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Machine learning and bayesian network based on fuzzy AHP framework for risk assessment in process units

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Risk assessment plays a crucial role in ensuring the safety of process units. Artificial intelligence has become increasingly prevalent in risk assessment and prediction, offering the potential for more precise outcomes when integrated with other techniques. This study is both descriptive and analytical in nature. The dataset utilized comprises 160 deviations identified through the HAZOP technique. A variety of evaluation algorithms were employed in this study, ranging from ensemble methods like Random Forest, Hist Gradient Boosting, XGBoost, and CatBoost, to traditional methods such as Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). This broad array of algorithms enabled a comprehensive comparison of diverse modeling approaches, encompassing conventional statistical methods and cutting-edge machine-learning techniques. Among the algorithms tested, Random Forest, XGBoost, and CatBoost exhibited exceptional performance on the training and test datasets, achieving near-perfect AUC scores and accuracy values of 1.0000. In the fusion of Bayesian networks and Multi-Criteria Decision Making (MCDM), the options "Corrosion in Electrolysis Cells" and "Damage and Explosion of Cells" were given higher priority over other options. The findings from this study suggest that machine learning techniques, along with the amalgamation of Bayesian networks and MCDM, can serve as effective tools for risk assessment and the prioritization of risk options. By leveraging these methodologies, suitable control and preventive measures can be implemented to mitigate risks effectively.

Keywords HAZOP, Machine learning, Risk assessment, MCDM, Bayesian Network

In recent decades, the widespread adoption of new technologies across industries has significantly enhanced human welfare. However, this progress has also introduced a new dilemma: workplace accidents, which have led to substantial human casualties[1]. According to the International Labour Organization (ILO) statistics, more than 2.78 million people lose their lives each year due to occupational accidents[2]. Occupational accidents cost the global economy $1.25 billion annually and lead to the death of 2 million people per year[3]. The rate of fatal occupational accidents is four times higher in developing countries compared to industrialized countries, and Iran is not an exception to this rule, with approximately 14,000 occupational incidents occurring annually[4]. Therefore, the need for prevention of accidents is considered a necessity for the survival of organizations. This requires identifying the causes of accidents before they occur, which today has been addressed in the form of a risk assessment and management approach[5,6]. The power industry is one of the high-risk industries among various sectors, as personnel working in power generation, transmission, and distribution are exposed to a range of occupational health hazards[7]. power plants are one of the most important factors and necessities for the growth and development of any country. They are a collection of industrial facilities used for the production of electrical energy[8]. Nuclear power plant One of the most efficient types of power plants is the combined

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cycle power plant, where optimal design can lead to reduced fuel costs[9]. In many power plants in Iran, due to geographical location and climatic conditions, the once-through cooling system, such as Heller towers and air-cooled condenser (ACC) systems, is used, which is the most suitable option for power plants located near the sea or rivers[10]. The chemical reactions in the chlorination unit of combined cycle power plants with a once-through cooling system result in the production of sodium hypochlorite and hydrogen gas[11,12]. Therefore, considering the risk of fire and explosion caused by hydrogen gas leakage, the evaluation of HSE risks in the chlorination unit of combined cycle power plants is essential. The significance of addressing these risks is not merely academic; it is of paramount importance for the sustainability and operational continuity of power plants[13]. The Hazard and Operability Study (HAZOP) technique is widely used for identifying system hazards and operational issues in industries like chemicals and power generation. This systematic method involves expert teams examining potential process deviations and their consequences based on operational parameters such as temperature and pressure[14]. Analyzing such large datasets requires advanced resources and techniques for data classification and pattern identification that cannot be achieved through traditional analytical tools[15]. With the development of artificial intelligence and the emergence of the era of big data, many researchers have utilized machine learning methods to conduct extensive research on risk assessment[16,17].

Organizational risk management plays a crucial role in the sustainable performance of financial institutions domestically and internationally. Older assessment methods are no longer able to meet the needs of processing various types of data, handling a large number of users, and achieving high-risk prediction accuracy[18,19]. Many researchers employ machine learning methods[20]. Predictive models for occupational accidents can be based on statistical learning or machine learning (ML). Given the vast amount of available data, ML replaces traditional statistical counterparts in predicting future events and has been widely used in various fields such as engineering, medical sciences, and finance, providing highly valuable results[21]. Machine learning (ML) is a subset of artificial intelligence that enables systems to learn patterns and make predictions from data without explicit programming[22]. In this study, ML techniques are applied to predict risks by analyzing historical data and identifying relationships between critical variables. Ensemble algorithms, such as Random Forest, XGBoost, and CatBoost, are utilized to enhance predictive accuracy and robustness. These algorithms combine predictions from multiple models to create a stronger overall prediction[23]. Ensemble methods are particularly effective in handling classification tasks, managing imbalanced datasets, and reducing the impact of noise, making them suitable for risk assessment in complex systems[24].

However, existing research indicates that machine-learning techniques have been limitedly used in occupational accident analysis[25]. In recent years, machine learning-based risk assessment models have emerged and proven to be more effective than traditional risk assessment methods[26–29]. Commonly used modern machine learning techniques include Backpropagation Neural Networks (BP), K-Nearest Neighbors (KNN), and Support Vector Machines (SVM)[30]. Additionally, tree-based machine learning methods are widely employed in risk assessment, such as basic decision tree models and more advanced ensemble approaches like Random Forest (RF), Gradient Boosting Decision Trees (GBDT), XGBoost, and LightGBM[31].

The focus of this research lies in the dynamic risk assessment of a combined cycle power plant, where risks are continuously evolving due to varying operational conditions. A dynamic risk assessment involves updating the primary risk number based on various factors such as the control system's performance, safety barriers, maintenance and inspection activities, human factors, and operational procedures. This method was developed to address limitations seen in other approaches like bow-tie[32]. Research on dynamic risk assessment in process facilities is ongoing[33].

The Bayesian belief network is a widely used method in dynamic risk assessment due to its ability to handle uncertainty and belief updating. This approach is effective in addressing complex issues by combining robust probabilistic methods with graphical representations. Bayesian networks can pinpoint components that are most likely to contribute to system risk[34]. When objective data is lacking and expert opinion is necessary, the Bayesian belief network offers a natural framework for understanding relationships between model components. It also offers a way to manage uncertainty, unpredictability, and complexity in decision support systems. The graphical and easily updatable nature of Bayesian Networks has made them increasingly popular in the process industry[35,36].

This study was conducted in a combined cycle power plant with a capacity of 968 megawatts. Seawater is used for cooling operations in this power plant. It consists of 162 units in the gas phase and 1 unit in the steam phase. One of the areas examined in this research is the chlorination unit, which is responsible for producing the required hypochlorite for chlorination purposes. Considering that this unit is one of the critical and hazardous units in the power plant, it was the focus of this study. Therefore, this study aimed to develop a method for risk assessment using machine learning and a Bayesian decision network based on multi criteria decision making[37].

It should be noted that obtaining reliable data is often challenging, resulting in difficulties when eliciting conditional probability tables (CPTs) for each node in a Bayesian network (BN). In such cases, CPTs are typically derived from expert opinions. However, it is important to acknowledge that human judgment is subjective and ambiguous, leading to inherent uncertainty in probability analysis[38]. To address the fuzziness and uncertainty associated with vague decision-making, the fuzzy analytical hierarchy process (fuzzy AHP) is employed. Fuzzy AHP utilizes fuzzy sets, membership functions, and fuzzy numbers to more effectively handle subjective evaluations and convert linguistic variables into probability values[39,40]. Therefore, in this study, fuzzy AHP is utilized to calculate the CPTs of the BN.

By employing expert elicitation and fuzzy theory to determine probabilities, FBN utilizes the same reasoning and inference algorithms as conventional BN for predictive analysis and probability updating. this study compares the results of fuzzy Bayesian networks (FBN) with traditional Bayesian networks, showing that FBN offers more detailed, transparent, and realistic insights, particularly when analyzing critical risk factors[41].

Literature review

The increasing complexity of industrial operations and the growing focus on safety management have driven significant advancements in risk assessment methodologies[42]. While traditional techniques remain valuable, they often encounter challenges in addressing uncertainties, evolving risk factors, and the intricate, nonlinear interactions between various contributing elements[43]. To overcome these limitations, researchers have introduced advanced computational approaches such as fuzzy logic, Bayesian networks, machine learning (ML) to improve risk prediction and decision-making in occupational and process safety[44].

These approaches have contributed to a more systematic, data-driven evaluation of risks, allowing for improved hazard identification, mitigation strategies, and decision-making processes within industrial safety management frameworks. Table 1 presents a comparative analysis of methodologies and key findings in risk assessment and process safety.

Method

This study is applied research aimed at identifying and evaluating the risk of a power plant's chlorine unit using machine learning, combining Bayesian networks and the fuzzy AHP method. Figure 1 illustrates the steps of implementing this method.

Data collection of the examined process

The text describes the methodology used for gathering necessary information through technical review, document analysis, and interviews with employees and experts. In this regard, initially, the relevant company's available resources and technical documents, as well as the chlorination unit's equipment and related diagrams, were studied. Subsequently, the Process Flow Diagram (PFD) and the Overall Equipment Layout,

Row	Author(s)	Study focus	Methodology/techniques	Key findings & contributions
1	Alauddin et al.[45]	HAZOP & ANN for Dust Explosion Testing	HAZOP study combined with ANN for predicting explosion parameters	ANN models accurately predict explosion severity, and HAZOP enhances reliability in modeling
2	Contessotto[46]	Phenomena-Based HAZOP Support	Graph-based modeling and automation using Python for HAZOP deviation analysis	Utomates deviation tracking, reduces human error, and improves efficiency in HAZOP studies
3	Bozorgi et al.[47]	Risk assessment and management of agricultural water systems	(FDBN) for multi-hazard risk assessment, incorporating fuzzy theory(WASPAS, TOPSIS, MultiMoora, and Copeland approach)	Provides a structured approach to handle uncertainties, supporting sustainable decision-making in water resource management
4	Li et al.[48]	Chlorination process safety management	Complex system modeling	Emphasized the interconnection of workers, equipment, materials, environment, and energy in safety modeling
5	Bassey et al.[49]	Loss of containment (LOC) incidents prediction	Machine learning (ML), CatBoost model	Achieved 95% accuracy in predicting LOC severity in offshore oil & gas facilities
6	Paltrinieri[20]	Risk assessment in Oil & Gas drilling	Deep Neural Network (DNN)	Showed high accuracy in risk prediction and potential for improving risk assessment
7	Li et al.[50]	Dynamic risk assessment of process operations	Bayesian Network (BN) + BRANN	Improved prediction accuracy by capturing nonlinear accident escalation scenarios
8	Wu et al.[51]	Hydrogen sulfide leakage risk	Bayesian Network	Identified critical vulnerable factors and estimated leakage probabilities
9	Meel and Seider[33]	Dynamic risk assessment in process facilities	Probability Estimation	Provided a dynamic methodology for accident probability estimation
10	Wang et al.[52]	HAZOP (Hazard and Operability) risk prediction	Data Mining, Naïve Bayes Algorithm	Improved accuracy and efficiency in hazard identification
11	Ekrampooya et al.[53]	Recommendation prediction from accident causes/consequences	NLP + Machine Learning (ML)	Achieved 93.7% accuracy (causes-based) and 89.5% accuracy (consequences-based) for safety recommendations
12	Single et al.[54]	Hazard inference in process safety	Ontologies, AI, Case-Based Reasoning, Support Vector Machine	Introduced structured hazard identification with AI-driven ontological reasoning
13	Pirbalouti et al.[55]	Safety–critical equipment modeling	HAZOP, Bow-tie Model, Bayesian Network	Improved system reliability and reduced maintenance costs through probabilistic analysis
14	Guo et al.[56]	Uncertainty assessment in risk analysis	Fuzzy Dynamic Bayesian Network (FDBN)	Demonstrated higher resilience and reliability than traditional Bayesian models
15	Liu et al.[57]	Dynamic risk assessment in deepwater drilling	Fault Tree Analysis, Bayesian Network	Provided a modular model for blowout risk evaluation and updates with new data
16	Li et al.[58]	Explosion accident risk (molten aluminum & water)	Fuzzy Bayesian Network (FBN)	Assessed explosion risks probabilistically to enhance safety management
17	Li et al.[59]	Mine ignition source risk	Fuzzy Bayesian Network (FBN), Fuzzy Analytic Hierarchy Process (FAHP)	Used expert decision-making with FAHP-based expert weight determination to improve model credibility
18	Xue et al.[60]	Multi-attribute decision-making (MADM) in risk assessment	Fuzzy Bayesian Network (FBN)	Developed a robust MADM model for complex decision-making under uncertainty
19	Zarei et al.[41]	Uncertainty management	Fuzzy Bayesian Network (FBN), Delphi Method	Integrated expert knowledge via the Delphi method for more reliable uncertainty modeling
20	Gul et al.[61]	Occupational risk assessment in production facilities	Stratified Bayesian Decision-Making, TOPSIS-Sort	Developed a structured Bayesian model for evaluating hazards and prioritizing risks in production environments

Table 1. A comparative review of methodologies and findings in risk assessment and process safety.

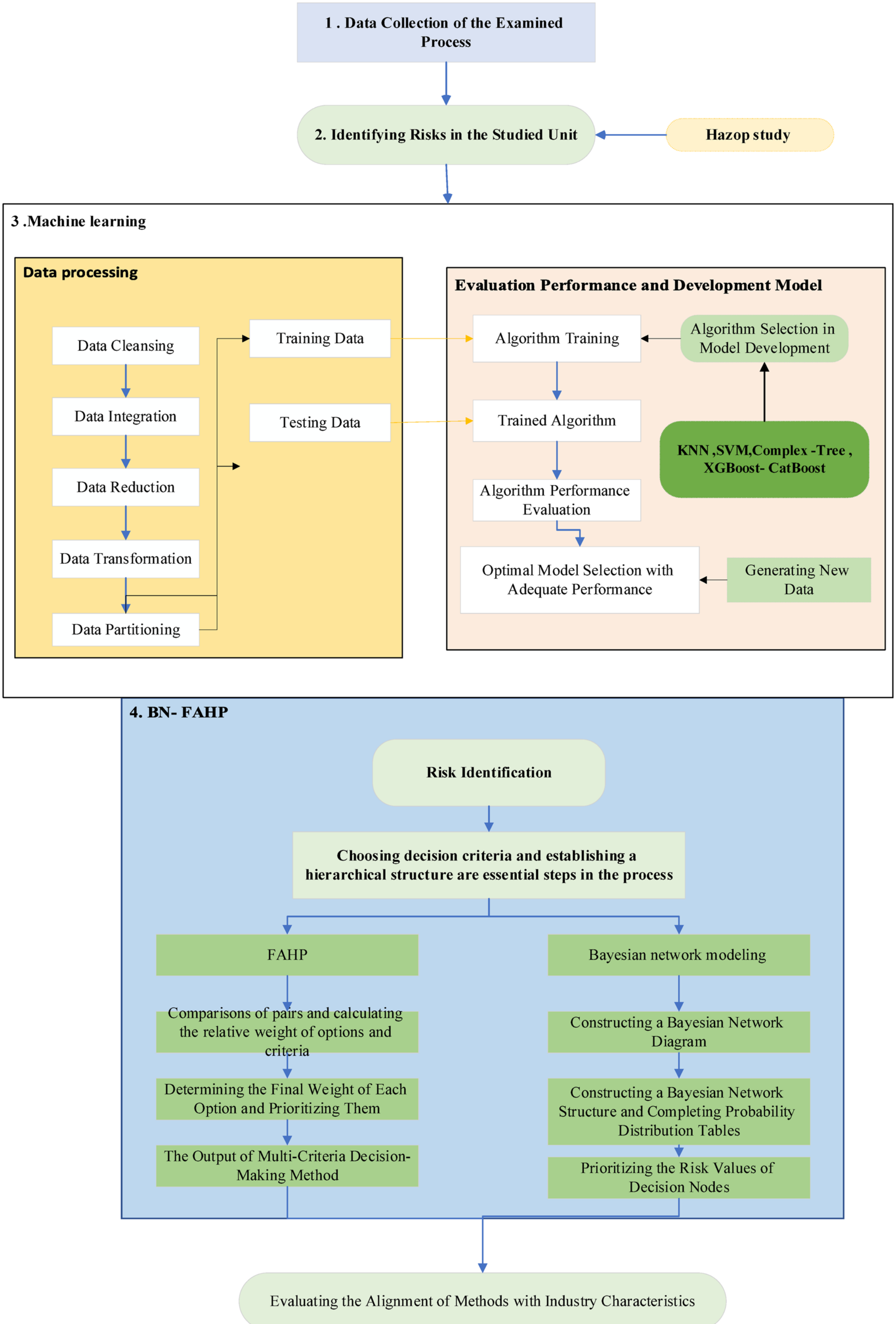

Fig. 1. Phases of study implementation process.

communication lines, instrumentation, control systems, and Interlock (P&ID) diagrams of the chlorination unit were prepared by the risk assessment team members. The risk assessment team, composed of the head of the power plant's chemical unit, the operator in charge of the chlorination unit, the shift supervisor, the technician responsible for instrument repairs, the technician responsible for electrical repairs, the technician responsible for mechanical repairs, and the power plant's HSE specialist, was formed to conduct the study on operations and hazards (HAZOP).

HAZOP study

HAZOP study is a practical and systematic technique for identifying hazards and operational problems in a system and determining their effects[62]. This technique is based on the principle that a system is safe when all its operational parameters, such as temperature, pressure, etc., are within normal and acceptable ranges. In this method, a team of experts examines potential process deviations from standard conditions and their potential effects using a set of keywords[63]. HAZOP analysis considers the entire system and examines each part to discover disturbances and deviations from the design objectives and evaluate their causes and consequences[64]. Subsequently, a structured approach is followed, which includes a well-defined set of terms for precise communication of analysis elements and documentation of results.

In this phase, the expert group divided the chlorination unit into 7 nodes based on the type of work involved. These nodes include the rectifier section, MV electrolyzer feeders, acid tanks, profit storage tanks, brine skids, brine water filters, net pit, forward osmosis pits, and chlorine storage tanks. The operational parameters studied in this research included water flow rate, current, voltage, oil temperature, fluid pressure in pipelines, pH of incoming water, and salt concentration of incoming water. Therefore, the individual effects of malfunctioning in each component and ultimately the impact on the normal operation of the unit due to various reasons such as equipment defects and human errors by the team members were examined, and the risk level was determined.

Machine learning

After gathering relevant information on risk assessment using Machine Learning (ML) methods, it was utilized to improve and enhance the Hazard and Operability (HAZOP) approach. Based on the assigned risk level, the probability, severity, and detection probability for each hazard were calculated, and the associated risk was categorized as high, medium, or low.

Table 2 presents comprehensive statistics of the data used in this study, including minimums, maximums, means, standard deviations, quantiles, kurtosis, and skewness, to aid in understanding the process.

Data processing

Data exploratory analysis is an approach to analyzing a dataset to understand its main features, which can be accompanied by visualization methods. Data cleansing is performed to manage missing values and noise. If the data is collected from different sources with different formats and structures, data integration is necessary. To reduce computational and processing costs, if there is no need to use all available data, a portion of the surplus data is set aside in the data reduction section. Data transformation includes tasks such as normalization, numerical variable handling, and encoding categorical variables. The algorithms used in this study are selected based on the type of problem, which is supervised machine learning. To eliminate the scale of numerical data, all numerical features will be normalized. Non-normalization of data may disrupt the training process of algorithms due to differences in input data scales. Statistical normalization method according to Eq. 1 will be used for data normalization.

$$X_{norm} = \frac{x - \mu x}{\partial x} \tag{1}$$

In this regard, x represents the input data, μx represents the mean of feature x, and ∂x represents the standard deviation of feature x. The nominal data values will also be encoded with numerical values of 0 and 1. After performing initial checks and data preparation, the mentioned algorithms will be applied to the dataset.

In this study, two sets of data, which are independent and dependent, were assigned to two different data frames, namely "X" and "y", for further processing. Additionally, the data was divided into training and testing data for model development. An 80% test size was considered, meaning that 80% of the total data was used for training and the remaining 20% for model testing.

	Probability	Severity	Detection	Risk
Mean	3.3000	6.3125	2.6500	57.3062
Std	1.3909	1.9593	1.2142	42.2234
Min	2.0000	1.0000	1.0000	2.0000
25%	2.0000	5.0000	1.0000	24.0000
50%	4.0000	7.0000	3.0000	42.0000
75%	4.0000	8.0000	3.0000	84.0000
Max	8.0000	9.0000	5.0000	180.0000
Kurtosis	0.2638	0.3883	-0.6560	0.0801
Skewness	0.8115	-0.7613	0.0604	0.9157

Table 2. Dataset descriptive statistics.

Model construction and performance evaluation

For this research project, we utilized Python software version 3.11.4 for both preprocessing and constructing our model. Our dataset was divided into two parts: 128 inputs were allocated for training and testing purposes, while the remaining 32 inputs were reserved for model evaluation.

The process of analyzing the dataset involved a systematic approach that aimed to preprocess the data and evaluate the performance of predictive models. Initially, we created a new column called 'Risk_binary', which transformed the 'Risk' values into a simpler binary classification format, making the subsequent analysis easier. By categorizing instances as either 1 or 0, we represented a risk level below 100 or 100 or higher, respectively. This made the dataset more amenable to classification algorithms.

In addition, it was deemed necessary to exclude the 'Risk' column from further calculations due to its strong correlation with the target variable, 'Risk_binary.' This precautionary measure was taken to address any potential issues of multicollinearity that could skew model predictions. By applying both the OneHotEncoder and LabelEncoder methods to the categorical data in the 'Category' column, we were able to effectively transform these variables into numerical formats, which are crucial for the proper implementation of machine learning algorithms.

In machine learning, selecting optimal parameter settings for algorithms is crucial as it directly influences the model's performance and predictive accuracy. One effective method for parameter tuning involves utilizing insights from the dataset's correlation matrix. The correlation matrix provides a comprehensive overview of the relationships between different features within the dataset. By examining the correlation coefficients between each pair of features, one can discern the degree and direction of their linear relationship. This information is invaluable for parameter selection as it helps identify relevant features and potential multicollinearity issues.

The values in this matrix range between $[-1, 1]$, and the closer these values are to 1, the stronger the positive correlation between the two variables. In other words, an increase in one variable is accompanied by an increase in the other variable. Negative values in the correlation matrix indicate a negative or inverse correlation between two variables, meaning that an increase in one is accompanied by a decrease in the other. A value of zero in this matrix indicates that there is no linear correlation between the two variables. Analyzing the values of the correlation matrix helps us identify patterns and relationships in the data, which can be useful in decision-making and modeling.

To improve the reliability of our model evaluations, we incorporated a cross-validation technique with 5 folds. This procedure entailed systematically splitting the dataset into training and testing subsets, resulting in a thorough evaluation of the model's performance across different data subsets. This helped to minimize overfitting and enabled us to obtain more precise assessments of the model's effectiveness, thereby ensuring increased dependability.

To obtain the best possible results from the algorithms considered in the analysis, the GridsearchCV method was employed. This method systematically explored a range of hyperparameter values, allowing for the identification of the optimal hyperparameters for each algorithm. By fine-tuning the models in this way, their predictive capabilities and generalization performance were significantly improved. Overall, this approach helped to ensure that the results obtained were as accurate and reliable as possible.

A wide range of evaluation algorithms were used, including various ensemble methods such as Random Forest, Hist Gradient Boosting, XGBoost, and CatBoost, as well as other methods like Logistic Regression, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). This diverse selection of algorithms facilitated an extensive comparison of different modeling approaches, incorporating traditional statistical methods and cutting-edge machine-learning techniques.

The performance evaluation of the model was carried out utilizing the roc_auc_score, accuracy, and F1 score metrics.

Let, TP be the number of true positives (correctly predicted positive instances), FN be the number of false negatives (incorrectly predicted negative instances), FP be the number of false positives (incorrectly predicted positive instances), and TN be the number of true negatives (correctly predicted negative instances). In addition, let TPR represent the True Positive Rate (Sensitivity) and FPR represent the False Positive Rate (1—Specificity), calculated as:

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

The ROC curve is then plotted by varying the threshold for classifying instances as positive or negative and calculating (TPR) and (FPR) for each threshold value. The area under this curve is computed to obtain the ROC AUC score.

The ROC AUC score ranges from 0 to 1, where a score of 1 indicates perfect classifier performance (i.e., the classifier achieves a true positive rate of 1 and a false positive rate of 0), while a score of 0.5 suggests random performance (i.e., the classifier is no better than random guessing).

For accuracy and F1 score, we have the following relations, respectively:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

The F1 score is the harmonic mean of precision and recall, providing a balance between these two metrics. It is calculated using the Eq. (4):

$$F1Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

where:

Precision is the ratio of true positives to the total number of predicted positives and is calculated as:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall (also known as sensitivity or true positive rate) is the ratio of true positives to the total number of actual positives and is calculated as:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

The F1 score ranges from 0 to 1, with 1 indicating perfect precision and recall, and 0 indicating the worst possible model performance. It is a useful metric for imbalanced datasets where the number of instances in one class is much larger than the other.

BN-FAHP

The Bayesian network is a hierarchical structure consisting of a set of objectives, options, criteria, and sub-criteria for decision-making. In this study, three types of nodes were chosen, including the probabilistic group, desirability node, and decision node, which are used in the BN structure. The decision nodes represent a set of options, the desirability node represents a set of objectives (decision priorities), and the probabilistic nodes consist of a set of criteria and sub-criteria. These criteria may be related to each other and can also be influenced by multiple factors. Figure 2 illustrates the hierarchical structure of BN networks in this study. Netica software was used for BN modeling in this study.

In the hierarchical fuzzy AHP method, a hierarchical structure is used to describe and analyze various criteria. This method allows for the modeling of different criteria in decision-making and risk assessment processes in a fuzzy manner using fuzzy logic. By considering the existing uncertainty and ambiguity, better decisions can be made regarding the evaluation of factors affecting risk. This method also identifies risk options. The main risk options used in the BN method are also utilized in the hierarchical structure of the MCDM method.

After establishing a hierarchical structure, the next step is to evaluate elements through pairwise comparison. Pairwise comparison is a process for comparing the importance, preference, or correctness of two elements relative to a higher-level element. The comparisons of risk options were conducted in the form of pairwise comparison matrices. In the first row, comparing the probability of occurrence and the intensity of effects relative to the objective as criteria for effective risk options, these two factors, as the main components of risk, have equal importance and each receives a priority of 1 and a weight of 0.5.

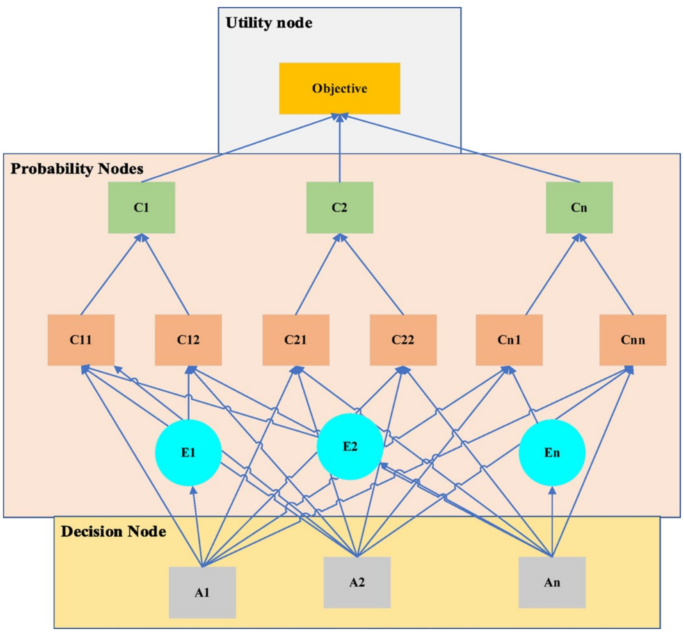

Fig. 2. Illustrates the hierarchical structure in Bayesian networks.

Row	Keyword	Cause	Consequence	Current Protection	Primary Risk	Decision criterion
1–1	Increase in output pressure	The closure of the Vanet hydrogen valve path mpus20/21aa286 is due to the deposition inside the cells	Increased pressure in the hydrogen vent path and the possibility of explosion due to severe leakage from the cells, as well as the potential for PVC piping rupture in the electrolyzer and its connected lines	The installation of a pressure gauge at the outlet of the MPUS21/20CP502 electrolyzer is lacking protective measures for pressure control	108	Unacceptable
2–1	Increased pressure	Excessive sedimentation in sewers, closed outlet valves, abnormal increase in ampere value, and high levels of chlorine reservoir are the issues at hand	The potential for PVC pipe cracking, leakage from sewers, and the risk of explosion due to hydrogen accumulation and increased pressure are the concerns	The location is mpus21/20cp502	108	Unacceptable
3–1	Pressure decrease	There is a leakage in the electrolyzer, and the input valve of MPUS20/21AA252 is closed	Regarding the flow switch mpus21/20cf001	Installation of Flow Switch in MPUS21/20CF001 Output	24	Acceptable
4–1	Flow reduction	Over time, an increase in sedimentation occurred, requiring sufficient time for acid leaching	Reducing the concentration of chlorine production can cause long-term damage to cells, increase output pressure, and potentially lead to hydrogen vent blockage	The installed pressure gauge, MPUS21/20CP502, indicates a local deposit inside the cells	96	Acceptable, but in need of revision

Table 3. An example of a risk assessment worksheet for the Electrolyzer unit using the HAZOP.

Number of identified deviations	Equipment name
3	Sea Water Forwarding Pumps
15	Saltwater Reservoir
2	Water Storage Tank
4	Saltwater Storage Tank
3	Saltwater Filter
3	Salt Transfer System
17	Electrolyzer
25	Rectifier
3	MV Leaders
10	Chlorine Storage Tank
54	Acid Storage Tank
5	Profit Injection Pumps for Net Profit
16	Net profit

Table 4. Number of identified deviations in the studied nodes using the HAZOP.

The pairwise comparison tables of options related to factors influencing risk were also completed based on expert judgments and the complete process unit characteristics. Then, the weight of each indicator relative to higher-level indicators (relative weight) was calculated using the eigenvector method, and by combining them, the final weight for each option of factors influencing risk was determined.

The BN method based on the hierarchical structure of MCDM, considering the relationships between variables and adjusting uncertainties, provides persuasive and acceptable results and offers a proper prioritization for developing suitable strategies to reduce risk. After prioritizing the factors influencing the risk, solutions are presented for reducing and managing the risks of power plants and dealing with them, along with the utilization of appropriate measures before the occurrence of hazards.

Results
Hazop study
To identify and evaluate the risks of the target unit, a team consisting of process, safety, instrumentation, mechanical, and safety experts was formed. Table 3 shows a sample risk assessment conducted at the node related to the electrolyzer. The results of the hazop study for the selected nodes are presented in Table 3, based on the number of deviations in each node. As seen in Table 4, the highest number of deviations is related to the acid tank with 54 deviations, and the lowest number of deviations is related to the water storage tank with 2 deviations**.**

Machine learning
As previously mentioned, we determined risk levels based on other factors such as Probability, Severity, and Detection. Figure 3 illustrates the risk behavior for all samples. As observed, the risk values fluctuate between 2 and 180 within the range.

For parameter setting, the correlation matrix is used based on the Risk feature. Figure 4 denotes the correlation matrix between features. Based on this figure there are strong relationship between Risk and Detection, Severity and Probability, and a moderate relationship between Risk and Electrolyzer and Rectifier.

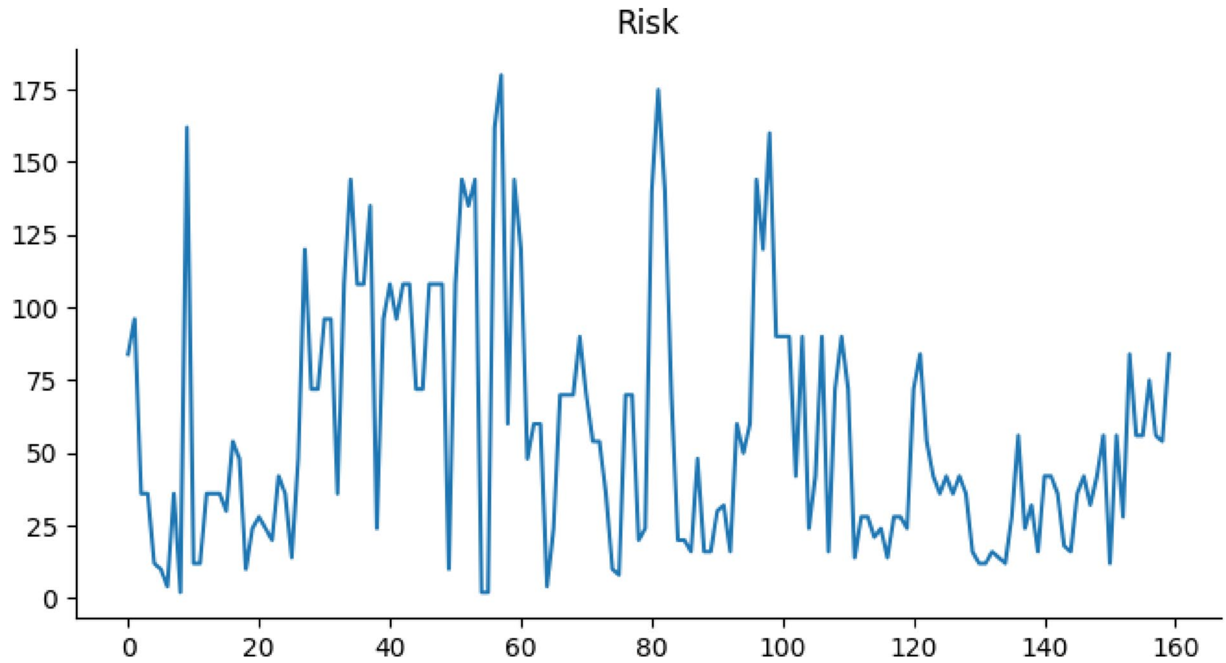

Fig. 3. Risk behavior.

A summary was compiled to provide a concise overview of the analysis results, outlining the algorithms utilized and their respective outputs. Table 5 serves as a valuable point of reference for evaluating and contrasting the performance of various models, aiding in selecting the optimal algorithm for the given task.

The table presents performance metrics for several machine learning models, each evaluated using different algorithms. The evaluation criteria focus on the models' ability to accurately classify or predict outcomes, as indicated by the corresponding evaluation scores. Additionally, the confusion matrix (Table 6) was computed for all methods, providing the following results for each approach:

Table 6 illustrates the confusion matrix, summarizing classification results for 32 outcomes derived from the test dataset. These outcomes include True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). For instance, TP cases correctly identify high-risk scenarios like hydrogen gas leakage, while TN cases represent correctly classified low-risk scenarios. Conversely, FP outcomes overestimate risks (e.g., mislabeling minor deviations as high-risk), and FN outcomes miss significant risks (e.g., failing to detect potential equipment failure).

BN-FAHP

In this study, a total of 30 nodes were used in Bayesian networks, and the specifications of these nodes are shown in Table 7. These nodes include the node name, the level of the node in the hierarchical structure, the state of the node, and its type in the BN structure. This evaluation includes one decision node with a set of risk options and a utility node as the main objective (risk assessment), and 28 potential nodes in the network structure. The criteria, sub-criteria, and other factors are potential nodes. In this structure, two main risk indicators (probability of occurrence and severity of effects) are the main criteria, and each of these criteria can be influenced by sub-criteria such as physical environment, organizational environment, and socio-economic environment. Quantitative relationships between variables are modeled through CPTs associated with each of these nodes. The probability values in these tables are expressed as percentages based on expert opinions in the tables. To complete the probability of occurrence for each scenario in the tables and to achieve better coordination, the probability values entered in the variable CPTs were taken from Table 8.

By forming the BN structure and completing the CPT for each node, the probability distribution of decision node options was also determined. Figure 5 illustrates the Bayesian network for evaluating the risk of the studied unit Based on Nitica-V7.01 software, Corrosion in Electrolysis Cells (CEC), and Damage and Explosion of Cells (DEC) are the most significant risks with values of 0.252 and 0.222, respectively. Explosion in Cells due to High Voltage (ECHV) and Explosion in cells due to High Current Flow (EHCF) were lower priority risks with values of 0.115 and 0.122, respectively.

To compare the results obtained from the Bayesian network, common methods such as MCDM were also used. The main risk options employed in the BN method were also utilized in a hierarchical structure. Figure 6 illustrates the hierarchical diagram of the studied unit.

The weights of each indicator relative to the higher level were calculated using the FAHP method, and the final weights for each risk option were determined. Based on the results obtained in this method, Corrosion in Electrolysis Cells (CEC) and Damage and Explosion of Cells (DEC) were assigned the first and second priorities,

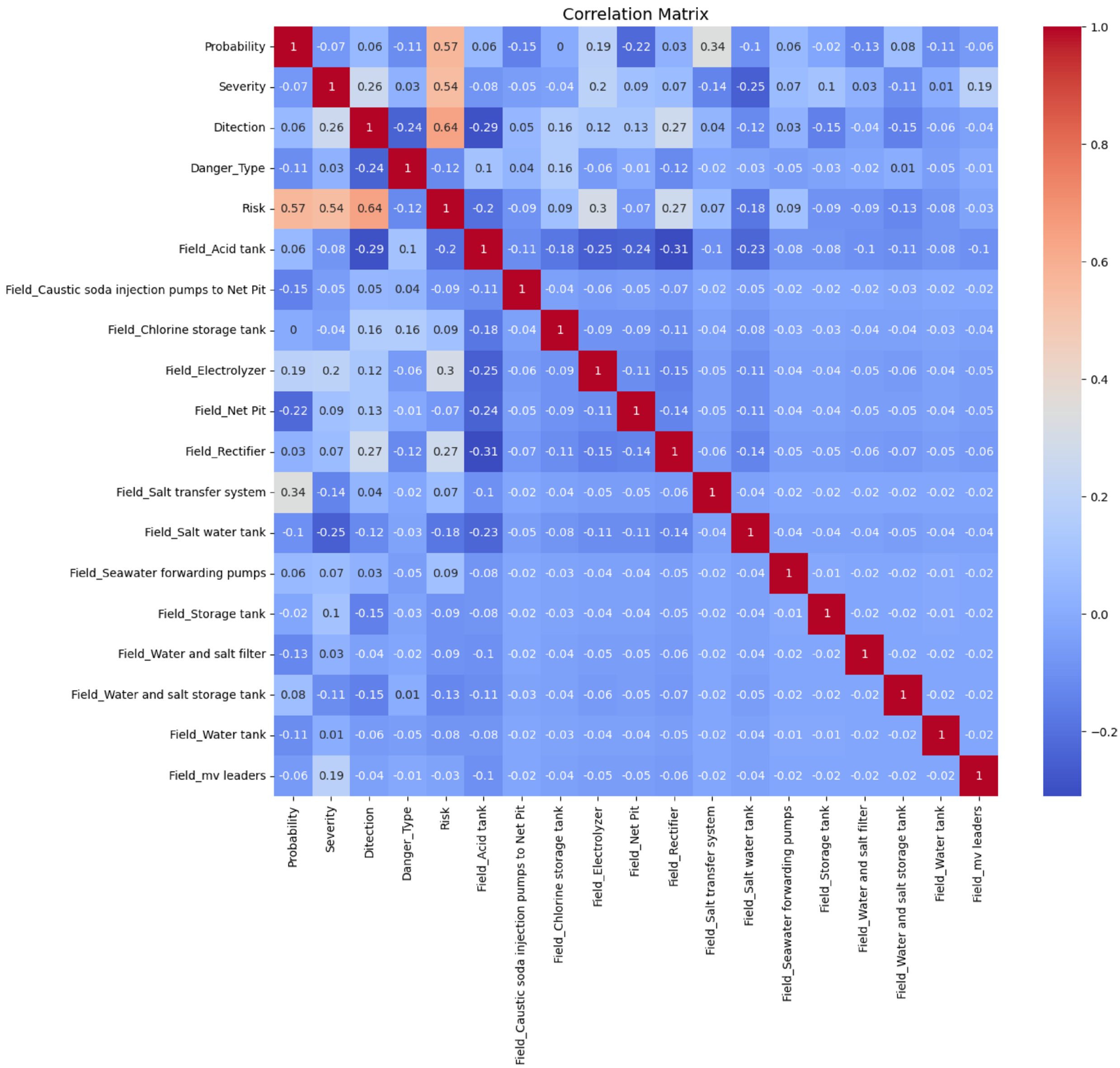

Fig. 4. Correlation matrix.

Algorithm	Best hyperparameters	Train best AUC	Test best AUC	Accuracy
Random Forest	max_depth = 10, n_estimators = 100	0.9933	1.00	1.0000
Hist Gradient Boosting	Learning rate = 0.01, max_iter = 200	0.9710	0.96	0.9375
XGBoost	learning rate = 0.2, n_estimators = 200	0.9940	1.00	1.0000
CatBoost	Iterations = 500, learning rate = 0.01	0.9929	1.00	1.0000
Logistic Regression	C = 10	0.9826	0.76	0.8750
K-Nearest Neighbors	metric = Euclidean, n_neighbors = 7, weights = distance	0.9976	1.0000	1.0000
Support Vector Machine	C = 0.1, gamma = scale, kernel = linear	1.0000	0.9630	0.9375

Table 5. The performance results of various machine learning models to predict risk acceptance.

respectively, with final weights of 0.238 and 0.217. Figure 7 illustrates the prioritization of the options' final weights using the FAHP method.

The above text illustrates the prioritization of risk options using two methods, FAHP and Bayesian Networks, as shown in Table 9. In both approaches, the options "Damage and Explosion of Cells (DEC)" and "Corrosion in Electrolysis Cells (CEC)" are assigned higher priority relative to the other risk options.

Algorithm	Confusion matrix
Random Forest	[[5 0] [0 27]]
Hist Gradient Boosting	[[5 0] [2 25]]
XGBoost	[[5 0] [0 27]]
CatBoost	[[5 0] [0 27]]
Logistic Regression	[[3 2] [2 25]]
K-Nearest Neighbors	[[5 0] [0 27]]
Support Vector Machine	[[5 0] [2 25]]

Table 6. The confusion matrix for all methods.

Node name	The level of a node in a hierarchical structure	Node states	Node type
Utility	Goal	–	Demand
Severity of Hazard	Criterion	Low, Moderate, High	Likely
Probability of Hazard	Criterion	Low, Moderate, High	Likely
Physical environment	Sub-criterion Level 1	Low, Moderate, High	Likely
Organizational environment	Sub-criterion Level 1	Low, Moderate, High	Likely
Economic and social environment	Sub-criterion Level 1	Low, Moderate, High	Likely
Closure of the Hydrogen valve	Sub-criterion Level 2	Completely closed, partially closed	Likely
The liquid level inside the tank	Sub-criterion Level 2	Low, High	Likely
Stress in cells	Sub-criterion Level 2	Low, Moderate, High	Likely
Electrolyzer pressure	Sub-criterion Level 2	Low, Moderate, High	Likely
Current fluctuation	Sub-criterion Level 2	Yes, No	Likely
Voltage fluctuation	Sub-criterion Level 2	Yes, No	Likely
Acid transfer	Sub-criterion Level 2	Low, Moderate, High	Likely
Reduction in seawater current	Sub-criterion Level 2	Low, Very Low	Likely
Rectifier operation	Sub-criterion Level 2	Suitable, Unsuitable	Likely
Reduction in salt content	Sub-criterion Level 2	Low, Very Low	Likely
Startup Checklist	Sub-criterion Level 3	Accept, non-Accept	Likely
Functioning of a Flow Switch	Sub-criterion Level 3	Work, Fail	Likely
Transmitters	Sub-criterion Level 3	Work, Fail	Likely
On-site Pressure Gauges	Sub-criterion Level 3	Work, Fail	Likely
Production Guidelines	Sub-criterion Level 3	Accept, non-Accept	Likely
Process Log Sheets	Sub-criterion Level 3	Accept, non-Accept	Likely
Rectifier Control Panel	Sub-criterion Level 3	Suitable, Unsuitable	Likely
Conductivity Meter	Sub-criterion Level 3	Work, Fail	Likely
On-site level gauge	Sub-criterion Level 3	Work, Fail	Likely
Manufacturer's guidelines	Sub-criterion Level 3	Suitable, Unsuitable	Likely
Human Error	Sub-criterion Level 3	An Accidental error, Capture Error, Identification Error, Misperception Error, Lack of Knowledge, Mindset, Over Under Motivation Error, Reasoning Error	Likely
Inadequate Training	Sub-criterion Level 4	Low, Moderate, High	Likely
Incompatibility between Person and Role	Sub-criterion Level 4	Accept, non-Accept	Likely
Risk Objects	Objects	Cracking in PVC Pipe(CPP)	Decision
		Hydrogen Explosion(HE)	
		Explosion in cells due to High Current Flow(EHCF)	
		Explosion in Cells due to High Voltage(ECHV)	
		Corrosion in Electrolysis Cells(CEC)	
		Damage and Explosion of Cells(DEC)	

Table 7. Specifies the characteristics of nodes in Bayesian network structures.

Dissection	Probabilistic values
The probability of a combined outcome for the parent nodes is very high	80–100
The result indicates a high probability of combining the states of the parent nodes	60–80
The result suggests an average probability of combining the states of the parent nodes	40–60
The result indicates a low probability of combining the states of the parent nodes	20–40
The result suggests a very low probability of combining the states of the parent nodes	< 20

Table 8. Methods for determining probabilistic values in CPT.

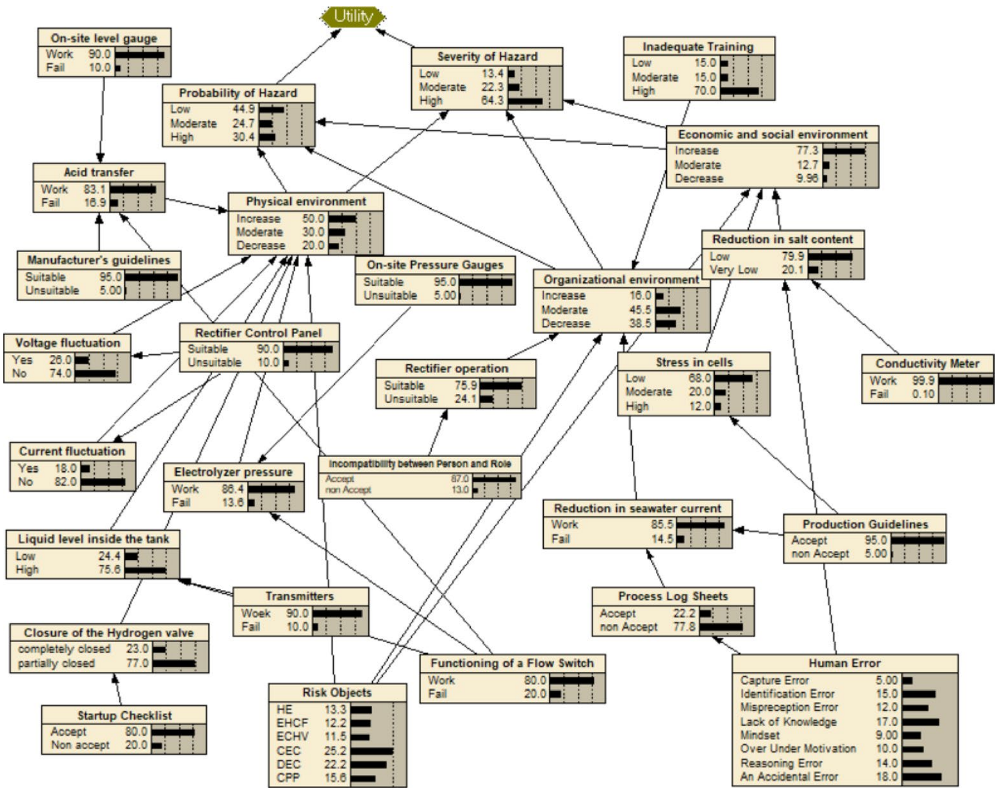

Fig. 5. Bayesian network structure for risk assessment of the study unit based on nitica-V7.01(https://www.norsys.com).

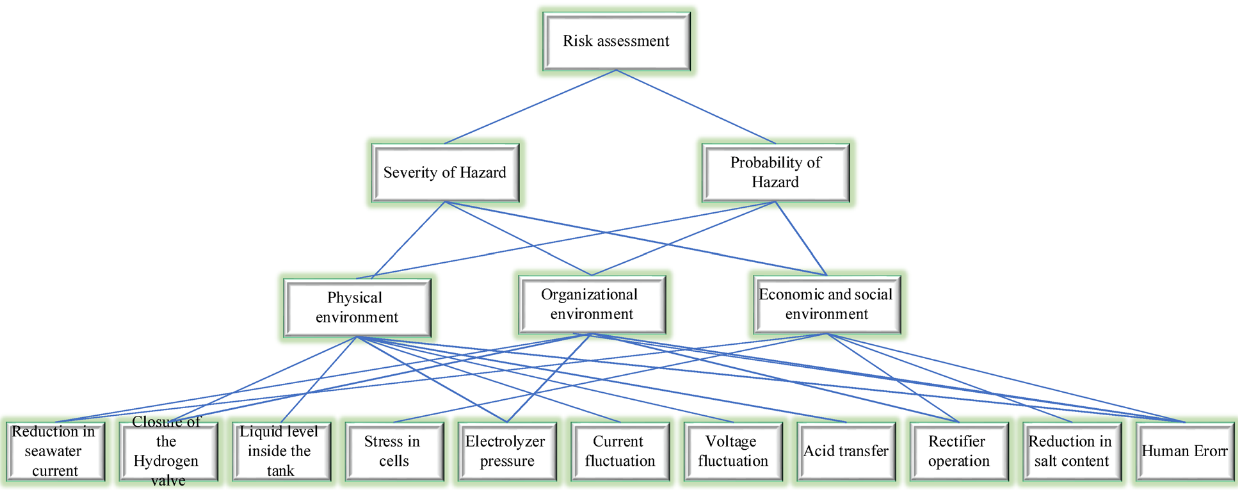

Fig. 6. Depicts the hierarchical structure of risk assessment for the studied unit.

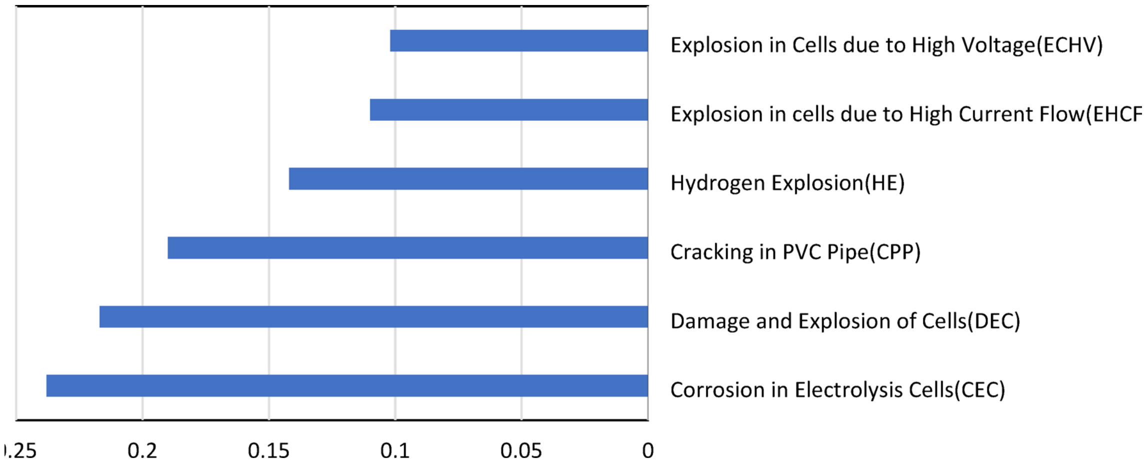

Fig. 7. Final prioritization of options in the FAHP method.

Risk options	Probabilistic values of the Bayesian method	Prioritization	Final weights of options in the MCDM method	Prioritization
Cracking in PVC Pipe(CPP)	0.155	3	0.19	3
Hydrogen Explosion(HE)	0.133	4	0.142	4
Explosion in cells due to High Current Flow(EHCF)	0.122	5	0.11	5
Explosion in Cells due to High Voltage(ECHV)	0.115	6	0.102	6
Corrosion in Electrolysis Cells(CEC)	0.222	2	0.238	1
Damage and Explosion of Cells(DEC)	0.252	1	0.217	2

Table 9. Comparison of prioritization results for risk assessment in FAHP and BN.

Discussion

In the realm of risk assessment, machine learning serves as a potent tool within the domain of artificial intelligence and data analysis. When it comes to safety, identifying and predicting risks and hazards within work and industrial environments are crucial tasks. Machine learning systems, possessing high processing capabilities and analytical prowess, excel at uncovering intricate patterns and relationships in risk-related data. This capability aids in the identification and prediction of influential risk factors. By leveraging machine learning algorithms and drawing insights from historical data and relevant factors, it becomes possible to forecast the types of incidents and risks associated with a particular unit, thereby enabling the implementation of appropriate safety measures and preventive actions.

During this study, a thorough examination of the data characteristics was conducted, and their statistical properties were analyzed. This exploratory phase was instrumental in preparing and refining the dataset for predictive modeling. The significance of this initial exploration lies not only in feature identification but also in the discovery of latent patterns, laying the groundwork for a more in-depth analysis.

At the heart of this research was the implementation and comparative evaluation of various predictive models. These models, employing diverse algorithms and assumptions, were rigorously tested and juxtaposed against each other, offering a comprehensive insight into their respective strengths and weaknesses. The spectrum of models ranged from traditional machine-learning techniques to advanced ensemble methods. Their performance was assessed using multiple metrics to ensure a robust model selection process.

Based on the results obtained from the hyperparameter tuning and model evaluation process, it is evident that several machine learning algorithms have performed exceptionally well in classifying the data based on the given features. Among the algorithms tested, Random Forest, XGBoost, and CatBoost have demonstrated outstanding performance on the training and test datasets, achieving near-perfect AUC scores and accuracy values of 1.0000. These algorithms have been effectively tuned with appropriate hyperparameters, such as max_depth, n_estimators, learning rate, and iterations, leading to robust and highly accurate models.

Furthermore, K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) have also exhibited commendable performance, achieving AUC scores and accuracy values close to 1.0000 on the test dataset. KNN has been optimized with hyperparameters including the choice of metric (Euclidean), number of neighbors[7], and weights (distance), while SVM has been fine-tuned with parameters such as C (0.1), gamma (scale), and kernel (linear). These results highlight the effectiveness of these algorithms in capturing complex patterns in the data and making accurate predictions.

However, it is worth noting that Hist Gradient Boosting and Logistic Regression have shown comparatively lower performance compared to the other algorithms. Despite achieving reasonably high AUC scores on the training dataset, their performance on the test dataset is relatively lower, indicating potential issues with overfitting or suboptimal hyperparameter tuning.

The results of the current study underscore the significant effectiveness of machine learning techniques in the realm of risk prediction and assessment. All techniques evaluated in this study demonstrated the ability to classify and forecast risks with a high level of accuracy. This notable level of accuracy suggests that these techniques could be valuable additions to the risk assessment and prediction toolkit for process units. Given the relative ease of implementation of machine learning techniques, the abundance of risk evaluation data, and the computational capabilities of modern computers, it is recommended to develop an operational system utilizing artificial intelligence, specifically machine learning techniques, for risk prediction and assessment within process units. One limitation encountered in this study was the availability of limited data, which could potentially lead to suboptimal performance of trained algorithms in risk classification for certain features.

In discussing the capabilities of machine learning in risk classification, a comparison can be drawn with the results obtained by Heo et al. in their study on fall injury risk prediction. All machine learning-based models exhibited superior performance compared to logistic regression. However, the performance differences among the five models were marginal (AUROC values of 0.700, 0.700, 0.699, 0.699, and 0.698 for CatBoost, LightGBM, XGBoost, Random Forest, and logistic regression, respectively)[65]. In the study conducted by Bassey, the CatBoost model emerged as the top performer with 95% accuracy. This was attributed to its innate ability to effectively handle categorical variables and missing data, along with its strength in preventing overfitting. These characteristics equipped CatBoost with exceptional performance, particularly essential for accurate severity predictions of hydrocarbon releases. These findings align closely with the outcomes observed in our own study[49].

An essential benefit of machine learning techniques lies in the abundance of powerful software tools available for their implementation. The presence of robust libraries in various programming languages has significantly simplified the application and adoption of machine learning principles. For those seeking a practical approach to automating the risk prediction process, the optimal choice would be to leverage machine learning techniques[66].

In a study conducted by RK Mazumder, the mean accuracy of various machine learning models after fivefold cross-validation was reported as follows: KNN (77%), Decision Tree (80%), Random Forest (85%), Naive Bayes (78%), AdaBoost (70%), XGBoost (84%), LGBoost (84%), and CatBoost (78%). Among these algorithms, Random Forest (RF) exhibited the highest accuracy in prediction[67].

The accuracy of these machine-learning algorithms was assessed using the confusion matrix, a method also employed in previous studies such as those by Mangalathu et al.[68] and Robles-Velasco et al.[69]. In the context of a confusion matrix, accuracy represents the overall percentage of correct predictions. However, in cases of imbalanced datasets, accuracy alone might be misleading. Therefore, considering additional metrics from the confusion matrix, such as recall and precision, can be valuable in assessing algorithm performance. Recall indicates the percentage of correct predictions for 'true positive' instances, while precision signifies the percentage of correct predictions for 'true negative' instances. The presence of False Positives (FP) and False Negatives (FN) in prediction results carries critical implications. FP outcomes, while increasing operational costs due to unnecessary safety measures, are less harmful than FN outcomes, which can result in undetected high-risk scenarios and potential incidents. In high-risk environments like power plants, prioritizing recall to minimize FN is paramount, even at the expense of a slightly higher FP rate. This approach ensures a proactive safety-first methodology.

MCDM methods are widely used today for their ease of implementation and execution in various decision-making domains. However, in complex issues such as risk assessment, they sometimes suffer from uncertainty. Bayesian networks are one of the methods that can reduce uncertainty. This method has advantages such as considering relationships between variables and uncertainties, integrating information from different formats with data and expert opinions, organizing scattered thoughts and opinions on a subject visually and simply, and allowing updates with the addition of variables or new data. These features make Bayesian networks flexible models with high capabilities in risk assessment[70].

To achieve a comprehensive solution for examining issues such as the assessment of risks in process units, integrating multi-criteria decision-making methods with Bayesian networks can be more effective compared to other approaches. Based on the results of Bayesian networks and prioritization of risk options, it can be stated that the options "Corrosion in Electrolysis Cells" and "Damage and Explosion of Cells" have a higher priority compared to other options. The BN method, based on a hierarchical structure considering relationships between variables and mitigating uncertainties, provides logical and acceptable results and offers a proper prioritization for developing suitable strategies to reduce process risks.

One of the main challenges of this research is the limited access to sufficient and high-quality data. The dataset, which includes 160 deviations identified through the HAZOP technique, may not be adequate to cover the full range of hazards and risks associated with the chlorination unit. This limitation can lead to issues such as overfitting of the model and a lack of generalizability to other process units. To address this issue, it is recommended to collaborate with various industries to collect more data and to use simulations to generate synthetic data related to different operational scenarios.

Incorporating contextual and behavioral factors into risk assessment can provide a better understanding of operational dynamics. To this end, collecting qualitative data through expert interviews and surveys, as well as considering operator behavior and their decision-making patterns in the model, can be beneficial.

This study shows that combined approaches based on machine learning and Bayesian networks can effectively be used to identify and assess risks in process units. However, to improve the accuracy and generalizability of the model, attention must be paid to data limitations, data quality, and contextual factors. By adopting the proposed approaches in future research, it is possible to develop stronger and more accurate models for risk assessment, ultimately contributing to improved safety and efficiency in industrial operations.

To improve risk assessment in process units, several promising directions can be explored. One critical step is broadening the range of data sources. Collaborating with diverse industries and utilizing publicly available databases can provide a richer dataset, enabling a more comprehensive understanding of potential risks. Another priority is the adoption of advanced data analytics. Techniques such as machine learning and real-time data monitoring systems offer significant potential for more dynamic and precise risk assessment.

Addressing uncertainty in risk models is another essential focus area. Developing Bayesian models that account for uncertainty and performing sensitivity analyses can help identify and prioritize the most critical factors influencing risk. Human factors also demand attention; understanding how human behavior impacts risk outcomes and designing tailored training programs can enhance operators' decision-making and response capabilities in high-stakes situations.

Emerging technologies offer exciting opportunities for innovation. The Internet of Things (IoT) can facilitate real-time data collection, while artificial intelligence tools can enable predictive analytics and proactive risk management strategies. Additionally, cross-industry benchmarking is valuable for identifying best practices and working towards standardized methodologies that can be applied across various sectors.

Finally, fostering collaboration with regulatory bodies is essential. Aligning research efforts with industry standards and contributing to the development of policies that promote safety and efficiency can ensure that new methodologies have practical, real-world impact. By pursuing these avenues, researchers can make significant strides in enhancing the safety, reliability, and operational performance of process units.

Conclusion

In the realm of risk assessment, machine learning serves as a potent tool within the domain of artificial intelligence and data analysis. When it comes to safety, identifying and predicting risks and hazards within work and industrial environments are crucial tasks. Machine learning systems, possessing high processing capabilities and analytical prowess, excel at uncovering intricate patterns and relationships in risk-related data.

The findings of this study suggest that ensemble methods such as Random Forest, XGBoost, and CatBoost, along with KNN and SVM, are well-suited for the classification task at hand, offering high accuracy and robust performance. Further experimentation and fine-tuning may be required for algorithms that have shown relatively lower performance, aiming to improve their generalization capabilities and overall effectiveness in real-world applications.

By combining Bayesian networks and multi-criteria decision-making methods, it is determined that the options "Corrosion in Electrolysis Cells" and "Damage and Explosion of Cells" have a higher priority compared to other options. Using this model, appropriate measures can be taken to control and reduce risk in the studied unit. Furthermore, the approach presented in this model can be utilized for prioritizing and evaluating risk options in other process units as well.

Data availability

Te datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

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Hassan Mandali, Elham Keighobadi, Saber Moradi Hanifi: wrote the main manuscript. Seyed Majid Ayat, Hossein Ebrahimi, Mohammad Ghashghaei: prepared figures and data analysised.

Declarations

Competing interests
The authors declare no competing interests.

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