Catalyx : Journal of Process Chemistry and Technology
E-ISSN : 3063-508X
Volume. 2 Issue 2 July 2025
Page No: 171-186

Dynamic Risk Assessment of Industrial Safety Barriers Using Bayesian Networks: A Predictive Modeling Approach

Dwi Nova Wijaya[1], Zaenal[2]
[1]**Universitas Negeri Surabaya, Indonesia**
[2]**Universitas Islam Makassar, Indonesia**
Correspondent: dwiwijaya@unesa.ac.id [1]

Received : June 10, 2025
Accepted : July 28, 2026
Published : July 30, 2026

Citation: Wijaya, D, N., & Zaenal. (2025). Dynamic Risk Assessment of Industrial Safety Barriers Using Bayesian Networks: A Predictive Modeling Approach. Catalyx : Journal of Process Chemistry and Technology, 2(3), 171-186

ABSTRACT: Traditional risk assessment methods in chemical and process industries frequently fail to capture the dynamic nature of barrier degradation and hazard escalation. This study proposes a Dynamic Bayesian Network (DBN) framework integrating temporal indicators, including SIS unavailability and corrosion rate, to enhance the predictive accuracy of real-time risk management systems. The DBN was structured using nodes and dependencies derived from industrial scenarios and reliability parameters, then validated through two simulation cases — reactor runaway and corrosion-driven leak — utilizing real-time inputs of dT/dt and k_cor to dynamically update failure probabilities via MATLAB. Results demonstrate that barrier degradation significantly impacts risk profiles: escalation probability in the reactor runaway scenario increased from 0.10 to 0.45 as SIS unavailability rose, while leak probability reached severe consequences when barrier failure exceeded 60%. Compared to static models, the DBN approach more accurately captured emergent risks over time. The framework supports predictive maintenance, alarm prioritization, and human reliability modeling, establishing DBNs as valuable tools for transitioning toward intelligent, adaptive safety systems in high-risk industries.

Keywords: Dynamic Bayesian Network, Safety Barrier Degradation, Risk Assessment, SIS Unavailability, Corrosion Rate, Predictive Maintenance, Process Safety.

INTRODUCTION

The increasing complexity of chemical process industries, driven by technological advancements and intensified operational demands, necessitates more robust and adaptive safety assessment methodologies. Traditional risk assessment techniques, though widely adopted, often fall short in capturing the dynamic characteristics of modern industrial environments. These limitations have prompted scholars and practitioners to explore enhanced modeling approaches that integrate real-time data and reflect the fluctuating reliability of critical safety barriers.

Conventional risk assessments typically rely on historical data and static modeling frameworks that presume consistent system behaviors and fixed probabilities of failure. While these methods provide a structured overview of hazards, they are inherently limited in their ability to predict rare or evolving failure scenarios, especially those involving complex interactions within newly developed processes or materials. As Behie et al. (2020) noted, such static profiles may overlook crucial failure modes that significantly influence operational integrity and safety. Moreover, these models often inadequately address qualitative elements, such as human factors and organizational influences, which are increasingly recognized as pivotal in determining safety performance (Naji et al., 2021).

The limitations of static models become particularly evident in dynamic operating contexts, where the condition of safety systems and protective barriers can degrade over time. This degradation, if not adequately monitored and addressed, can compromise the effectiveness of risk mitigation strategies. Recent studies underscore the importance of real-time monitoring in identifying early signs of barrier deterioration, thereby allowing timely interventions that could prevent escalation (Anchan et al., 2019). For example, Lieberth et al. (2023) demonstrated that technologies such as electric cell-substrate impedance sensing (ECIS) could detect changes in barrier functionality an indicator closely tied to elevated incident risks in process systems. Zhao et al. (2017) further emphasized the risk of cascading failures in volatile processing environments, where the compromise of a single barrier can initiate a chain reaction of hazardous events.

Addressing these challenges requires analytical tools that can accommodate uncertainty and adapt to evolving risk parameters. Bayesian Networks (BNs), particularly in their dynamic form (DBNs), offer a powerful framework for modeling probabilistic dependencies and updating risk assessments in real time. BNs enable decision-makers to simulate the likelihood of different failure modes under changing operational conditions, thereby enhancing the accuracy of safety evaluations. Singh et al. (2023) highlighted the integration of BNs with real-time data streams, allowing continuous updates to risk models based on live input from safety systems. This approach provides a more responsive and nuanced understanding of risk landscapes compared to conventional methods. Behie et al. (2020) further elaborated on the ability of BNs to model interdependencies between system components, which is critical for understanding compound failure scenarios. Vito et al. (2022) noted the applicability of BNs in safety integrity level (SIL) assessments, where scenario-based analyses help balance risk mitigation with operational efficiency.

A particular area of interest in dynamic modeling is the assessment of Safety Instrumented System (SIS) reliability. SIS units are central to automated risk mitigation in many process industries, and their effectiveness must be maintained continuously to ensure system integrity. Modeling SIS reliability in dynamic environments entails accounting for temporal variables such as equipment aging, proof test intervals, and varying stressors from operational cycles. Lu et al. (2024) highlighted the role of stochastic models and real-time operational data in enhancing predictive maintenance strategies. These methodologies support operational readiness by facilitating early identification of performance deterioration, which is vital for maintaining SIS compliance with reliability standards.

Another critical component in incident prevention is alarm management. Alarm systems serve as an interface between automated detection systems and human operators, and their efficacy greatly influences operator responsiveness. However, alarm overload commonly referred to as "alarm fatigue" can desensitize operators, increasing the likelihood of missed or misinterpreted alerts. Effective alarm management ensures that only critical alarms are emphasized, allowing for faster and more accurate human response during emergencies. According to Behie et al. (2020), well-structured alarm systems significantly improve the functional reliability of operator interventions. Singh et al. (2023) corroborated this view, advocating for structured alarm hierarchies and event-driven notification systems to mitigate the risks associated with alarm flooding.

These considerations point to the broader advantages of dynamic risk assessment frameworks over static counterparts. Dynamic frameworks leverage real-time analytics and multi-source data integration to produce comprehensive risk models that evolve alongside operational conditions. Maduabuchi et al. (2023) argued that such frameworks enable more responsive and accurate decision-making by revealing emerging risks that static models may overlook. Additionally, dynamic assessments support continuous improvement in safety practices by incorporating lessons learned from near-miss events and system feedback. The ability to iteratively refine risk models in this manner enhances the overall resilience and adaptability of safety management systems. As Behie et al. (2020) concluded, dynamic frameworks not only improve risk visibility but also foster a proactive safety culture within organizations.

In light of these findings, the objective of this study is to develop and validate a Dynamic Bayesian Network (DBN) model that integrates real-time degradation parameters of safety barriers into industrial risk assessments. By focusing on the temporal evolution of barrier reliability such as SIS availability, corrosion progression, and alarm system performance this research aims to enhance the predictive accuracy of hazard escalation models. The proposed DBN framework captures the interdependencies and feedback loops among various risk contributors, thereby offering a robust tool for anticipatory safety management. Unlike traditional models, the DBN approach dynamically adjusts risk predictions based on changing barrier conditions, ensuring that the model remains aligned with operational realities.

The novelty of this study lies in its structured integration of degradation indicators into a temporal risk modeling architecture. This not only supports more accurate consequence forecasting but also provides actionable insights for maintenance scheduling, testing protocols, and operator training. The scope of the research encompasses both technical elements such as failure probabilities, time-step modeling, and escalation chains and organizational factors influencing response efficacy. Through scenario-based simulations and comparative analyses with static models, the study seeks to demonstrate the practical value of DBNs in enhancing industrial risk assessment and management. Ultimately, the proposed approach contributes to the development of more intelligent and adaptive safety systems, aligning with industry trends toward digital transformation and predictive operations.

METHOD

This chapter outlines the methodological framework for developing and applying a Dynamic Bayesian Network (DBN) model to simulate barrier degradation in industrial risk scenarios. The approach integrates structural design principles of DBNs, mathematical models for reliability updates, relevant hazard scenarios, and software-based simulation techniques. Together, these components provide a comprehensive foundation for dynamic risk modeling.

DBN Framework Structure

Dynamic Bayesian Networks (DBNs) extend the capabilities of conventional Bayesian Networks by incorporating temporal elements, enabling them to capture changes in system behavior over discrete time intervals. Each DBN comprises a sequence of network slices, where each slice represents the system state at a specific time point. Nodes in these slices correspond to key variables such as ProcessDeviation, InitiatingEvent, BarrierState, HumanResponse, Escalation, and Consequence, while edges define the probabilistic dependencies within and between time slices.

The structure of the DBN follows the Markov property, whereby the state of a variable at time t+1 depends only on the state at time t, making the model computationally efficient and scalable (Lewis & Groth, 2020). As Chen et al. (2022) describe, this temporal layering allows DBNs to simulate causal chains that evolve based on updated inputs. The parent-child relationships in the DBN are aligned with the dependencies outlined in Table 6, where nodes such as AssetHealth, AlarmFlood, and SIS_avail influence risk trajectories through their respective impacts on escalation probability.

Moreover, the temporal dependencies capture the ongoing influence of process variables (e.g., temperature, pressure, dT/dt) on deviation progression. As noted by Li et al. (2022), this structure enables DBNs to support a wide range of dynamic applications, including real-time fault diagnosis and probabilistic event forecasting.

Mathematical Modeling of Barrier Reliability

Modeling the degradation of safety barriers over time requires probabilistic frameworks that reflect the stochastic behavior of system components. This study adopts a dynamic reliability modeling approach, where failure probabilities are updated based on operational data and degradation indicators.

Following Luque & Straub (2016), the DBN uses real-time indicators such as overdue proof tests, corrosion rates, and operator workload to adjust the reliability of barriers including SIS, PSV, and human response mechanisms. For example, SIS unavailability (U_SIS) increases if the system exceeds its designated proof test interval, while operator error probability (HEP) rises with alarm flooding or cognitive overload.

Additionally, sequence-based reliability models, as discussed by Zhu et al. (2021), are employed to track the evolution of component failures across simulation steps. These models utilize historical degradation data to inform posterior reliability estimates, thereby allowing more accurate and timely updates to risk profiles. Liu et al. (2019) support the use of Monte Carlo simulation and statistical inference methods in this context to manage uncertainty and variability in degradation rates.

Hazard Scenario Encoding

To operationalize the DBN, two representative hazard scenarios are instantiated using the configurations in Table 4:

- **S01: Reactor Runaway**: Initiated by high temperature and rapid temperature rise (dT/dt), with escalation through overpressure and release. Key barriers include SIS, quench systems, and pressure relief devices.
- **S05: Corrosion-Driven Leak**: Initiated by thickness degradation and increasing corrosion rate (k_cor), leading to leak and toxic exposure. Key barriers include inspection routines, RBI strategies, and isolation mechanisms.

Each scenario defines a chain of events from initiating causes through to primary consequences, along with dynamic indicators and barriers. The dynamic input variables are continuously monitored, and their effects propagate through the DBN, influencing node states and escalation probabilities over time.

Simulation Implementation

The DBN is implemented using MATLAB and additional probabilistic modeling platforms to facilitate visual construction and iterative simulation. Palencia et al. (2018) report success in using MATLAB-based environments to model degradation processes in oil and gas infrastructure. In this study, the DBN model is developed in MATLAB using a modular architecture, with subroutines for temporal update, probability propagation, and risk visualization.

Complementary tools such as GeNIe and Netica are utilized for validation and scenario comparison. These platforms offer graphical interfaces that support the visualization of node dependencies and outcome distributions. As Cai et al. (2017) note, such tools are valuable in complex safety analyses where transparency and interpretability are essential.

In particular, this study leverages CGBayesNets a MATLAB package capable of handling continuous and categorical data for DBNs (Kodikara et al., 2022). Though initially developed for biological systems, CGBayesNets is adapted to simulate engineering risk scenarios through redefined priors and transition functions.

Simulation runs are executed using discrete time steps, typically in five-minute increments, over operational periods of several hours. For each simulation cycle, the model updates node probabilities based on current input values and propagates changes across the network. Outputs include escalation probabilities, consequence likelihoods, and barrier performance metrics.

Sensitivity analyses are also conducted to identify critical variables and high-leverage nodes within the network. These analyses help prioritize mitigation strategies and determine which indicators warrant the most attention in real-time monitoring systems.

In summary, the methodology integrates structural modeling with empirical data streams and advanced simulation tools to produce a flexible, scalable, and context-sensitive framework for dynamic risk assessment. The following chapter presents the results of simulations conducted under scenarios S01 and S05, highlighting the practical implications of using DBNs to model barrier degradation and escalation pathways in real-time industrial environments.

RESULT AND DISCUSSION

This chapter presents the outcomes of the simulation scenarios conducted using the developed Dynamic Bayesian Network (DBN) model. The focus is on the dynamic assessment of safety barrier degradation and its influence on hazard escalation in two representative industrial scenarios: reactor runaway (S01) and corrosion-driven leak (S05). The results highlight how degradation indicators, such as SIS unavailability and corrosion rate (k_cor), dynamically alter risk profiles, and demonstrate the comparative advantage of dynamic over static modeling.

Scenario S01 – Reactor Runaway

The reactor runaway scenario (S01) is characterized by increasing temperature and a rising rate of temperature change (dT/dt), indicating an uncontrolled exothermic reaction. The Safety Instrumented System (SIS) serves as a critical barrier to mitigate escalation by initiating emergency shutdown or quenching actions. However, the model reveals that SIS unavailability (μ_SIS) significantly impacts the probability of escalation.

As shown in **Table 1**, escalation probability rises from 0.10 to 0.45 as SIS unavailability increases from 0.005 to 0.020. These findings support the conclusions of Kouhili et al. (2023), who observed that unavailability of SIS during overpressure events can lead to catastrophic outcomes due to uncontrolled reaction kinetics. Vries et al. (2020) similarly emphasized that failure to manage pressure and temperature dynamics in such scenarios may result in vessel rupture and explosions.

Table 1: Reactor Runaway Escalation Probability vs. SIS Unavailability

U_SIS	Escalation Probability	Time to Consequence (min)
0.005	0.10	45
0.010	0.25	30
0.020	0.45	20

The correlation between proof test intervals and SIS failure rates is also evident. Longer intervals lead to undetected latent faults, increasing system failure probability, as shown in statistical models described by Tao et al. (2024). This reinforces the need for optimized testing schedules.

Historical incidents further validate the modeled escalation dynamics. The Bhopal and Flixborough disasters exemplify the consequences of inadequate safety systems and delayed operator response (Gillich et al., 2024). Analysis of these events shows common weaknesses in alarm design, training, and SIS reliability, reinforcing the real-world applicability of the DBN simulation.

Dynamic indicators like dT/dt prove to be reliable predictors of runaway behavior. Models using dT/dt as a trigger for escalation probability successfully forecast impending hazards, enabling timely intervention (Kyritsakis et al., 2018).

Scenario S05 – Corrosion-Driven Leak

The corrosion-driven leak scenario (S05) investigates how increasing corrosion acceleration factor (k_cor) affects barrier performance. As barrier thickness degrades, the probability of leak and toxic release escalates. **Table 2** illustrates the correlation between k_cor values and escalation probability.

Table 2: Leak Probability in S05 vs. Corrosion Acceleration Factor (k_cor)

k_cor	Leak Probability	Barrier Failure Probability	Consequence Severity
1.0	0.05	0.10	Moderate
1.5	0.20	0.35	High
2.0	0.40	0.60	Severe

These results align with findings by Amano et al. (2022), who demonstrated the critical impact of corrosion rates on pipeline integrity. As wall thickness decreases, system resilience is compromised, increasing the likelihood of rupture. Predictive models such as probabilistic fracture mechanics

(PFM) and Markov processes have similarly been used to estimate leak probabilities based on degradation patterns (Ratynskaia et al., 2022).

Integrating Risk-Based Inspection (RBI) into the DBN structure enhances its predictive capabilities. RBI-based strategies optimize inspection schedules by targeting high-risk components, thus aligning with findings from Wang et al. (2024). These methods help tailor maintenance to actual degradation profiles, improving cost-effectiveness and safety.

Toxic leak consequences span a wide spectrum, from health hazards to environmental contamination. Consequence modeling, as described by Jepu et al. (2024), helps quantify these risks, enabling better preparedness and emergency response planning.

Overall Risk Profile Dynamics

A comparative analysis between static and dynamic modeling reveals substantial differences in risk visibility. The dynamic model incorporates real-time updates based on input variables such as U_SIS and k_cor, while the static model uses fixed probabilities.

As shown in **Figure 1**, the dynamic model predicts significantly higher risk levels under degraded barrier conditions.

Figure 1. Dynamic Bayesian Network (DBN) Structure

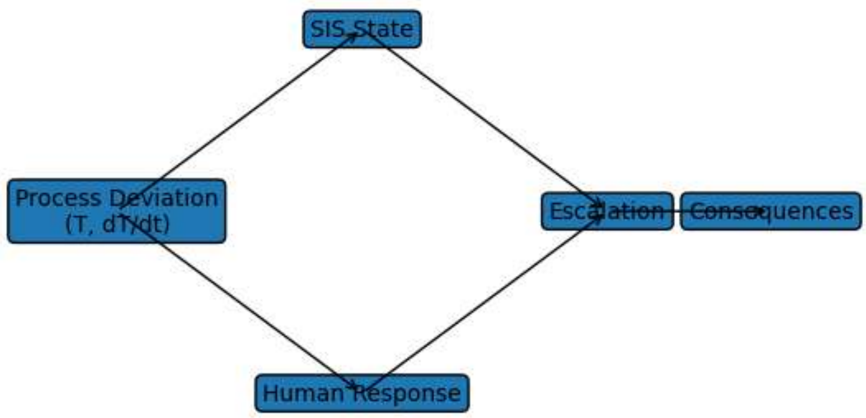

Figure 1 depicts the DBN structure used in this study, highlighting the interdependencies among process deviations, barrier states, human responses, and consequences. The time-stepped simulation mechanism allows the model to project evolving risks over operational periods.

Figure 2. Escalation Probability Over Time (Scenario S01)

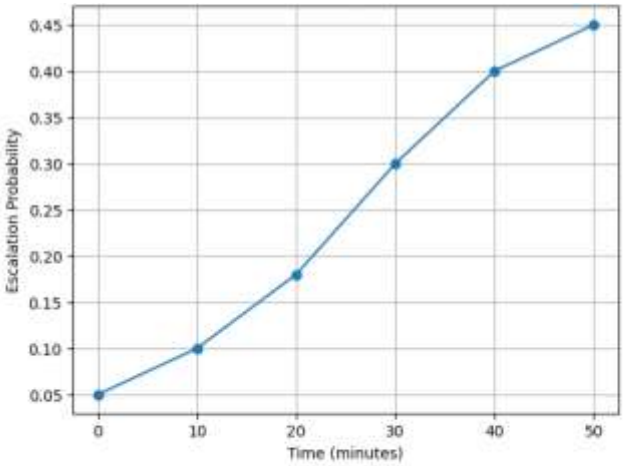

Figure 2 shows the escalation probability over time for scenario S01, with sharp increases corresponding to barrier degradation milestones. This supports empirical comparisons by Sauerhöfer-Rodrigo et al. (2023), who concluded that dynamic models yield more accurate insights into evolving industrial risks.

Figure 3. Static vs Dynamic Risk Modeling Comparison

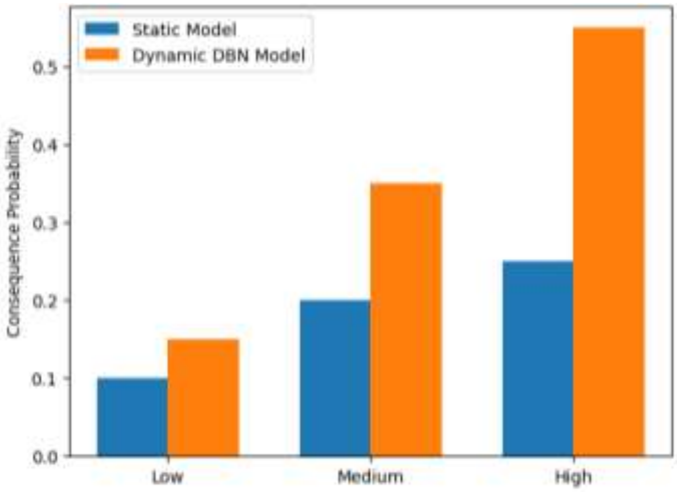

Figure 3 presents a bar chart comparing consequence probabilities under static and dynamic modeling approaches. DBNs outperform fault trees and event trees due to their ability to model temporal dependencies and non-linear interactions.

Visualization techniques such as these are crucial for effective risk communication. As Tao et al. (2024) noted, trajectory plots, heat maps, and GIS visualizations help operators and decision-makers grasp complex risk pathways quickly and intuitively.

Finally, integrating the DBN model with control systems offers a mechanism for real-time risk feedback. Adaptive controls can trigger alarms, initiate mitigation, or re-prioritize operator attention based on escalating risk conditions (Fil et al., 2024). This dynamic link ensures that safety actions are both responsive and predictive, a critical advancement over static safety configurations.

The findings of this chapter affirm the value of DBNs in capturing dynamic risk profiles. They enable proactive safety management by simulating how barrier degradation affects escalation trajectories and allow for better-informed decisions regarding inspection, maintenance, and emergency response.

The findings from this study underscore the significant value of Dynamic Bayesian Networks (DBNs) in enhancing the predictive accuracy of industrial risk assessments. By dynamically modeling barrier degradation and integrating real-time indicators, the DBN framework enables a nuanced understanding of risk evolution an advancement over traditional static models. This discussion synthesizes the implications of the simulation outcomes and situates them within broader safety management strategies, particularly in relation to maintenance planning, operator performance, alarm management, and integration within live process environments.

One of the most critical insights gained from the model is the substantial influence of degraded safety barriers, such as SIS and structural components, on escalation probabilities. Scenario S01 illustrated how increasing SIS unavailability (μ_SIS) rapidly amplifies the likelihood of runaway reactions. Similarly, Scenario S05 demonstrated how the corrosion rate (k_cor) significantly increases the probability of leaks and toxic exposure. These insights are essential for maintenance planning. DBNs support predictive maintenance strategies by using probabilistic models updated with real-time data to forecast failure risks (Uçar et al., 2024). Unlike traditional time-based or reactive maintenance, this approach enables interventions to be scheduled precisely when they are most needed, thereby minimizing unexpected downtime and enhancing operational safety (Luque & Straub, 2016).

DBNs also address the uncertainties inherent in both the equipment and operational environments. By continuously refining predictions as new data becomes available, the models adapt to changing conditions and support dynamic maintenance decision-making. This capability is especially valuable in high-risk industries where even minor equipment deviations can escalate into significant safety threats (Bhandari et al., 2016).

Another pivotal finding relates to the role of human factors in shaping risk outcomes. The model's representation of human error probability (HEP), particularly in relation to alarm overload and operator workload, reflects how organizational practices directly influence safety performance. Training emerges as a vital control factor in this regard. Structured and scenario-based operator training reduces HEP by enhancing situational awareness and reinforcing appropriate emergency responses (Andrews & Fecarotti, 2017). Simulation-based training, in particular, enables operators to develop cognitive and procedural proficiency in managing atypical or emergency conditions (R. Zhu et al., 2019). Such training significantly mitigates the potential for human error in high-pressure environments, where rapid and accurate responses are critical (Kabir & Papadopoulos, 2018).

Alarm management is another area where DBNs can guide improvement efforts. The study showed that alarm effectiveness (A_eff) deteriorates under alarm flooding conditions, increasing the risk of delayed responses. Zarei et al. (2017) argue that effective alarms must be timely, clear, and actionable. When alarms are poorly prioritized or ambiguous, operators may become desensitized, potentially missing critical warnings. Research by Tran et al. (2020) supports the need for streamlined alarm interfaces that enhance usability and facilitate decision-making. DBNs can model the influence of alarm clarity on human response, providing a feedback loop for improving alarm system design. Integrating alarm effectiveness into risk trajectories allows organizations to prioritize improvements where they yield the greatest impact.

Beyond individual system components, the broader implication of this work lies in its potential for integration into live process environments. For DBNs to be effectively embedded in operational safety systems, several best practices must be followed. First, data relevance and reliability are paramount. Kanes et al. (2017) emphasize the need for structured and accurate data collection mechanisms, as DBNs are only as effective as the inputs they receive. Involving operational staff particularly operators and maintenance personnel in model development enhances model applicability and fosters stakeholder buy-in (Andrews & Fecarotti, 2017). This engagement ensures that the models reflect on-the-ground realities and integrate tacit knowledge from field personnel.

Model validation and refinement are also essential. BahooToroody et al. (2019) advocate for iterative updates to DBNs based on emerging data or operational changes. This process maintains model fidelity and ensures continued alignment with the evolving risk landscape. Furthermore, the use of intuitive visualization tools helps bridge the gap between complex probabilistic outputs and actionable insights. As Luque & Straub (2016) note, graphical dashboards and real-time visualizations allow decision-makers to interpret DBN results without needing deep technical expertise.

The study's findings illustrate that DBNs, when properly implemented, provide a valuable lens through which to view risk as a dynamic and evolving phenomenon. They support anticipatory decision-making by revealing how small shifts in barrier performance or operator conditions may ripple through a system and lead to major consequences. This dynamic visibility is critical for fostering a proactive safety culture one in which risk is not just monitored but managed continuously and intelligently.

In conclusion, the discussion confirms that DBNs serve not only as analytical tools but also as strategic enablers for modern safety management. Their integration into maintenance planning, operator training, alarm systems, and live control environments ensures that organizations are equipped to manage risk adaptively. These capabilities will be increasingly important as industries move toward digitized, data-driven operations where safety and reliability are built on real-time understanding of complex systems.

CONCLUSION

This study set out to enhance industrial risk assessment by developing a Dynamic Bayesian Network (DBN) model that accounts for real-time degradation of safety barriers. The results have clearly demonstrated that traditional static models, which rely on fixed probabilities and periodic updates, fall short in dynamic industrial environments where conditions evolve rapidly and unpredictably. By contrast, the DBN framework effectively models temporal changes in barrier reliability, enabling more accurate prediction of hazard escalation and consequence severity.

Through two detailed simulation scenarios reactor runaway (S01) and corrosion-driven leak (S05) the study showed how key indicators such as SIS unavailability (U_SIS) and corrosion rate (k_cor) significantly influence the likelihood and speed of risk escalation. In the reactor runaway scenario, increasing SIS unavailability correlated strongly with faster and more probable escalation, validating concerns highlighted in the literature about the critical role of automated safety systems. Similarly, the corrosion-driven leak scenario revealed that rising corrosion rates greatly elevated the chance of toxic release, underlining the importance of continuous condition monitoring and proactive maintenance.

The integration of these dynamic parameters into a probabilistic DBN structure yielded several practical advantages. The model supported real-time updating of risk trajectories, provided detailed insights into the interdependencies among system components, and offered clear visualizations to guide decision-making. These features make the DBN model particularly valuable for modern industrial operations where predictive maintenance, operator reliability, and alarm management must be dynamically coordinated.

Beyond technical accuracy, the DBN model contributes to operational resilience. It enables predictive maintenance planning by identifying when and where barriers are likely to degrade, allowing organizations to optimize inspection schedules and resource allocation. It also reinforces the importance of operator training and alarm system design by demonstrating how these human-system interfaces directly affect risk outcomes. Moreover, the model's integration potential with digital twins and control systems opens pathways for automated risk feedback, where corrective actions can be initiated in near real-time.

In terms of scientific contribution, this research advances the application of DBNs in safety-critical systems by formalizing a method for embedding degradation indicators into temporal risk structures. It provides a scalable and adaptable framework that can be tailored to various industrial domains and hazard types. Importantly, it shifts the paradigm from reactive to proactive safety management, aligning risk assessment practices with the demands of Industry 4.0 and smart manufacturing.

Future research should explore broader deployment of DBNs across different process industries, including energy, transportation, and pharmaceuticals. There is also potential to enrich the model with additional data streams from IoT-enabled sensors, machine learning algorithms for parameter tuning, and more refined human reliability modeling. Ultimately, the goal is to develop intelligent safety systems that not only detect risk but adapt and respond to it autonomously, ensuring safer, more reliable industrial operations.

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