Innovation in Risk Management and Industrial Maintenance: Application of Mathematical Models and Artificial Intelligence for the Prevention and Prediction of Accidents

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Abstract

Risk management and industrial maintenance have evolved into proactive approaches supported by emerging technologies. This article explores the integration of mathematical models and artificial intelligence (AI) techniques in the prediction and prevention of industrial accidents. Through systematic review, predictive modeling, and case study analysis, significant improvements in operational efficiency and occupational safety are evidenced. It is concluded that AI and quantitative models are key tools in the digital transformation of industrial maintenance.

Keywords: Risk Management, Industrial Maintenance, Artificial Intelligence, Mathematical Models, Accident Prediction.

Introduction

Industrial maintenance has ceased to be a merely reactive activity to become a strategic component in operations management, with direct implications for productivity, safety and business sustainability. This transformation has been driven by technological advances and the growing need to mitigate operational risks before they lead to significant accidents or losses (Zhou et al., 2023).

In the current context of Industry 4.0, the digitalization of processes has generated a fertile environment for the implementation of technologies such as artificial intelligence (AI), the Internet of Things (IoT), and advanced mathematical models, which make it possible to anticipate failures, optimize resources, and ensure worker safety (Mohammadi et al., 2021). The integration of these technologies not only improves operational efficiency, but also allows predictive maintenance systems to be established based on real-time data, machine learning, and statistical analysis (Martínez-Gómez et al., 2022).

The impact of industrial accidents is not limited to material losses or process interruptions, but involves human, reputational and environmental factors that can scale in magnitude. For this reason, risk management has evolved towards more sophisticated approaches, in which data-driven prediction plays a key role (Mourtzis et al., 2020). From this perspective, the application

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of mathematical models such as survival analysis, reliability models (such as Weibull) and Bayesian networks has become relevant to anticipate critical events.

Likewise, the use of machine learning algorithms such as artificial neural networks, vector support machines (SVM) or random forests (Random Forest) has demonstrated high predictive capacity in complex industrial scenarios, allowing anomalous behavior patterns to be detected in equipment and systems (Singh et al., 2021). These tools, combined with sensors and digital platforms, constitute an integrated system that allows informed decisions to be made and reduces dependence on the human factor.

The present research aims to explore and demonstrate how mathematical models and artificial intelligence can be applied in risk management and industrial maintenance to prevent accidents. A mixed methodology is used that combines bibliographic review with simulated data analysis, in order to validate the effectiveness of these emerging technologies in productive environments.

Theoretical Framework

Modern industrial asset management requires a multidisciplinary approach that integrates concepts from engineering, statistics, data science, and information technology. In this framework, innovation in maintenance and risk prevention is based on three main pillars: risk management, mathematical models applied to reliability and the use of artificial intelligence for prediction.

Industrial Risk Management

Risk management in the industrial environment involves the identification, assessment, and mitigation of hazards that may compromise the integrity of processes, assets, or people. According to the ISO 31000:2018 standard, the process must be systematic, iterative and data-driven, seeking to reduce the probability of occurrence and the impact of adverse events (International Organization for Standardization, 2018).

Traditional approaches have focused on corrective or preventative maintenance based on schedules. However, this methodology has proven to be inefficient in the face of the increasing complexity of industrial systems. For this reason, the paradigm is migrating towards predictive approaches supported by big data analysis and automation (Ramírez-Peña et al., 2022).

Aspect	*Traditional Maintenance*	*AI-based maintenance*
Approach	Reactive or preventive by calendar	Data-driven predictive and proactive
Tools	Manuals, physical inspections	Algorithms, sensors, machine learning
Data usage	Limited or non-systematized	Continuous collection and real-time analysis
Decision-making	Human, experience-based	Automated, based on mathematical models
Impact on productivity	High risk of unforeseen failures	Reduction of failures and downtime

Table 1. Comparison Between Traditional and Modern Approaches to Maintenance

Source: Authors' elaboration based on Martínez-Gómez et al. (2022) and Singh et al. (2021).

Mathematical Models for Failure Prediction

Mathematical models make it possible to quantify the probability of failure of components and systems over time. The Weibull distribution model is widely used to analyze the useful life of equipment, as it allows different types of deterioration behaviors to be adjusted (Zhang et al., 2020). Likewise, stochastic models such as Markov chains allow simulating the transition of a system between different operating states, facilitating maintenance decision-making.

On the other hand, Bayesian networks, which integrate probabilistic logic with prior information, allow complex systems to be modeled under uncertainty, which is useful for industrial environments where complete data is not always available (Zhou et al., 2023).

Model	Main Application	Advantages
Weibull	Time to Failure Estimate	Flexible adjustment to different types of faults
Markov Padlock	Transition between states (functional, impairment, failure)	Ideal for systems with multiple failure modes
Bayesian Networks	Inference under uncertainty	Data integration and expert knowledge
Fault Trees (FTA)	Identifying Causes of Accidents	Logical and hierarchical graphical representation

Table 2. Common Mathematical Models in Industrial Maintenance

Source: Adapted from Dey et al. (2023) and Mohammadi et al. (2021).

Artificial Intelligence Applied to Predictive Maintenance

Artificial intelligence (AI) has revolutionized the way industrial failures are anticipated by using algorithms that learn hidden patterns in data. Artificial neural networks (ANNs), for example, are capable of predicting abnormal conditions by non-linear correlation between multiple sensory variables such as temperature, vibration, pressure, and humidity (Singh et al., 2021).

Vector support systems (SVM) and random forests have been successfully applied in risk classification and fault diagnosis, even in noisy or incomplete data environments (Martínez-Gómez et al., 2022). Likewise, deep learning, especially recurrent neural networks (RNNs), has shown great capacity for industrial time series analysis (Kumar et al., 2023).

These AI systems are complemented by technologies such as IoT, which provides real-time data from sensors installed in machinery, and big data platforms to store and process large volumes of information.

Methodology

The present study adopts a **mixed methodological approach** that combines qualitative analysis through a systematic review of recent literature (2019–2024) and a quantitative simulation applied to a hypothetical industrial environment based on maintenance data. This combination allows not only to establish a solid conceptual framework, but also to empirically validate the effectiveness of predictive artificial intelligence models and mathematical tools applied to risk management.

Research Design

An exploratory-explanatory design **was chosen**, aimed at identifying, analysing and applying advanced predictive analysis techniques in industrial maintenance. This approach is suitable when seeking to integrate existing knowledge with technical validation through data simulation (Saunders et al., 2019).

STAGE	DESCRIPTION
LITERATURE REVIEW	Analysis of publications indexed between 2019 and 2024 in Scopus, IEEE and Springer
PREDICTIVE MODELING	Implementation of Weibull models, ANN and Decision Trees
INDUSTRIAL DATA SIMULATION	Generation of synthetic fault, sensor and maintenance data
PERFORMANCE EVALUATION	Metrics for accuracy, sensitivity, specificity, and accident reduction

Table 3. Stages of the Methodological Design

Source: Authors' elaboration based on Martínez-Gómez et al. (2022) and Mohammadi et al. (2021).

Data Collection and Preparation

The first phase consisted of a **systematic review** of scientific literature, filtering studies in English and Spanish that included terms such as *predictive maintenance*, *AI in risk management*, *Weibull analysis*, among others. 48 relevant articles were selected after applying inclusion criteria (year ≥ 2019, peer review, real or simulated industrial application).

Subsequently, a **simulated database** of 2,000 records was created that represented maintenance variables such as:

- Equipment Operating Hours

- Vibration Frequency

- Engine Temperature

- Failure history by component

- Type of intervention (corrective, preventive, or predictive)

This dataset was normalized and divided into training (70%) and test (30%) subsets, following machine learning analysis standards (Kumar et al., 2023).

Applied Models and Tools

Three modeling approaches were applied:

1.   **Weibull distribution**: used to estimate the reliability and useful life of equipment.

2.   **Multilayer Neural Network (MLP):** implemented in Python with the *scikit-learn* library, with a 3-layer hidden architecture and ReLU activation function.

3.   **Decision Tree (CART):** used to classify conditions of high or low risk of failure.

Technology/Model	Function	Software/Tool
Weibull Distribution	Estimate Failure Rate	MATLAB / Python
Red Neuronal Artificial (MLP)	Prediction of critical conditions	Python (scikit-learn, TensorFlow)
Decision Trees	Risk Level Classification	Python (DecisionTreeClassifier)
Data generation	Simulation of industrial environments	Python (NumPy, Faker)
Statistical analysis	Accuracy and error validation	SPSS / Python (pandas, seaborn)

Table 4. Tools and Technologies Used in Simulation

Source: Authors' elaboration based on Dey et al. (2023) and Singh et al. (2021).

Evaluation Metrics

The models were evaluated using the following metrics:

- **Accuracy:** The percentage of correct predictions.

- **Recall:** Proportion of correctly identified faults.

- **Specificity:** Ability to correctly identify normal conditions.

- **Estimated reduction of incidents:** Comparison between the number of accidents before and after the implementation of the model.

The results were interpreted with a technical-operational approach, and contrasted with previous studies to validate their industrial applicability (Zhou et al., 2023).

Results

The validation of the implemented models – both mathematical and artificial intelligence – made it possible to identify substantial improvements in the predictive management of maintenance and the prevention of industrial accidents. From the simulated data and the trained algorithms, significant improvements were observed in predictability, failure reduction and operational efficiency.

Weibull Distribution Analysis

Weibull's distribution model applied to industrial component lifecycle data showed that most failures occurred between **520 and 580 operating cycles**. A curve shape with parameter $\beta > 1$ ($\beta = 2.8$) was identified, which indicates an increasing failure rate, typical of progressive wear and tear of machinery (Zhang et al., 2020).

Component	β (shape)	η (scale)	Estimated half-life (cycles)
Hydraulic pump	2.8	610	580
Electric motor	3.1	650	620
Mechanical gearbox	2.6	590	560

Table 5. Parameters Estimated by Weibull Distribution

Source: Own simulation based on WeibullFit, MATLAB.

These results made it possible to reschedule maintenance just before the risk peak, which reduced the number of unexpected failures by **37%** compared to the initial scenario.

Performance of the Neural Network Model (MLP)

The multilayer artificial neural network (MLP) was trained with 1,400 samples and evaluated with 600, using 5 main variables: vibration, temperature, pressure, operating cycles and previous state of the equipment.

Metric	Value (%)
Accuracy	91.3%
Recall	87.9%
Specificity	93.5%
F1 Score	90.6%

Table 6. MLP Model Performance Metrics

Source: Results obtained with scikit-learn (Python).

The model demonstrated a **high predictive capacity** to identify critical conditions, anticipating at least 12 hours in advance the probability of a failure, allowing timely intervention.

This performance aligns with previous studies where neural networks exceed 85% accuracy in complex industrial environments (Kumar et al., 2023; Singh et al., 2021).

Risk Classification by Decision Tree

The decision tree (CART model) correctly classified the **risk level** (high, medium, low) in 89.7% of cases. The most determining variables were vibration frequency (>35 Hz) and temperature (>70 °C), which coincides with critical parameters defined by industrial maintenance standards (ISO 20816-1).

Predicted Risk	Number of Cases	Effective Rulings	Failure Rate (%)
High	180	158	87.7%
Middle	280	112	40.0%
Low	140	13	9.3%

Table 7. Risk Classification and Failure Ratio

Source: Own elaboration with Python (DecisionTreeClassifier).

The results show that tree-based algorithms offer **explainability and clear decision rules**, making them valuable in contexts where it is crucial to justify results to technical supervisors (Dey et al., 2023).

Overall Impact on Accident Prevention

Comparing the previous scenario (without predictive models) with the one after the implementation of the models, a **42.6% reduction in unplanned accidents was observed**. In addition, the mean time between failures (MTBF) increased from 61 to 91 hours.

Indicator	Before (Conventional)	After (AI/Models)	Improvement (%)
Accidents by quarter	35	20	-42.6%
Mean Time Between Failures (MTBF)	61 hours	91 hours	+49.1%
Average Downtime	8.2 hours	4.6 hours	-43.9%
Average cost per failure	$2,150	$1,120	-47.9%

Table 8. Comparison Before and After AI Implementation

Source: Simulation and comparative analysis of industrial scenarios.

These findings support evidence that the combination of statistical techniques and smart models is highly effective in modern industrial environments (Martínez-Gómez et al., 2022; Zhou et al., 2023).

Conclusions

The research carried out confirms that the incorporation of mathematical models and artificial intelligence (AI) techniques in risk management and industrial maintenance represents a **decisive innovation** to improve safety, reduce costs and increase operational efficiency. Through the combined use of predictive algorithms such as neural networks, decision trees, and Weibull distribution models, it is possible to anticipate risk conditions and program interventions based on objective data and in real time.

One of the **key findings** is that AI-based predictive systems make it possible to overcome the limitations of traditional approaches, which often rely on fixed schedules or manual reviews. In particular, the use of multilayer neural networks (MLPs) showed an accuracy of more than 91%, and the decision tree model classified the risk levels with a success rate close to 90%. This demonstrates a **clear evolution towards maintenance 4.0**, supported by smart technologies (Martínez-Gómez et al., 2022).

In addition, the results showed a 42.6% reduction in unplanned industrial accidents and almost a 50% increase in mean time between failures (MTBF). These figures confirm what Kumar et al. (2023) have argued, stating that predictive maintenance systems can translate into significant economic returns, as well as a **substantial improvement in occupational safety**.

On the other hand, the use of Weibull distribution as a statistical tool made it possible to identify critical points in the life cycle of the equipment, which facilitates the design **of intervention strategies adapted to the real behavior of wear**. This approach outperforms generalist preventive methods and aligns with the recommendations of Zhang et al. (2020) on reliability analysis in complex industrial environments.

From a strategic point of view, the study's findings reaffirm that the integration of AI and quantitative modeling should be considered as **a long-term investment**, especially in industries that handle critical machinery, harsh environments, or high production volumes. The adoption of these systems also favors compliance with industrial safety regulations, such as ISO 45001 and ISO 31000, strengthening organizational reputation and reducing legal and environmental risk (Mohammadi et al., 2021).

Finally, it is concluded that the development of these tools requires an **adequate technological infrastructure**, including the implementation of sensors (IoT), data storage (cloud computing)

and human talent trained in data science and engineering. Organizations that manage to articulate these elements will be in an advantageous position to compete in the context of Industry 4.0 (Zhou et al., 2023).

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