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A Bayesian Network Approach to Dynamic Risk Assessment of Hydrogen Refueling Stations

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Hydrogen is a promising energy vector, especially for hard-to-abate sectors such as heavy-duty transport. However, establishing a robust and safe hydrogen infrastructure, including hydrogen refueling stations (HRS), is crucial to realize this potential. Risk assessment plays a pivotal role in identifying and mitigating potential hazards to ensure the safe and reliable operation of HRS.
Traditional risk assessments for new technologies like hydrogen often face challenges due to insufficient data and uncertainties. Bayesian Networks (BNs) offer a flexible framework to address these challenges by incorporating probabilistic reasoning and expert knowledge, enabling decision-making even with incomplete information.
In this study, BNs were applied to analyze an HRS, focusing on quantifying uncertainty using the concept of total probability bias. The methodology involved several key steps: First, an FMEA (Failure Modes and Effects Analysis) was employed for hazard identification, while a Bow-Tie (BT) diagram was used to model worst-case scenarios. Second, the BT was transformed into a BN to represent event connections and identify potential failure points visually. Third, Relevant reliability data for components and systems were integrated into the BN to provide estimates of failure probabilities. Finally, the BN was dynamically updated with new operational data, allowing for continuous refinement of risk assessments, improved risk mitigation strategies, and more informed decision-making processes.
Using Bayesian network modeling, this dynamic risk assessment method enables faster and more accurate risk evaluations, enhancing risk management and decision-making. The approach offers a flexible framework that incorporates uncertainty quantification, supporting the safe integration of hydrogen into the energy landscape.

Keywords: Hydrogen Refueling Stations; Risk Assessment; Bayesian Networks; Uncertainty.

1. Introduction

The rapid expansion of the hydrogen economy necessitates a robust and evolving risk assessment framework for hydrogen refueling stations (HRS) (Bartolucci et al. 2021). As these stations transition from remote locations to densely populated urban areas, the potential for accidents and their associated impacts significantly increase. This necessitates a shift from traditional, static risk assessment methods towards more dynamic and data-driven approaches that can effectively capture the evolving nature of risks within these complex systems.

Most hydrogen refueling stations rely on off-site production. They transport hydrogen to the stations using tube trailers. Once the hydrogen arrives, it is compressed and stored in different pressure bundles. This compression process generates a lot of heat. If this heat isn't managed properly, it can raise the storage temperature, increasing the risk of leaks and explosions. Hydrogen refueling stations face more safety challenges than regular gas stations due to hydrogen's properties and the complexity of their systems. Serious accidents, like the 2019 explosion in Gangwon Province, South Korea (Alcock, Shirvill, and Cracknel 2001), and a fire at a station near Oslo, Norway (Cristina Galassi et al. 2012), highlight how dangerous hydrogen-related incidents can be for people and property.

Earlier, hydrogen refueling stations were placed in remote areas, and their safety was mostly evaluated using traditional methods. Techniques like Failure Mode and Effects Analysis (FMEA), Hazard and Operability Study (HAZOP), and Fault Tree Analysis (FTA) were used to identify risks and ensure the designs were safe. However, as these stations spread to urban areas, the focus shifted to quantitative risk assessments (QRA) (Suzuki et al. 2021). These methods combine qualitative techniques with probability analysis to evaluate how likely accidents are and how severe they could be.

Modern risk assessments use various methods. Risk identification utilizes methods like Event Tree Analysis (ETA) and Hazard Identification (HAZID) (Cristina Galassi et al. 2012) to find key factors that could lead to accidents. For accident probability analysis, tools like Bayesian Networks (BN), Bow-tie (BT) analysis, and Dynamic Bayesian Networks (DBN) are becoming more common (Wang and Gao 2023). These tools help researchers model relationships and address uncertainties in hydrogen system risks.

Specialized tools and models are now widely used to evaluate the impact of hydrogen-related accidents. Models like PHAST from DNV and HyRAM from Sandia National Laboratories assess potential damages and effects in specific scenarios.(Gye et al. 2019; Zhiyong, Xiangmin, and Jianxin 2010; Kwon, Choi, and Yu 2022). These tools help measure how severe accidents could be, leading to better risk management and risk reduction strategies.

Traditionally, risk assessments have been static, focusing on fixed probabilities and single scenarios. However, hydrogen refueling stations deal with dynamic and changing risks that require adaptable methods. Dynamic Bayesian Networks (DBNs) have emerged as a valuable tool for real-time risk modeling (Wang, Zhang, and Gao 2022) as they continuously update probabilities based on new data, offering a clearer picture of evolving risks. For instance, research has demonstrated how DBNs can assess risks in offshore drilling and analyze domino effects in chemical processes, highlighting their ability to predict cascading impacts and visualize interactions between different accident factors. These capabilities make DBNs particularly well-suited for addressing the complex and dynamic nature of risks in hydrogen refueling stations.

The expansion of hydrogen refueling stations offers both opportunities and challenges for the hydrogen energy sector. While traditional and quantitative risk assessment methods have proven useful, the move toward dynamic models like DBNs marks a significant advancement. These models effectively address the complex and evolving nature of hydrogen-related risks, allowing for more accurate and real-time risk assessments. By enhancing the ability to predict and mitigate risks, DBNs improve the safety, reliability, and sustainability of hydrogen infrastructure, facilitating the broader adoption of hydrogen as a clean energy source.

Therefore, the present study focused on addressing uncertainties and minimizing total probability bias inherent in emerging hydrogen technologies utilizing the Bayesian Network (BN) framework for dynamic risk assessment of hydrogen refueling stations (HRS). By leveraging probabilistic reasoning and expert knowledge, this research aims to quantify uncertainties and evaluate potential biases, enabling informed decision-making despite incomplete or uncertain data. The study integrates reliability data into the BN model to provide accurate failure probability estimates while minimizing bias, dynamically updating the model with operational data for continuous risk refinement. Finally, the implications of uncertainty quantification and bias reduction on risk mitigation strategies are explored, aiming to enhance risk management and support the safe integration of hydrogen into the energy landscape

2. Methodology:

2.1. *Framework for Risk Assessment*

This study presents a Comprehensive Risk Assessment and Uncertainty Quantification Framework for Hydrogen Refueling Stations (HRS), developed as part of the DNV HySafe project within DNV's Low Carbon Research group (DNV, n.d.). This framework leverages Bayesian Networks (BNs) to dynamically assess risks and quantify uncertainties associated with various operational scenarios. This methodology allows for the identification and analysis of various risk factors associated with HRS and aids in determining the probabilistic relationships between different variables that influence safety and operational outcomes. The flowchart of the developed Bayesian network is presented in Fig 1

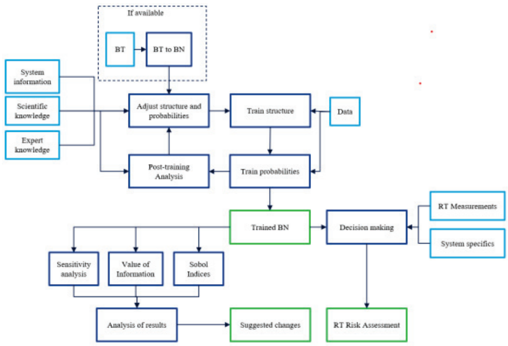

Fig1:Flowchart for Bayesian network framework

The framework for the Bayesian Network (BN)-based risk assessment is designed to systematically address uncertainties and enhance risk evaluations through iterative learning and analysis. The process begins by converting an existing Bow-Tie (BT) diagram into a BN, if one is available, to create an initial representation of event connections and failure points. The BN is then trained using available data, with its structure and probabilities adjusted based on domain knowledge to ensure alignment with real-world scenarios. If sufficient data is available, the BN structure is further refined, and its probabilities are trained using this data. The trained BN is analyzed with domain expertise to verify its reasonableness and accuracy. If the BN performs well, the process continues; otherwise, the training and adjustment steps are repeated, incorporating insights gained from previous iterations.

Once the Bayesian Network (BN) is validated, it analyzes the system through advanced analytical algorithms, such as Gradient Sensitivity, Value of Information, and Sobol Indices. These tools assist in identifying critical variables, evaluating the impact of uncertainties, and prioritizing risk mitigation strategies. The outputs from the BN analysis are then employed to assess the system's risk profile and guide decision-making processes. Ultimately, the BN is used for real-time risk assessment by incorporating system-specific data and real-time measurements. The updated posterior probability distributions generated by the BN facilitate dynamic and precise risk evaluations, promoting proactive risk management and ensuring the safe operation of the system. This iterative and data-driven framework guarantees ongoing improvement and adaptability in risk assessment processes.

2.1. *System Definition and Scope*

The first step in constructing the Bayesian Network for HRS risk assessment is defining the boundaries of the system. This involves identifying the major subsystems that make up the HRS, such as storage tanks, compressors, dispensers, pipelines, and sensors. Each subsystem may have its own set of risks and interactions, making it essential to delineate their roles in the broader system clearly. Key risk scenarios, including hydrogen leaks, over-pressurization, fire, and explosions, are identified. These events have significant safety implications and must be modeled accurately to provide meaningful risk assessments. The system's scope should balance comprehensiveness with manageability, as including too many variables can render the model computationally intensive and difficult to interpret, while too few variables may fail to capture critical risk factors.

2.2. *Variable Identification*

Once the system boundaries and key risk scenarios are defined, the next task is to identify the critical variables, or nodes, that influence the risk landscape. A careful selection process is necessary to ensure the model is both computationally feasible and capable of providing useful predictions. If too many variables are included, the resulting Bayesian Network may become overly complex, computationally intensive, and challenging to interpret. Conversely, excluding important variables may limit the model's predictive power. When selecting variables to include, it is important to consider the availability of relevant data or models. Variables should only be included if their influence on the system is known and quantifiable, either through experimental data, mathematical models, or expert opinion. If the influence of a variable is not well understood but is deemed critical, efforts should be made to find or develop a suitable model to represent its effect on the system. For example, in the case of equipment leaks, it is necessary to define what types of equipment can leak, how many instances exist, the likelihood of such leaks, and the characteristics of a leak once it occurs. Additionally, factors such as whether a leak is contained and the layout of the HRS, which may significantly influence the risk, must also be considered. However, detailed modeling of certain aspects, such as the exact layout of the station or complex simulations, may be outside the scope of this initial modeling framework

2.3. *Causal Relationships*

A crucial aspect of building a Bayesian Network is establishing the causal relationships between variables. These relationships often emerge from expert opinion and domain knowledge, though they can also be inferred from data, especially where correlations between variables can be observed. However, distinguishing causality from mere correlation can be challenging, and expert judgment is often required to interpret the system dynamics accurately. For example, the impact of an explosion or fire can depend on a number of variables, such as the location and number of people in proximity to the event, the weather conditions (e.g., wind), and the characteristics of the leak (e.g., leak rate and whether it is contained). It is also essential to model the ignition process, as ignition cannot occur without a preceding leak, and a leak itself may occur randomly based on certain frequencies. These causal dependencies must be carefully defined to ensure the network accurately reflects the underlying processes and interactions.

2.4. *Bayesian Network Construction*

The Bayesian Network is constructed by systematically representing the risk landscape of hydrogen refueling stations through the identification and interconnection of causal relationships among variables. In this methodology, we restrict the nodes to discrete values, which greatly enhances computational efficiency. Continuous variables can be approximated through discretization, simplifying the model without sacrificing significant detail. While some aspects of this approach may not be applicable to BNs that use continuous random variables (RVs), discretization offers a practical solution for most applications involving discrete risk events and probabilities.

2.5. *Node Definition and Variable Representation*

Each node in the Bayesian Network represents a random variable that corresponds to a specific aspect of the system, such as a physical value (e.g., pressure, temperature), an event (e.g., leak occurrence), or a characteristic influencing other nodes. When defining nodes, it is important to consider their role in the analysis. If a particular variable is not critical for the analysis or does not contribute to understanding the risk, it may be appropriate to merge multiple nodes into a single aggregate node. However, there may also be cases where seemingly less important nodes should be included due to the specific analysis being conducted.

In practice, Bayesian Networks often represent only scalar values for simplicity and efficiency. If a variable is distributed over time or space, the focus of the analysis might be on specific values or intervals rather than the entire distribution. For example, one might be interested in predicting the temperature at specific times or locations, rather than modeling the temperature function across the entire system. In such cases, parameters describing the function (e.g., time or location) can be treated as nodes, and the function itself can be evaluated only when necessary. This approach allows for more focused analysis, optimizing the network's efficiency while retaining sufficient detail for meaningful risk assessments.

3. Data Requirements and Assumptions

3.1. *Data Requirements*

The construction and validation of a Bayesian network (BN) for risk assessment requires accurate data to ensure model reliability. The data can be categorized as follows:

- Failure Data: Historical records of equipment failures and their frequencies are essential for understanding potential risks.
- Operational Data: Information on system conditions like pressure, temperature, and maintenance schedules, which influence the likelihood of failures.
- Environmental Data: Details on environmental factors such as weather and external hazards that can impact failures.
- Other Data: Includes human error probabilities, safety system performance, and material properties, which are important for

addressing specific risks and validating the BN's robustness.

3.2. *Assumptions*

In the absence of comprehensive and detailed data, assumptions are necessary to fill data gaps and enable the development of the Bayesian Network. These assumptions are primarily informed by literature and expert judgment and are outlined below.

3.2.1. *Leak Rates per Unit of Equipment*

(i) It is assumed that the probability of leaks occurring in different equipment units is independent.

(ii) Although intuitive reasoning suggests some degree of dependency between leak probabilities—for instance, similar operational or environmental conditions affecting multiple units—quantifying this dependency is challenging. As a result, independence is assumed for simplicity.

iii) Future iterations of the model could include this dependency as an uncertain random variable or derive estimates of dependence from the literature to improve accuracy.

iv) Leak rates for individual units are based on values reported in DNV Guideline Hydrogen QRA.

3.2.2. *Consequence Triggering Assumptions*

A hazardous consequence is possible only if a leak is both uncontained and ignited. Ignition may occur before the system shutdown is fully complete in some cases. Thus, the model's shutdown probability must account for the likelihood that shutdown happens early enough to avoid ignition consequences. The shutdown probability estimates are derived from literature but may not reflect real-world variations. Uncertainty is included in the shutdown probabilities, with the highest likelihood values aligning with literature estimates while also considering the potential for higher failure probabilities.

By explicitly acknowledging these data requirements and assumptions, the Bayesian Network development is made transparent, with a clear roadmap for future refinements. This approach ensures a balanced trade-off between the model's current utility and its potential for improvement as better data becomes available

3.3.3. *Individual risk and definition*

In the present study, the results are presented in terms of individual risk. Hazardous situations at a hydrogen refueling station may affect three categories of individuals. These categories are defined as follows: (1) station operators and maintenance personnel, (2) station customers, and (3) third parties, such as nearby residents. Each group has unique exposure patterns, requiring specific risk evaluations.

Station operators and maintenance personnel are exposed to significant risks due to their time spent in high-risk areas like hydrogen storage and dispensing zones. Despite their familiarity with operations, they remain vulnerable to hydrogen leaks, ignition events, and high-pressure system failures, especially during maintenance tasks involving pressurization and repairs. Comprehensive risk assessments must consider both the likelihood and consequences of incidents.

Station customers, including drivers and passengers, face shorter exposure times while refueling, making them more susceptible to risks despite their limited knowledge of hydrogen safety. Key risks include leaks or ignitions during refueling and exposure to potential fires or explosions.

Third parties, such as nearby residents and pedestrians, also face risks depending on the station's layout and surrounding population density. Hazards include blast overpressures and thermal radiation from fires or explosions. Probabilistic models help estimate risk based on local infrastructure.

Common risk factors for all groups include proximity to high-risk areas, exposure duration, and the effectiveness of safety measures like barriers and emergency protocols, with population density playing a crucial role for third parties.

4. Results and Discussion

4.1. *Estimating Individual Risk Using the Bayesian Network Model*

The Bayesian Network (BN) model provides a sophisticated approach for estimating individual risks associated with various stakeholders within a hydrogen refueling station, including workers, customers, and residents. Individual risk is assessed by introducing different types of evidence into the model, such as operational failures (e.g., leaks), safety barrier status, or real-time sensor data. The incorporation of such evidence enables the model to simulate different risk scenarios and calculate the associated probabilities of harm for each stakeholder group. This dynamic capability of the BN model is crucial for effective risk management in complex, safety-critical systems.

As illustrated in Table 1, the individual risks (IR) for each stakeholder group are calculated under a variety of operational scenarios. These risks are influenced by factors such as the likelihood of presence in the facility during an incident, the severity of the hazard, and the distance from the potential source of the incident.

Workers are identified as facing the highest individual risks, which is consistent with the assumption that their proximity to operational areas increases their likelihood of encountering a hazardous event. This observation underscores the importance of strict safety protocols for workers who operate in or near high-risk zones.

Customers, conversely, exhibit significantly lower individual risks. The lower probability of their presence in the hazardous area (coupled with the transient nature of their visit) results in a much-reduced likelihood of being affected by an incident.

Residents, due to their distance from the facility, face relatively low risks, though their risk is higher compared to customers, primarily due to potential exposure to larger-scale incidents such as explosions.

Table 1. Individual risks (IR) for the three categories under different scenarios.

Scenario	IR (Worker)	IR (Customer)	IR (Residence)
Without evidence	0.0019	<1e-5	0.0003
Storage Tank Leak	0.0049	<1e-5	0.0004
Dispenser Failure	0.0019	<1e-5	0.0004
Leak + No Shutdown	0.0524	0.0002	0.1091
Ignition and Explosion	0.1507	0.0007	0.0151

Interestingly, the introduction of a leak by itself does not substantially elevate the individual risks for all categories. This can be attributed to the fact that most hydrogen leaks are non-igniting and are typically mitigated before reaching catastrophic levels. However, when the scenario involves a leak with no system shutdown, there is a notable increase in risk, particularly for workers and residents. Workers' individual risk increases significantly to 0.0524, reflecting their closer proximity to operational areas, while residents experience an even more pronounced risk escalation (0.1091), as the propagation of a leak could affect a larger area, including residential zones.

In extreme cases, such as ignition and explosions, the individual risks for both workers and residents rise dramatically, emphasizing the catastrophic consequences of such events. The risk for workers increases to 0.1507, while for residents, the risk is lower at 0.0151, yet still elevated compared to baseline conditions. This result further highlights the need for effective mitigation strategies, particularly in high-consequence scenarios.

The ability to dynamically adjust risk assessments using real-time evidence, such as data from sensors or operational conditions, is one of the key strengths of the BN model. In scenarios where there is no prior evidence (i.e., under normal conditions), risks for all categories remain low. However, once specific evidence is introduced (e.g., a leak or failure of safety barriers), the BN model recalculates the individual risks, enabling immediate and informed decision-making. Such real-time risk assessments allow operators to implement proactive safety measures, such as triggering emergency shutdown systems or activating additional safety barriers, thereby mitigating the potential impact on the most vulnerable groups.

4.2. *Identifying Sub-System Leak Sources*

An additional strength of the BN model is its capacity to identify the most likely sub-system responsible for a leak under different operational conditions. This is achieved by introducing evidence of a leak (either ignited or non-ignited) into the model and assessing the likelihood of each sub-system being the source of the incident.

The results, as presented in Table 2, indicate the relative probabilities for each sub-system contributing to a leak event.

Under normal leak conditions, the compression system emerges as the most likely source of a leak, with a probability of 0.4717, closely followed by the storage system at 0.4061. This suggests that the compression system, which typically operates under high pressure, is particularly vulnerable to failures, and its integrity requires close monitoring.

When the leak is ignited, the storage system becomes the most probable source, with a probability of 0.4670, slightly exceeding the compression system at 0.4447. This shift in probabilities is significant, as it indicates that the ignition of a leak may be more likely to originate from the storage system, which typically contains large volumes of hydrogen under high pressure. The increased risk associated with ignited leaks highlights the critical importance of fire detection systems and the rapid response mechanisms designed to mitigate ignition.

Table 2 Relative probabilities for each sub-system contributing to a leak event

Scenario	Tube Trailer Leak	Storage Leak	Dispenser Leak	Compression System Leak
Leak	0.1319	0.4061	0.0584	0.4717
Ignited Leak	0.1630	0.4670	0.1116	0.4447

Moreover, the analysis reveals that the probabilities for all sub-systems increase in the case of an ignited leak, suggesting a higher likelihood of simultaneous failures across multiple components. This outcome is consistent with the nature of catastrophic incidents, where the failure of one component may trigger a chain reaction, leading to the failure of other connected systems. This emphasizes the importance of integrated safety measures across the entire infrastructure rather than focusing on individual components in isolation.

The tube trailer and dispenser systems, while contributing to a lesser extent, still represent potential sources of leaks. Their lower probabilities suggest that while these components are generally less likely to fail, their failure can still have significant consequences, mainly if they are part of a larger incident involving multiple system failures.

These findings underscore the need for a comprehensive safety approach that addresses potential vulnerabilities across all subsystems. Identifying the compression and storage systems as primary sources of leaks calls for targeted interventions to strengthen these components. In particular, maintenance and monitoring protocols should be enhanced for these systems, including regular inspection of pressure containment structures and implementation of advanced leak detection and shutdown mechanisms.

4.2. *Insights of dynamic risk assessment*

This study illustrates the demonstration of dynamic updates to risk probabilities. For instance, under normal operating conditions, the Bayes Network (BN) model calculates a baseline of individual risks for stakeholders (workers, customers, and residents) as relatively low. However, when specific evidence, such as a hydrogen leak or dispenser failure, is introduced, the model recalculates risks using forward analysis. This process updates the probabilities of harm for each stakeholder group based on new evidence, providing a clear picture of how the risk landscape evolves. In scenarios like a leak without a system shutdown, the individual risk for workers significantly increases (from 0.0019 to 0.0524), while residents experience an even greater rise (from 0.0003 to 0.1091) due to the potential for larger-scale impacts. The backward analysis further enhances the model's utility by identifying the most likely sources of incidents. For example, when a leak is detected, the BN model assesses the probabilities of different subsystems (e.g., storage, compression, dispenser) being the source. Under normal leak conditions, the compression system is identified as the most probable source (0.4717), while in the case of an ignited leak, the storage system becomes the primary suspect (0.4670). This ability to pinpoint likely failure sources allows for targeted interventions, such as improving maintenance protocols or activating specific safety measures. The BN model also supports scenario-based risk analysis, simulating various operational conditions to assess their impact on individual risks. For example, in extreme scenarios like ignition and explosions, the individual risk for workers rises dramatically to 0.1507, while residents face a lower but still significant risk of 0.0151. These insights highlight the catastrophic consequences of such events and emphasize the need for robust mitigation strategies. By dynamically updating probabilities and providing actionable insights, the BN model empowers operators to implement proactive safety measures, such as emergency shutdowns or additional safety barriers, in response to evolving risks. This real-time adaptability ensures that risk assessments remain accurate and relevant, enhancing hydrogen refueling stations' overall safety and reliability.

5. Conclusion

This study highlights the effectiveness of a Bayesian Network (BN) approach for dynamic risk assessment and uncertainty quantification in hydrogen refueling stations (HRS). The BN model's ability to incorporate real-time data and dynamically update risk probabilities enables proactive risk management, even under rapidly changing conditions. The model quantifies uncertainties by integrating probabilistic reasoning and expert knowledge, providing a comprehensive understanding of potential hazards and their impacts on stakeholders such as workers, customers, and residents.

The BN framework supports scenario-based analysis, identifying high-consequence events like ignited leaks or explosions and evaluating their associated risks. It also identifies likely sources of failure, enabling targeted safety improvements. In conclusion, this study demonstrates that the BN approach enhances the accuracy and reliability of risk assessments while facilitating real-time decision-making. By addressing operational complexities and uncertainties, the framework contributes to safer and more resilient hydrogen infrastructure, supporting the broader adoption of hydrogen as a clean energy source.

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