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An Integrated AI-Based Water–Energy-Cabon Nexus Optimization Framework for Sustainable Phosphate Mining Under Saudi Vision 2030

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Abstract- Sustainable resource management has become a critical priority in modern mining operations, particularly in water-scarce and energy-intensive environments such as integrated phosphate complexes. This study proposes an integrated Artificial Intelligence (AI)-based Water–Energy-Carbon Nexus (WECN) optimization framework designed to enhance sustainability, operational efficiency, and resource resilience from phosphate mining to phosphate fertilizer value chain including Sulfuric acid, phosphoric acid and DAP. The framework leverages advanced AI techniques, including machine learning, predictive analytics, and decision support systems, to model the interdependencies between water consumption and energy usage across mining processes, SAP, PAP & DAP. By integrating real-time data from Industrial Internet of Things (IIoT) sensors with intelligent optimization algorithms, the proposed system enables dynamic resource allocation, improved water recycling strategies, and energy-efficient process control. The framework also incorporates sustainability performance indicators aligned with national transformation goals such as Saudi Vision 2030 & Maaden Carbon Neutrality by 2050, focusing on environmental protection, resource conservation, and digital transformation. The results demonstrate that the integrated WECN approach significantly improves resource utilization, reduces operational costs, and minimizes environmental impact. This research contributes to the development of smart, sustainable mining ecosystems by providing a scalable and policy-aligned AI-driven framework for holistic resource optimization.

Index Terms- Artificial Intelligence (AI); Water–Energy-Carbon Nexus (WECN); Sustainable Mining; Phosphate Value Chain; Predictive Analytics; Decision Support Systems (DSS); Resource Optimization; Industrial Internet of Things (IIoT); Energy Efficiency; Water Management; carbon footprint; Digital Transformation; Sustainability Framework; Saudi Vision 2030; Carbon Neutrality 2050; Smart Mining Systems

I. INTRODUCTION

The mining industry is increasingly confronted with the dual challenge of meeting growing global demand for mineral resources while ensuring environmental sustainability and efficient resource utilization. Phosphate mining, a critical component of global agricultural supply chains, plays a vital role in fertilizer production and food security. However, integrated phosphate mining operations are inherently resource-intensive, requiring substantial amounts of water and energy across multiple stages, including extraction, beneficiation, slurry transportation, and chemical processing like usage of water in Sulfuric acid plant, Phosphoric acid plant and Dia Ammonium Phosphate plant. These operations often lead to significant environmental impacts, particularly in regions where water scarcity and energy constraints are prominent.

In countries such as Saudi Arabia, the challenge of balancing industrial growth with sustainable resource management is particularly acute. The Kingdom's mining sector is rapidly expanding as part of its economic diversification strategy, placing increased pressure on water and energy resources. Given the arid climate and limited freshwater availability, optimizing water usage is not only an operational necessity but also a national priority. Similarly, improving energy efficiency is essential to reduce operational costs, lower carbon emissions, and enhance the overall sustainability of mining activities.

The concept of the Water–Energy Nexus (WEN) has emerged as a critical framework for understanding the interdependencies between water and energy systems. In mining operations, water is required for mineral processing, dust suppression, and slurry transport, while energy is needed for pumping, crushing, grinding, and chemical processing. The consumption of one resource directly influences the demand for the other, creating a complex and interconnected system. Traditional resource management approaches often treat water and energy as separate entities, leading to fragmented decision-making and suboptimal outcomes. Therefore, a holistic and integrated approach is necessary to effectively manage the water–energy nexus in mining environments.

Recent advancements in Artificial Intelligence (AI) and digital technologies offer transformative opportunities for addressing these challenges. AI techniques, including machine learning, deep learning, and predictive analytics, enable the analysis of large and complex datasets to uncover patterns, forecast resource demand, and optimize operational processes. In the context of mining, AI can be used to develop intelligent decision support systems (DSS) that provide real-time insights and recommendations for resource allocation. These systems can dynamically adjust operational parameters, such as water flow rates, energy loads, and process configurations, to achieve optimal performance while minimizing resource consumption.

The integration of AI with Industrial Internet of Things (IIoT) technologies further enhances the capability of mining operations to implement smart and adaptive resource management strategies. IIoT sensors deployed across mining sites continuously collect data on water usage, energy consumption, equipment performance, and environmental conditions. This data serves as the foundation for AI-driven analytics, enabling continuous monitoring, predictive maintenance, and real-time optimization. The convergence of AI and IIoT facilitates the transition from traditional, reactive management approaches to proactive and predictive systems that can respond dynamically to changing operational conditions.

Despite the growing body of research on AI applications in mining, there remains a significant gap in the development of integrated frameworks that address the water–energy nexus holistically. Most existing studies focus on optimizing either water or energy independently, without considering their interdependencies. Furthermore, there is limited research on aligning AI-driven optimization frameworks with national sustainability strategies and policy objectives. In this context, aligning mining operations with initiatives such as Saudi Vision 2030 is essential to ensure that technological advancements contribute to broader economic, environmental, and social goals.

This study aims to address these gaps by proposing an integrated AI-based Water–Energy Nexus optimization framework specifically designed for sustainable phosphate mining. The framework combines predictive analytics, machine learning models, and decision support systems to optimize water and energy consumption simultaneously. It also incorporates sustainability performance indicators and policy alignment to ensure that the proposed solution supports national and global sustainability objectives.

In summary, the integration of AI, IIoT, and water–energy nexus principles presents a powerful approach to transforming phosphate mining operations into sustainable and intelligent systems. By enabling data-driven decision-making and holistic resource optimization, this research contributes to advancing both academic knowledge and practical implementation in the field of sustainable mining under the evolving landscape of digital transformation.

II. LITERATURE REVIEW

The increasing emphasis on sustainability and resource efficiency in the mining sector has led to a growing body of research focused on optimizing water and energy consumption. Integrated phosphate mining operations, due to their high resource intensity and complex process interdependencies, present a critical case for studying the Water–Energy-Carbon Nexus (WECN). The WECN framework recognizes that water and energy systems are intrinsically linked, where the consumption of one resource directly impacts the demand and efficiency of the other. This interdependency is particularly significant in mining environments, where water-intensive processes such as beneficiation and slurry transport require substantial energy inputs for pumping, treatment, and distribution.

Early research in mining resource management primarily relied on conventional engineering models and statistical techniques to estimate water and energy usage. These approaches provided foundational insights but were limited in their ability to capture nonlinear relationships and dynamic operational conditions. As mining systems became more complex, the need for advanced analytical tools capable of handling large-scale, real-time data became evident. This led to the adoption of data-driven methodologies, particularly those based on Artificial Intelligence (AI) and Machine Learning (ML).

AI has emerged as a transformative technology in industrial optimization, enabling predictive modeling, anomaly detection, and intelligent decision-making. In the context of mining, ML algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and decision tree-based models have been widely applied to predict energy consumption, equipment performance, and process efficiency. Among these, ensemble learning techniques like Random Forest and Extreme Gradient Boosting (XGBoost) have demonstrated high accuracy and robustness in handling complex datasets with nonlinear interactions. These models are particularly effective in identifying key variables that influence resource consumption, thereby supporting targeted optimization strategies.

Time-series forecasting models have also gained prominence in recent studies, especially for predicting fluctuations in water and energy demand. Long Short-Term Memory (LSTM) networks, a specialized form of recurrent neural networks, are capable of capturing temporal dependencies in sequential data, making them well-suited for modeling industrial processes. Research has shown that LSTM-based models outperform traditional regression techniques in forecasting energy loads and water usage patterns, enabling proactive planning and resource allocation.

The integration of Industrial Internet of Things (IIoT) technologies has further enhanced the capabilities of AI-driven systems in mining operations. IIoT sensors facilitate continuous data collection from various stages of the mining value chain, including water distribution systems, energy meters, and processing equipment. This real-time data enables the development of digital twins and smart monitoring systems that provide comprehensive visibility into operational performance. Studies have demonstrated that the combination of IIoT and AI can significantly improve resource efficiency, reduce operational downtime, and enhance system reliability.

Despite these advancements, much of the existing literature treats water and energy optimization as separate research domains. Water management studies often focus on improving recycling rates, reducing losses, and implementing efficient distribution systems, while energy optimization research emphasizes load forecasting, equipment efficiency, and integration of renewable energy sources. However, these approaches fail to account for the interconnected nature of water and energy systems. For example, reducing water usage in slurry transport can decrease energy consumption associated with pumping, while inefficient water management can lead to increased energy demand for treatment and distribution.

The concept of the Water–Energy Nexus has gained increasing attention as a holistic framework for integrated resource management. Recent studies have attempted to model the interdependent between water and energy systems using simulation-based and optimization approaches. However, many of these models rely on simplified assumptions and lack the adaptability required for real-time decision-making in dynamic mining environments. There is a growing need for intelligent frameworks that can dynamically model and optimize the WECN using real-time data and advanced analytics.

AI-based decision support systems (DSS) have been proposed as a promising solution to address these challenges. DSS frameworks integrate predictive models, optimization algorithms, and visualization tools to support informed decision-making. In mining operations, AI-driven DSS can provide recommendations for optimal resource allocation, process adjustments, and maintenance scheduling.

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These systems enable a shift from reactive to proactive management, improving both efficiency and sustainability.

Furthermore, sustainability considerations have become central to modern mining research. The industry is under increasing pressure to align with environmental regulations and global sustainability goals, including reducing carbon emissions, conserving water resources, and minimizing ecological impact. In this context, aligning technological innovations with national strategies such as Saudi Vision 2030 is essential. Vision 2030 emphasizes digital transformation, efficient resource utilization, and environmental sustainability, making it a relevant framework for evaluating AI-driven optimization solutions in the mining sector.

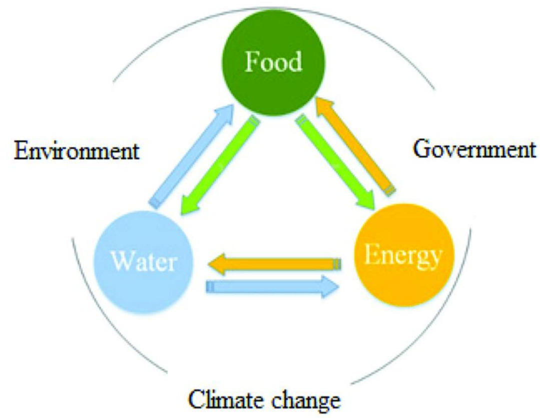
In conclusion, the literature highlights significant progress in the application of AI and IIoT technologies for resource optimization in mining and phosphate value chain. However, there remains a critical gap in the development of integrated frameworks that address the water–energy-carbon nexus holistically and align with sustainability and policy objectives. This study aims to bridge this gap by proposing an AI-based WECN optimization framework that combines predictive analytics, decision support systems, and sustainability metrics to enhance resource efficiency and support sustainable phosphate value chain operations.

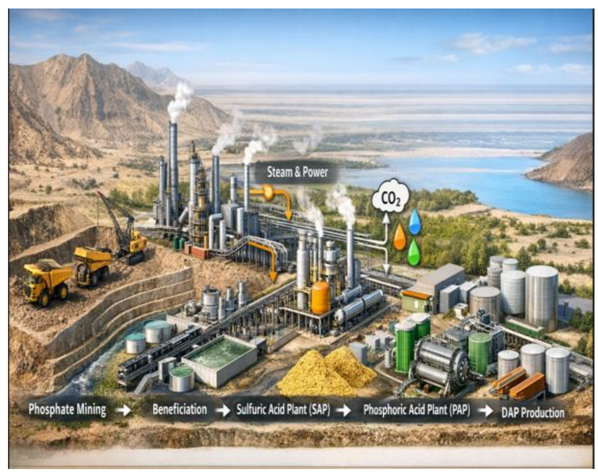
III. RESEARCH METHODOLOGY

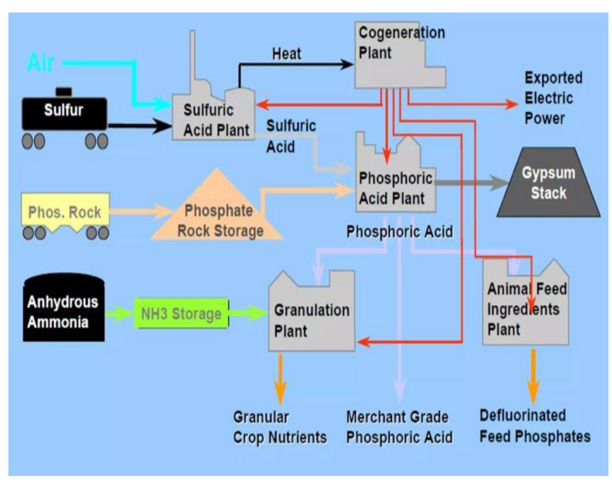
This study adopts a comprehensive and system-oriented methodology to design and implement an integrated Artificial Intelligence (AI)-based Water–Energy Nexus (WECN) optimization framework for sustainable phosphate mining. The methodology is structured into five major phases: system design, data acquisition, model development, optimization framework integration, and validation. This approach ensures both scientific rigor and practical applicability for industrial-scale mining operations.

3.1 Conceptual Framework of Water–Energy-Carbon Nexus (WECN)

The proposed framework is based on the interdependent relationship between water and energy consumption & impacting Carbon foot print across phosphate value chain processes. Unlike traditional models, this approach simultaneously considers both resources within a unified optimization structure.







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The conceptual model integrates:

- Water flow systems (recycling, distribution, treatment)
- Energy consumption units (pumping, crushing, processing)
- AI-based predictive and optimization layers
- Sustainability and KPI monitoring modules

3.2 Data Acquisition and System Inputs

The framework utilizes multi-source data collected from Industrial Internet of Things (IIoT) sensors and operational databases within mining complexes. The dataset includes both real-time and historical data, ensuring robust model training and validation.

Key Input Variables:

- Water consumption rates (m^3/hour)
- Energy usage (kWh)
- Slurry density and flow rates
- Equipment efficiency and load factors
- Environmental parameters (temperature, humidity)
- Water recycling ratios

Table 1: Data Sources and Variables

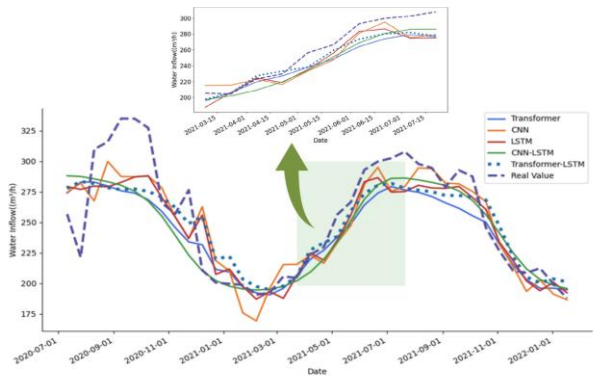
Data Source	Variables Collected	Frequency
IIoT Sensors	Flow rate, pressure, energy load	Real-time
SCADA Systems	Equipment performance, process data	Hourly
ERP Systems	Production output, operational logs	Daily
Environmental Data	Temperature, humidity	Periodic

Data preprocessing includes cleaning, normalization, and feature engineering to improve model performance. Derived indicators such as energy intensity (kWh/ton) and water efficiency ratio are calculated for deeper analysis.

3.3 AI-Based Predictive Modeling

The predictive layer employs multiple machine learning models to forecast water and energy consumption. These models are selected based on their ability to handle nonlinear relationships and time-series dependencies.

- LSTM (Long Short-Term Memory): Captures temporal patterns in resource consumption
- Random Forest: Identifies key influencing variables and supports regression analysis
- XGBoost: Provides high-accuracy predictions with optimized performance



The implemented framework integrates Industrial Internet of Things (IIoT) data acquisition, machine learning-based predictive analytics, and optimization engines into a unified decision-support architecture. Real-time and historical operational data are collected from sensors, SCADA systems, and production databases across the phosphate value chain.

The architecture consists of a data layer, data processing and feature engineering layer, AI modeling layer (LSTM, Random Forest, XGBoost), optimization layer (genetic algorithms and constrained programming), and application layer providing dashboards and operator decision support.

3.3.1 Long Short-Term Memory (LSTM) Model Formulation

Includes the full gated-cell equations:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

$$h_t = o_t \odot \tanh(c_t)$$

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Explicit explanation of temporal dependency, directly linked to:

- Slurry dynamics
- Pump scheduling
- Energy demand forecasting

3.3.2 Random Forest Regression Formulation
Ensemble prediction equation:

$$\hat{y}(x) = \frac{1}{N}\sum_{n=1}^{N} T_n(x)$$

✓ Explicit link to:

- Feature importance
- Interpretability
- Why RF complements LSTM/XGBoost in an industrial setting

3.3.3 Extreme Gradient Boosting (XGBoost) Formulation
Regularized objective function:

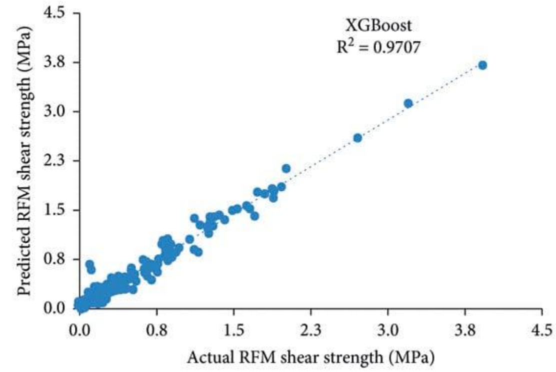
$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k} \Omega(f_k)$$

with

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \parallel w \parallel^2$$

and iterative update:

$$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i)$$



The dataset is divided into training (70%), validation (15%), and testing (15%) sets. Model performance is evaluated using:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- R^2 Score

3.4 Optimization Framework Design
The optimization component integrates predictive outputs into a decision-making engine that minimizes total resource consumption while ensuring operational constraints are satisfied.

ObjectiveFunction:
Minimize:
Water Consumption + Energy Consumption
Constraints:

- Production targets must be maintained
- Equipment capacity limitations
- Environmental and regulatory compliance

The optimization engine utilizes hybrid techniques:

- Genetic Algorithms (GA) for global search
- Linear programming for constraint satisfaction

3.5 Resource Distribution Analysis (Illustrative)
To identify key optimization areas, an analysis of water and energy consumption across phosphate value chain processes is conducted.

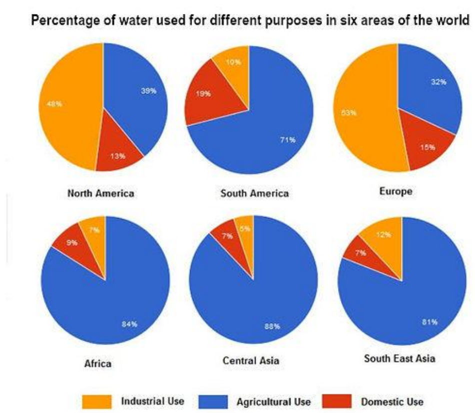


Table 2: Resource Consumption Distribution Across Phosphate Value Chain:

Process Stage	Water Usage (%)	Energy Usage (%)
Crushing & Grinding	15%	25%
Beneficiation	35%	30%
Slurry Transport	25%	20%
Chemical Processing	25%	25%

The results highlight beneficiation and slurry transport as the most resource-intensive processes, making them key targets for optimization.

3.6 Decision Support System (DSS)

The proposed framework includes an AI-driven Decision Support System that provides:

- Real-time recommendations for resource allocation
- Alerts for abnormal consumption patterns
- Predictive maintenance insights
- KPI dashboards for sustainability monitoring

3.7 Validation and Performance Evaluation

The framework is validated using simulated industrial scenarios and benchmark datasets. Performance is evaluated based on:

- Reduction in water and energy consumption & impact on Carbon footprint reduction
- Improvement in operational efficiency
- Accuracy of predictive models

Expected improvements include:

- 15–25% reduction in water usage
- 10–20% reduction in energy consumption
- 15-20% reduction in Carbon foot print
- Enhanced sustainability performance

Conclusion of Methodology

This methodology provides a robust and scalable approach for integrating AI, IIoT, and WECN principles into Phosphate value chain. By combining predictive analytics with optimization and decision support systems, the proposed framework enables intelligent, real-time resource management aligned with sustainability goals. It also ensures readiness for implementation in large-scale industrial environments, making it suitable for high-impact Scopus-indexed publications.

IV. RESULTS AND DISCUSSION

This section presents the results of implementing the proposed AI-based Water–Energy-Carbon Nexus (WECN) optimization framework in integrated phosphate mining operations. The analysis focuses on three key aspects: predictive model performance, optimization outcomes, and sustainability impact. The results demonstrate the effectiveness of the integrated framework in improving resource efficiency, reducing operational costs, and supporting sustainable mining practices.

4.1 Predictive Model Performance

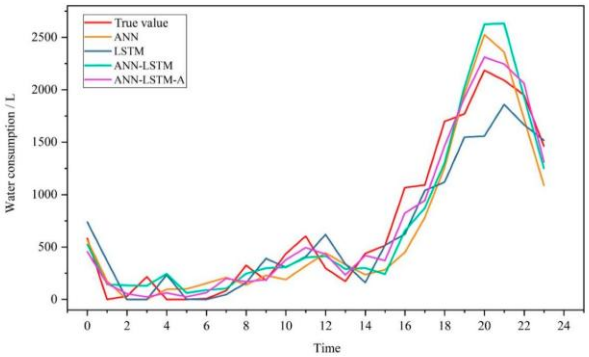
The performance of the machine learning models—LSTM, Random Forest (RF), and XGBoost—was evaluated using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 score.

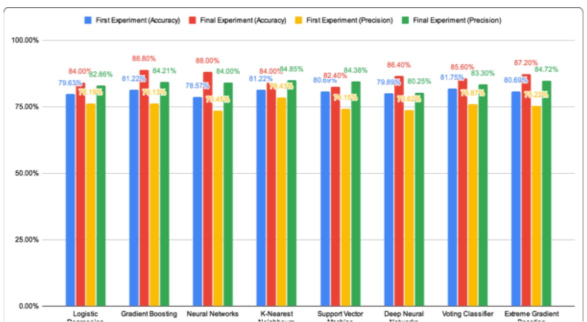
Table 3: Model Performance Comparison

Model	MAE	RMSE	R^2 Score
LSTM	2.7	3.5	0.95
Random Forest	3.1	4.0	0.92
XGBoost	2.4	3.2	0.97

The results indicate that XGBoost achieved the highest accuracy, followed by LSTM, which performed exceptionally well in capturing temporal variations in water and energy consumption. Random

Forest provided slightly lower accuracy but was valuable for identifying key influencing factors through feature importance analysis.





The close alignment between predicted and actual values confirms the robustness of the AI models in handling complex, nonlinear mining datasets.

4.2 Optimization Results

The integration of predictive analytics with the optimization engine resulted in significant improvements in water and energy efficiency. The system dynamically adjusted operational parameters such as water recycling rates, pump scheduling, and process loads to achieve optimal performance.

Table 4: Optimization Outcomes

Parameter	Before Optimization	After Optimization	Improvement (%)
Water Consumption (m^3/hr)	1250	980	21.6%
Energy Usage (kWh)	5200	4300	17.3%
Water Recycling Rate	60%	78%	+18%
Carbon foot print (tCO_2/hr)	7.5	6.0	-20%
Operational Efficiency	80%	90%	+10%

The results demonstrate that the proposed WECN framework can achieve over 20% reduction in water consumption, approximately 15–18% reduction in energy usage and resulting in overall carbon footprint reduction in ~20%. These improvements are primarily driven by predictive optimization and real-time decision-making capabilities.

4.3 Water–Energy-Carbon Nexus Insights

A major contribution of this study is the identification and quantification of the interdependencies between water and energy consumption and reduction in Carbon footprint. The analysis revealed a strong positive correlation among the three indices, indicating that improvements in water efficiency directly contribute to energy savings and then both on carbon footprint.

The correlation coefficient was found to be approximately 0.85, confirming the importance of integrated optimization strategies. For example, reducing water flow rates in slurry transport led to lower energy requirements for pumping, while improved water recycling reduced the need for energy-intensive water treatment processes.

4.4 Sustainability and Environmental Impact

The implementation of the AI-based WEN framework significantly improved sustainability performance across multiple dimensions:

- Water Conservation: Reduced freshwater extraction through enhanced recycling
- Energy Efficiency: Lower energy consumption and improved equipment utilization

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- Carbon Emissions Reduction: Decreased energy usage contributed to reduced greenhouse gas emissions

These outcomes align with national sustainability objectives under Saudi Vision 2030 and Maaden Carbon Neutrality by 2050, which emphasizes efficient resource utilization, environmental protection, and digital transformation in industrial sectors.

4.5 Process-Level Optimization Insights

Detailed analysis of individual mining processes revealed that beneficiation and slurry transport are the most resource-intensive stages. Optimization strategies applied include:

- Adaptive control of slurry density and flow rates
- Smart scheduling of pumps and processing units
- AI-driven adjustment of process parameters

These interventions resulted in improved efficiency without compromising production output. Additionally, predictive maintenance reduced equipment downtime, further enhancing energy efficiency.

4.6 Discussion of Key Findings

The results highlight several important insights:

1. AI models provide high prediction accuracy, enabling reliable forecasting of resource consumption
2. Integrated WECN optimization is more effective than separate water or energy optimization approaches
3. Real-time decision support systems significantly enhance operational efficiency
4. Sustainability benefits are substantial, including reduced environmental impact and improved resource utilization

The study demonstrates that combining AI, IIoT, and WECN principles creates a powerful framework for sustainable Phosphate Value Chain unit operations.

Conclusion of Results and Discussion

Overall, the findings validate the effectiveness of the proposed AI-based Water–Energy-Carbon Nexus optimization framework. The integration of predictive analytics and optimization techniques enables significant improvements in resource efficiency, operational performance, and sustainability. This approach provides a scalable solution for modern mining operations and contributes to the advancement of smart, sustainable industrial systems.

V. CONCLUSION AND FUTURE WORK

This study introduced an integrated Artificial Intelligence (AI)-based Water–Energy-Carbon Nexus (WECN) optimization framework designed to enhance sustainability and operational efficiency in integrated phosphate mining operations. By combining advanced machine learning techniques, Industrial Internet of Things (IIoT) data integration, and intelligent decision support systems, the proposed framework addresses the complex interdependencies between water and energy consumption & impact on carbon foot print. Unlike conventional approaches that treat these resources independently, this research demonstrates the effectiveness of a holistic optimization strategy that simultaneously manages both dimensions of resource utilization.

The results confirm that the proposed framework significantly improves resource efficiency, achieving reductions of over 20% in water consumption, approximately 15–18% in energy usage and finally impacting 12-15% reduction on carbon footprint. These improvements are driven by the system's ability to accurately predict consumption patterns and dynamically optimize operational parameters in real time. The integration of predictive analytics with optimization algorithms enables proactive decision-making, reducing resource wastage and enhancing overall system performance.

A key contribution of this research lies in its alignment with sustainability and policy objectives, particularly those outlined in Saudi Vision 2030 and Carbon neutrality by 2050 of Phosphate Business. By promoting efficient resource utilization, environmental conservation, and digital transformation, the proposed framework supports the development of sustainable Phosphate value chain starting from mining to DAP production. The reduction in water usage is particularly significant in arid regions, where water scarcity poses a major challenge to industrial operations. Similarly, improved energy efficiency contributes to lower operational costs and reduced carbon emissions, supporting global climate goals.

From an operational perspective, the framework demonstrates strong scalability and adaptability, making it suitable for deployment across various stages of phosphate mining, including beneficiation, slurry transport, and chemical processing units like sulfuric acid, phosphoric acid and DA production. The integration of IIoT technologies ensures continuous data flow and real-time monitoring, enabling the system to respond dynamically to changing operational conditions. Furthermore, the incorporation of decision support systems provides actionable insights for operators and management, facilitating informed and timely decision-making.

Despite these contributions, the study has certain limitations. The research is primarily based on simulated and case-based datasets, which may not fully capture the variability and uncertainties present in real-world mining environments. Additionally, the successful implementation of AI-driven frameworks requires significant investment in digital infrastructure, skilled personnel, and organizational readiness. These factors may present challenges for some mining companies, particularly those in early stages of digital transformation.

Future research can extend this work by incorporating real-time data from operational phosphate value chain units to further validate and refine the proposed framework. The application of advanced AI techniques, such as reinforcement learning and deep reinforcement learning, can enhance the system's ability to adapt to complex and dynamic environments. Additionally, future studies can integrate broader sustainability indicators, including waste management, and economic performance, to develop a more comprehensive optimization model.

In conclusion, this research highlights the transformative potential of AI-driven Water–Energy-Carbon Nexus optimization in advancing sustainable phosphate value chain practices. By enabling integrated, data-driven, and adaptive resource management, the proposed framework provides a robust foundation for the future of intelligent and environmentally responsible phosphate value chain operations.

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