To ISO 1461 Standard Using The Taguchi Method. *Proceedings of the International Conference on Industrial Engineering and Operations Management Manila*, *Philippines*, *March 7-9*, 2023 679–689.

Pamba, A. G., & Taifa, I. W. R. (2024). Mapping and Conceptualising on Eco-Innovation Practices Environmental Performance. In C. Machado & J. P. Davim (Eds.), *Smart Engineering Management. Management and Industrial Engineering*. Springer, Cham. doi:10.1007/978-3-031-52990-0_5

Parmar, J., Sharma, D. K., Khyati, P., & Sweta, P. (2022). *A Review on Galvanizing Coating Defects : Causes and Remedies*. ***34***(4), 535–542.

Pokorny, P., Kolisko, J., Balik, L., & Novak, P. (2016). *Effect Of Chemical Composition of Steel on The Structure of Hot – Dip Galvanized Coating*. Metalurgija **55**(1), 115–118.

Reséndiz-Flores, E. O., Altamirano-guerrero, G., Costa, P. S., Salas-reyes, A. E., Salinas--Rodríguez, A., & Goodwin, F. (2021). *Neural Networks and Multi-Objective Genetic Optimization*. 1–14.

Romero, G., & Alabazares, David Lara, I. P. (2014). *Robust Control Techniques Applied to the Hot-Dip Galvanizing Process Robust Control Techniques Applied to the Hot-Dip Galvanizing Process*. *December 2020*. doi:10.4028/www.scientific.net/AMM.459.212

Rose, A., Wandera, C., & Favor, E. (2021). *Parameters Influencing the Hot Dip Galvanizing Processes of Sheet Metal*. **6**(1), 1–9. doi:10.11648/j.ajmsp.20210601.11

Sami I. J. Al-rubaiey, Eyad N. Jasim, B. I. J.

(2015). Prediction the Thickness Layer of Galvanized Iraqi Electrical Poles Using Mathematical. *Diyala Journal of Engineering Sciences, Conference Articles* 713–721 https://djes.info/index.php/djes/article/view/404

Setiawan, R., & Santosa, B. (2021). Regression analysis in predicting coating application lifetime on asset integrity project. *IOP Conference Series: Materials Science and Engineering*, **1072**(1), 1–9. doi:10.1088/1757-899x/1072/1/012040

Shukla, S. K., Sadhukhan, A. K., & Gupta, P. (2017). Development of ANN Model for Prediction of Coating Thickness in Hot Dip Galvanizing Process. *International Journal of Materials Science and Engineering* **5**(2),60–68. doi:10.17706/ijmse.2017.5.2.60-68

So, H., Yoon, H. G., & Chung, M. K. (2011). CFD analysis of sag line formation on the zinc-coated steel strip after the gas-jet wiping in the continuous hot-dip galvanizing process. *ISIJ International*, **51**(1), 115–123. doi:10.2355/isijinternational.51.115

Sumitomo, Y. (2018). " NSblade TM " / Application of Advanced Air Knife to Hot Dip Continuous Galvanizing Line — Improvement of operational stability at high speed production. *Nipponsteel & Sumikin Engineering Technical Report* **9**(1), 1–9. https://www.eng.nipponsteel.com/en/r_and_d/reports/vol09/

Takeishi, Y., & Morino, H. (2000). Mechanism and prevention of edge over coating in continuous hot-dip galvanizing. *ISIJ International*, **40**(11), 1127–1133. doi:10.2355/isijinternational.40.1127

Tanzania Bureau of Standards (TBS). (2017). *Finalized Tanzania Standard | FTZS 1476:2017, Hot-Dip aluminium - Zinc coated plain, corrugated and troughed steel sheets - Specification*. https://www.tbs.go.tz/uploads/files/COMPULSORY%20LIST%202023.pdf

Verma, N., Sharma, V., Badar, M. A., & Choubey, N. (2022). Optimization of Zinc Coating Thickness by Unreplicated Factorial Design of Experiments in Hot-Dip Galvanization Process. *International Journal of Precision Engineering and Manufacturing*, *December*. doi:10.1007/s12541-022-00695-2

Wang, Y. (2018). Study on Influence Factors of zinc layer thickness via Response Surface Method, Taguchi Method and Genetic Algorithm. *Industrial Engineering & Management*, ***07*(**01), 1–10. doi:10.4172/2169-0316.1000245

Xiong, T., Ren, J., Luo, C., & Zuo, R. (2022). Analysis of coarse stripes of alloyed hot-dip galvanized steel sheets. *Journal of Physics: Conference Series*, **2390**(1), 1–5. doi:10.1088/1742-6596/2390/1/012017

Yadav, S. (2021). Performance observation of hot dip galvanization for steel sheets. *Materials Today: Proceedings*, *46*, 6700–6703. doi:10.1016/j.matpr.2021.04.169