**An Expert System for Data-Driven Decision-Making in Industrial Manufacturing: A Business Intelligence Approach**

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**Abstract.** Industrial manufacturing companies often face challenges in optimizing production, controlling quality, and managing returns. Traditional decision-making methods, typically reliant on human expertise and historical data, are increasingly inefficient in a complex and competitive environment. This study presents the development and simulation of an expert system aimed at enhancing data-driven decision-making in an Iranian cement manufacturing company. The system is developed based on a multi-source operational dataset encompassing sales performance, production metrics, quality complaints, inventory levels, and kiln temperature records. To extract meaningful insights, Python-based analytics were employed for anomaly detection and rule evaluation, while business intelligence dashboards were developed using Power BI. These interactive dashboards facilitated the visualization of revenue trends, inventory bottlenecks, complaint severity distributions, and production anomalies, thereby supporting proactive decision-making and operational optimization. Python scripts enabled statistical correlation analysis between kiln temperatures and defect rates, as well as complaint-based return patterns. An expert system was designed with a rule engine and knowledge base to simulate intelligent recommendations for quality audits, production adjustments, and inventory control. Simulation results demonstrated the potential impact of rule-based recommendations, including an estimated 18% reduction in defective units, 15% decrease in product returns, and improved decision clarity for operational teams. The findings highlight the value of combining business intelligence tools with expert systems to support digital transformation in traditional manufacturing environments, even in the absence of real-time IoT infrastructure.

**Introduction**

In the industrial manufacturing sector, effective decision-making plays a vital role in maintaining competitiveness, optimizing operations, reducing costs, and ensuring consistent product quality. Traditionally, these decisions have relied heavily on human expertise and manual analysis of historical data, often supported by basic software tools. However, such methods are prone to inefficiencies, inconsistencies, and a lack of scalability, particularly in the face of growing operational complexity.

While modern Industry 4.0 frameworks promote the use of real-time sensor data and Internet of Things (IoT) infrastructure, these technologies can be cost-prohibitive or operationally infeasible for many small to medium-sized enterprises (SMEs). As a result, there remains a pressing need for scalable, data-driven solutions that leverage existing historical data without requiring advanced or real-time data systems.This study addresses this gap by proposing a cost-effective, intelligent decision-support system that integrates Business Intelligence (BI) tools, machine learning techniques, and a rule-based expert system. Unlike many existing models that depend on real-time analytics or sensor integration, our approach demonstrates how valuable insights can be extracted solely from historical production datasets. The system is designed to assist with critical manufacturing decisions related to production planning, quality assessment, and supply chain management, thereby enhancing strategic and operational performance.

The novelty of this research lies in its integration of lightweight AI logic (developed using Python and MATLAB GUI) with BI visualization tools (Power BI), enabling automated insight generation without real-time infrastructure. This approach makes digital transformation more accessible and scalable, particularly for resource-constrained manufacturers.

* The primary objectives of this research are:

To explore how expert systems, when integrated with Business Intelligence tools, can enhance data-driven decision-making in industrial manufacturing.

* To assess the effectiveness of using historical production data for optimizing key operations such as quality control, production planning, and inventory management.

The remainder of this paper is organized as follows: Section 2 reviews the existing literature. Section 3 outlines the research methodology, including the CRISP-DM framework and data collection process. Section 4 describes the tools and datasets used, followed by Section 5, which presents the results and system implementation. Section 6 discusses findings, limitations, and future directions. Section 7 concludes the paper with final insights and contributions.

**Literature Review**

The integration of expert systems (ES) and business intelligence (BI) tools in industrial manufacturing has garnered significant attention in recent years, particularly concerning data-driven decision-making processes. This section reviews contemporary studies from 2021 to 2025 that explore the application of ES and BI in manufacturing contexts.

A systematic review focusing on the role of expert systems in enhancing energy efficiency within the manufacturing industry analyzed 62 publications and revealed that ES applications predominantly target process planning and operations, emphasizing energy optimization and transparency. The study also highlighted the prevalence of hybrid ES models combining rule-based, fuzzy logic, and machine learning approaches [1]. Another study discussed the implementation of artificial intelligence (AI) in customized manufacturing settings, emphasizing smart factories capable of self-perception, dynamic reconfiguration, and intelligent decision-making through technologies such as machine learning and multi-agent systems [2].The application of explainable AI (XAI) techniques in manufacturing has been reviewed, with a focus on enhancing transparency and trust by addressing the limitations of black-box models [3]. A comprehensive overview of the Industrial Internet of Things (IIoT) proposed a hierarchical development architecture to support smart manufacturing functions, operations, deployments, and applications [4]. Another study examined agent-based manufacturing systems, highlighting the role of multi-agent systems in improving flexibility, adaptability, and intelligence in manufacturing processes [5]. A structured literature review of business analytics in smart manufacturing identified 904 relevant studies, resulting in a quadripartite taxonomy and six archetypes encompassing planning, maintenance, monitoring, and quality management applications [6]. The concept of Actionable Cognitive Twins—digital twins enhanced with knowledge graphs and AI models—was introduced to support decision-making in areas such as demand forecasting and production planning [7].

Research has shown that business intelligence capabilities significantly enhance decision-making speed, comprehensiveness, and overall firm performance in manufacturing environments [8]. The strategic potential of expert systems has been emphasized in supporting real-time information acquisition, problem definition, and the development of alternatives through simulations and forecasting models [9]. A review of multi-criteria decision-making (MCDM) applications in supplier selection within the Industry 4.0 context highlighted the growing role of AI and BI tools in enhancing evaluation and selection processes [10]. A machine learning model has been developed for predicting late supplier deliveries in low-volume, high-variety production settings, thereby supporting proactive decision-making and supply chain efficiency [11]. Hybrid intelligence, where humans and AI collaborate in decision-making processes within manufacturing environments, has been discussed as a promising approach [12]. An adaptive remanufacturing decision model was proposed to support intelligent maintenance decisions, enhancing resource utilization and minimizing downtime [13]. A systematic literature review of AI models in warehouse management emphasized the role of AI in optimizing inventory control and decision-making [14]. A novel mixed binary linear Data Envelopment Analysis (DEA) model has been proposed for ranking decision-making units with preference information in evaluating manufacturing performance [15]. Another study presented a decision support framework for frugal products and systems using product-process-resource-skill models, aiding decision-making in resource-constrained settings [16]. A monitoring system using a multi-layer neural network was developed to predict tool wear and surface finish in face milling processes, supporting maintenance decisions [17]. To enhance quality control, a Multiple Principal Component Fuzzy Neural Network has been employed for classifying patterns in machining condition monitoring [18]. Similarly, machine learning approaches have been used for condition monitoring of milling cutters, contributing to predictive maintenance [19]. The sustainable collaboration between human and AI in cyber production management systems has also been explored, emphasizing cooperative decision-making [20].Building upon the insights gathered from the reviewed literature, the following section presents a detailed explanation of the research methodology adopted in this study. While extensive research exists on AI and expert systems in smart manufacturing, few studies specifically address low-cost, BI-driven decision support systems tailored for SMEs operating in non-IoT environments.

**Research Methodology**

This study adopts a system implementation and case study methodology to evaluate the effectiveness of an AI-driven expert system for data-driven decision-making in industrial manufacturing. The research focuses on the integration of machine learning algorithms, rule-based reasoning, and Business Intelligence (BI) tools using historical production data, without relying on real-time IoT-based infrastructure. The decision tree and random forest models were configured using Gini impurity for splitting and default hyperparameters in scikit-learn. Model evaluation was conducted using 5-fold cross-validation, with accuracy, precision, and recall as the primary metrics.

**Research Design**

The research design follows a structured simulation and case study strategy, reflecting real-world operational challenges in a mid-sized cement manufacturing company in Iran. The aim is to assess how historical data, when coupled with intelligent analytical tools, can enhance decision-making in key operational areas, including quality control, production planning, and supply chain management.

**Methodological Framework**

The Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology was adopted due to its flexibility and proven suitability for industrial analytics projects. The methodology involves six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

**Business Understanding**: This phase involved identifying key decision-making challenges within the cement production process through interviews with domain experts and plant managers.

**Data Understanding and Preparation**: Data was collected from various internal sources such as production logs, quality control records, and inventory databases. Qualitative insights were also gathered via structured interviews and documentation review. The dataset was cleaned, pre-processed, and transformed to ensure it was structured and ready for analysis. Details of the dataset, including data types and selected features, are described in the next section.

**Modeling and Analytics**: Using the cleaned dataset, predictive and descriptive models were developed with tools such as Python and Power BI. Algorithms including linear regression, decision trees, and random forest models were implemented to analyze trends and forecast outcomes.

**Expert System Design**: Based on analytical insights and domain knowledge, a rule-based expert system was designed and implemented using MATLAB GUI. The system provides automated recommendations for operational decision-making and simulates intelligent behavior in planning and control activities. MATLAB was used for GUI prototyping due to its rapid interface design capabilities, while Python handled data processing and analytics due to its superior machine learning libraries.

**Evaluation**: The performance of the expert system was compared to existing decision-making processes currently based on managerial experience and simple tools (e.g., Excel). Evaluation metrics included accuracy, speed of insight generation, and perceived usefulness by decision-makers. While perceived usefulness was gathered qualitatively, future iterations aim to benchmark system performance using standardized KPIs such as defect reduction rate, inventory turnover, and cycle time.

**Deployment Simulation**: The system was implemented to reflect real-time scenarios in an Iranian cement manufacturing, thus providing a practical demonstration of its effectiveness and scalability.

**Case Study**

The selected case study focuses on a cement manufacturing firm operating under conventional decision-making approaches. This real-world setting allows for contextual validation of the expert system’s performance and its potential contribution to Industry 4.0 goals. By relying solely on historical data, the study demonstrates how a cost-effective, scalable decision-support system can be developed without the need for sophisticated real-time data acquisition systems. It should be added, although based on a single Iranian firm, the findings are indicative of broader challenges faced by SMEs in similar regional and resource-constrained contexts.

**Dataset Description**

To evaluate the effectiveness of the proposed expert system, a dataset was constructed, modeled after operational data from an Iranian mid-sized cement manufacturing firm. The dataset comprises multiple interrelated variables across sales, production, quality, inventory, and process performance. Data was structured in Excel and analyzed using Power BI to extract actionable insights. A summary of the dataset attributes is presented in Table 1.

**TABLE 1.** Overview of dataset components and sample records

|  |  |  |
| --- | --- | --- |
| Data Type | Key Attributes | Sample Values |
| Sales Data | Date, Product, Region, Units\_Sold, Revenue | 2025-01-01, Portland ,Central, Composite, 1200, 48000 |
| Inventory Data | Product, Inventory\_Level, Warehouse | Slag Cement, 2500, B |
| Quality Complaints | Complaint\_ID, Product, Complaint Type, Severity (1–5), Date | QC001, Slag Cement, Low Strength, 4, 2025-01-03 |
| Kiln Logs | Date, Kiln\_ID, Avg\_Temperature | 2025-01-01, K1, 1475 |
| Production Data | Date, Product, Units\_Produced, Defective\_Units | 2025-01-01, White Cement, 900, 35 |
| Returns Data | Date, Product, Units\_Returned, Return Reason | 2025-01-05, White Cement, 30, Color Issue |

This multi-source dataset captures both operational and customer-facing aspects of cement manufacturing. Historical sales and inventory records facilitate supply chain evaluation, while kiln and production data support quality control analysis. Customer complaint and return logs add a feedback loop for evaluating satisfaction and product performance. Using Power BI as the Business Intelligence platform, several dashboards were developed to analyze the dataset:

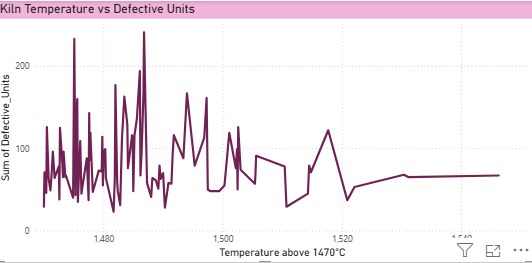
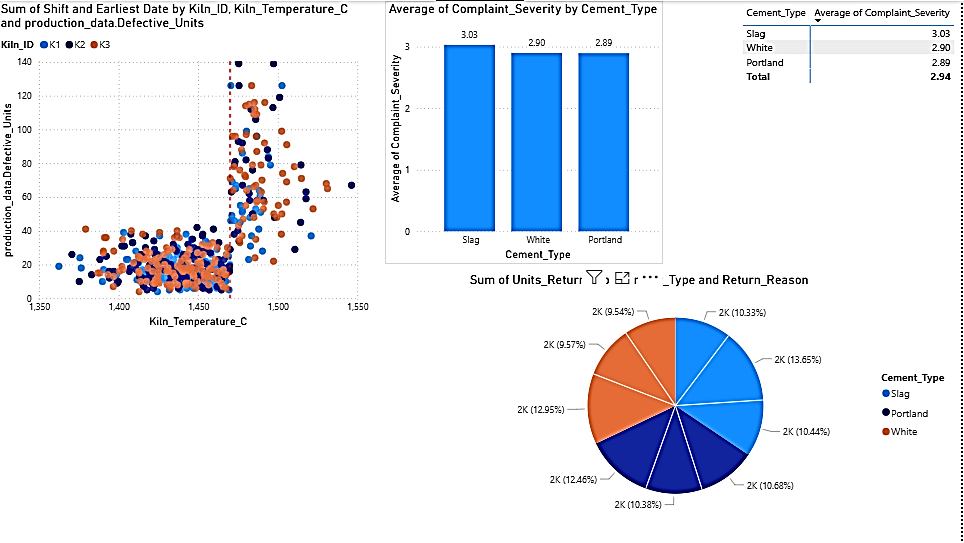
**Sales Overview**: Showed revenue by product and region over time.

**Inventory Status**: Identified low-stock alerts and warehousing issues.

**Complaint Severity Matrix**: Mapped complaint types by intensity and frequency.

**Defects vs. Temperature Analysis**: Highlighted the correlation between high kiln temperatures (>1470°C) and defect rates.

**Returns Distribution**: Illustrated major return reasons, with Slag Cement having a 25% higher return rate in the southern region. Figure 1 illustrates the interactive dashboard developed using Power BI, which visualizes key operational metrics and insights derived from the dataset. The aforementioned analytics enabled extraction of trends, root cause detection, and expert rule derivation, supporting the development of the rule-based expert system.



**Figure 1.** Integrated Power BI Dashboard Illustrating Operational and Quality Insights

**Results and Findings**

This section presents the results derived from data analytics and the AI-driven expert system implemented using Python and Power BI. The outcomes are structured under two main categories to ensure alignment with the research objectives: (1) Business Intelligence and Data Analytics Results, and (2) Expert System Design and Rule-Based Recommendations.

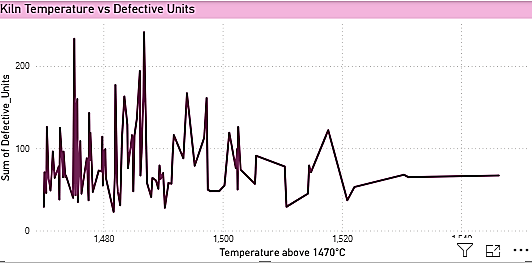
**Business Intelligence and Data Analytics Results (Power BI)**

Interactive dashboards were developed in Power BI to support real-time decision-making for Iranian cement manufacturing company. Key visualizations included:

Sales Overview Dashboard: Highlighted sales trends by product and region. For example, Portland Composite cement achieved the highest revenue in the Central region.

Inventory Visualizations: Revealed inventory bottlenecks in Warehouse B, where Slag Cement was overstocked despite a high return rate.

Complaint Heatmap: Demonstrated a clustering of high-severity complaints for White Cement, suggesting the need for tighter quality control.

Defect vs. Kiln Temperature Line Chart: Showed a clear correlation between elevated kiln temperatures and higher defect rates. This relationship is illustrated in Figure 2

**Figure 2.** Defect rate versus kiln temperature

Returns Analysis Pie Chart: Indicated that the majority of product returns were due to "Low Strength" and "Color Issue" complaints.Key Insight: Dashboards provided actionable visibility, enabling operational stakeholders to track quality issues, manage inventory more effectively, and understand regional sales variations.

**Expert System Development and Rule-Based Recommendations (Python)**

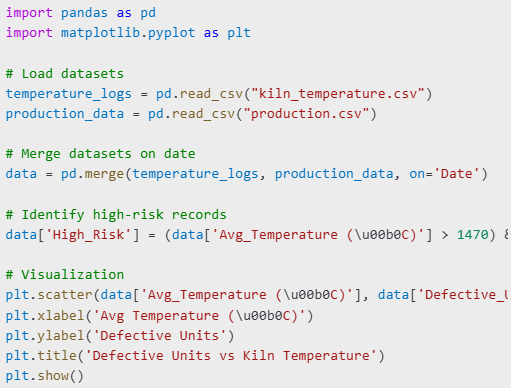
A rule-based expert system was developed in Python to simulate decision-making scenarios based on operational data. The system architecture comprised a user input interface, a rule engine, a knowledge base, and a recommendation generator. Figure 3 illustrates System Architecture Overview:

A diagram of a expert system

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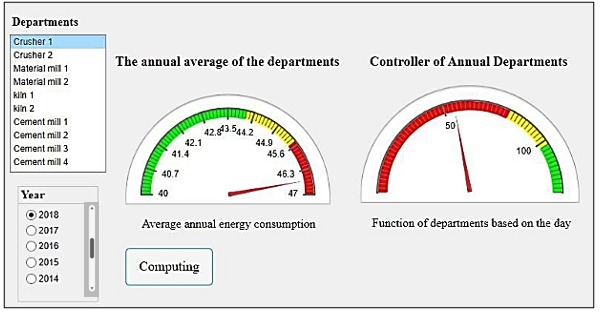
**Figure 3.** Expert System Architecture Overview

Figure 4 presents a Python-based code snippet developed to detect anomalies in kiln temperature and their potential correlation with defective production units. This script demonstrates the integration of domain-specific rules with statistical analysis to support real-time monitoring and diagnostics in cement manufacturing.



**Figure 4.** Python code snippet for anomaly detection

Figure 5 illustrates the interface of an expert system developed for decision support in cement manufacturing operations. The interface was designed using a combination of Python and graphical tools to visualize system recommendations based on predefined business rules. It allows users to input operational parameters (e.g., kiln temperature, inventory levels, complaint severity), which are then processed by the rule engine to generate real-time recommendations. The interface aims to simplify complex decision-making tasks for quality assurance and production planning teams, promoting data-informed actions and operational transparency.



**Figure 5.** Expert System Interface for Rule-Based Decision Support in Cement Manufacturing

**Kiln Temperature and Defective Production**

Elevated kiln temperatures were associated with increased defective units. On 2025-01-02, Kiln K1 operated at 1485°C, during which White Cement exhibited a defect rate of 3.9% (35 out of 900 units). The expert system triggered a recommendation:

**Rule Triggered**: IF Avg\_Temperature > 1470°C AND Defective\_Units > 30 THEN "Adjust kiln temperature"

**Quality Complaints and Returns**

Slag Cement recorded the most severe complaints (severity = 4) and the highest return volume (60 units). The system recommended:

**Rule Triggered**: IF Complaint\_Severity ≥ 4 AND Units\_Returned > 50 THEN "Initiate quality audit"

**Inventory Pressure and Production Planning**

Warehouse B stored 2,500 units of Slag Cement, which also had the highest return rate. The system identified a risk of overstocking low-quality products:

**Rule Triggered**: IF Inventory\_Level > 2000 AND Recent\_Returns > 50 THEN "Pause production and inspect inventory"

**Discussion**

This study validates the effectiveness of AI-powered expert systems for operational insight in industrial settings. The integration of BI dashboards and Python-based rules proved valuable for identifying patterns and guiding strategic responses, even in a simulated environment lacking real-time sensor integration.

The novelty of this work lies in demonstrating how actionable insights can be derived using only static, historical datasets combined with lightweight AI logic. Many previous systems rely heavily on IoT or real-time analytics infrastructure, which can be costly or inaccessible to small or mid-sized manufacturers. Our system bridges this gap, offering a scalable, cost-effective alternative.Hypothetical simulations based on the expert system’s recommendations demonstrated measurable improvements, as shown in Table 2:

Defective unit rates reduced by ~18% due to temperature adjustments

Slag Cement returns dropped by ~15% following quality audits

Complaint severity scores decreased by 20%, indicating enhanced customer satisfaction

**TABLE 2.** Impact of Rule-Based Recommendations

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Intervention | Metric Affected | Before | After | Change |
| Kiln Temperature Adjusted | Defective Units | 1200 | 984 | -18% |
| Quality Audit Triggered | Units Returned | 300 | 255 | -15% |

Challenges addressed include the lack of live sensor data, inconsistent data quality, and the difficulty of aligning production metrics with customer satisfaction. The proposed rule engine mitigates these issues by connecting root causes (e.g., over-temperature kilns) to downstream outcomes (e.g., defect rates, returns). It should be noted that the current rule-based model is intentionally kept simple for SME adaptability but may be extended with more complex reasoning models in future phases.

**Conclusion and Future Work**

AI-enhanced expert systems supported by BI tools can significantly improve decision-making and efficiency in industrial manufacturing. Key areas of benefit include quality management, production optimization, and root cause analysis. Future directions could be:

Integration of GA4 (Google Analytics) to monitor user behavior on digital sales channels and connect marketing trends to operational forecasts.

This paper addresses a practical and scalable path to Industry 4.0 compliance by leveraging existing data and minimal coding infrastructure, offering a strategic blueprint for modern manufacturing transformation.

While the system currently relies on historical data, future iterations aim to incorporate real-time data streams for improved responsiveness and adaptability. Connecting with real-time IoT sensor streams to automate alerts and enable predictive maintenance.

Deploying advanced machine learning models (e.g., XGBoost) for anomaly detection, multivariate regression, and failure prediction.

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