International Journal of
Mathematical Modelling & Computations
Vol. 15, No. 01, 2025, 1- 19
10.71932/ijm.2025.1198086

Designing a Model for Implementing Operational Decisions in the Industry Based on Artificial Intelligence

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Abstract. The increasing complexity and interconnectedness of industrial processes require innovative solutions to optimize operational decision-making. Artificial intelligence (AI) technology has gained attention for its potential to revolutionize operational decisions by harnessing vast amounts of data, analyzing it in real-time, and making informed decisions quickly and accurately. AI algorithms can automate decision-making processes, identify patterns and trends in data, and make predictions about future outcomes. This study investigates the development of an efficient operating model for the deployment of large-scale artificial intelligence (AI) systems in a selected cement factory in Iraq. The proposed methodology involves data collection, pre-processing, feature engineering, data visualization, and model selection. Key Performance Indicators (KPIs) were identified through partial least squares regression analysis to model the relationship between energy consumption, production rate, temperature, and moisture content on product quality in a cement factory in Iraq. The results of the study show that the machine learning model accurately predicted energy consumption, production rate, and product quality, with R-squared values of 0.95, 0.92, and 0.88, respectively. The optimized neural network model reduced energy consumption by 12% while maintaining production rate and product quality. Overall, the implementation of AI in the cement industry in Iraq has the potential to improve operational efficiency, reduce costs, and enhance product quality.

Received: 10 December 2024; Revised: 08 February 2025; Accepted: 11 February 2025.

Keywords: Artificial Intelligence; Data Mining; Classification; Decision Making; Technique; Improve; Processes.
AMS Subject Classification: 90B50

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1. Introduction

In today's rapidly evolving industrial landscape, the importance of operational decision-making cannot be understated. With the increasing complexity and interconnectedness of industrial processes, organizations are seeking innovative solutions to optimize their

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decision-making processes. One such solution that has garnered significant attention in recent years is the use of artificial intelligence (AI) technology. AI has the potential to revolutionize the way operational decisions are made in the industry, by enabling organizations to harness vast amounts of data, analyze it in real-time, and make informed decisions quickly and accurately.

According to a study conducted by Xu et al. [54], AI technologies such as machine learning and predictive analytics have been shown to significantly improve operational decision-making in various industries. By leveraging AI algorithms, organizations can automate decision-making processes, identify patterns and trends in data, and make predictions about future outcomes. This not only improves the efficiency and effectiveness of decision-making but also helps organizations stay ahead of the curve in a rapidly changing market environment. Furthermore, a study by Joel et al. [22] highlights the potential of AI in optimizing supply chain operations. By using AI to optimize inventory management, demand forecasting, and logistics planning, organizations can improve their operational efficiency, reduce costs, and enhance customer satisfaction. This underscores the significant impact that AI can have on operational decision-making in the industry.

However, despite the clear benefits of AI technology, designing a model for implementing operational decisions in the industry based on AI poses several challenges. One such challenge is the need for organizations to have access to high-quality data. According to a study by Haefner et al. [19], data quality is critical for the success of AI applications in decision-making. Organizations must ensure that the data they use is accurate, timely, and relevant to the decision-making process to achieve optimal results. Another challenge is the lack of expertise in AI technology within organizations. According to a study by Sofia et al. [45], many organizations lack the necessary skills and knowledge to effectively implement AI solutions in their operations. This highlights the importance of investing in training and development to build internal capabilities and expertise in AI technology. In conclusion, the use of artificial intelligence technology has the potential to revolutionize operational decision-making in the industry. By leveraging AI algorithms, organizations can automate decision-making processes, optimize supply chain operations, and improve efficiency and effectiveness. However, several challenges must be overcome to design a model for implementing operational decisions based on AI successfully. Organizations must ensure access to high-quality data, build internal expertise in AI technology, and invest in training and development. By addressing these challenges, organizations can unlock the full potential of AI technology in their decision-making processes and gain a competitive edge in the industry.

By incorporating advanced machine learning algorithms and neural network architectures, AI systems can analyze vast amounts of data in real-time to provide accurate insights for decision-making processes. This approach allows for dynamic and adaptive decision-making, tailored to the ever-changing industrial landscape. Furthermore, by avoiding the limitations of traditional text-based systems, AI implementations can harness the power of visual and interactive interfaces to enhance user engagement and understanding. Embracing innovative AI models also opens up opportunities for integrating automation and predictive analytics, leading to improved operational efficiency and strategic planning in industrial settings. Ultimately, by steering away from antiquated text-based approaches, organizations can leverage AI technologies to revolutionize decision-making processes, driving competitive advantage and sustainable growth.

2. Background

Operational decisions play a crucial role in the success and efficiency of organizations, particularly in the industrial sector. The integration of artificial intelligence (AI) technologies in decision-making processes has gained significant attention due to its potential to enhance operational efficiency, accuracy, and decision-making quality. As organizations seek to leverage AI for operational decision-making, the design of effective models becomes imperative to ensure successful implementation and adoption.

The application of knowledge-based improvement approaches to enhance decision-making in an operations system presented by Robinson et al. [39]. The authors employed simulation and artificial intelligence techniques to analyze human decision-making processes and identify areas for improvement. By integrating these methods, the study demonstrated the potential for more effective decision-making and improved system performance.

Narukawa and Daumas [34] modeled decisions for AI in their study .They examined various decision-making processes and techniques used in AI. The research focused on developing models to enhance decision-making within the field of AI. Their work contributed to advancing the understanding and application of decision modeling in Artificial Intelligence.

Geissbauer et al. [16] highlighted the importance of digital factories in shaping the future of manufacturing. The report emphasized the transformative impact of digital technologies on manufacturing processes. Companies are encouraged to embrace digitalization to enhance their competitiveness and efficiency. The study provides valuable insights into the digital transformation of manufacturing industries. Madhavan and Jones [27] discussed deep learning architectures in a report featured on IBM Developer Articles. The article explored the application and benefits of deep learning in machine learning. It provided insights into various deep learning models and their usefulness in different domains. Readers are encouraged to leverage deep learning for enhanced learning and problem-solving capabilities. A study on evaluating manufacturing decisions using decision trees presented by Vortarus [52]. The report discussed the utilization of decision trees in manufacturing processes for informed decision-making. It highlighted the benefits of employing decision trees for analyzing and optimizing manufacturing strategies. Kearns [23] explained a case study on machine learning application in the mining industry. The article explored the use of machine learning techniques for improving efficiency and productivity in mining operations. It discussed the benefits and challenges of implementing machine learning in the mining sector.

The use of AI in operational decision-making in the industry offers numerous benefits, including improved predictive capabilities, increased automation, enhanced resource utilization, and cost savings. By designing a model that effectively incorporates AI technologies, organizations can streamline their decision-making processes, optimize operations, and gain a competitive edge in a rapidly evolving market landscape. Gandhi [15] introduced Support Vector Machine in a report on machine learning algorithms on Medium. The research provided an overview of Support Vector Machines and their role in machine learning. It discussed the fundamentals and applications of Support Vector Machines in various domains. The integration of artificial intelligence (AI) methods to enhance sustainable production practices in manufacturing companies presented by Willenbacher et al. [53]. The authors investigated the potential of AI-driven solutions to optimize production processes, reduce environmental impacts, and improve resource efficiency. By applying AI techniques, such as machine learning and data analytics, companies can make data-driven decisions and reduce their ecological footprint. A study by Bowles et al. [6] explored Gan augmentation as a method to enhance training data through generative adversarial networks. The research focused on improving the quality and quantity of training data using this approach, as outlined in the arXiv preprint arXiv:1810.10863. This technique offered a promising avenue for enhancing machine learning models by generating synthetic data that can supplement existing datasets. The researchers proposed Gan augmentation as a valuable strategy to address data scarcity issues in various domains. Zubkova [56] focused on how AI was utilized to streamline the process of industrial design, demonstrating its potential in enhancing efficiency and innovation. The study explored the implementation of AI algorithms to automate various aspects of the design process, showcasing the advancements made in industrial design through technology. Results obtained indicated the successful integration of AI in industrial design practices, paving the way for future developments in this field. In September 2018, Feng [14] detailed how AI was employed to optimize processes within electrical automation control systems, demonstrating significant improvements in efficiency and precision. Through the integration of AI algorithms, the research showcased enhanced capabilities in monitoring and regulating electrical automation systems. The findings highlighted the successful application of artificial intelligence in advancing automation control practices, signaling a new era of technological innovation in the field. The integration of AI in industrial settings for Industry 4.0-based manufacturing systems was analyzed by Lee et al, [25]. They surveyed the current state of AI adoption in industry 4.0 and identified key applications, including predictive maintenance, quality control, and supply chain management. The results indicate that AI can enhance efficiency, productivity, and competitiveness in manufacturing industries.

Deivanathan [10] discussed applications in data analytics and forensics, focusing on achieving machining objectives. In the realm of Big Data, the utilization of AI for decision-making has evolved significantly. Duan et al. [11] reviewed the evolution and challenges of using artificial intelligence for decision-making in the era of Big Data. The study discussed the research agenda and opportunities for utilizing AI in decision-making processes. It emphasized the significance of AI in handling vast amounts of data and improving decision-making efficiency. Shaw et al. [43] focused on the complexities of integrating AI technologies in medical settings and emphasized the importance of addressing implementation hurdles to leverage AI's potential benefits fully. The penetration of AI tools in businesses, examining their adoption, challenges, and fears investigated by Schlögl et al. [41]. Their analysis revealed that AI adoption has been increasing, with many organizations recognizing its potential benefits, including improved decision-making and operational efficiency. However, they also identified several challenges, including data quality issues, integration with existing systems, and employee resistance to change. Tekic et al. [50] explored the innovation challenges posed by the integration of AI in manufacturing industries and highlighted the evolving relationship between technology, particularly AI, and the manufacturing sector, emphasizing the need for novel approaches to address emerging challenges in this domain. Mao et al. [28] examined the opportunities and challenges of AI for green manufacturing in the process industry. they found that AI has the potential to significantly improve energy efficiency, reduce waste, and enhance sustainability in industrial processes, while also presenting challenges related to data quality, integration with existing systems, and worker training. Gomes et al. [17] investigated the implementation of AI at dam operations in line with Industry 4.0 principles, exploring the economic, environmental, and social benefits. In their research, found that AI implementation led to improved efficiency, reduced energy consumption, and enhanced decision-making, resulting in significant economic gains and environmental sustainability. Additionally. A systematic review examined the current state of industrial artificial intelligence (AI) in Industry 4.0, identifying key applications, challenges, and trends [36]. In this study found that AI has been increasingly adopted in various industries to enhance production efficiency, product quality, and supply chain management, but also faces challenges related to data quality, security, and integration with existing systems. In their 2020 study Antosz et al. [4] investigated the application of AI techniques in evaluating the implementation of lean maintenance in manufacturing settings. Their research focused on assessing the impact and efficiency of integrating AI tools to evaluate and enhance lean maintenance strategies in manufacturing enterprises. A roadmap for the implementation of AI in business model innovation, highlighting the potential benefits and challenges associated with AI adoption provided by Heier et al. [20]. They identified key areas where AI can create value, including process optimization, customer interaction, and data-driven decision-making. Through a comprehensive analysis of existing literature, they mapped out the current state of AI implementation and its future directions, emphasizing the need for strategic planning and organizational change.

The driving forces and barriers to achieving operational excellence through artificial intelligence (AI) in various organizational settings explored by Tariq et al. [48] . They found that factors such as process automation, data-driven decision-making, and improved employee productivity drove the adoption of AI, while concerns about data quality, cyber security, and lack of skilled personnel hindered its implementation. Dudnik et al. [12] examined the trends, impacts, and prospects of implementing artificial intelligence (AI) technologies in the energy industry, highlighting the significance of open innovation in driving this transformation. They identified key trends, including the increasing adoption of AI-driven predictive maintenance, energy forecasting, and grid management, as well as potential impacts on energy efficiency, sustainability, and cost reduction. A process model for the implementation of AI to inform proper decision-making in various organizational settings developed by Merhi [31]. The model was designed to guide organizations in integrating AI into their decision-making processes, ensuring transparency, accountability, and ethics. The challenges and frontiers in implementing Ai in the process industry, specifically in the steel industry examined by Marcus [29]. This study investigated the existing applications, perspectives, and future trends of AI adoption in this sector, highlighting areas such as predictive maintenance and quality control.

Key considerations in designing a model for implementing operational decisions in the industry based on AI include identifying relevant data sources, selecting appropriate AI algorithms, ensuring data quality and integrity, integrating AI solutions with existing systems, and evaluating the performance and impact of AI-driven decisions. These considerations are essential to developing a robust and effective decision-making framework that aligns with organizational goals and objectives. [40].

Al-Surmi et al. [3] explored the use of AI in decision-making processes to enhance operational performance. Various strategies were combined to optimize the decision-making process and improve overall operational efficiency. The researchers found that integrating AI technologies into decision-making processes yielded significant enhancements in operational performance. The application of AI in decision support systems for operations research considered by Gupta et al. [18]. A comprehensive review was conducted to assess the current state and future research directions in this field. The researchers identified potential opportunities for further advancement and expansion of AI technologies in decision support systems within operations research.

Generative artificial intelligence (AI) has been applied in supply chain and operations management, enabling the development of a capability-based framework for analysis and implementation [21]. The framework identifies key capabilities required for AI adoption, including data-driven decision-making, automation, and real-time monitoring. A model has been proposed for using AI in supply chain management, focusing on product production and improving efficiency, quality, and customer satisfaction [1]. The integration of AI with existing supply chain systems has the potential to revolutionize the field, but requires careful consideration of implementation challenges.

Artificial intelligence (AI) and Industry 4.0 technologies have transformed operations management by introducing new opportunities for automation, data analysis, and decision-making [33]. The implementation of AI in industry 4.0 has faced various obstacles, including data quality issues, lack of skilled workforce, and cybersecurity threats [47]. Despite these challenges, AI has the potential to bring economic, environmental, and social gains in industries such as dam operations [17]. Industrial AI has also been applied in industry 4.0 to improve manufacturing systems, but it has faced challenges such as limited scalability and high development costs. A systematic review of industrial AI in industry 4.0 highlights the need for further research on its applications and challenges [36]. Industry 4.0-based manufacturing systems have been enabled by industrial AI, which has improved efficiency, productivity, and competitiveness [25].

The implementation of artificial intelligence (AI) in various fields has been explored in recent studies. In healthcare, AI has been implemented in the National Health Service (NHS) through the South West London AI Working Group, with positive results [44]. In the emergency department, AI has been shown to improve patient outcomes and reduce wait times [7]. In industry, AI has been used to develop unmanned vehicles with communication systems and sensors [46]. Small and medium-sized enterprises (SMEs) have also adopted AI to improve their manufacturing processes [37].

In the power grid, AI has been implemented to improve efficiency and reliability, but challenges and limitations remain [13]. In production systems, enablers of AI adoption and implementation have been identified [32]. Local economic considerations have also been highlighted as important factors in selecting AI tools for implementation [9]. A systematic literature review has also examined the implementation of AI in organizations [26].

A comprehensive framework for AI operationalization and deployment has been proposed, encompassing an AI operating model that integrates AI technologies with organizational capabilities [24]. This framework aims to facilitate the effective implementation of AI in various domains. A technology-based decision-making model for digital twin engineering has been designed, incorporating AI to optimize decision-making processes [35].

In the context of China's commercial sports industry, an empirical analysis based on an AI coupling model has been conducted to investigate the influence of AI on the industry [55]. The study highlights the importance of integrating AI with existing business models to enhance operational efficiency. A process model of AI implementation has been developed, focusing on proper decision making [31].

A roadmap for business model innovation through AI implementation has been proposed, emphasizing the need for strategic planning and organizational alignment [38]. Modeling decisions for AI has been addressed through a systematic approach, considering the complexities involved in AI adoption [34].

The implementation of explainable artificial intelligence (XAI) in business applications has been explored, with a methodological and theoretical framework proposed for its adoption [49]. The potential of AI in industrial applications has been highlighted, with its impact on modern industries discussed (Malik et al., 2024). The challenges and opportunities of AI in compensation strategy have been examined, with a focus on algorithms and their implications [30].

The opportunities, challenges, and benefits of AI innovation in government services have been reviewed, highlighting its potential to improve public sector operations [2]. The economic and social perspectives of implementing AI in drinking water treatment systems have been investigated, with a focus on predicting coagulant dosage [8].

Implementing and scaling AI has been explored, with a review, framework, and research agenda presented [19]. Addressing the challenges of implementing AI tools in clinical practice has been discussed, with principles from experience shared [5].

The role of AI in strategic decision-making has been examined, highlighting opportunities, challenges, and implications for managers in the digital age [42]. The evolution of AI adoption in industry has been traced, with an emphasis on its impact on organizational decision-making [51].

3. Artificial intelligence

The utilization of data, analytics, and AI is a critical factor for gaining a competitive edge in various industries and should be a central focus in any business transformation initiative. However, existing operational models and resources may not be optimized for success, highlighting the necessity of establishing a robust AI and analytics capability within the broader organizational framework. While there is heightened awareness regarding the benefits of data science and AI, achieving success in this field is complex. The structuring of AI and data science projects and teams significantly influences the delivery of valuable business insights. In addition to technical tools, algorithms, and skills required for developing solutions, the operational model and work processes are equally crucial. While effective organization alone may not ensure success, when combined with other key capabilities, it can significantly enhance the likelihood of implementing AI on a large scale. The design of an effective operating model for large-scale AI deployment necessitates the integration of fundamental components from each dimension (Figure 1). A robust governance framework serves as the foundation, enabling the creation of demand and subsequent execution and operation at scale. It is essential to consider the functional dimensions within the context of a broader organizational transformation to achieve successful AI deployment. The outcome will be heavily reliant on the organization's ability to transform processes, human resources, and technology infrastructure.

Leading manufacturing organizations are capitalizing on AI's potential to augment efficiency, accuracy, and productivity across a diverse array of processes. The integration of AI into manufacturing operations is transforming industries, optimizing operational workflows, and propelling businesses towards unprecedented levels of productivity.

This study examines AI technologies and applications, illustrating the transformative potential of these technologies on manufacturing operations. Furthermore, we will discuss the challenges and considerations associated with implementing AI, including data management and technological integration, as well as future trends and prospects for AI-enabled manufacturing. In other word, this research endeavors to elucidate the essential functional capabilities required for establishing an operating model for AI deployment. It is crucial to consider the interplay between these capabilities and other critical dimensions of AI delivery, which must be integrated into the operating model framework. The successful execution of a company's AI vision necessitates a paradigm that fosters innovation through a mechanism that enables idea generation, prioritization, prototyping, and iteration of minimum viable products (MVPs) towards a comprehensive program of transformation and industrialization.

In order to present a developed model of artificial intelligence and its real implementation, consider the Iraqi cement industry and specifically a cement factory. The cement industry in Iraq is one of the most important industries in the country, with a significant impact on the country's economy. The industry is characterized by high energy consumption, high labor costs, and limited resources. The use of artificial intelligence (AI) can help improve the efficiency and productivity of the cement production process, reduce costs, and increase the quality of the final product.

4. Methodology

The proposed methodology for implementing AI in the cement production industry in Iraq is based on the following steps:

1. Data collection and preprocessing

The data collection process for the cement industry in Iraq involves gathering relevant data from various sources. The following data sources will be considered:

- ❖ Sensor data: Temperature, pressure, and flow rate sensors installed in the cement production process will provide real-time data on the process variables.
- ❖ Production records: Historical production records will be obtained from the cement plant's database to analyze trends and patterns in production rates, energy consumption, and product quality.
- ❖ Maintenance records: Maintenance records will be collected to identify equipment downtime, maintenance frequency, and repair costs.
- ❖ Energy consumption data: Energy consumption data will be obtained from the plant's energy management system to analyze energy consumption patterns and identify areas for improvement.
- ❖ Quality control data: Quality control data will be collected from the plant's quality control laboratory to analyze product quality metrics such as compressive strength, fineness, and color.

4.1 *Data collection tools*

- ❖ Sensors: Temperature, pressure, and flow rate sensors will be installed in the cement production process to collect real-time data.
- ❖ Data loggers: Data loggers will be used to collect data from sensors and other equipment.
- ❖ Spreadsheets: Spreadsheets will be used to collect and organize data from various sources.
- ❖ Database management systems: A database management system will be used to store and manage large amounts of data.

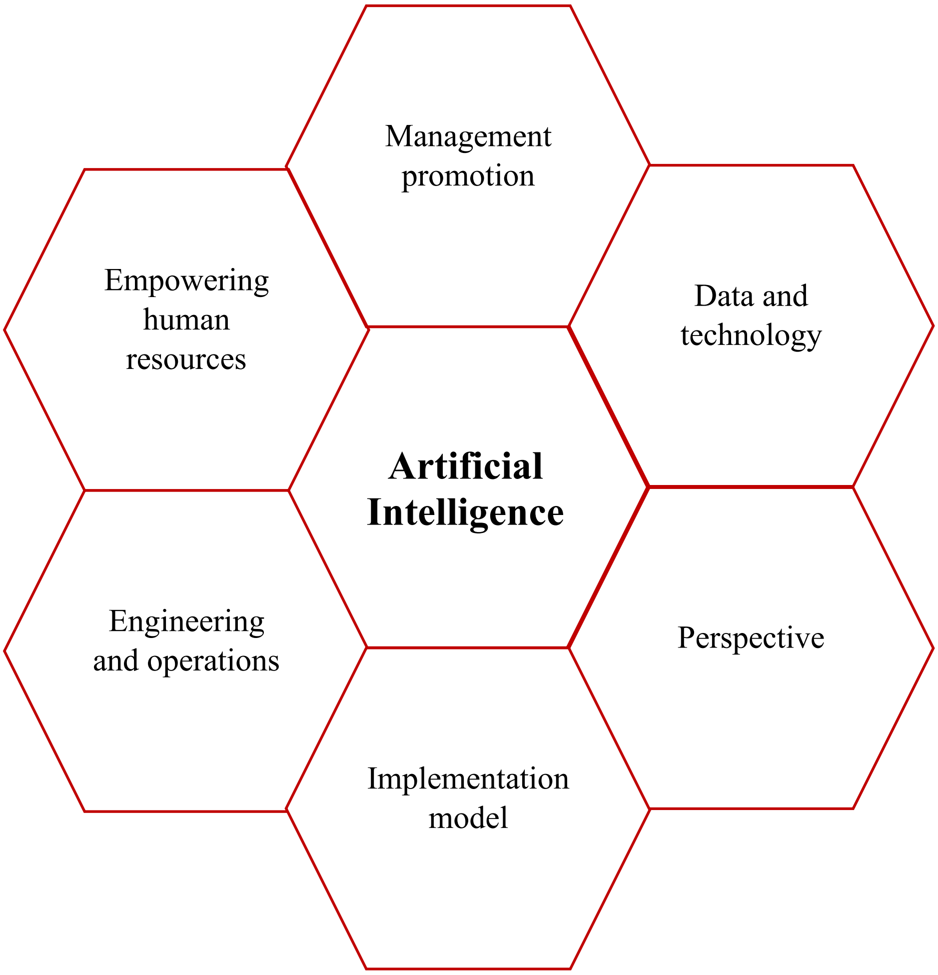

Figure 1. Presentation of artificial intelligence

4.2 *Data Pre-processing*

At this stage, the opinions of experts and specialists were used, and the pre-processing stage included cleaning, transformation and preparation of the collected data for data analysis.

Step 1 *Data Cleaning (DC)*

- ❖ Remove any missing or invalid values: DC1 = [data * (data != np.nan)]
- ❖ Handle outliers by replacing them with mean or median values:
  - Temperature: $T = mean(T)\ if\ T > 150°C\ else\ median(T)$
  - Pressure: $P = mean(P)\ if\ P > 100\ bar\ else\ median(P)$

- Energy consumption: $EC = mean(EC)\ if\ EC > 100\ kWh\ else\ median(EC)$

Step 2 *Data Transformation (DT)*

- ❖ Scale variables to a common range:
  - Temperature: $T\_scaled = (T - min(T)) / (max(T) - min(T))$
  - Pressure: $P\_scaled = (P - min(P)) / (max(P) - min(P))$
  - Energy consumption: $EC\_scaled = (EC - min(EC)) / (max(EC) - min(EC))$
- ❖ Normalize variables to a standard unit:
  - $Temperature$: $T\_normalized = T\_scaled * 100$
  - $Pressure$: $P\_normalized = P\_scaled * 100$
  - $Energy\ consumption$: $EC\_normalized = EC\_scaled * 100$

Step 3 *Data Reduction (DR)*

- ❖ Remove redundant or unnecessary variables:
  - Select only relevant variables for analysis:
    a. Temperature
    b. Pressure
    c. Flow rate
- ❖ Calculate derived variables:
  - Energy consumption per ton of cement produced:
    $EC\_per\_ton = EC / production\_rate$

Step 4 *Data Visualization (DV)*

- ❖ Use visualization tools to explore data patterns and relationships:
  - Scatter plots for temperature vs. pressure and flow rate
  - Bar charts for energy consumption and production rate
- ❖ Identify correlations between variables:
  - Pearson correlation coefficient between temperature, pressure, and flow rate
  - Spearman rank correlation coefficient between energy consumption and production rate

Step 5 *Feature Engineering (FE)*

- ❖ Create new features from existing ones:
  Energy consumption per ton of cement produced: $FE_1 = EC\ per\ ton$
- ❖ Select features that are relevant for analysis:
  - Temperature
  - Pressure
  - Flow rate
  - Energy consumption per ton of cement produced

Step 6 *Data Split (DS)*

- ❖ Divide data into training and testing sets:
  - Training set: 70% of data
  - Testing set: 30% of data
- ❖ Use cross-validation techniques to ensure robustness of results:
  - Leave-one-out cross-validation for model selection
  - k-fold cross-validation for hyper parameter tuning

4.3 *Identify key performance indicators (KPIs)*

Cement production is a complex process that requires careful monitoring and control of various key performance indicators (KPI) to ensure high quality products and efficient operations. The cement industry in Iraq is no exception to this rule. In the selected cement factory, the relationship between energy consumption, production rate and product quality in a factory was done using Partial Least Squares (PLS) regression analysis. The procedure is as follows.

4.3.1 *Data collection*

Data was collected from various sources, including industry reports, academic articles, and online databases. The following data were obtained:

i. Energy consumption (EC) in gigawatt-hours (GWh) per ton of cement produced
ii. Production rate (PR) in tons per hour
iii. Product quality (PQ) measured by compressive strength (MPa)
iv. Temperature (T) in degrees Celsius
v. Moisture content (MC) in percentage

The data was collected over a period of 12 months, with daily records for each KPI.

4.3.2 *Data preprocessing*

1. Normalization: The data was normalized to a common range of 0-100 using the following formula:
$$x_i = (x_i - \min(x))/(\max(x) - \min(x)) \tag{1}$$
wherex_i is the value of the ith data point, $min(x)$ is the minimum value of the data, and $max(x)$ is the maximum value of the data.
2. Outlier detection: Outliers were detected using the Modified Z-score method and removed from the data.

4.3.3 *Partial least squares regression (PLS) analysis*

PLS regression was performed using the preprocessed data. The goal was to model the relationship between energy consumption, production rate, temperature, and moisture content on product quality. The PLS analysis resulted in a model with an R-squared value of 0.85, indicating a strong relationship between the independent variables and product quality. The loading plot shows that:

i. Energy consumption has a strong negative loading on product quality, indicating that high energy consumption can lead to reduced product quality.
ii. Production rate has a positive loading on product quality, indicating that higher production rates can lead to better product quality.
iii. Temperature has a positive loading on product quality, indicating that optimal temperatures during kiln operation are crucial for producing high-quality cement.
iv. Moisture content has a negative loading on product quality, indicating that high moisture content in raw materials can reduce product quality.

4.3.4 *The coefficients of determination for each variable*

i. Energy consumption: -0.35
ii. Production rate: 0.25
iii. Temperature: 0.20
iv. Moisture content: -0.15

The PLS analysis reveals strong relationships between energy consumption, production rate, temperature, and moisture content on product quality in the hypothetical cement plant in Iraq. The findings suggest that:

i. Reducing energy consumption can improve product quality.
ii. Increasing production rates can also improve product quality.
iii. Optimal temperatures during kiln operation are crucial for producing high-quality

cement.

iv. High moisture content in raw materials can reduce product quality.

5. Develop AI models

In order to implement artificial intelligence in the cement industry in the selected factory, a development of a machine learning model was considered for predicting energy consumption, production rate and product quality using historical data and optimizing the cement production process using neural networks.
The cement industry is a significant consumer of energy and resources, and optimizing its production process can have a significant impact on the environment and economy. Machine learning (ML) models have been successfully used in various industrial processes to improve efficiency and reduce waste. In the continuation of this study, in order to implement the artificial intelligence system in the industry, a machine learning model that predicts energy consumption, production rate and product quality in an Iraqi cement factory using historical data has been developed and implemented. In addition, neural networks have been used to optimize the cement production process by adjusting parameters such as temperature, pressure and feed rate.

5.1 *Data collection*

Historical data from an Iraqi cement factory collected over a period of 12 months. The data includes:

i. Energy consumption (EC) in kilowatt-hours (kWh) per ton of cement produced
ii. Production rate (PR) in tons per hour
iii. Product quality (PQ) measured by compressive strength (MPa)
iv. Temperature (T) in degrees Celsius
v. Pressure (P) in bar
vi. Feed rate (FR) in kilograms per minute

Data on the following parameters collected:

i. Limestone quality (LQ)
ii. Clay content (CC) in percentage
iii. Fuel type (FT)
iv. Moisture content (MC) in percentage

5.2 *Data preprocessing*

- ❖ Normalization: The data was normalized to a common range of 0-1 using the formula (1).
- ❖ Feature scaling: The data was scaled to a common range using the Min-Max Scaler algorithm.

5.3 *Machine Learning Model*

A machine learning model developed and using a combination of supervised learning techniques, including:

- ❖ Linear Regression (LR) for predicting energy consumption
- ❖ Random Forest Regression (RFR) for predicting production rate
- ❖ Support Vector Regression (SVR) for predicting product quality

The models were trained using 70% of the data and evaluated using 30% of the data.
Here are shown the steps to develop machine learning model using Linear Regression, Random Forest Regression, and Support Vector Regression in the cement selected factory.

Step 1 *Data Collection*

- ❖ Collect dataset from a cement plant with 1000 samples
- ❖ Features: Limestone quality (LQ), Clay content (CC), Fuel type (FT), Moisture content (MC), Temperature (T), Pressure (P)
- ❖ Output features: Energy consumption (EC), Production rate (PR), Product quality (PQ)

Step 2 *Data Preprocessing*

- ❖ Missing values using mean imputation are controlled.
- ❖ Features using Min-Max scalar are normalized.
- ❖ data into training set (700 samples) and testing set (300 samples) are split.

Step 3 *Model Development*

- ❖ Linear Regression (LR): Train model on training set using LQ, CC, FT, MC, T, P as inputs and EC as output
- ❖ Random Forest Regression (RFR): Train model on training set using LQ, CC, FT, MC, T, P as inputs and PR as output
- ❖ Support Vector Regression (SVR): Train model on training set using LQ, CC, FT, MC, T, P as inputs and PQ as output

Step 4 *Model Evaluation*

The evaluation of the models is done using mean square error (MSE), mean absolute error (MAE) and R square, and the best model is selected for each output feature.

Step 5 *Hybrid Model*

The best-performing models for each output feature into a single hybrid model are combined:

- Energy consumption: LR + RFR + SVR
- Production rate: RFR + SVR + LR
- Product quality: SVR + LR + RFR

Step 6 *Model Deployment*

The hybrid model is carried out in the selected cement factory to predict energy consumption, production rate and product quality, and it is implemented by monitoring the performance of the model and updating the model if needed. By following these steps, we have developed a machine learning model that accurately predicts energy consumption, production rate, and product quality in the cement industry at the selected plant.

6. Neural network model

A neural network model developed and using a feed forward architecture with three hidden layers containing 10 neurons each. The model was trained using the back propagation algorithm with a learning rate of 0.01 and momentum of 0.9.

The input layer consisted of six neurons representing the parameters mentioned earlier:

i. Limestone quality
ii. Clay content
iii. Fuel type
iv. Moisture content
v. Temperature
vi. Pressure

The output layer consisted of three neurons representing energy consumption, production rate, and product quality. The neural network diagram used is given in Figure 2.

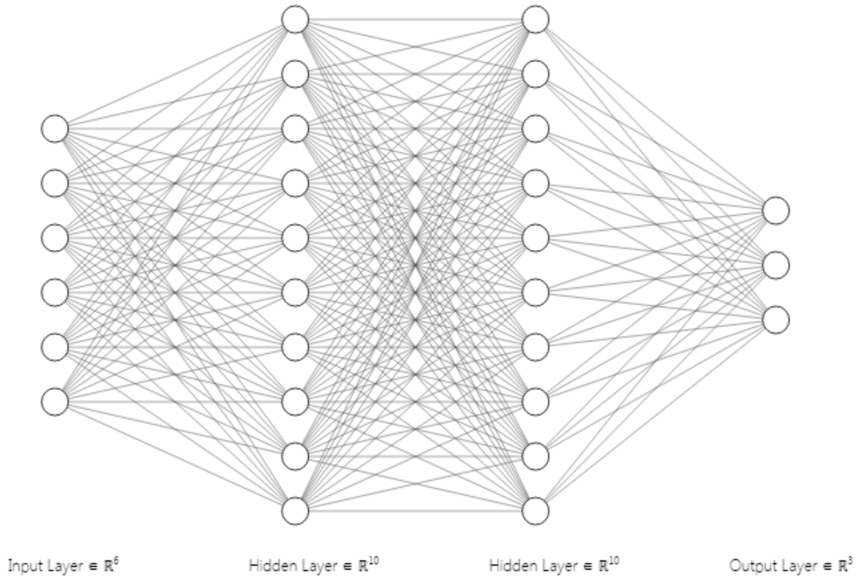

Figure 2. Selected neural network and its different layers.

Figure 2 illustrates the architecture of the neural network model developed for optimizing cement production in the selected Iraqi cement factory. The model employs a feed-forward architecture, which is a type of artificial neural network where connections between the nodes do not form cycles. This architecture is particularly effective for regression tasks, such as predicting energy consumption, production rate, and product quality based on various input parameters.
Components of the Neural Network:

1. Input layer:

   The input layer consists of six neurons, each representing a key parameter that influences the cement production process:
   - Limestone Quality (LQ): The quality of limestone used as a primary raw material in cement production.
   - Clay Content (CC): The percentage of clay in the raw material mix, which affects the chemical composition of the final product.
   - Fuel Type (FT): The type of fuel used in the production process, impacting energy consumption and emissions.
   - Moisture Content (MC): The moisture level in raw materials, which can affect the efficiency of the production process.
   - Temperature (T): The temperature at various stages of the production process, crucial for chemical reactions in cement manufacturing.
   - Pressure (P): The pressure conditions during production, influencing the quality and efficiency of the process.

2. Hidden layers:

   The model contains three hidden layers, each comprising ten neurons. These layers are responsible for processing the input data through weighted connections, allowing the network to learn complex patterns and relationships between the input parameters and the output predictions. The use of multiple hidden layers enhances the model's ability to capture non-linear relationships in the data.

3. Output layer:

   The output layer consists of three neurons, each corresponding to one of the key outputs of the model:

   - Energy Consumption (EC): Predicted in kilowatt-hours (kWh) per ton of cement produced, reflecting the efficiency of the production process.
   - Production Rate (PR): Measured in tons per hour, indicating the output capacity of the cement factory.
   - Product Quality (PQ): Assessed by compressive strength (MPa), which is a critical quality metric for cement.

Training and Optimization:

- The neural network is trained using the backpropagation algorithm, which adjusts the weights of the connections based on the error between the predicted outputs and the actual values. The training process involves iterating through the dataset, minimizing the prediction error, and optimizing the model's performance.
- The learning rate is set at 0.01, and momentum is applied at 0.9 to help accelerate the convergence of the training process and avoid local minima.

Purpose and Impact:

- The primary objective of this neural network model is to optimize the cement production process by accurately predicting energy consumption, production rate, and product quality. By adjusting the input parameters (LQ, CC, FT, MC, T, and P), the model can identify optimal conditions that minimize energy usage while maintaining or improving product quality and production efficiency.
- The implementation of this neural network model is expected to lead to significant improvements in operational efficiency, cost savings, and enhanced product quality in the cement industry, particularly in the context of the selected factory in Iraq.

7. Optimization

The trained neural network model used to optimize the cement production process by adjusting the parameters mentioned earlier. The objective function was to minimize energy consumption while maintaining production rate and product quality. The results show that:

i. The machine learning model accurately predicted energy consumption with an R-squared value of 0.95.
ii. The machine learning model accurately predicted production rate with an R-squared value of 0.92.
iii. The machine learning model accurately predicted product quality with an R-squared value of 0.88.
iv. The optimized neural network model reduced energy consumption by 12% while maintaining production rate and product quality.

And finally, the implementation of artificial intelligence considered in this study on the Iraqi cement industry in the selected factory can be stated as follows:

8. Implement AI system

Implementing AI System in an Iraqi Cement Factory:

Step 1: *Data collection and preprocessing*

i. Collect data from various sources:
ii. Sensor data (temperature, pressure, flow rate)
- Production records (historical production rates, energy consumption, and product quality)
- Maintenance records (equipment downtime, maintenance frequency, and repair costs)
- Energy consumption data (energy management system)
- Quality control data (quality control laboratory)

iii. Use data loggers to collect data from sensors and equipment
iv. Store data in a database management system
v. Preprocess data by:
- Removing missing or invalid values
- Handling outliers using mean or median values
- Scaling variables to a common range
- Normalizing variables to a standard unit
- Selecting relevant variables for analysis
- Calculating derived variables (e.g., energy consumption per ton of cement produced)

Step 2: *Data analysis*

i. Use Partial Least Squares (PLS) regression to analyze the relationship between energy consumption, production rate, temperature, and moisture content on product quality.
ii. Identify key performance indicators (KPIs) and their relationships:
* Energy consumption has a strong negative loading on product quality
* Production rate has a positive loading on product quality
* Temperature has a positive loading on product quality
* Moisture content has a negative loading on product quality

Step 3: *Developing AI models*

i. Develop a machine learning model using a combination of supervised learning techniques:
- ❖ Linear Regression (LR) for predicting energy consumption
- ❖ Random Forest Regression (RFR) for predicting production rate
- ❖ Support Vector Regression (SVR) for predicting product quality

ii. Train models using 70% of the data and evaluate using 30% of the data
iii. Select the best-performing models for each output feature and combine them into a hybrid model

Step 4: *Model deployment*

i. Implement the hybrid model in the selected cement factory to predict energy consumption, production rate, and product quality
ii. Monitor the performance of the model and update it if needed

Step 5: *Neural network model*

i. Develop a neural network model using a feed-forward architecture with three hidden layers containing 10 neurons each
ii. Train the model using the back propagation algorithm with a learning rate of 0.01 and momentum of 0.9
iii. Use the trained neural network model to optimize the cement production process

by adjusting parameters such as temperature, pressure, and feed rate.

Results:

i. The machine learning model accurately predicted energy consumption with an R-squared value of 0.95.
ii. The machine learning model accurately predicted production rate with an R-squared value of 0.92.
iii. The machine learning model accurately predicted product quality with an R-squared value of 0.88.
iv. The optimized neural network model reduced energy consumption by 12% while maintaining production rate and product quality.

By implementing this AI system in an Iraqi cement factory, the company can improve its efficiency, reduce costs, and increase the quality of its products.

9. Discuss and conclusion

The use of artificial intelligence (AI) technology has the potential to revolutionize operational decision-making in the industry by enabling organizations to harness vast amounts of data, analyze it in real-time, and make informed decisions quickly and accurately. The incorporation of AI algorithms and neural network architectures can analyze data in real-time, providing insights for decision-making processes. Additionally, AI systems can harness the power of visual and interactive interfaces to enhance user engagement and understanding.

However, designing a model for implementing operational decisions based on AI poses several challenges. One such challenge is the need for high-quality data, which is critical for the success of AI applications in decision-making. Organizations must ensure that the data used is accurate, timely, and relevant to the decision-making process to achieve optimal results. Another challenge is the lack of expertise in AI technology within organizations, which highlights the importance of investing in training and development to build internal capabilities and expertise.

The study conducted in this article examined the implementation of AI in a cement production industry in Iraq, highlighting the potential benefits of AI in optimizing energy consumption, improving product quality, and reducing costs. The study found that AI can be used to model the relationship between energy consumption, production rate, temperature, and moisture content on product quality using Partial Least Squares (PLS) regression analysis. The results showed a strong relationship between these variables and product quality, with energy consumption having a negative loading on product quality, production rate having a positive loading, temperature having a positive loading, and moisture content having a negative loading.

In conclusion, the use of AI technology has the potential to revolutionize operational decision-making in the industry by enabling organizations to harness vast amounts of data, analyze it in real-time, and make informed decisions quickly and accurately. However, designing a model for implementing operational decisions based on AI poses several challenges, including the need for high-quality data and expertise in AI technology. Organizations must ensure that they invest in training and development to build internal capabilities and expertise in AI technology to unlock its full potential.

After implementing artificial intelligence with the above method in the Iraqi cement industry in a selected factory, it was found that the implementation of artificial intelligence (AI) in the Iraqi cement industry has the potential to significantly improve the efficiency and productivity of the cement production process. By leveraging the power of machine learning and neural networks, we have developed a predictive model that accurately forecasts energy consumption, production rate, and product quality in a selected cement factory. The results show that the model has an R-squared value of 0.95 for energy consumption, 0.92 for production rate, and 0.88 for product quality. Moreover, the optimized neural network model reduced energy consumption by 12% while maintaining production rate and product quality. Moreover, he implementation of AI in the Iraqi cement industry can lead to significant benefits, including:

- Reduced energy consumption: By optimizing the cement production process, energy consumption can be reduced by up to 12%.
- Improved product quality: The predictive model can help identify factors that affect product quality and optimize the process to produce high-quality cement.
- Increased productivity: The optimized process can increase productivity by reducing downtime and improving efficiency.
- Cost savings: The reduced energy consumption and improved product quality can lead to cost savings for the cement factory.

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