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ORIGINAL RESEARCH

Advancing sustainability in complex systems: integrating environmental strategy with statistical modelling

Shahrooz Bamdad[1]

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Abstract

This paper explores the need for strategic ways to improve sustainability and reduce environmental impacts within the mining industry. It is about to catalyse social change through the promotion of interdisciplinary collaboration, community engagement, policy influence, and awareness-raising. The study emphasizes the negative environmental effects of employing residue instead of pure concentrate, including higher levels of heavy metal impurities like lead, zinc, nickel, arsenic, and cadmium. It also highlights the detrimental impacts on nearby agricultural land, sediments, and water bodies through thorough analytics, highlighting the necessity of taking preventative action. In this study, a statistical modelling tool is presented to adjust the parameters of the zinc manufacturing process. In order to address significant multi-collinearity, the paper uses statistical modelling techniques, specifically ridge regression, to identify important input-output factors in the zinc ingot process. Waste management is significantly improved and brought into compliance with environmental regulations by modifying process parameters under the direction of corporate environmental management tools. The results support the use of these tactics in mining operations to improve environmental sustainability. Through insights pertinent to academics, corporate managers, and professionals in the interdisciplinary field of environmental management and sustainability, this research adds to the conversation on balancing environmental concerns with industrial practices. The outcome highlights the extensive ramifications for neighbouring agricultural land, sediments, and aquatic bodies, which demonstrate the detrimental effects on local residents. This imperils not just the livelihoods of those who depend on agriculture but also the availability of clean water, which is critical to the health and welfare of the local populace. These results show the critical need for preventative actions to protect public health and conserve essential natural resources, underscoring the relationship between environmental sustainability and social welfare.

Keywords Sustainable practices · Environmental impact mitigation · Mining process · Waste residue utilization · Soil and water contamination · Ridge regression

✉ Shahrooz Bamdad
sh.bamdad2000@yahoo.com

[1] Business School, Birmingham City University, Birmingham, UK

1 Introduction

The activity of mineral metal processing industries has changed the amount of some elements in the nearby areas from their natural state and created environmental anomalies (Xu et al., 2023; Uzunoglu et al., 2024; Yadav et al., 2022). The environment of the nearby areas receives its most negative effects from the accumulation of tailings and residues that are left as cake in the margins of rivers and waterways or open fields, mainly agricultural (Ali et al., 2022; Ahmadov & Helo, 2018; Kitsikopoulos et al., 2018). From an industrial view, these cakes - which are actually the residues from the flotation, smelting, and concentrate production processes - may have lost more toxic heavy metals, but from an environmental perspective, they contain multiple times the allowable limits of potentially toxic elements (Zou et al., 2019). The amount of these elements in some samples is more than 10,000 parts per million (ppm) of zinc and more than 4000 ppm of lead, nickel and cadmium. The most reflection of these anomalies can be seen in the sediments and water of the region, but the agricultural soil is also affected by these pollutions and has major environmental anomalies (Wade et al., 2022).

From a sustainability perspective, the intricate relationship between public health, environmental degradation, socioeconomic dynamics, and governance challenges highlights the necessity for integrated approaches that tackle social and environmental aspects (Akter et al., 2024; Colapinto et al., 2020; Sabbaghnia et al., 2024). It addresses a number of crucial societal, environmental, and economical aspects: (i) *Public health concerns*: The buildup of tailings and residues from the companies that process mined metals presents serious health dangers, especially to the local communities. When potentially harmful metals like lead, nickel, and cadmium are found in excess of permissible limits, locals may be exposed to contaminated water, sediments, and agricultural land, which could have a negative impact on their health. (ii) *Environmental justice*: Environmental justice is raised by the fact that communities near industrial activity bear a disproportionate amount of the burden of environmental contamination. These communities, which are frequently disenfranchised or economically poor, suffer the most from the effects of the environment but have little authority and resources to solve or lessen these problems. (iii) *Economic impacts*: For nearby communities that depend on agriculture and natural resources for their livelihoods, the contamination of agricultural land and water bodies may have serious economic ramifications. Decreased agricultural output, deteriorated water quality, and possible health hazards could cause economic upheaval in the area and widen socioeconomic divides. (*iv*) *Social resilience and empowerment*: Understanding environmental anomalies and their effects emphasizes how crucial community empowerment and resilience are. To protect their environment and health, local communities may band together to demand stronger environmental laws, keep industrial parties accountable, and support remediation initiatives. (*v*) *Policy and regulatory frameworks*: The requirement for strong legislative and regulatory frameworks is reflected in the need for standards to limit pollution levels. Enforcing environmental regulations and safeguarding the welfare of communities impacted by industrial operations require strong governance and enforcement systems.

In this regard, different factory output standards have been established in recent years; their implementation has sometimes been accompanied by a requirement and occasionally by a recommendation (ElMassah, 2018). The emphasis on the requirement and adherence to permissible limits with standards, particularly in developed countries, has led many nations to associate the development of the metal industry - especially the non-ferrous industries - with green management (Yu et al., 2023). As a result, the environmental preservation and the expansion of industries have had the least confrontation (Li et al., 2023). The most fundamental standards are based on the quantity of elements in the factory's air and the allowable output limits of purification systems.

On the other hand, since there were previously high-quality reserves available, the extracted mineral was either used directly or slightly modified as a raw material for other businesses. There is currently a consideration of more low-quality reserves due to the depletion of high-quality ones (Hu et al., 2020). To reach the consumer market, standard mineral resources require enrichment and concentration processes. The science of mineral processing is crucial because, in the absence of the enrichment step, the recovered minerals cannot be employed directly in industry and face significant difficulties in operating as mineral mines, which are the foundation of economic activity. Lack of access to high-quality reserves has increased residue utilization, which has resulted in environmental issues.

As mentioned earlier, one of the challenges facing zinc ingot manufacturers is the lack of zinc ore access with good grades. Hence, some of these plants use residue that complicates process settings. As the residue is used, the process variables undergo significant changes and the impurities' rate intensifies.

Recent literature emphasises the need of monitoring heavy metal exposure by biomonitoring and improved analytical methods. For example, Zeren Cetin (2024) evaluated the suitability of plant species for cadmium biomonitoring at varied traffic densities and determined that Nerium oleander was the most effective species due to its high cadmium accumulation, particularly in unwashed plant organs. This study highlights the importance of vegetation in tracking airborne pollutants in urban contexts. Çetin (2024) studied chromium contents in various tissues of Picea orientalis L., finding age- and direction-dependent patterns related to industrial exposure. The study showed that long-term biomonitoring with trees may efficiently track environmental contamination trends in both forested and urban areas. In addition to this work, Cebi Kilicoglu and Zeren Cetin (2024) evaluated five tree species for their vanadium accumulation capacity in a substantially polluted location, indicating Cupressus arizonica and Cedrus atlantica as particularly effective due to their significant uptake in wood tissues. These studies highlight the increasing reliance on biological and statistical approaches to detect and manage environmental contamination. In contrast to plant-based biomonitoring, the current study advances this discourse by directly optimising zinc production processes using ridge regression and polynomial modelling, particularly when dealing with low-grade residues, thereby bridging process efficiency and environmental sustainability.

Particularly, this research aims to model and estimate, using residue, the pulp and acid leaching operations in the zinc ingot production process. This operation is performed to dissolve and activate zinc and impurities. To do this, a ridge regression approach is used. In this way, the key process input and output parameters are first examined and extracted. The required data is then collected, and the data are modeled using second-order polynomial regression with interaction effects. One of the major challenges in modeling is the high dependency between the input variables, which has been handled using the ridge regression. Thus, the ridge regression is first fitted on the data. After confirming the accuracy of the model, the output of the operation is estimated according to the type of residue compounds.

The study's primary methodological innovation is the integration of ridge regression with second-order polynomial regression, which includes interaction effects, to predict and optimise pulp and acid leaching operations using low-grade residue. Ridge regression is especially effective at addressing multicollinearity, a prevalent issue in process data, while also assuring model stability and reliable parameter estimates. By combining it with a second-order polynomial model, the method captures complicated nonlinear linkages and interactions among process variables, which are crucial for properly forecasting and optimising operational outcomes. Additionally, using a mathematical programming approach, the optimized process adjustments are calculated to simultaneously meet quality and environmental criteria. This hybrid modelling framework is employed in a real-world industrial environment, where the usage of low-grade residue adds significant uncertainty and complexity to the process. Unlike traditional modelling approaches, which frequently presume high-quality input or overlook variable interdependence, this method offers a robust, data-driven solution that improves process efficiency and environmental compliance. To the best of our knowledge, this combination of approaches has never been used in zinc production settings with such complex input materials, making a unique addition to both methodology and industrial practice.

The study significantly advances knowledge and directs actions in the field of environmental management within the mining industry with its thorough analysis, useful recommendations, and emphasis on the interaction between environmental sustainability and social welfare. The work makes a substantial contribution to the conversation on environmental sustainability in the mining sector by emphasizing a number of important factors, including: (i) *identification of environmental issues*: The study identifies and highlights the adverse effects on the environment that result from the use of residue from mining operations. In particular, the elevated levels of heavy metal impurities have a negative impact on the nearby water bodies, sediments, and agricultural land. In doing so, it draws attention to important environmental issues that the mining industry faces. (ii) *Proposal of strategic solutions*: The work puts out a set of strategic recommendations meant to enhance environmental sustainability and mitigate its effects. Some of these include the use of statistical modeling techniques, such as ridge regression, to address multi-collinearity and optimize waste management procedures. These solutions offer workable strategies for improving sustainability in mining operations and reducing environmental damage. (iii) *Promotion of interdisciplinary collaboration and awareness*: In order to accelerate social change and achieve environmental sustainability goals, the study emphasizes the significance of interdisciplinary collaboration, community participation, policy impact, and awareness-raising initiatives. It encourages cooperation between regulatory agencies, business, and academics, which promotes an all-encompassing strategy for tackling environmental issues. (*iv*) *Relevance to multiple stakeholders*: Academics, corporate managers, environmental management specialists, and legislators are just a few of the stakeholders who may find value in the research findings and insights provided in the study. It supports informed decision-making and the development of policies targeted at striking a balance between industrial practices and environmental concerns by offering practical insights and evidence-based solutions. (v) *Emphasis on social welfare*: Prioritizing social welfare significantly, the paper emphasizes the vital connection between social welfare and environmental sustainability, stressing the possible negative effects on the livelihoods and access to clean water of local populations.

Prioritizing the welfare of communities impacted by mining operations, it pushes for preventative measures to safeguard public health and preserve natural resources.

The rest of the paper is organized as follows: Sect. 2 provides a comprehensive literature review, emphasizing the research gap and positioning this study within the larger body of work. Section 3 discusses the materials and methods, which include the zinc ingot manufacturing process, data collecting, research design, and the use of ridge regression and second-order polynomial regression with interaction effects. Section 4 includes the findings from the environmental assessment, process modelling, optimization, and validation. Section 5 gives an in-depth discussion of the findings, while Sect. 6 concludes the study's key takeaways and implications.

2 Literature review

Data analysis using statistical modeling involves the use of mathematical and statistical techniques to create a simplified representation of a complex system or process. Statistical models are used in various fields, including science, engineering, economics, health, social sciences, political speeches, price index, financial markets and more, to gain insights, make estimations, and test hypotheses (Crescenzi, 2024; Dobers & Söderholm, 2009; Ficcadenti & Cerqueti, 2024; Gardes & Maistre, 2023; Giansante et al., 2023; Groenewegen et al., 2018; Scognamiglio, 2024; Sardy & Ma, 2024; Welford & Gouldson, 1993). Chemical process statistical modeling is one use case for data analysis using an environmental approach (Zhong et al., 2021). Chemical process output estimation is a multidisciplinary field that combines elements of environment, chemistry, engineering, statistics, and data science. The choice of modeling technique and the success of the estimation process depend on the specific characteristics of the chemical process, the availability of data, and the objectives of the estimation, e.g., control, optimization, and quality assurance (Ferraty et al., 2010).

One of the important polluting chemical processes with many applications is the zinc ingot production process. Zinc is a chemical element with the symbol Zn and atomic number 30. Zinc is the first element in group 12 in the periodic table. More than 12 million tons of zinc are produced annually in the world. More than half of it is used for galvanization, about 14% is employed in zinc-based alloys, mostly used in the die-casting industry, and 10% is utilized in brass and bronze production. Significant amounts are also consumed in zinc rolled, which includes roofing, gutter, and downpipe. The rest is used in zinc oxide and zinc sulfate (Bush & Kassel, 2006; Perret et al., 2007).

Hydrometallurgy is the general method of zinc production. Hydrometallurgical production is based on mineral concentrates, and the process is such that the leaching operation is performed first. In this stage, zinc concentrate is added to the leach tank. Other additives include sulfuric acid, water, effluent, and return solution (spent electrolyte) with a specified and controlled volume. The purpose of this operation is to convert the zinc in the concentrate to the zinc sulfate solution. The next operation is purification. In this step, the redundant elements that are soluble must be removed from the final solution. This operation is performed in several phases by adding additives. The next operation is the production of a zinc sheet or electrowinning. In this stage, by passing the electric current, the zinc sulfate produced in the previous operation is decomposed, the zinc in the solution is deposited on the cathode plates, and the zinc sheet is made. These sheets are separated from the cathode after 24 h. The final operation is smelting and casting or zinc ingot production. In this final stage, the zinc sheets extracted from the electrowinning operation are poured into the smelting furnace, and after melting, the resulting melt is poured into the casting molds. After cooling, the zinc metal is removed from the molds as ingots, and after packaging, it is ready to be consumed (Antrekowitsch et al. 2014; Borg et al., 2003). The chemical process used to produce zinc ingots is extremely environmentally harmful and involves many intricate details, necessitating modeling and study.

Chemical process analysis calculates the output of a chemical process as a function of the inputs. Several studies have covered this kind of research (Ordóñez-De León et al., 2020). Soft modeling techniques try to analyze the measured data of a process (Elemary, 2019; Akpolat, 2019; Brown et al., 2009; Maeder & Neuhold, 2007; Norman & Maeder, 2006). There are primary sources of information for chemical process modeling (Espenson, 1995; Wilkins, 1991). A summary of chemical process modelling and analysis is presented in Table 1.

Analogies with the current state of the art demonstrate that: (i) Regarding wide-ranging coverage of modelling approaches, the literature review offers a thorough summary of the

Table 1 Related studies to modelling and analysis of chemical processes

Process	Subject matter	References
AlZn liquid melt	Investigation of solidification such as stir casting, compo casting, pressurized solidification, squeeze casting, and extrusion in the semisolid state.	Savas and Altintas (1993), Lo et al. (1989)
AlZn liquid melt	Microstructural refinement	Zhu and Liu (1993), Guerriero et al. (1986)
AlZn liquid melt	Examining processing methods that may be able to lessen the severity of dimensional instability	Lo et al. (1992), My Kura and Murphy (1986)
AlZn alloy	Investigation of mechanical properties	Gaber et al. (2007), Bailey et al. (1990)
Mg-Zn alloy	Hardening characteristics	Rokhlin and Oreshkina (1988, Clark (1965)
Mg-Zn alloy	Examining the relationship between aluminum and carbon nanotubes	Choi et al. (2009, 2011)
Alloy systems containing nanoparticles	The simulation and modeling of deformation mechanisms	Ward et al. (2006), Liu and Sun (2005)
Mg-Zn magnesium alloy	Evaluation of strength and ductility	Paramsothy and Gupta (2013)
Mg–Zn–Y alloy	Evaluation of formation mechanism	Xu et al. (2006), Lee et al. (2005)
Mg–Zn–Y alloy	Discussion of strength	Kim and Bae (2004), Singh et al. (2003)
Mg–Zn–Y alloy	Mechanical and strength properties investigation	Wang et al. (2011), Somekawa et al. (2011), Kim et al. (2010)

several statistical modelling approaches that are applied in data analysis, including soft modelling techniques. It also discusses main knowledge sources for chemical process modelling. This extensive coverage is indicative of the variety of methods available for chemical process analysis. (ii) The review focuses only on the chemical process involved in producing zinc ingots, emphasizing the significance of this particular process and its effects on the environment.

In this way, the research gap can be identified: (i) *Including environmental factors*: The incorporation of environmental issues into statistical modelling methodologies seems to be lacking, despite the literature study discussing numerous modelling techniques and their applications in chemical process analysis. To better understand and minimize the severe environmental implications associated with chemical processes such as the manufacturing of zinc ingots, further research is required that explicitly incorporates environmental considerations into modelling frameworks. (ii) *Complexity of multidisciplinary analysis*: Chemical process output estimation is recognized in the review as being multidisciplinary, incorporating aspects of the environment, chemistry, engineering, statistics, and data science. Addressing the difficulties in combining so many fields into a coherent statistical modelling framework, however, may represent a research gap. Subsequent investigations may concentrate on creating multidisciplinary methodologies that proficiently represent the intricate interplay among chemical phenomena, environmental elements, and socio-economic aspects. (iii) *Validation and application of modelling techniques*: The study provides an overview of different modelling strategies utilized in chemical process analysis; nevertheless, there can be a lack of information regarding the validation and practical application of these techniques in industrial settings. Subsequent studies may concentrate on verifying modelling methodologies using empirical data from real-world industrial operations and evaluating their efficacy in enhancing process productivity and ecological sustainability.

Overall, further research could fill in gaps regarding the integration of environmental considerations, interdisciplinary analysis, and validation of modelling approaches in practical settings, even though the literature review offers a solid foundation for understanding current statistical modelling techniques and their applications in chemical process analysis.

In several ways, this work can help address the noted research gaps. (i) *Incorporating environmental factors*: The study emphasizes the significance of including environmental issues into statistical modelling approaches by highlighting the detrimental environmental implications of using residue in the zinc ingot production process. The study's emphasis on environmental implications draws attention to the need for modelling frameworks that specifically take environmental issues into account, which addresses this gap. (ii) *Addressing complexity of multidisciplinary analysis*: The work highlights the multidisciplinary character of output estimation for chemical processes and the difficulties in integrating different domains into a cohesive modelling framework. The work illustrates a useful strategy for managing the complexity of multidisciplinary analysis by using statistical modelling techniques like ridge regression to uncover significant input-output characteristics in the zinc ingot process. (iii) *Validating and applying modelling techniques*: According to the study, process parameters are changed under the guidance of corporate environmental management tools to greatly improve waste management and bring it into line with environmental requirements. This may address the gap in validating and implementing modelling approaches by indicating a useful application of statistical modelling techniques in actual industrial settings. Additionally, the study emphasizes the need of validating modelling approaches to improve process productivity and ecological sustainability by stressing the necessity of taking proactive measures to safeguard public health and save natural resources.

Overall, by offering insights into the integration of environmental factors, multidisciplinary analysis, and validation of modelling methodologies in real-world situations within the mining industry, this study helps to address the research gaps that have been identified.

3 Methods and materials

3.1 Methodology and research design

To ensure that the methodological approach is both robust and practical, this study incorporates a well-structured modelling and optimisation framework. Ridge regression is used to successfully address multicollinearity among process variables, ensuring model stability and dependability in the presence of interdependent inputs. This is complemented by a second-order polynomial regression with interaction effects, which captures complex nonlinear relationships and interactions between operational parameters. The combined methodology is then used to predict and optimise the pulp and acid leaching processes while using low-grade residue, which has not been fully studied in prior studies. Importantly, the model's optimised settings are confirmed by comparing process outcomes before and after the adjustments are implemented. This validation confirms the methodology's practical applicability and capacity to inform process modifications that are consistent with both quality and environmental objectives.

This study uses a mixed-method, four-phase research methodology that includes environmental sampling, statistical modelling, optimisation, and validation. The general purpose is to evaluate and improve the zinc manufacturing process using low-grade wastes, with an emphasis on both environmental and operational efficiency.

Phase 1: *Environmental Assessment*.

The first phase is focused on assessing the environmental impact of zinc production tailings and residues on the surrounding ecosystem. Field sampling takes place on a variety of environmental media, including tailings, cakes, agricultural soil, and water near zinc production sites. These samples are then analysed in a laboratory to identify the amounts of heavy metals like zinc (Zn), lead (Pb), cadmium (Cd), and nickel. The measured values are compared to international environmental and health standards to detect any discrepancies. The outcome of this phase is the identification of pollution hotspots and the creation of a baseline dataset, which serves as both motivation and justification for subsequent interventions.

Phase 2: *Process Data Collection and Modelling*.

The second phase entails creating a predictive model of the pulp and acid leaching operations used in zinc production from low-grade residues. Operational data, including input and output process variables, are obtained from industrial operation. To account for nonlinear effects, a second-order polynomial regression model with interaction terms is used, while ridge regression is used to reduce multicollinearity, improving model stability and prediction accuracy. The result is a validated model that can predict outputs such as metal recovery rates and impurity levels depending on operational parameters and residue qualities.

Phase 3: *Process Optimisation*.

The third phase focusses on optimising process parameters to strike a balance between product quality and environmental performance. This is accomplished by constructing an optimisation problem with mathematical programming tools. The objective is to maximise the estimated output model in the previous phase while the minimum and maximum values of each input are therefore regarded as constraints. The result is a set of optimised process parameters that aim to improve both sustainability and economic efficiency.

Phase 4: *Validation and Practical Application*.

In the last stage, the optimised process parameters are evaluated in an industrial context to validate the proposed methodological approach. Post-adjustment samples are obtained and compared to the baseline data established before adjustments. This comparison enables the evaluation of improvements in product quality, impurity reductions, and increased environmental compliance. The outcome is empirical validation of the entire framework, demonstrating its practical efficacy and real-world applicability. Figure 1 shows the research design visually.

3.2 The process and data

In this paper, the process of zinc ingot production in one of the mining process plants is examined. Zinc mineral concentrate, which is extracted from the mines, is the primary source of feed for this plant. Due to the lack of access to the required amount of this feed, the factory has also used residue. The production process in this plant includes the stages of leach (liquid-solid extraction), solution purification, electrowinning, smelting and casting. The input concentrate that has zinc and impurities is controlled, and its amount of moisture and zinc is determined. Concentrate feeding to the production line is done, and by adding water and sulfuric acid, grout making is performed. This activates zinc and other impurities. Then lime water is added to the solution and neutralizes it. To remove the principal impuri-

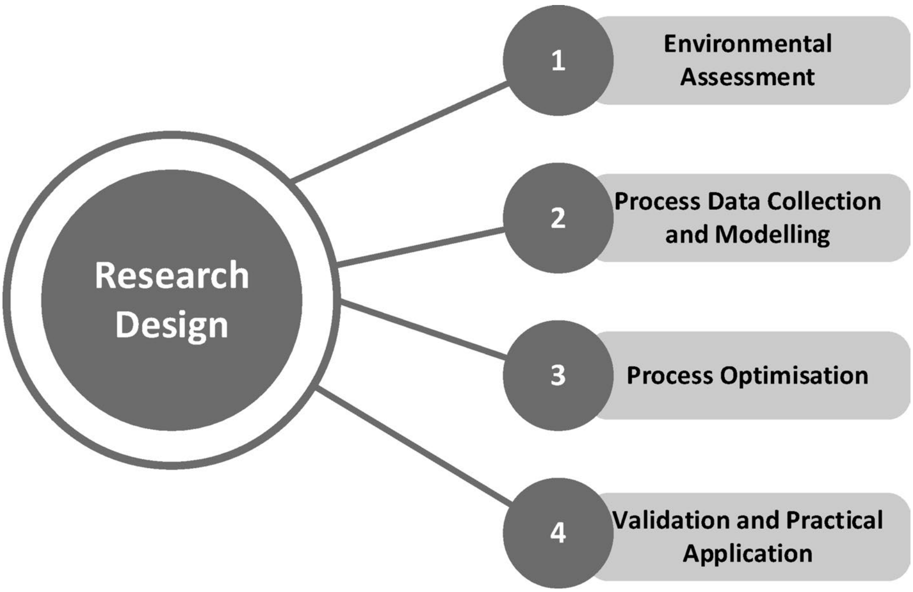

Fig. 1 Research design

ties, two stages of hot and cold solution purifications are performed. The quality of purification is directly impacted by the pulp and acid leaching stages. In the purification of the hot solution, where the process temperature is set at 75–85 °C, some impurities are removed. In cold solution purification, the process temperature is set in the range of 70–75 °C, and other impurities are removed. The solution of the cold purification stage, which is called fresh, has 75–85 gr/liter of zinc, and the number of impurities is 1–2 ppm. This solution is sent for electrowinning. In this stage, by creating an electric current in the anode and cathode, the zinc sits as a sheet on the cathode plate, and at the end, the zinc sheets are poured into the smelting furnaces and then transferred to the casting molds, which are transformed into zinc ingots after cooling. Figure 2 shows the schematic of the process.

According to ISO 752, the plant produces zinc with grade Zn-3, and its chemical composition is shown in Table 2. As is evident, the least amount of impurities, like lead, cadmium, etc., should be kept.

Zinc production generates a significant amount of impurities, which is one of the process issues brought on by using residues rather than mineral zinc concentrate. As a result, the operation violates environmental regulations and contaminates the nearby soil and water. In order to model and estimate the output of the early stages of the process - pulping and acid washing - this paper focuses on these activities. The production process can be green if the results of this operation can activate the impurities to an acceptable level. An outline of the pulping and acid washing procedures is provided in Fig. 3.

The input and output variables for the pulp and acid leaching operations are displayed in Table 3.

According to the investigations and plant experts' opinions, as well as the study of pulp and acid leaching operations, the output variable of the operation is considered as the zinc concentration of the acid grout, which, based on Eq. (1), is a function of the following variables:

$$\begin{aligned}
&\text{“}Zn concentration of\ acid\ grout\text{”} = f(\text{“}Concentrate\ zinc\ content\text{”}, \text{“}Concentrate\ weight\text{”},\\
&\text{“}Concentrate\ moisture\ content\text{”}, \text{“}pH\ of\ acid\ grout\text{”}, \text{“}H^+\ concentration\ of\ acidgrout\text{”},\\
&\text{“}Zn\ content\ of\ spent\ electrolyte\text{”}, \text{“}H^+\ of\ spent\ electrolyte\text{”},\\
&\text{“}Weight\ of\ Sulfuric\ acid\text{”}, \text{“}Zn\ concentration\ of\ zinc\ and\ iron\ sulfate\ solution\text{”},\\
&and \text{“}H^+\ concentration\ of zinc\ and\ iron\ sulfate\ solution\text{”}).
\end{aligned} \tag{1}$$

Hence, based on a statistical modelling approach, the dependent variable is as follows:

- Zinc concentration of acid grout (gr/lit).

Also, the independent variables are:

- Concentrate zinc content (%).
- Concentrate weight (kg).
- Concentrate moisture (%).
- pH of acid grout.
- H^+ concentration of acid grout (gr/lit).
- Zn content of spent electrolyte (gr/lit).
- H^+ of spent electrolyte (gr/lit).

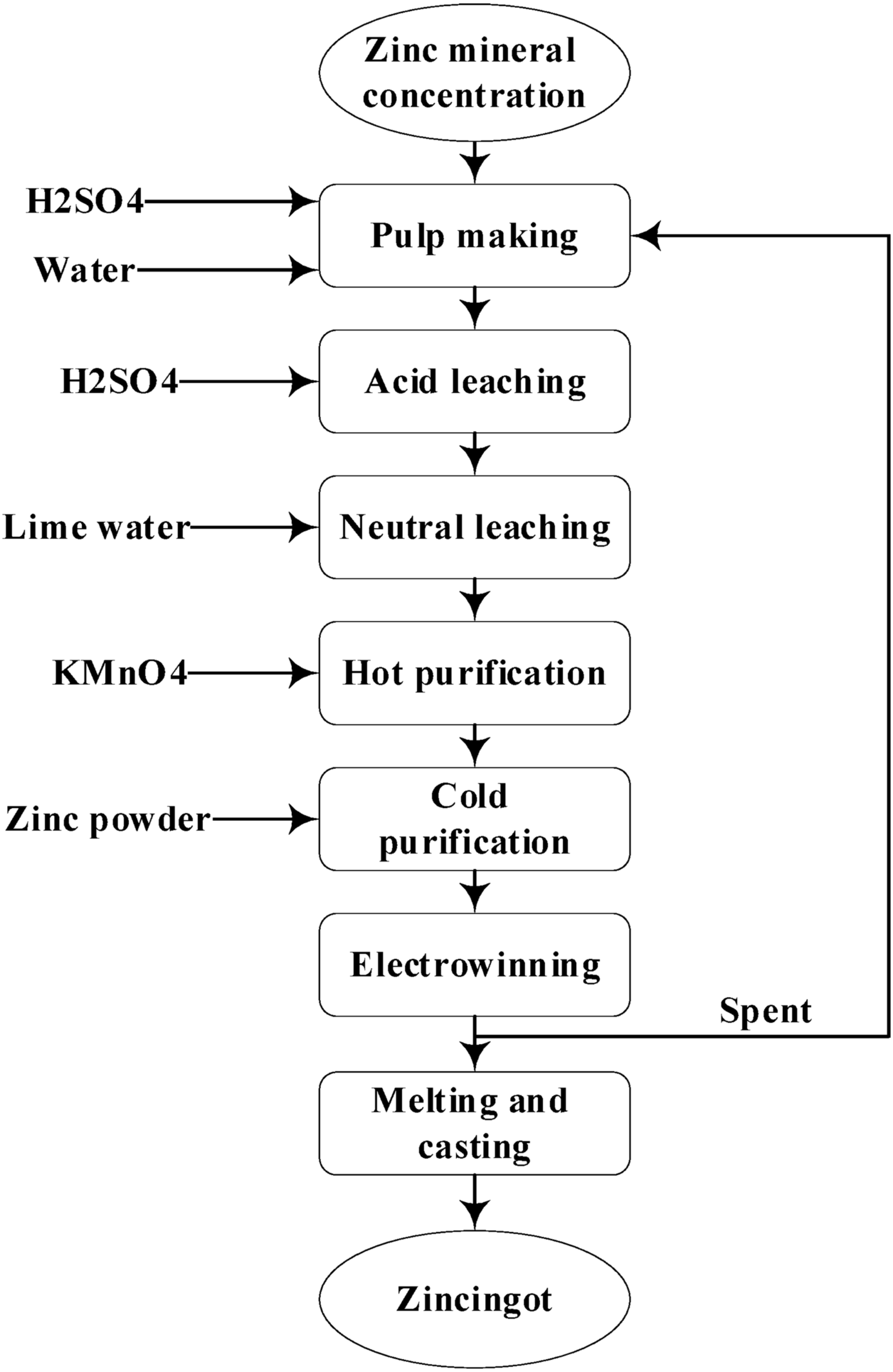

Fig. 2 Schematic of zinc ingot operations

Table 2 Zn-3 grade chemical composition of zinc ingots based on ISO 752

Designation	Pb	Fe	Cd	Al	Cu	Sn	Permitted total	Minimum Zinc content
Zn-3	0.03	0.02	0.01	0.1	0.002	0.001	0.05	99.95

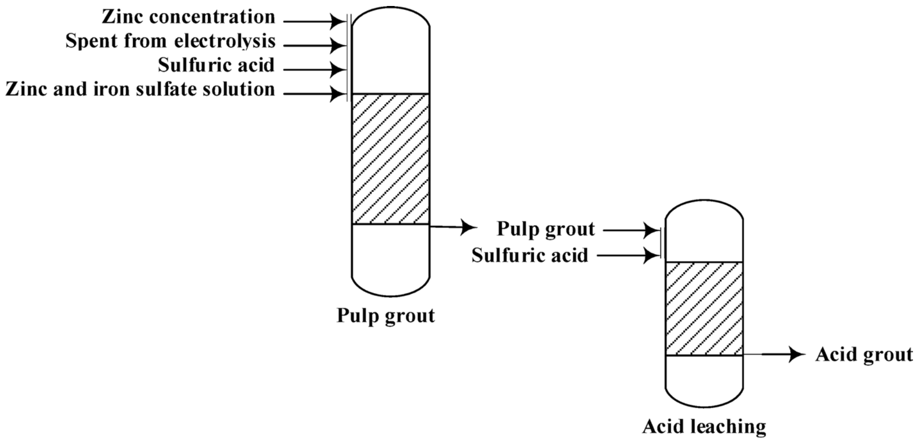

Fig. 3 Pulping and acid leaching operations

Table 3 The variables involved in the process of pulp and acid leaching

Input variables	Output variables
Concentrate zinc content (%)	Zn concentration of acid grout (gr/lit)
Concentrate weight (kg)	PH of acid grout
Concentrate moisture (%)	H^+ concentration of acid grout (gr/lit)
Zn content of spent electrolyte (gr/lit)	
$H^+$of spent electrolyte (gr/lit)	
Weight of Sulfuric acid input to the pulping (kg)	
Zn concentration of zinc and iron sulfate solution (gr/lit)	
H^+ concentration of zinc and iron sulfate solution (gr/lit)	

- Weight of Sulfuric acid input to the pulping (kg).
- Zn concentration of zinc and iron sulfate solution (gr/lit).
- H^+ concentration of zinc and iron sulfate solution (gr/lit).

These variables were chosen because of their operational importance in the pulping and acid leaching stages of the zinc production process. The dependent variable was chosen because it indicates the level of impurity activation and zinc dissolution in the early processing phases, which has a direct impact on both product quality and environmental pollution levels.

To collect data, 17 working days were monitored and controlled in three shifts. Thus, 168 pieces of information on the input and output variables were taken away from the process. Applying the supervisory control and data acquisition (SCADA) system has made use of the mean computations.

3.3 Ridge regression

A statistical modelling approach used to model relationships between variables is regression (Montgomery & Runger, 2010). Regression has several uses, including engineering, physics, chemistry, economics, management, etc. (Femenias et al., 2020; Kardos & Clement, 2020; Ocanha et al., 2020; Chen et al., 2020; Aggarwal et al., 2020; Guillén-Gosálbez et al., 2020; AbouZid et al., 2020; Montgomery et al., 2015).

Model $y = \beta_{\circ} + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon$ is called multiple linear regression where y is a dependent variable, $x_1, x_2, ..., x_k$ are k independent variables, and $\beta_j; j = 0,1, ..., k$ are called regression coefficients.

If there is no linear relation between the independent variables, they are called orthogonal. But, if there is a near-linear dependency between the independent variables, then it is said that there is collinearity. In severe collinearity, the use of the regression model can be deceptive or erroneous (Montgomery et al., 2015).

Collinearity sources: Multiple regression model is written as $\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\epsilon}$ so that $\boldsymbol{y}$ is a $n \times 1$ vector of response or dependent variables, $\boldsymbol{X}$ is a $n \times p$ matrix of independent variables, $\boldsymbol{\beta}$ is a $p \times 1$ vector of unknown model parameters, and $\boldsymbol{\epsilon}$ is a $n \times 1$ vector of random errors as $\epsilon_i \sim NID(0, \sigma^2)$. It is assumed that the response and independent variables have been centered and scaled to unit length. Therefore, $\boldsymbol{XX'}$ is a $p \times p$ correlation matrix between independent variables and $\boldsymbol{X'y}$ is a $p \times 1$ vector of correlation between independent and response variables.

If the j^{th} column of the $\boldsymbol{X}$ matrix is shown with $\boldsymbol{X}_j$, then we have: $\boldsymbol{X} = [\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_p]$. Therefore, $\boldsymbol{X}_j$ represents the n level of the j^{th} independent variable. Vectors $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_p$ are linearly dependent if a set of constant parameters $\boldsymbol{t}_1, \boldsymbol{t}_2, \ldots, \boldsymbol{t}_p$, which not all zero, exist as follows:

$$\sum_{j=1}^{p} \boldsymbol{t}_j \boldsymbol{X}_j = 0 \tag{2}$$

Collinearity is defined as a linear dependency between X columns. If Eq. (2) is correct for a subset of the X columns, then the $\boldsymbol{XX'}$ matrix rank is lower than the p and $(\boldsymbol{XX'})^{-1}$ does not exist. If Eq. (2) exists for a subset of the X columns, then it is said that there is a collinearity.

The effects of collinearity can be described as follows: Severe collinearity causes large variance and covariance to estimate the minimum squares of regression coefficients. Also, collinearity makes the estimates of the minimum squares very large in terms of absolute value. Also, if there is strong collinearity, the least-squares method provides a weak estimate of each parameter.

There are various methods to identify collinearity, one of the most common being the variance inflation factor (VIF). This value is obtained as $VIF = (1 - R_j^2)^{-1}$ so that R_j^2 is the determination coefficient of fitting x_j on $n-1$ other independent variables. If the VIF is much larger than 10, then it indicates that there is collinearity.

There are also several ways to deal with collinearity, in which a ridge regression is used here. In the least-squares method, $\widehat{\beta}$ is an unbiased estimator of β ; i.e. $E\left(\widehat{\beta}\right)=\beta$. Due to the Gauss–Markov property, this estimator has the least variance among all unbiased estimators. But if there is collinearity, the value of this variance is considerable. The ridge regression method follows estimates whose variance is much less than the estimator of the least-squares but also tolerates a slight bias. The ridge estimator is obtained by solving a modified version of the ordinary least-squares method. If the ridge estimator is shown by $\widehat{\beta}_R$, then its value is obtained by solving Eq. (3):

$$(\boldsymbol{X'X}+\boldsymbol{kI})\widehat{\beta}_{\boldsymbol{R}}=\boldsymbol{X'y}\ or\ \widehat{\beta}_{\boldsymbol{R}}=(\boldsymbol{X'X}+\boldsymbol{kI})^{-1}\boldsymbol{X'y} \tag{3}$$

where $k\geq\ 0$ and is a constant value determined by the analyst.

If $k=0$, then the least-squares estimators are obtained. As k increases, the $\widehat{\beta}_R$ bias will increase too. Generally, ridge estimates lead to equations that estimate future observations better than the least-squares method. Hoerl and Kennard (1976) suggested that the k is obtained by examining the ridge trace, a diagram of $\widehat{\beta}_R$ versus k. The goal is to select a small, reasonable amount of k for which the $\widehat{\beta}_R$ is stable (de Souza et al., 2021).

4 Results

The study's results are structured into four key subsections to provide a comprehensive understanding of the environmental and process implications. First, the environmental study assesses tailings and cakes, soil, and water samples and compares the results to relevant environmental criteria to determine contamination levels. Second, the process analysis involves examining the collected data, statistical modelling with ridge regression, and assessing model fitness to find the relationships between input and output variables in the zinc production process. Third, the optimisation phase concentrates on refining process parameters to reduce impurities and improve environmental performance. Finally, the validation stage assesses the effectiveness of the proposed solutions by analysing and comparing impurity data acquired before and after adjustments to processes.

4.1 Environmental analysis

In this study, the mineral processing plant that uses residue and its adjacent area are examined from an environmental perspective. The aforementioned region has developed agriculture and animal husbandry in addition to the mineral industry. This is because, from an environmental view, the adjacency of industrial regions, agriculture, and animal husbandry may result in some anomalies, the principles of which need to be thoroughly examined (JECFA, 2011a, b). The vicinity made it necessary to investigate these industries to offer suggestions and untangle the potential pollutants in the region. In the area, all the water sources eventually flow into the ocean, but many of the rivers flow through the nearby cities. Hence, water protection is crucial because there isn't much subsurface water in the area under investigation. The water in the area where the zinc industry is concentrated can pose a risk to water users. Also, the predominant winds in the region are said to be southwest in February, March and April. This information is crucial for determining which way the wind in the area is dispersing pollutants. Therefore, the necessity of this study can be seen in environmentally conscious industries that can successfully adhere to recognized agricultural, animal husbandry, and similar standards.

In this regard, a thorough analysis of the factory's outputs was carried out to ascertain the level of environmental pollution, which served as evidence for the need for this study. The following presents the results. Over the course of the factory's many years of operation, a large amount of tailings containing varying concentrations of occasionally hazardous and toxic elements have been released into the areas close to the plant. Thus, determining the amount of input into the water and soil as well as the source of pollution should be the first step. The most effective way to sample produced cakes is to do so gradually and continuously using the deposited mineral materials as a guide. Since surface samples of these masses are impacted by atmospheric factors, it can be generally concluded that they are not representative samples. The rifle sampling method was applied to sample cakes (Truscott, 1962). This method involved inserting a pointed tube into the cakes and using the samples inside the tube to represent a portion of the cake's non-aerated area.

Additionally, the region's agricultural soil was gathered in accordance with soil sampling guidelines, which took into account the depth of the sample as well as the amount of soil that was accessible down to around 50 cm. Trapezoids were used as the sampling grid for this operation, and a sample was taken from each of the trapezoid's four corners as well as its center (Reedman, 1979). The samples were prepared for chemical analysis in the following order: drying, crushing, sieving, homogenous division and powdering. Following a 105 degrees' Celsius oven dry cycle, the samples were sieved to a mesh size of 200 to create a powder ready for final analysis.

Moreover, samples of the region's rivers and water resources were collected in specially designed containers that had been prepped for this purpose and cleaned with weak acid. These containers, which were prepared for measuring heavy elements in water, added 2 milliliters of manganese sulfate solution, sodium iodide and sulfuric acid for every 20 milliliters of water. The aforementioned containers were shipped to the laboratory under standard circumstances. Four degrees Celsius were these conditions for the solution in question.

In order to identify environmental pollutants, the area was first coded, and three variables were taken into consideration based on the nature of the materials in the area. The investigation of surface and subsurface water sources, industrial and mineral effluents, and agricultural lands are these three variables. 19 samples of agricultural soil, 5 samples of industrial water, 19 samples of cake and surrounding sediments, and 7 samples of drinking and agricultural water were taken and sent to the lab. The outputs are analyzed in the following, and all corresponding data are given in Online Resource[1] (supplementary materials attached to the paper).

4.1.1 Tailings and cakes analysis

When locals, plants, and animals experience conflicts with their natural state, environmental preservation will take on a true and tangible meaning (Shinn et al., 2000). The study area is

[1] https://www.researchgate.net/publication/392499955_Supplementary_Data_source.

receptive to this significance. The region's environment has unintentionally deteriorated to its most catastrophic state due to the close and effective connection between the plant and its products with people's lives. This connection can be attributed to the proximity of the metal industry with agriculture and animal husbandry. The alluvial and drainage systems in the area appear to have made it more likely that elements will find their way into the water and soil as a result of sewage discharge, which could have negative effects on the local population. Thus, in this context, more basic solutions ought to be taken into consideration.

The tailings analysis reveals a high concentration of pollutants in the tailings that endangers international standards (USEPA, 1999). Lead, zinc, cadmium and any combination of these ores shouldn't contain more than the standards depicted by the red lines in Fig. 4. Nevertheless, it appears that the region's factory output is having issues with both the method of environmental discharge and statistical data.

As demonstrated by the statistics of the final output current limitations in Fig. 1, the concentration of waste is much higher than the expected limit, which goes against the mining industry's consideration of agreements for sudden output due to a significant volume of production waste by USEPA (1999) standards. This figure presents the findings from the location-specific analysis of 19 cake samples. The amount of lead, zinc and cadmium elements in these samples, which were collected from the area around the cake depot and its surrounding areas, is evident. There are far more than heavy elements than is permitted. Given the abovementioned justifications, it is reasonable to conclude that any waste spill on the surface poses a serious risk to the environment and public health.

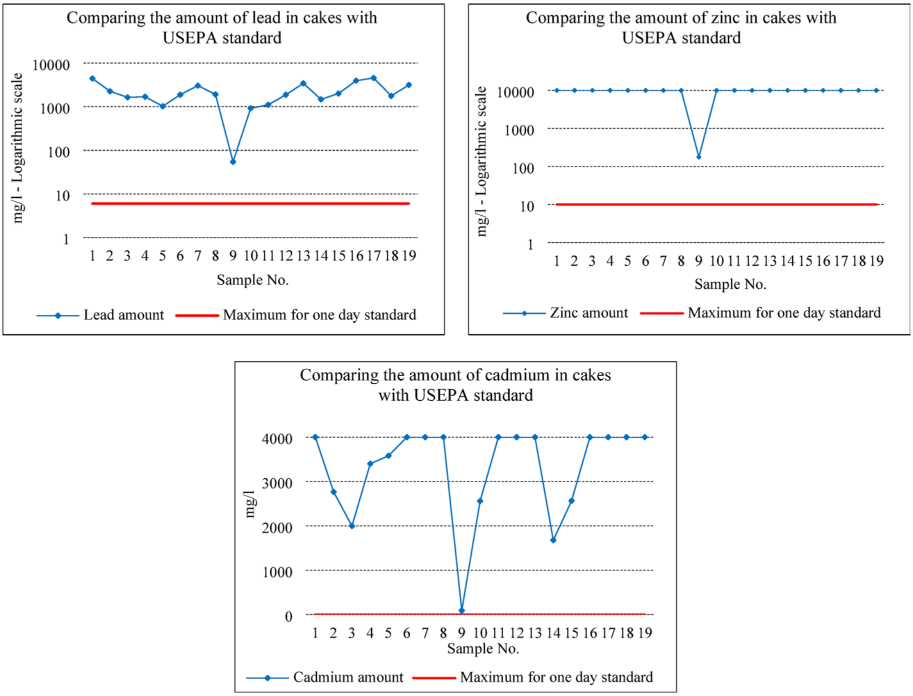

Fig. 4 Comparing the amount of heavy metals in cakes with the USEPA standard

4.1.2 Soil analysis

Soil is inevitably contaminated because, of the approximately 19 samples taken from agricultural soil, the majority fell out of the standard amount allowed of soil, as depicted in Fig. 5. This figure demonstrates the required limit of various elements in soil and biological bodies.

Figure 5, which presents soil standards, is prepared based on the standards of the US Department of Agriculture (NRCS, 1999). The graphs show how this difference has increased the risk of harming local crops due to the gap between the allowable limit and the current amount. Accordingly, the average levels of lead, zinc, cadmium, arsenic, and nickel in the region's agricultural soil are all several times higher than the standard limits of elements in the soil. Additionally, zinc contamination is the most common type found in the area's soil.

4.1.3 Water analysis

The leached cakes appear to have an impact on the water samples as well. This is confirmed by sampling surface water (rivers) and wastewater accumulation pools. The analysis of the samples demonstrates that in surface water as well as in industrial samples, the standards of permissible limits of the elements have been violated (Fig. 6).

Based on the information provided, it can be concluded that the leachate from the factories' cakes and sewage from their pools is toxic and contains far more than what is allowed to be released into the environment. Although with the current level of information, it is not possible to give a numerical approximation of the volume of groundwater pollution and its spatial distribution; however, the risk of groundwater pollution is substantial. The analysis of drinking and agricultural water reveals that the highest anomalies are found in the average levels of cadmium, zinc, lead and arsenic, respectively. The World Health Organization's drinking water recommendations demonstrate how internationally recognized health and safety organizations pay close attention to the concentration of unique elements and mineral compounds in drinking water, including the maximum amount of heavy metals that is acceptable (World Health Organization, 2021). According to the standard, none of the samples obtained in Fig. 6 can be consumed without first undergoing chemical purification.

In conclusion, the presented analysis demonstrate that the lead, zinc, arsenic, cadmium, and nickel levels in the region's drinking and agricultural waters are significantly higher than the allowable limit specified in the global environmental and health standards. This suggests that pollutants from cakes and industrial and mineral waste have made their way into the waterways. In the meantime, the polluted areas are correlated with the periphery of the ingot factory. However, it appears likely that pollutants will be carried by wind and water to surrounding areas, including neighboring watersheds. When it comes to cadmium, zinc and lead in drinking water, this level of contamination is more noticeable. It is important to consider a solution to lessen these abnormalities, as it has also been observed in the soil and water. Additionally, the high concentration of hazardous and toxic elements found in industrial leachate and effluents has led to the belief that if these elements find their way into the water and soil of the study region, they will have consequences for the surrounding area's environment and ecosystem as a whole. In addition, adjusting the process in such a way as to reduce pollutants is definitely crucial.

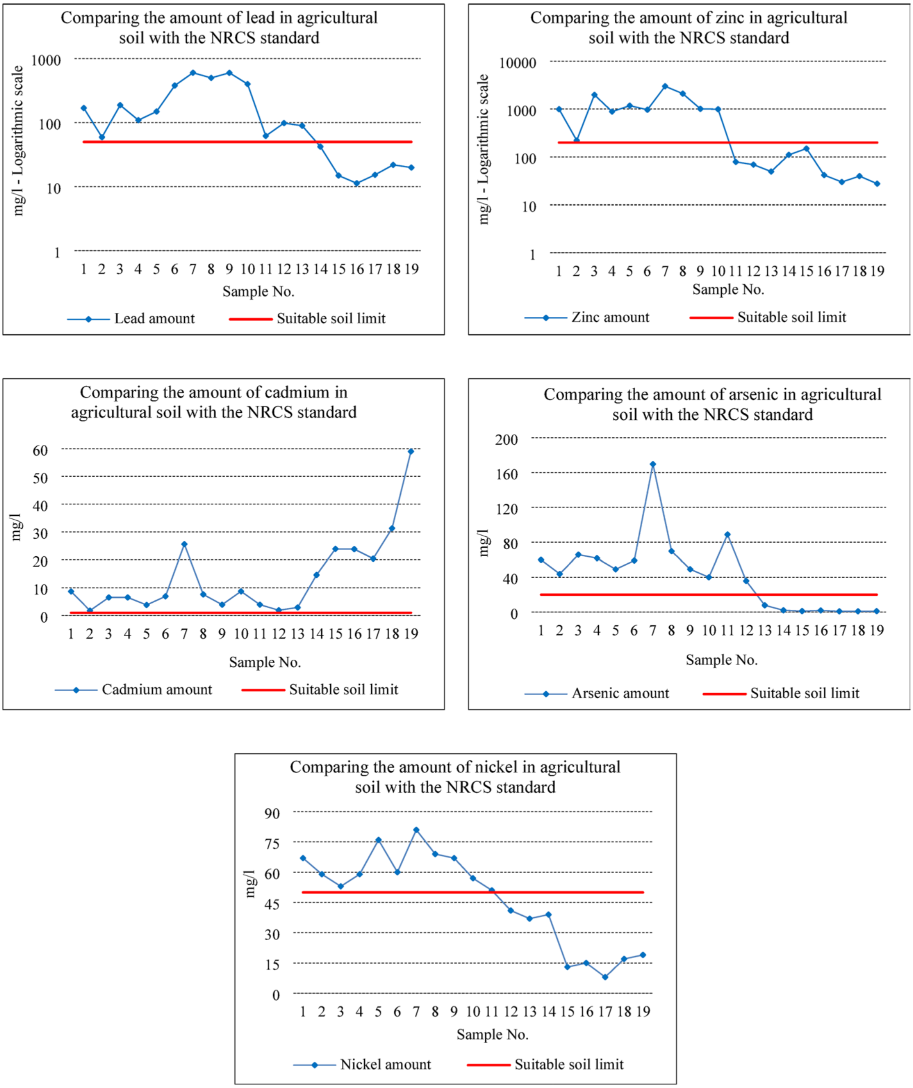

Fig. 5 Comparison of the amount of heavy metals in the soils of the investigated area with the NRCS standard

4.2 Process analysis

The process data in this study included 17 working days, which contained 168 data related to processing input and output variables, and all corresponding data are given in Online Resource[2] (supplementary materials attached to the paper). From these data, 144 (85%) and 24 (15%) randomly selected data are used to train and test the model, respectively. The definition of process input and output variables is as Table 4.

[2] https://www.researchgate.net/publication/392499955_Supplementary_Data_source.

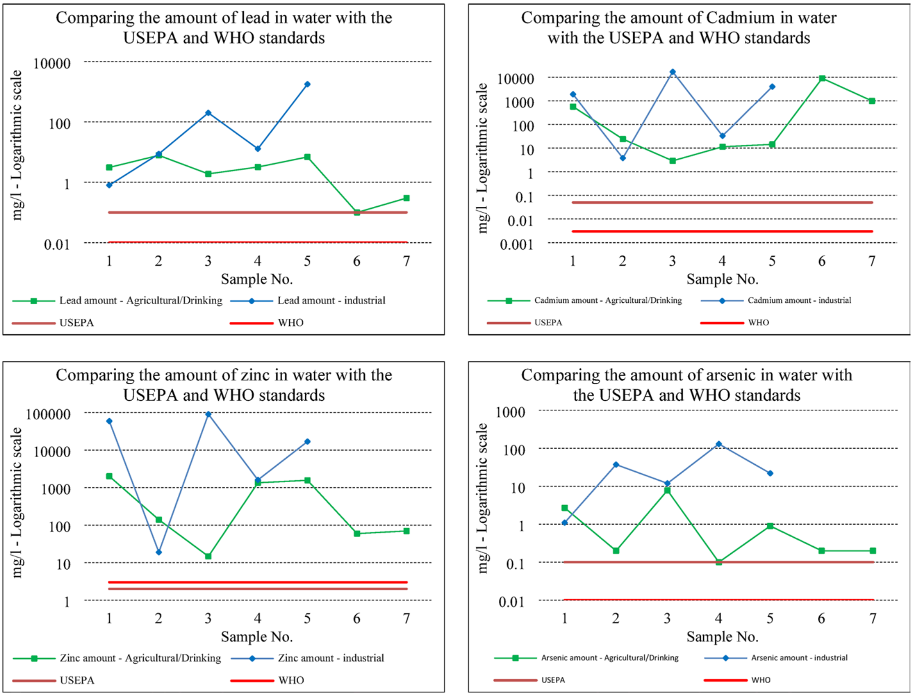

Fig. 6 Comparison of the amount of heavy metals in the water with WHO and USEPA standards

To describe data, descriptive statistics analysis of process input and output variables is used, which is shown in Table 5.

$$
\begin{aligned}
y = {} & x_1 + x_2 + \cdots + x_{10} \\
& + x_1 \times x_2 + x_1 \times x_3 + \cdots + x_1 \times x_{10} + x_2 \times x_3 + x_2 \times x_4 + \cdots + x_2 \times x_{10} \\
& + x_3 \times x_4 + x_3 \times x_5 + \cdots + x_3 \times x_{10} + x_4 \times x_5 + x_4 \times x_6 + \cdots + x_4 \times x_{10} \\
& + x_5 \times x_6 + x_5 \times x_7 + \cdots + x_5 \times x_{10} + x_6 \times x_7 + x_6 \times x_8 + \cdots + x_6 \times x_{10} \\
& + x_7 \times x_8 + x_7 \times x_9 + x_7 \times x_{10} + x_8 \times x_9 + x_8 \times x_{10} + x_9 \times x_{10} \\
& + x_1^2 + x_2^2 + \cdots + x_{10}^2
\end{aligned} \tag{4}
$$

Model fitting: As mentioned earlier, out of 168 data, 144 data are randomly selected for model fitting. To fit the model, the independent variables were scaled using unit normal scaling (subtracting the average, i.e., centering, and dividing by the standard deviation). Table 6 shows the outcome of fitting the second-order polynomial model using the least-squares approach and interaction effects.

According to the fitted model, it is observed that $R^2 = 95.52\%$ and $s = 0.964486$. However, by examining the model, it can be seen that the VIF values are very large ($max\ VIF = 399.80$), and this indicates the existence of collinearity in the model. Therefore, this model can only be used for interpolation, and the extrapolation of values outside the defined range is problematic.

Ridge regression is used to solve the collinearity problem. So, all variables (dependent and independent) are standardized, i.e. each variable is first centralized by subtracting the

Table 4 Model inputs and outputs notations

	Variables	Unit	Notation
Model output	Zn concentration of acid grout	gr/lit	Y
Model inputs	Concentrate zinc content	%	x_1
	Concentrate weight	kg	x_2
	Concentrate moisture content	%	x_3
	pH of acid grout	–	x_4
	H^+ concentration of acid grout	gr/lit	x_5
	Zn content of spent electrolyte	gr/lit	x_6
	$H^+$of spent electrolyte	gr/lit	x_7
	Weight of sulfuric acid	kg	x_8
	Zn concentration of zinc and iron sulfate solution	gr/lit	x_9
	H^+ concentration of zinc and iron sulfate solution	gr/lit	x_{10}

Table 5 Descriptive statistics of the model inputs and outputs

Variable	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	Y
Total Count	168	168	168	168	168	168	168	168	168	168	168
Mean	31.103	91,661	31.762	1.8071	9.626	22.869	87.161	3952.4	24.411	96.637	81.292
StDev	3.878	12,255	3.964	0.1578	1.77	1.519	2.712	1087.8	2.217	8.033	3.275
Minimum	22	75,000	24	1.45	4.9	19	81	2000	21	80	73
Q1	27	83,000	29.8	1.7	9	22	85	3000	23	91	79
Median	32	90,000	32	1.8	9.8	23	87	4000	24	96	81
Q3	34.5	95,000	33.8	1.9	10	24	89	4000	26	102	84
Maximum	35.8	120,000	39.3	2.4	19.6	27	93	8000	34	120	92
Range	13.8	45,000	15.3	0.95	14.7	8	12	6000	13	40	19
IQR	7.5	12,000	4	0.2	1	2	4	1000	3	11	5
Mode	34.5	90,000	32	1.8	9	23	88	4000	24	98	81
N for Mode	23	35	20	44	43	44	28	66	37	18	34
Skewness	− 0.71	1.12	− 0.25	1.07	1.24	− 0.1	− 0.11	1.28	1.73	0.53	0.52
Kurtosis	− 0.35	0.46	0.05	2.79	6.3	0.02	− 0.59	2.93	5.19	0.67	− 0.08

StDev standard deviation, *Q1* first quartile, *Q3* third quartile, *IQR* interquartile range

It is generally accepted that the second-order polynomial model with interaction effects is a suitable experimental model for data related to chemical processes. Montgomery et al. (2015). Accordingly, a second-order polynomial regression model with interactions is considered as follows:

mean and dividing by the square root of the corrected sum of the squares. To achieve the ridge solution, the equation $\widehat{\beta}_{\boldsymbol{R}} = (\boldsymbol{X'}\,\boldsymbol{X} + \boldsymbol{kI})^{-1}\boldsymbol{X'}\,\boldsymbol{y}$ must be solved for different values of k ($0 \leq k \leq 1$). This is done using MATLAB software, and the result is as Fig. 7.

Based on the ridge trace, the routine is to select k large enough that the ridge regression coefficients are stable. On the other hand, they should not be too large to introduce additional bias and increase the residual mean squares. According to Fig. 7, there is no significant change in the residual mean squares for $k = 0.032$. Therefore, for this value, the ridge regression model is fitted. The estimation of ridge regression can be calculated using the ordinary least-squares method and adding standardized data as:

Table 6 Results of the second-order polynomial regression model

Term	Coef	SE coef	T-value	*P* value	VIF	Term	Coef	SE coef	T-value	*P* value	VIF
Constant	82.427	0.649	126.96	0.000		x2 * x6	− 3.349	0.875	− 3.83	0.000	88.34
x1	− 2.685	0.637	− 4.22	0.000	62.39	x2 * x7	− 2.447	0.565	− 4.33	0.000	24.27
x2	1.786	0.605	2.95	0.004	56.19	x2 * x8	0.786	0.636	1.24	0.22	39.66
x3	1.066	0.707	1.51	0.136	76.89	x2 * x9	− 2.569	0.579	− 4.43	0.000	115.24
x4	− 0.77	0.264	− 2.91	0.005	10.73	x2 * x10	− 2.032	0.42	− 4.84	0.000	19.24
x5	− 0.884	0.24	− 3.68	0.000	8.88	x3 * x4	− 1.975	0.623	− 3.17	0.002	61.34
x6	0.725	0.332	2.18	0.032	16.95	x3 * x5	− 3.966	0.626	− 6.34	0.000	46.46
x7	1.373	0.337	4.08	0.000	17.42	x3 * x6	2.498	0.636	3.93	0.000	85.9
x8	0.778	0.387	2.01	0.048	23	x3 * x7	2.139	0.576	3.71	0.000	58.49
x9	− 0.288	0.425	− 0.68	0.5	27.8	x3 * x8	− 3.374	0.607	− 5.56	0.000	37.27
x10	0.55	0.345	1.6	0.114	18.25	x3 * x9	2.968	0.837	3.55	0.001	200.49
x1 * x1	7.407	0.946	7.83	0.000	211.1	x3 * x10	− 2.639	0.45	− 5.86	0.000	41.49
x2 * x2	− 1.749	0.518	− 3.38	0.001	78.9	x4 * x5	0.367	0.434	0.85	0.401	84.29
x3 * x3	− 0.876	0.514	− 1.7	0.092	64.83	x4 * x6	1.505	0.533	2.83	0.006	21.33
x4 * x4	− 0.138	0.156	− 0.89	0.378	16.45	x4 * x7	3.729	0.552	6.75	0.000	26.66
x5 * x5	− 0.07	0.242	− 0.29	0.774	73.58	x4 * x8	2.618	0.333	7.86	0.000	11.46
x6 * x6	2.306	0.495	4.66	0.000	88.66	x4 * x9	1.545	0.354	4.36	0.000	39.79
x7 * x7	0.223	0.351	0.64	0.527	31.77	x4 * x10	3.581	0.446	8.03	0.000	14.43
x8 * x8	− 0.5	0.131	− 3.81	0.000	12.38	x5 * x6	0.525	0.431	1.22	0.226	13.61
x9 * x9	0.045	0.238	0.19	0.852	61.17	x5 * x7	2.1	0.442	4.75	0.000	26.6
x10 * x10	1.486	0.19	7.84	0.000	13.25	x5 * x8	2.662	0.39	6.83	0.000	15.29
x1 * x2	0.95	1.15	0.83	0.411	**399.8**	x5 * x9	1.874	0.413	4.54	0.000	32.56
x1 * x3	− 7.31	1.16	− 6.3	0.000	242.52	x5 * x10	3.426	0.445	7.7	0.000	16.84
x1 * x4	2.652	0.502	5.28	0.000	62.05	x6 * x7	2.367	0.713	3.32	0.001	123.11
x1 * x5	3.185	0.625	5.09	0.000	72.8	x6 * x8	− 1.186	0.553	− 2.14	0.035	29.16

Table 6 (continued)

Term	Coef	SE coef	T-value	*P* value	VIF	Term	Coef	SE coef	T-value	*P* value	VIF
x1 * x6	− 5.071	0.905	− 5.6	0.000	128.45	x6 * x9	− 0.232	0.364	− 0.64	0.526	13.73
x1 * x7	− 4.982	0.636	− 7.84	0.000	51.1	x6 * x10	2.219	0.381	5.82	0.000	20.41
x1 * x8	4.732	0.802	5.9	0.000	73.17	x7 * x8	0.027	0.351	0.08	0.939	15.91
x1 * x9	− 5.553	0.723	− 7.68	0.000	224.41	x7 * x9	0.3	0.315	0.95	0.345	9.16
x1 * x10	4.321	0.66	6.55	0.000	43.03	x7 * x10	1.64	0.317	5.18	0.000	18.92
x2 * x3	1.818	0.978	1.86	0.067	148.79	x8 * x9	− 4.393	0.625	− 7.03	0.000	30.23
x2 * x4	2.1	0.43	4.88	0.000	49.98	x8 * x10	2.733	0.377	7.24	0.000	14.49
x2 * x5	2.236	0.488	4.58	0.000	71.01	x9 * x10	− 0.303	0.326	− 0.93	0.356	16.74

Model summary

S	R-sq	R-sq(adj)	R-sq(pred)
0.964486	95.52%	91.79%	80.94%

Regression equation

Y = 82.427–2.685 × 1 + 1.786 × 2 + 1.066 × 3–0.770 × 4–0.884 × 5 + 0.725 × 6 + 1.373 × 7
+ 0.778 × 8–0.288 × 9 + 0.550 × 10 + 7.407 × 1 * x1–1.749 × 2 * x2–0.876 × 3 * x3–0.138 × 4 * x4
− 0.070 × 5 * x5 + 2.306 × 6 * x6 + 0.223 × 7 * x7–0.500 × 8 * x8 + 0.045 × 9 * x9 + 1.486 × 10 * x10
+ 0.95 × 1 * x2–7.31 × 1 * x3 + 2.652 × 1 * x4 + 3.185 × 1 * x5–5.071 × 1 * x6–4.982 × 1 * x7
+ 4.732 × 1 * x8–5.553 × 1 * x9 + 4.321 × 1 * x10 + 1.818 × 2 * x3 + 2.100 × 2 * x4 + 2.236 × 2 * x5
− 3.349 × 2 * x6–2.447 × 2 * x7 + 0.786 × 2 * x8–2.569 × 2 * x9–2.032 × 2 * x10–1.975 × 3 * x4
− 3.966 × 3 * x5 + 2.498 × 3 * x6 + 2.139 × 3 * x7–3.374 × 3 * x8 + 2.968 × 3 * x9–2.639 × 3 * x10
+ 0.367 × 4 * x5 + 1.505 × 4 * x6 + 3.729 × 4 * x7 + 2.618 × 4 * x8 + 1.545 × 4 * x9 + 3.581 × 4 * x10
+ 0.525 × 5 * x6 + 2.100 × 5 * x7 + 2.662 × 5 * x8 + 1.874 × 5 * x9 + 3.426 × 5 * x10 + 2.367 × 6 * x7
− 1.186 × 6 * x8–0.232 × 6 * x9 + 2.219 × 6 * x10 + 0.027 × 7 * x8 + 0.300 × 7 * x9 + 1.640 × 7 * x10
− 4.393 × 8 * x9 + 2.733 × 8 * x10–0.303 × 9 * x10

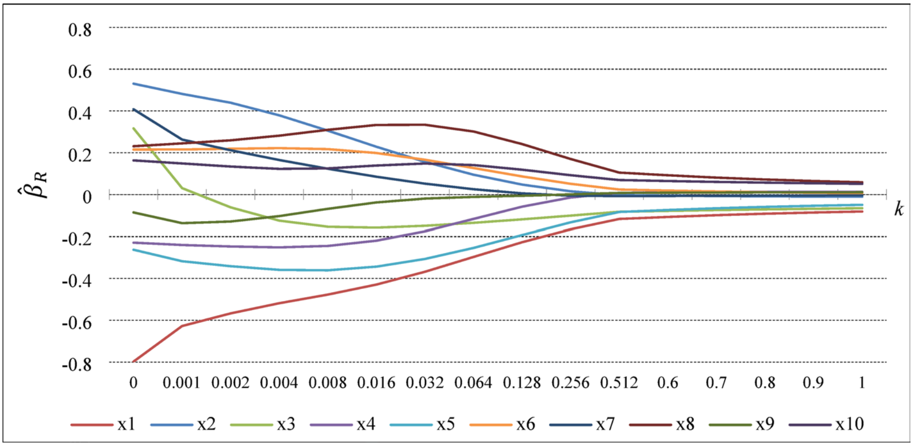

Fig. 7 Ridge trace

$$\boldsymbol{X_A} = \begin{bmatrix} X \\ \sqrt{\boldsymbol{k}}\ \boldsymbol{I_p} \end{bmatrix}, \quad \boldsymbol{y_A} = \begin{bmatrix} y \\ \theta_{\boldsymbol{p}} \end{bmatrix} \tag{5}$$

As $\sqrt{\boldsymbol{k}}\ \boldsymbol{I_p}$ is a diagonal matrix of $\boldsymbol{p} \times \boldsymbol{p}$, so that its diagonal elements are the square root of the biasing parameter, and $\theta_{\boldsymbol{p}}$ is a $\boldsymbol{p} \times 1$ vector of zeros. In this case, the ridge estimates are computed as:

$$\widehat{\beta}_{\boldsymbol{R}} = (\boldsymbol{X'_A X_A})^{-1} \boldsymbol{X'_A y_A} \tag{6}$$

Accordingly, using Minitab software, the regression equation is as Table 7.

According to this model, it can be seen that the VIF has been significantly reduced, and therefore, the collinearity problem has been solved, as the maximum value of VIF is reduced from 399.80 to 18.32. However, in the ridge regression model, the R^2 has decreased, and the reason is to solve the model collinearity problem. The ridge model based on the original regressors is as follows:

$$\begin{aligned}
\hat{y} = {} & 82.3217 - 1.2388x_1 + 0.521x_2 - 0.5016x_3 - 0.5884x_4 - 1.0321x_5 \\
& + 0.5622x_6 + 0.1757x_7 + 1.1244x_8 - 0.0640x_9 + 0.4982x_{10} \\
& - 0.2906x_1x_2 - 0.4824x_1x_3 + 0.0373x_1x_4 + 0.5966x_1x_5 - 0.5634x_1x_6 \\
& - 1.2102x_1x_7 - 0.5008x_1x_8 - 0.4351x_1x_9 - 0.2352x_1x_{10} \\
& + 0.4420x_2x_3 + 0.3914x_2x_4 + 0.2440x_2x_5 - 0.0855x_2x_6 \\
& + 0.0048x_2x_7 + 0.4889x_2x_8 - 0.4348x_2x_9 - 0.5791x_2x_{10} \\
& - 0.1660x_3x4 - 1.2762x_3x_5 - 0.1404x_3x_6 + 0.0346x_3x_7 \\
& - 0.7848x_3x_8 - 0.4513x_3x_9 - 0.6944x_3x_{10} + 0.5135x_4x_5 \\
& + 0.0818x_4x_6 + 0.4867x_4x_7 + 1.4531x_4x_8 - 0.2460x_4x_9 \\
& + 1.3968x_4x_{10} - 0.0653x_5x_6 + 0.3971x_5x_7 + 0.6943x_5x_8 \\
& + 0.5072x_5x_9 + 1.8685x_5x_{10} - 0.1663x_6x_7 + 0.1368x_6x_8 \\
& - 0.7793x_6x_9 + 1.2962x_6x_{10} - 0.4428x_7x_8 - 0.01x_7x_9 \\
& + 0.7540x_7x_{10} - 2.0966x_8x_9 + 0.9226x_8x_{10} + 0.5389x_9x_{10} \\
& + 1.0549x_1^2 + 0.1972x_2^2 - 0.9891x_3^2 + 0.1484x_4^2 + 0.2039x_5^2 \\
& - 0.0944x_6^2 - 0.2572x_7^2 - 0.5770x_8^2 - 0.2624x_9^2 + 0.2970x_{10}^2
\end{aligned}$$

To verify the obtained model, 24 randomly selected data are used to test the model. The results of estimating the fitted model $(\boldsymbol{y})$ along with the actual values are as Table 8.

According to Fig. 8, which shows the fitted versus actual y, the mean absolute error $(MAE = \frac{1}{N}\sum |y_{actual} - \widehat{y}|)$, mean absolute percentage error $(MAPE = \frac{1}{N}\sum \left|\frac{y_{actual} - \widehat{y}}{y_{actual}}\right|)$ and mean squared error $(MSE = \frac{1}{N}\sum (y_{actual} - \widehat{y})^2)$ are calculated as 3.298, 0.040 and 16.509, respectively, which is small and acceptable.

4.3 Optimization

At this stage, the process is optimized using mathematical programming, following the development of a model that accurately represents the operation. The minimum and maximum values of each input are therefore regarded as constraints, and the model that was

Table 7 Ridge regression results

Term	Coef	SE coef	T-value	*P* value	VIF	Term	Coef	SE coef	T-value	*P* value	VIF
x1	− 0.368	0.127	− 2.9	0.004	9.38	x3 * x10	− 0.238	0.126	− 1.89	0.06	9.29
x2	0.156	0.137	1.14	0.255	10.94	x4 * x5	0.26	0.147	1.77	0.079	12.68
x3	− 0.149	0.133	− 1.12	0.263	10.29	x4 * x6	0.017	0.107	0.16	0.873	6.75
x4	− 0.1748	0.0942	− 1.86	0.066	5.19	x4 * x7	0.109	0.115	0.95	0.345	7.67
x5	− 0.3066	0.0906	− 3.38	0.001	4.8	x4 * x8	0.354	0.0925	3.83	0	5
x6	0.167	0.109	1.53	0.129	6.95	x4 * x9	− 0.105	0.131	− 0.8	0.426	10.04
x7	0.0522	0.0962	0.54	0.588	5.41	x4 * x10	0.285	0.0924	3.08	0.002	4.99
x8	0.334	0.105	3.18	0.002	6.43	x5 * x6	− 0.0134	0.0979	− 0.14	0.891	5.6
x9	− 0.019	0.111	− 0.17	0.862	7.15	x5 * x7	0.111	0.125	0.89	0.374	9.12
x10	0.148	0.1	1.48	0.14	5.84	x5 * x8	0.167	0.104	1.6	0.111	6.35
x1 * x2	− 0.121	0.175	− 0.69	0.492	17.99	x5 * x9	0.168	0.12	1.4	0.164	8.42
x1 * x3	− 0.155	0.176	− 0.88	0.379	18.06	x5 * x10	0.4127	0.0939	4.4	0	5.15
x1 * x4	0.014	0.137	0.1	0.919	10.91	x6 * x7	− 0.062	0.158	− 0.39	0.694	14.51
x1 * x5	0.195	0.146	1.33	0.185	12.54	x6 * x8	0.032	0.102	0.31	0.757	6.11
x1 * x6	− 0.169	0.139	− 1.21	0.228	11.36	x6 * x9	− 0.1899	0.0957	− 1.99	0.049	5.35
x1 * x7	− 0.326	0.122	− 2.68	0.008	8.65	x6 * x10	0.368	0.121	3.05	0.003	8.51
x1 * x8	− 0.128	0.133	− 0.96	0.34	10.4	x7 * x8	0.1206	0.0962	1.25	0.212	5.41
x1 * x9	− 0.216	0.177	− 1.22	0.224	**18.32**	x7 * x9	− 0.0023	0.0878	− 0.03	0.979	4.51
x1 * x10	− 0.056	0.126	− 0.45	0.656	9.34	x7 * x10	0.248	0.113	2.19	0.03	7.5
x2 * x3	0.132	0.158	0.84	0.402	14.51	x8 * x9	− 0.442	0.117	− 3.78	0	7.99
x2 * x4	0.154	0.128	1.2	0.231	9.57	x8 * x10	0.223	0.0941	2.37	0.019	5.17
x2 * x5	0.101	0.128	0.79	0.431	9.65	x9 * x10	0.162	0.109	1.5	0.137	6.89
x2 * x6	− 0.022	0.13	− 0.17	0.867	9.88	x1 * x1	0.388	0.163	2.37	0.019	15.62
x2 * x7	0.001	0.102	0.01	0.995	6.08	x2 * x2	0.081	0.153	0.53	0.6	13.76
x2 * x8	0.116	0.122	0.95	0.345	8.74	x3 * x3	− 0.371	0.137	− 2.71	0.008	10.93

Table 7 (continued)

Term	Coef	SE coef	T-value	P value	VIF	Term	Coef	SE coef	T-value	P value	VIF
x2 * x9	− 0.193	0.16	− 1.21	0.229	14.87	x4 * x4	0.0927	0.0972	0.95	0.342	5.52
x2 * x10	− 0.145	0.106	− 1.36	0.176	6.6	x5 * x5	0.173	0.136	1.27	0.207	10.86
x3 * x4	− 0.05	0.139	− 0.36	0.718	11.35	x6 * x6	− 0.043	0.147	− 0.29	0.771	12.56
x3 * x5	− 0.333	0.12	− 2.76	0.007	8.49	x7 * x7	− 0.099	0.111	− 0.9	0.37	7.14
x3 * x6	− 0.049	0.136	− 0.36	0.721	10.83	x8 * x8	− 0.3706	0.0888	− 4.17	0	4.61
x3 * x7	0.011	0.124	0.09	0.929	9.04	x9 * x9	− 0.207	0.156	− 1.32	0.189	14.32
x3 * x8	− 0.189	0.113	− 1.68	0.096	7.48	x10 * x10	0.1366	0.0888	1.54	0.126	4.61
x3 * x9	− 0.183	0.167	− 1.09	0.276	16.4						
Model Summary											
S	R-sq	R-sq(adj)	R-sq(pred)								
0.042015	74.58%	63.11%	41.51%								

Regression Equation

Y = -0.368 × 1 + 0.156 × 2–0.149 × 3–0.1748 × 4–0.3066 × 5 + 0.167 × 6 + 0.0522 × 7
+ 0.334 × 8–0.019 × 9 + 0.148 × 10–0.121 × 1 × 2–0.155 × 1 × 3 + 0.014 × 1 × 4 + 0.195 × 1 × 5
− 0.169 × 1 × 6–0.326 × 1 × 7–0.128 × 1 × 8–0.216 × 1 × 9–0.056 × 1 × 10 + 0.132 × 2 × 3
+ 0.154 × 2 × 4 + 0.101 × 2 × 5–0.022 × 2 × 6 + 0.001 × 2 × 7 + 0.116 × 2 × 8–0.193 × 2 × 9
− 0.145 × 2 × 10–0.050 × 3 × 4–0.333 × 3 × 5–0.049 × 3 × 6 + 0.011 × 3 × 7–0.189 × 3 × 8
− 0.183 × 3 × 9–0.238 × 3 × 10 + 0.260 × 4 × 5 + 0.017 × 4 × 6 + 0.109 × 4 × 7 + 0.3540 × 4 × 8
− 0.105 × 4 × 9 + 0.2850 × 4 × 10–0.0134 × 5 × 6 + 0.111 × 5 × 7 + 0.167 × 5 × 8 + 0.168 × 5 × 9
+ 0.4127 × 5 × 10–0.062 × 6 × 7 + 0.032 × 6 × 8–0.1899 × 6 × 9 + 0.368 × 6 × 10 + 0.1206 × 7 × 8
− 0.0023 × 7 × 9 + 0.248 × 7 × 10–0.442 × 8 × 9 + 0.2230 × 8 × 10 + 0.162 × 9 × 10 + 0.388 × 1^2
+ 0.081 × 2^2–0.371 × 3^2 + 0.0927 × 4^2 + 0.173 × 5^2–0.043 × 6^2–0.099 × 7^2
− 0.3706 × 8^2–0.207 × 9^2 + 0.1366 × 10^2

Table 8 Fitted versus actual value

$\widehat{y}$	Actual Y	$\widehat{y}$	Actual Y	$\widehat{y}$	Actual Y
78.87383	86	92.45054	83	75.44147	79
83.50212	82	79.01478	84	77.21689	83
83.41776	79	81.58915	83	83.2824	80
86.22237	79	85.09507	83	79.21883	80
80.08671	83	79.86848	78	82.81519	83
80.40321	85	79.50287	80	83.05979	88
82.28315	81	79.2502	82	82.52978	85
82.28315	81	77.69591	82	84.55778	85

obtained in the previous section is regarded as the objective function. This mathematical model is represented by Eq. (7). The Appendix contains a detailed depiction of this mathematical model.

$$\max \widehat{y} \tag{7}$$

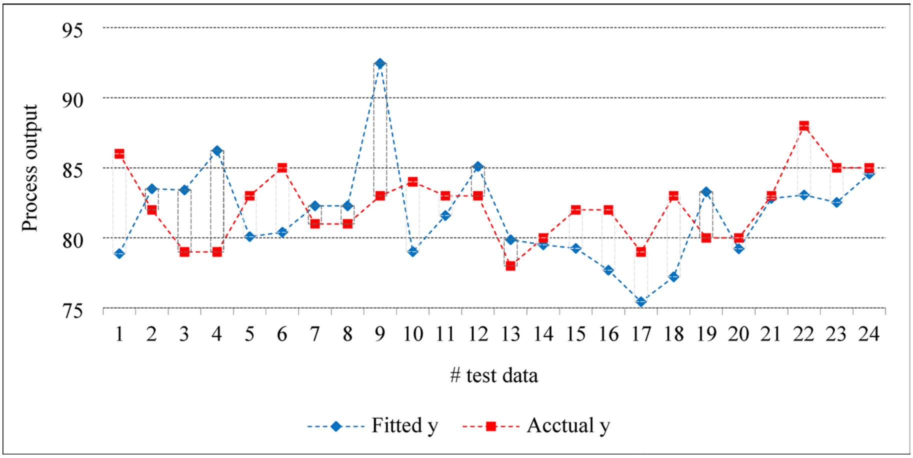

Fig. 8 Fitted versus actual y

$$subject\ \ to\ :min_i \leq x_i \leq max_i\ ;\ i = 1,\ \cdots, 10$$

where $\widehat{y}$ is the ridge model based on the original regressors, min_i and max_i are the i^{th} minimum and maximum values of input i, respectively.

The optimal solutions are obtained by solving Eq. (7) with the aid of mathematical solvers like Lingo, where the input variables are classified into two groups: adjustable and non-adjustable parameters. Therefore, the concentrate weight, concentrate moisture content, pH of acid grout and weight of sulfuric acid are adjusted at 120,000 kg, 39.3%, 2.4 and 8000 kg, respectively. These values are used to modify the process, and the outcomes are examined in the following section.

4.4 Validation

Following the process adjustments, impurity rate data are analyzed both before and after implementing the proposed solutions to validate the results. As a result, 107 purification samples were collected before the modifications and another 107 after the modifications; all corresponding data are provided in the Online Resource[3] (supplementary materials attached to the paper). The descriptive statistics are presented in Table 9.

Statistical hypothesis testing is performed to ascertain whether there is a significant difference between the mean rate of impurities before and after the corrections. Owing to the substantial sample size ($n = 107$), a normal distribution of the population is presumed. To compare the average values, the null hypothesis $H_\circ\ : \mu_{\ After} - \mu_{\ Before} \leq\ 0$ is taken into account. According to Table 10, which represents the test results, the null hypothesis is not rejected. Consequently, it is determined that the average impurity rates following the process adjustments are lower than they were previously, thereby rejecting the equality of averages assumption.

[3] https://www.researchgate.net/publication/392499955_Supplementary_Data_source.

Table 9 Descriptive study of the data both before and after the suggested adjustments

	Total purifications	Lead		Nickel		Cadmium	
		Mean	St. dev *	Mean	St. dev	Mean	St. dev
Before	107	13.21	2.98	2.82	0.26	2.11	0.77
After	107	11.22	2.34	2.71	0.30	1.86	0.61

**St. dev* standard deviation

Table 10 The test results for the hypothesis of average impurity equality before and after process adjustment

	Lead		Nickel		Cadmium	
	p value	T-value	*p* value	T-value	*p* value	T-value
Test result	1.000	− 5.43	0.998	− 2.87	0.996	− 2.65

5 Discussion

This section provides a detailed interpretation of the study's findings and investigates their broader implications. It is organised into three main subsections: suggested strategies, which presents practical recommendations for improving process performance based on the analysis; managerial insights, real-life applications, and perspectives, which connects the results to actionable guidance for industry professionals, policymakers, and local communities; and theoretical and methodological contributions, which emphasises the academic significance of the research by detailing its addition.

5.1 Suggested strategies

The improved strategies suggested in this study focus on improving environmental sustainability and lowering harmful emissions in the zinc manufacturing process using statistical modelling for process optimization in conjunction with environmental management practices. These strategies include the following:

- *Adjustment of Key Process Parameters Using Ridge Regression*: Ridge regression is used to address multicollinearity among input variables and identify key parameters impacting output quality during pulping and acid leaching phases. By fine-tuning factors such as concentrate weight, concentrate moisture, pH of acid grout, and sulfuric acid input, the process can be optimized to drastically reduce heavy metal contaminants in the output.
- *Reducing Impurity Load in Early Process Stages*: The study recommends preventive control over post-treatment measures by focussing on the initial stages of zinc production (pulping and acid leaching). This method effectively reduces the quantity of contaminants (such as lead, cadmium, and nickel) that enter the downstream operations and the environment.
- *Application of Waste Management Best Practices*: Modifying process parameters not only increases efficiency but also ensures compliance with corporate environmental management systems. This enables greater residue waste management and reduction, bringing businesses closer to meeting environmental regulations.
- *Data-Driven Decision-Making*: The modelling technique enables informed decision-

making by giving quantitative evidence of each variable's impact on environmental output. This allows the company to make scientifically sound adjustments that benefit both environmental performance and production stability.

- *Integration of Environmental and Social Considerations*: In addition to technical improvements, the study recommends strategies for broader environmental protection and community welfare, including monitoring water and soil quality in nearby zones, engaging stakeholders, and supporting policy reforms for long-term sustainability.

The combination of modelling, operational adjustments, and environmental stewardship results in a holistic improvement framework targeted at reducing the ecological and social implications of the zinc manufacturing process.

5.2 Managerial insights, real life applications and perspectives

In order to achieve sustainable operations, the managerial insights gained from this study highlight the significance of proactive environmental management, stakeholder involvement, and regulatory compliance. Businesses can retain operational efficiency and profitability while simultaneously making contributions to social welfare and environmental sustainability through the integration of these insights into their decision-making processes. In particular, this study offers decision-makers a variety of managerial insights. (i) *Environmental impact mitigation strategies*: Industry sector decision-makers can learn practical methods to enhance sustainability and lessen environmental effects. Businesses can reduce harmful environmental effects such as heavy metal pollution and water contamination by concentrating on waste management optimization and changing process parameters. (ii) *Interdisciplinary collaboration promotion*: The study emphasizes how crucial interdisciplinary cooperation is to solve environmental problems. To create comprehensive solutions that strike a compromise between industrial practices and environmental concerns, decision-makers might encourage cooperation amongst a variety of stakeholders, including environmental scientists, engineers, legislators, and community members. (iii) *Community engagement and stakeholder management*: To address the wide-ranging effects of mining operations on nearby communities, decision-makers should give priority to community engagement and stakeholder management initiatives. Companies can increase social acceptance of their operations, reduce conflict, and develop trust by promoting cooperation, transparency, and communication with the local population. (iv) *Compliance with environmental regulations*: The work emphasizes how important it is to align waste management procedures with environmental laws. It is imperative for decision-makers to guarantee that their activities comply with pertinent laws and regulations in order to avert legal liabilities and uphold a favorable corporate image. (v) *Long-term sustainability planning*: When organizing environmental sustainability projects, decision-makers should take a long-term view. Businesses may safeguard the health of the public, preserve vital natural resources, and ensure the welfare of present and future generations by making investments in preventative measures and conservation strategies. Overall, this study's managerial insights highlight how crucial proactive environmental management, stakeholder involvement, and regulatory compliance are to attain sustainable operations. Businesses can retain operational efficiency and profitability while simultaneously making contributions to social welfare and environmental sustainability through the integration of these insights into their decision-making processes.

This study has several real-world applications, such as waste management, social engagement, environmental compliance, policy influence, and public health protection. Businesses can balance their industrial operations with environmental considerations and contribute to social welfare and environmental sustainability by putting study findings into action. Particularly, this work has a wide range of significant real-world applications. (i) *Improved waste management practices*: The research findings can be utilized by businesses to enhance their waste management procedures. Waste generation can be reduced, and environmental standards can be better complied with by changing process parameters and implementing corporate environmental management systems. (ii) *Enhanced environmental compliance*: The research findings offer valuable information that mining businesses can utilize to maintain compliance with environmental legislation and standards. Businesses can more effectively assess and reduce their environmental impact by employing statistical modeling approaches such as ridge regression to pinpoint important input-output parameters in the complex process. (iii) *Community engagement and stakeholder collaboration*: Businesses can make better use of the research's findings to interact with stakeholders and local communities. They can develop connections with neighboring communities that are mutually beneficial, reduce conflict, and increase trust by educating the public about the environmental effects of their operations and encouraging interdisciplinary collaboration. (iv) *Policy influence and advocacy*: The research results can be utilized to guide advocacy and policy-making initiatives that support environmental sustainability in the industry sector. Businesses can promote regulations that encourage sustainable practices and responsible resource management by working with legislators, industry groups, and non-governmental organizations. (v) *Public health protection*: Preventive actions based on study findings can assist save vital natural resources and safeguard public health. Companies can protect the health and welfare of locals and guarantee the supply of clean water for communities by addressing the wide-ranging effects of mining activities on nearby agricultural land, sediments, and water bodies.

The research perspectives cover a number of important areas that warrant further investigation and advancement. It suggests enhancing statistical modeling techniques to better understand environmental processes, integrating social and economic factors into sustainability frameworks, and assessing the effectiveness of sustainability initiatives. It also suggests exploring policy and regulatory frameworks that incentivize sustainable practices and support environmental stewardship. It also calls for innovative approaches to community engagement and stakeholder participation in environmental decision-making processes. These perspectives aim to advance knowledge and practice in environmental management and sustainability, promoting evidence-based policies, practices, and interventions that protect public health and enhance social welfare in affected communities.

5.3 Theoretical and methodological contributions

This work makes theoretical and methodological contributions to the field of environmental management and sustainable mining practices:

- *Theoretical contributions*.

The study adds to the theoretical discourse on the integration of environmental sustainability and industrial processes by focussing on how residue-based zinc production affects neighboring ecosystems, public health, and socioeconomic dynamics. It adds to the current literature by establishing a direct link between environmental deterioration, social wellbeing, and the operational parameters of mineral processing. Furthermore, it emphasizes the importance of interdisciplinary approaches that combine engineering, environmental science, and social policy to address sustainability issues in mining operations.

- *Methodological contributions*.

Methodologically, the work uses ridge regression modelling to address multicollinearity issues among process variables, improving the robustness and interpretability of statistical analysis in industrial settings. It presents a structured optimization framework for adjusting process parameters with the purpose of lowering contaminants and aligning waste management with environmental guidelines. Furthermore, the study uses a before-and-after validation technique with real sample data from soil, water, and sediment to experimentally validate the effectiveness of the proposed process improvements. This methodological integration provides a replicable approach in conducting similar industrial sustainability assessments.

These contributions not only enrich academic literature, but also provide practical direction for industry practitioners, policymakers, and researchers seeking data-driven solutions to environmental and social concerns in industrial settings.

6 Conclusion

This paper conducts a thorough analysis into the environmental and operational dynamics of zinc production from low-grade residues, an area that remains underexplored despite its growing industrial relevance and environmental consequences. The study develops and applies an integrated framework that combines environmental evaluation, advanced statistical modelling, process optimisation, and empirical validation to address both ecological and technical issues related with zinc manufacture. The findings show that process optimisation based on robust statistical approaches can greatly increase not just product quality, but also environmental compliance and sustainability.

The environmental evaluation phase indicated widespread pollution in tailings, cakes, agricultural soils, and local water sources. Heavy metals like lead, cadmium, zinc, nickel, and arsenic were found at concentrations that exceeded internationally accepted environmental and public health standards. This emphasises the crucial need for enhanced residue management practices, as well as the necessity for industrial operators to reassess their environmental risk profiles. Furthermore, the results indicate that these contaminants are not contained but are likely to spread through the air, water, and soil, potentially affecting broader ecosystems and human health in nearby communities. This generates a need for comprehensive environmental monitoring and remediation strategies that go beyond regulatory compliance and include proactive environmental stewardship.

In response to these environmental hazards, the study created a predictive and optimised statistical modelling framework that employs ridge regression to manage multicollinearity and a second-order polynomial regression to capture nonlinear interactions among process variables. The model displayed great prediction accuracy and interpretability, establishing a solid foundation for detecting and adjusting key operational parameters. Concentrate weight, concentrate moisture content, sulphuric acid input, and acid grout pH all had a substantial impact on output quality and contaminant levels. By optimising these factors with mathematical programming techniques, the model facilitated in the development of an actionable solution that was both technically feasible and environmentally advantageous.

The proposed solutions' practical effectiveness was empirically evaluated by comparing impurity levels before and after they were implemented. The statistical testing of 107 pre- and post-implementation samples revealed a considerable reduction in heavy metal impurities, demonstrating the robustness and practical application of the suggested optimisation framework. This empirical evidence supports the notion that making targeted adjustments to process parameters can significantly reduce environmental impacts while maintaining or even increasing production efficiency.

This paper offers concrete strategies for enhancing process sustainability from the managerial and policy standpoint. These include the implementation of data-driven decision-making, preventive rather than reactive pollution control, and aligning industrial practices with environmental and social governance standards. The findings offer valuable insights for industry stakeholders, environmental regulators, and community leaders. Companies can apply the methodology to achieve long-term environmental compliance, decrease liabilities, and improve their corporate reputation. Policymakers can then use the evidence to push for stricter waste discharge regulations and the implementation of sustainable process optimization technologies.

This research's real-world applications span multiple domains. For industries, the framework provides a blueprint for building environmentally responsible process operations that are sensitive to both technological and ecological constraints. For communities, it provides a scientific foundation for environmental advocacy and health care. It provides researchers and academic institutions with a replicable and scalable scientific solution to similar industrial sustainability concerns.

Theoretically, the study contributes to the expanding body of literature on the integration of environmental and industrial process management. It demonstrates a clear empirical link between process conditions and environmental results, emphasising the importance of interdisciplinary approaches that combine engineering, environmental science, and policy. Methodologically, it improves the application of ridge regression and polynomial interaction modelling in complex industrial settings characterised by multicollinearity and nonlinear effects. A comprehensive validation step using real environmental samples further strengthens the study framework's reliability and replicability.

In summary, this work offers a scientifically sound, practically viable, and policy-relevant roadmap for enhancing zinc manufacturing processes from low-grade residues. By combining advanced statistical modelling techniques with real-world environmental data and optimisation tools, it provides a comprehensive solution to one of the pressing challenges in sustainable mining. The method not only improves the efficiency and quality of industrial production, but it also prioritises environmental health and social welfare, aligning industrial practices with larger sustainability objectives. This work establishes a solid foundation for future research aimed at closing the gap between industrial productivity and environmental responsibility in the context of extractive industries.

Appendix

Representation of the optimization model as per Eq. (7):

max = 82.3217–1.2388 * x1 + 0.521 * x2–0.5016 * x3–0.5884 * x4 −1.0321 * x5
+ 0.5622 * x6 + 0.1757 * x7 + 1.1244 * x8 − 0.064 * x9 + 0.4982 * x10
−0.2906 * x1 * x2–0.4824 * x1 * x3 + 0.0373 * x1 * x4 + 0.5966 * x1 * x5 − 0.5634 * x1 * x6
−1.2102 * x1 * x7 − 0.5008 * x1 * x8 − 0.4351 * x1 * x9 − 0.2352 * x1 * x10
+ 0.4420 * x2 * x3 + 0.3914 * x2 * x4 + 0.244 * x2 * x5 − 0.0855 * x2 * x6
+ 0.0048 * x2 * x7 + 0.4889 * x2 * x8 − 0.4348 * x2 * x9 − 0.5791 * x2 * x10
−0.1660 * x3 * x4 − 1.2762 * x3 * x5 − 0.1404 * x3 * x6 + 0.0346 * x3 * x7
−0.7848 * x3 * x8 − 0.4513 * x3 * x9 − 0.6944 * x3 * x10 + 0.5135 * x4 * x5
+ 0.0818 * x4 * x6 + 0.4867 * x4 * x7 + 1.4531 * x4 * x8 − 0.246 * x4 * x9
+ 1.3968 * x4 * x10 − 0.0653 * x5 * x6 + 0.3971 * x5 * x7 + 0.6943 * x5 * x8
+ 0.5072 * x5 * x9 + 1.8685 * x5 * x10 − 0.1663 * x6 * x7 + 0.1368 * x6 * x8
−0.7793 * x6 * x9 + 1.2962 * x6 * x10 − 0.4428 * x7 * x8 − 0.01 * x7 * x9
+ 0.7540 * x7 * x10 − 2.0966 * x8 * x9 + 0.9226 * x8 * x10 + 0.5389 * x9 * x10
+ 1.0549 * x1 * x1 + 0.1972 * x2 * x2 − 0.9891 * x3 * x3 + 0.1484 * x4 * x4 + 0.2039 * x5 * x5
−0.0944 * x6 * x6 − 0.2572 * x7 * x7 − 0.577 * x8 * x8 − 0.2624 * x9 * x9 + 0.297 * x10 * x10;
x1 >= 22;
x1 <= 35.8;
x2 >= 75,000;
x2 <= 120,000;
x3 >= 24;
x3 <= 39.3;
x4 >= 1.45;
x4 <= 2.4;
x5 >= 4.9;
x5 <= 19.6;
x6 >= 19;
x6 <= 27;
x7 >= 81;
x7 <= 93;
x8 >= 2000;
x8 <= 8000;
x9 >= 21;
x9 <= 34;
x10 >= 80;
x10 <= 120;

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Data availability Data is provided as the supplementary material.

Declarations

Conflict of interest The author has no relevant financial or non-financial interests to disclose.

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