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SIPPRA Framework For Condition And Risk Monitoring In Hydrogen Fueling Stations

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Hydrogen technologies are positioned to play an important role in decarbonizing transportation to address global climate imperatives. However, widespread adoption of hydrogen fuel faces barriers, including the need to ensure reliability, availability, and safety of fueling stations. Unscheduled maintenance is more frequent and costly for hydrogen fueling infrastructure than for gasoline stations (Kurtz, Bradley and Gilleon 2024), and extended downtimes can lead to missed fueling opportunities and loss of consumers at a pivotal stage of technology deployment. Fuels involve safety risks that must be appropriately addressed to ensure broader public acceptance of fuel cell electric vehicles and hydrogen fueling infrastructure. To address these issues, we need innovative reliability and risk analysis methods to streamline hydrogen infrastructure management.

Recent advances in digitalization and sensor technology continue to offer new chances to glean data-driven insights with respect to hydrogen system safety and reliability (Correa-Jullian and Groth 2022; Moradi and Groth 2019). However, effectively using the large volume of data that results to feed decision-making remains a huge challenge, especially in complex engineering systems (Moradi and Groth 2020). To date, two major reliability engineering subfields, Quantitative or Probabilistic Risk Assessment (QRA or PRA) and Prognostics and Health Management (PHM), have demonstrated ability to use data to drive system reliability improvement (Lewis and Groth 2023). Each has distinct benefits but faces specific constraints. While PHM stands out for its ability to effectively manage large, multi-dimensional data and support predictive analysis, its application is mainly at the component level and is limited in system-level perspective. PRA, on the other hand, provides a holistic approach that can help integrate various data types to fully assess complex systems; nevertheless, limitations in applying advanced machine learning (ML) techniques and providing predictive capabilities (Moradi and Groth 2020).

In this research, we are applying a novel framework known as SIPPRA—the systematic integration of PHM and PRA—for operational risk monitoring, for the first time, in a hydrogen infrastructure. Previously validated in non-hydrogen contexts including nuclear power and oil and gas (Lewis and Groth 2023; Moradi et al. 2022; Moradi et al. 2020), this approach systematically restructures and integrates PHM and PRA methodologies to combine their strengths and overcome individual limitations. We are currently gathering information about the hydrogen fueling stations under study, including operational and failure data, P&IDs, maintenance records, and insights into the system's functional logic. Our sources of information include industry-leading companies in the hydrogen sector and national laboratories based in the U.S. and Germany.

Our analytical framework for this research is structured into two main parts: system-level and subsystem-level analyses. For the former, our focus is on understanding the system’s functional logic, its architecture, and interdependencies among the various subsystems (Moradi and Groth 2020). In developing scenarios for system failures and conducting consequence analyses, this process integrates both component and system-level functionalities: encapsulating complex interactions among various hydrogen fueling station components located within the overarching system architecture. We rely on a number of methodologies when constructing this model including traditional PRA/QRA tools (e.g., fault trees and event trees) as well as more advanced probabilistic graphical models such as Bayesian networks, in lockstep with specific analysis objectives (Moradi et al. 2020).

For subsystem-level analysis, we will begin with collecting operational data, including digital monitoring data, and maintenance logs for each component. This extensive data collection lays the foundation for developing accurate component-level condition monitoring (CM) models, with our study using ML models for handling multidimensional data and ability to operate even in the absence of detailed information about physics of the problem (Moradi and Groth 2020). The development of these models involves making critical decisions about various hyperparameters—such as model structure and learning parameters—and they are then applied to assess component performance in real time. We will also develop a Bayesian process for periodic model updates using new data, given the dynamic nature of components and conditions means parameters are not static throughout the life of the system or the model.

At the final stage, we determine the overall state of the fueling station by analyzing the condition of each individual subsystem, with an estimate then made regarding system operational life based on a combination of these assessments. If the system displays faults, our model enables us to identify potential root causes, assess the severity, and understand the likely propagation of the fault throughout the system via forward-backward inference through the logic model (Moradi et al., 2022). Continually monitoring the operation of the entire system allows us to assess and predict its operational risk, and we can do so by considering all subsystem-level assessments as well as their interactions represented in the logic model.

The success of our SIPPRA framework, however, depends on the availability of a proper reliability data format to feed our algorithms. This can be achieved in part by the hydrogen component reliability database (HyCReD) (Groth et al., 2024). HyCReD offers a structured format for component reliability data which can play a key role in our current hydrogen safety research. Our initial steps involve leveraging HyCReD to optimize SIPPRA data input, therefore, we plan to develop algorithms that can process raw data from the control systems and maintenance logs of hydrogen refueling stations—converting them into the HyCReD format.

In conclusion, our research is the first to draw together two distinct well-known reliability techniques to monitor hydrogen fueling station risks. Our approach allows for the simultaneous application of data-driven PRA and risk-informed PHM to support decision (Moradi et al., 2020). The proposed architecture has already shown its effectiveness in various real-world non-hydrogen systems. This research now aims to adapt SIPPRA to hydrogen systems which are marked by a range of specific features and challenges. This includes distinctive chemical and physical properties, infrastructure requirements, and advanced technologies, which contribute to unique failure modes, operational dynamics, and safety considerations (Ahad et al., 2023). Thanks to the unique datasets provided by our collaborators from hydrogen industry, we are conducting research to assess the viability of the proposed framework in hydrogen systems (Moradi et al., 2020). Finally, if we succeed, this versatile architecture will be the first step toward more widespread implementation of systematically integrated PHM and PRA algorithms across diverse systems and provide important capabilities for hydrogen fueling infrastructure management. This supports our broader objective of advancing hydrogen energy systems and points to the key role that innovative reliability approaches such as SIPPRA can play in developing the sustainable energy future.

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