

An Intelligent Decision Support System for Hazard Identification and Risk Assessment in Fertilizer Industries

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Abstract

Fertilizer manufacturing is a complex industrial process involving hazardous chemicals, high-temperature and high-pressure operations, rotating machinery, storage facilities, and potentially toxic or flammable substances. Conventional Hazard Identification and Risk Assessment (HIRA) methods such as Hazard and Operability Study (HAZOP), Failure Mode and Effects Analysis (FMEA), Fault Tree Analysis (FTA), and risk matrices are valuable for process-safety management but often depend heavily on expert knowledge and periodic assessment. This paper proposes an Intelligent Decision Support System (IDSS) for improving hazard identification and risk assessment in fertilizer industries through the integration of industrial safety knowledge, risk assessment techniques, machine learning, and decision-support mechanisms. The proposed framework collects process, equipment, environmental, and historical incident information; identifies potential hazards; estimates likelihood and severity; classifies risk levels; and recommends appropriate control measures. A hybrid architecture combining rule-based reasoning with machine-learning techniques is proposed to improve interpretability while supporting predictive risk assessment. The system can provide real-time or near-real-time risk information through a user interface and generate prioritized recommendations for safety personnel. The proposed framework is intended to support—not replace—qualified safety professionals and established process-safety procedures. The research provides a foundation for developing an intelligent, explainable, and data-driven approach to industrial risk management in fertilizer manufacturing.

Keywords: Hazard Identification, Risk Assessment, Fertilizer Industry, Intelligent Decision Support System, Artificial Intelligence, Machine Learning, HAZOP, FMEA, Predictive Risk Assessment, Process Safety.

Introduction

The fertilizer industry plays an important role in agricultural production and food security. Manufacturing processes commonly involve chemicals such as ammonia, nitric acid, sulfuric acid, phosphoric acid, urea, and various intermediate and finished products. Depending on the production process, workers and facilities may be exposed to toxic releases, fires, explosions, pressure-related failures, chemical exposure, equipment failures, and other occupational and process-safety hazards.

Industrial accidents may result from a combination of equipment malfunction, process deviations, inadequate maintenance, human error, environmental conditions, and failures of safety barriers. Consequently, systematic hazard identification and risk assessment are essential components of process safety management.

Traditional HIRA techniques generally involve identifying hazards, estimating the likelihood and consequences of hazardous events, assigning a risk level, and selecting appropriate control measures. Although these approaches are widely used, several challenges remain. Risk assessments may be performed periodically rather than continuously, large quantities of heterogeneous safety data can be difficult to analyze manually, and the quality of the assessment can depend significantly on the experience of the assessment team.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and decision-support technologies provide opportunities to improve industrial safety management. Sensor measurements, maintenance records, inspection reports, incident databases, operating conditions, and environmental information can potentially be integrated into an intelligent system capable of identifying patterns associated with increased risk.

This research proposes an Intelligent Decision Support System (IDSS) for hazard identification and risk assessment in fertilizer industries. The proposed system combines conventional safety methodologies with data-driven intelligence to provide risk prioritization and decision support.

Problem Statement

Existing hazard identification and risk assessment approaches in fertilizer industries face several limitations:

1. Risk assessments may depend substantially on expert judgment.
2. Large volumes of operational and maintenance data are difficult to analyze manually.
3. Conventional risk matrices generally provide static rather than continuously updated risk information.
4. Historical incidents and near-miss information may not be effectively incorporated into future risk assessments.
5. Different hazard-analysis techniques may produce fragmented information.
6. Early indicators of developing hazardous conditions may not be recognized in time.
7. Safety recommendations may not always be prioritized according to changing operational conditions.

Therefore, there is a need for an intelligent decision-support framework capable of integrating multiple sources of safety information and assisting safety professionals in identifying and prioritizing hazards.

Research Objectives

The main objective of this research is to develop an intelligent decision-support framework for hazard identification and risk assessment in fertilizer industries.

The specific objectives are:

- To identify major process, chemical, mechanical, occupational, fire, and environmental hazards in fertilizer manufacturing.
- To develop a structured database of hazards, causes, consequences, and control measures.
- To integrate conventional HIRA methodologies with artificial intelligence techniques.
- To develop a machine-learning model for risk-level prediction.
- To incorporate historical incident and near-miss information into risk assessment.
- To develop an explainable decision-support mechanism for safety professionals.
- To prioritize hazards according to estimated risk.
- To recommend appropriate preventive and mitigating controls.
- To evaluate the proposed framework against conventional risk-assessment approaches.

Research Questions

The research is guided by the following questions:

RQ1: Can an intelligent decision-support system improve the consistency of hazard identification?

RQ2: Can machine-learning techniques assist in predicting industrial risk levels from process and historical safety data?

RQ3: Can a hybrid rule-based and machine-learning architecture provide more interpretable risk recommendations?

RQ4: How effectively can the proposed system prioritize hazards and recommend control measures?

RQ5: What are the limitations of applying AI-based decision support to industrial process safety?

Literature Review

Hazard Identification and Risk Assessment

Hazard identification involves recognizing sources or conditions that can potentially cause injury, environmental damage, equipment loss, or process disruption. Risk assessment generally considers the likelihood of occurrence and the potential consequence of a hazardous event.

Common approaches include HAZOP, FMEA, FTA, Event Tree Analysis, What-If Analysis, and risk matrices.

HAZOP systematically examines process deviations using guide words such as *No*, *More*, *Less*, *Reverse*, and *Other Than*. FMEA evaluates potential failure modes and their effects. FTA uses a top-down logical structure to determine combinations of failures that can result in an undesired event.

These techniques provide strong methodological foundations but can require considerable expert effort, particularly for complex facilities.

Artificial Intelligence in Industrial Safety

AI techniques can analyze large datasets and identify relationships that may not be easily recognized through manual analysis. Classification algorithms can be used to categorize risk levels, while regression models can estimate numerical risk scores. Clustering techniques can identify groups of similar operating or incident conditions.

Potential machine-learning algorithms include:

- Decision Trees
- Random Forest
- Support Vector Machines
- Logistic Regression
- Gradient Boosting
- Artificial Neural Networks
- Explainable AI techniques

However, industrial safety applications require high levels of transparency and validation. A model should therefore provide an understandable explanation for its risk prediction rather than functioning solely as a black box.

Intelligent Decision Support Systems

An IDSS combines data, domain knowledge, analytical models, and user interaction to assist decision-makers. In an industrial safety context, an IDSS can provide:

- Hazard alerts
- Risk ranking
- Trend analysis
- Failure prediction
- Recommended controls

- Historical comparisons
- Investigation support

The proposed research combines these capabilities within a unified framework.

Proposed Methodology

The proposed methodology consists of six major stages:

Data Acquisition → Data Preprocessing → Hazard Identification → Risk Prediction → Decision Support → Recommendation and Visualization

Data Acquisition

The system may collect data from multiple sources:

- Process parameters
- Equipment condition
- Temperature
- Pressure
- Flow rate
- Gas concentration
- Vibration
- Maintenance records
- Inspection records
- Accident records
- Near-miss reports
- HAZOP worksheets
- FMEA records
- Environmental conditions
- Safety observations
- Operator reports

For a prototype M.Tech study, historical and simulated datasets can be used when access to confidential industrial data is unavailable.

Data Preprocessing

The collected data may contain missing values, inconsistent formats, duplicate observations, and noisy measurements. Data preprocessing therefore includes:

1. Data cleaning
2. Missing-value treatment
3. Outlier analysis
4. Data normalization
5. Feature encoding
6. Feature selection
7. Dataset balancing

The processed data are then supplied to the hazard-analysis and prediction modules.

Hazard Classification

The system can classify hazards into several categories.

Hazard Category Examples

Chemical	Toxic exposure, corrosive chemicals, chemical release
Process	High pressure, high temperature, process deviation
Fire	Flammable material release, ignition
Explosion	Combustible atmosphere, pressure-related events
Mechanical	Rotating machinery, equipment failure
Electrical	Electrical faults, short circuits
Occupational	Slips, falls, ergonomic hazards
Environmental	Chemical emissions, accidental discharge
Storage	Leakage, incompatible storage, overpressure

The classification can be customized for the specific fertilizer process under study.

Risk Assessment Model

A conventional risk matrix can be incorporated as a baseline.

A simple conceptual formulation is:

$$R=L\times SR=L\times S$$

where:

- RR = risk score
- LL = likelihood
- SS = severity

For example, likelihood and severity may each be represented using a five-level scale. However, the exact scales and acceptance criteria should be defined according to the selected industrial standard and organization-specific risk criteria.

The proposed IDSS can supplement this static assessment with a data-driven prediction.

Proposed Risk Categories

Risk Level General Interpretation		Decision
Low	Acceptable with routine controls	Monitor
Moderate	Additional controls may be required	Review
High	Significant risk	Prioritize corrective action
Critical	Potentially unacceptable risk	Immediate management attention

These categories are illustrative and must be adapted to the applicable safety-management framework.

Machine-Learning Model

The proposed study can compare multiple classification algorithms.

Decision Tree

A Decision Tree generates interpretable rules based on input features. Its interpretability makes it useful for safety applications.

Random Forest

Random Forest combines multiple decision trees and can improve prediction robustness. It can also provide feature-importance information.

Support Vector Machine

SVM can classify complex patterns in multidimensional datasets and may be useful where the dataset is relatively small but contains informative features.

Artificial Neural Network

ANN models can represent nonlinear relationships among process variables and risk outcomes. However, additional explainability mechanisms may be required.

Recommended Experimental Strategy

The study can train several models and compare them using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC
- Confusion matrix
- Training time
- Explainability

The best model should not be selected solely on accuracy. For industrial safety, interpretability, robustness, false-negative performance, and operational suitability are also important.

Explainable AI Component

Explainability is an important feature of the proposed system.

When the system identifies a high-risk condition, the user should be able to understand why the prediction was made.

For example, an explanation may identify factors such as:

- Abnormal pressure trend
- Increased temperature
- Equipment maintenance overdue
- Previous failure history
- Increased gas concentration

Techniques such as feature importance, SHAP-based explanations, or interpretable decision trees can be investigated.

The objective is to ensure that the safety engineer receives not only a risk score but also supporting evidence for the recommendation.

Decision-Support Workflow

The proposed workflow is:

1. Collect operational and safety data.
2. Validate and preprocess the data.
3. Identify potential hazards using rules and historical information.
4. Extract relevant features.
5. Predict risk using trained ML models.
6. Compare the prediction with conventional risk assessment.
7. Generate an explanation of the prediction.
8. Rank identified hazards.
9. Recommend appropriate control measures.
10. Display the results on a safety dashboard.
11. Store the assessment for future analysis.

Experimental Design

For experimental evaluation, the dataset should contain observations representing different operating and safety conditions.

Possible input features include:

$$X = \{P, T, F, G, V, M, E, H\} \quad X = \setminus \{P, T, F, G, V, M, E, H\}$$

where:

- PP = pressure-related features
- TT = temperature-related features
- FF = flow-related features

- GG = gas/chemical concentration
- VV = vibration or equipment-condition features
- MM = maintenance information
- EE = environmental factors
- HH = historical safety information

The target variable can be a risk category or an appropriately defined risk score.

The dataset can be divided into training, validation, and testing subsets. Cross-validation should be considered where the dataset size permits.

Performance Evaluation

The proposed IDSS can be evaluated at two levels.

Machine-Learning Performance

The predictive models can be evaluated using:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

For safety applications, recall for high-risk events should receive particular attention because failing to identify a genuinely hazardous condition may have more serious consequences than generating an additional warning.

Decision-Support Performance

The overall system can additionally be evaluated through:

- Hazard identification coverage
- Agreement with expert assessments
- False-alarm rate
- Response time
- Recommendation relevance
- Explainability
- User acceptance
- Consistency of risk ranking

Discussion

The proposed IDSS represents a hybrid approach rather than a replacement for established process-safety methodologies. Conventional techniques such as HAZOP and FMEA provide structured domain knowledge, while machine learning can identify patterns in historical and operational data.

The major advantage of the hybrid architecture is that it can combine expert knowledge with data-driven prediction. This is particularly important in safety-critical environments, where purely data-driven models may encounter unfamiliar situations or insufficient training data.

Another important advantage is explainability. A safety professional should be able to understand the principal factors contributing to an elevated risk prediction. This can improve trust and support informed decision-making.

However, several challenges must be considered. Industrial incident datasets are often limited because serious accidents are relatively rare. Data may also be incomplete, inconsistent, confidential, or biased toward reported events. Furthermore, changes in equipment, operating procedures, maintenance practices, or production conditions can affect model performance over time.

Therefore, the proposed system should be treated as a decision-support tool and should operate under appropriate human oversight.

Research Gap

The following research gaps can be addressed through the proposed work:

- Limited integration between conventional HIRA methods and machine-learning models.
- Insufficient use of historical near-miss and operational data in dynamic risk assessment.
- Lack of explainable AI mechanisms in safety-oriented risk prediction.
- Limited integration of hazard identification, risk prediction, and recommendation into one decision-support platform.
- Need for continuous model validation under changing industrial operating conditions.

The proposed research addresses these gaps through an integrated hybrid IDSS architecture.

Novelty of the Proposed Work

The potential contributions of the research are:

1. A unified intelligent framework integrating hazard identification and risk assessment.
2. Integration of rule-based safety knowledge with machine-learning prediction.
3. Explainable risk prediction for improved user trust.
4. Dynamic prioritization of identified hazards.
5. Integration of historical safety information with current operating conditions.
6. Automated generation of risk-assessment reports and safety recommendations.
7. A modular architecture that can potentially be adapted to different fertilizer manufacturing processes.

Conclusion

This paper proposed an Intelligent Decision Support System for hazard identification and risk assessment in fertilizer industries. The proposed framework integrates conventional safety-analysis techniques, domain knowledge, machine learning, explainable AI, and decision-support functionality.

The system is designed to collect heterogeneous industrial safety information, identify potential hazards, estimate risk, prioritize hazardous conditions, explain the factors contributing to the prediction, and provide safety recommendations. The hybrid architecture addresses an important limitation of purely manual or purely data-driven approaches by combining expert knowledge with analytical intelligence.

For an M.Tech research project, the proposed framework provides opportunities for significant experimental work in machine learning, explainable AI, database management, risk analytics, and industrial safety. Future implementation and validation using real or appropriately constructed industrial datasets can establish the effectiveness, generalizability, and practical value of the proposed approach.

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