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A Framework for Transforming Process Control System Data from a Hydrogen Fueling Station into HyCReD Data

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Reliability data for hydrogen infrastructure components is essential for developing Quantitative Risk Assessment (QRA) for these technologies, which in turn is necessary for a safer deployment and expansion of the hydrogen market. However, there is currently a lack of hydrogen component reliability data available for these systems, thus limiting the usefulness of insights obtained from these QRA. The Hydrogen Component Reliability Database (HyCReD) has been proposed as a tool for reliability data collection and as a source for future QRAs. In this paper, we develop a digital tool that automatically processes data coming from Process Control System (PCS) in a hydrogen fueling station, detects the relevant failure events for hydrogen systems during its operation, and then logs the event information into HyCReD. To build this tool, we first categorized the station components in hydrogen service, their specific failure modes, and the specific failure mechanisms that are relevant to a QRA. Then, we identified the data available in the station PCS and the methods available for diagnosing the relevant failure events. The resulting tool is divided into three steps: (1) PCS data collection through an API, (2) data analysis for the detection and diagnosis of new failure events, and (3) logging that event into HyCReD. Finally, we discuss the potential for expanding the detection and diagnosis to more complex failure modes present in a hydrogen fueling station. This digital tool is set for implementation and validation on an experimental hydrogen fueling site. The goal for this digital tool is to be applicable to every kind of hydrogen fueling station and to be extendable to similar hydrogen technologies.

Keywords: Reliability data, hydrogen safety, HyCReD, hydrogen fueling stations

1. Introduction

Safety codes and standards (SCS) are essential for enabling a wider, safer deployment of hydrogen infrastructure. SCS employ quantitative risk assessment (QRA), a formal and systematic tool, to quantify the overall risks of these technologies. However, the QRA developed for current SCS have used generic components failure data obtained from other industries, owing to a lack of hydrogen-specific component reliability data (West et al. 2022).

The Hydrogen Component Reliability Database (HyCReD) was designed to address these issues by enhancing the availability and quality of hydrogen-specific failure data to support QRA and reliability studies (Groth et al. 2024). Several of the gaps found in other collection databases were addressed for developing HyCReD, in particular, defining the failure modes, failure mechanisms, leak detection and the occurrence of hydrogen accumulation after an incident; essential information which is not accounted for in the current hydrogen reliability databases. To date, the collection of failure events in HyCReD has been done manually from previous public failure cases, a time-consuming task which requires the analysis of multiple sources for details on the event.

In this work, we propose a digital framework to partially automate the collection of failure events into the HyCReD format for components and equipment in a hydrogen fueling station. The reliability and availability of hydrogen fueling stations represent a challenge to the widespread deployment of this infrastructure, stemming from high failure rates and the system downtime caused by those events (Kurtz et al. 2020). Thus, HyCReD provides insight into how to address a critical barrier to adoption of early-stage hydrogen technologies.

The structure of this paper is as follows. Section 2 presents the background information for this work: the structure of HyCReD, the characteristics of the hydrogen fueling station where this case study is applied, and a review of the current methods for failure diagnostics. Section 3 presents the high-level overview of the framework, the stages and requirements for its process and the procedure for the automatic diagnosis and logging into HyCReD. Section 4 discusses the potential benefits of the framework, depth achievable on the diagnosis, and future work regarding the development and implementation.

2. Data and methods

2.1 HyCReD

As it was introduced, HyCReD was designed to enhance the quality of hydrogen-specific failure data by addressing several aspects missing in other data collection tools (Groth et al. 2024). This database is structured with 31 data fields describing the characteristics of a failure incident, involving 3 data categories: 14 fields corresponding to the system information, 12 fields to the event description and 5 fields to the maintenance details. System information summarizes the facility characteristics where the incident occurred, event description details the causes and consequences of the incident, and the maintenance information documents the service performed to resolve the incident. Table 1 summarizes the data fields present in HyCReD. The U.S National Renewable Energy Laboratory (NREL) and the University of Maryland (UMD) are developing a data coding guide that provides further explanations on the HyCReD fields and how to interpret data (Robinson et al. 2024).

Table 1: HyCReD Fields

#	HyCReD field	Data type	Category
1	Facility Identification	Categorical	System Information
2	Facility Type	Categorical	
3	Service/Usage	Categorical	
4	Facility Nominal Working Pressure (bar)	Numerical	
5	H_2 Phases on Site	Categorical	
6	Equipment Description	Narrative	
7	Subsystem	Categorical	
8	Functional Group	Categorical	
9	Component	Categorical	
10	Component Nominal Working Pressure (bar)	Numerical	
11	Component Maximum Allowable Working Pressure (MAWP) (bar)	Numerical	
12	Component Population	Numerical	
13	Installation Date	Datetime	
14	P&ID Part Number	Categorical	
15	Date & Time of Event	Datetime	Event Description
16	Phase of Operations	Categorical	
17	Failure Mode	Categorical	
18	Failure Mechanism	Categorical	
19	Failure Root Cause Description	Narrative	
20	Failure Severity	Categorical	
21	H2 release?	Categorical	
22	H2 release size	Numerical	
23	Accumulation?	Categorical	
24	Detection?	Categorical	
25	Detection notes	Narrative	
26	Ignition? (yes/no)	Categorical	
27	Consequences	Narrative	Maintenance Details
28	Date & Time Repair Started	Datetime	
29	Date & Time Repair Completed	Datetime	
30	Date & Time Station Restarted	Datetime	
31	Maintenance Description	Narrative	

2.2 Hydrogen fueling station

The fueling station in consideration for this case study is currently under construction at the H2Safety@BAM Competence Center for safe hydrogen technologies, which is part of the German Institute for Federal Materials Researching and Testing (Bundesanstalt für Materialforschung und-prüfung (BAM)). This station will serve as a test platform for the development of digital-based solutions for ensuring the safety and reliability of this hydrogen technology under the German QI-Digital initiative ("QI-Digital Initiative," n.d.). The station can store up to 330 kg of gaseous hydrogen and supply it compressed at both 35 and 70 MPa, for industrial and light-duty vehicles.

From the Process and Instrumentation Diagram (P&ID) of the planned station, the components were categorized for type and functional group according to the taxonomy developed for HyCReD. A total of 180 components are found in the station, out of which 167 are under hydrogen service. Among the most common types are valves, with 73 in total among manual, shut-off, check and needle valves; sensing equipment with 62 components, and pressure relief devices with 14. Table 2 summarizes every component by type.

Table 2: Count of components in station by type

Component	Count
Check valve	7
Compressor	1
Fitting	5
Flexible unloading hose	1
Flow control valve	7
Heat exchanger	1
Hose	2
Hydrogen filter	7
Manual valve	40
Pressure regulator	3
Pressure relief device	14
Pressure sensor	42
Shut-off valve	19
Tank type I	6
Tank type IV	2
Temperature sensor	20
Water process line	3
Total	180

For each component type, the expected failure modes were then identified using the taxonomy for fueling stations defined in HyCReD. The identification of the failure modes was supported by a Hazard and Operability (HAZOP) study conducted by representatives from BAM, the fueling station manufacturer, and a risk consultant. During this analysis, various on-site parameters of the station were evaluated, considering potential consequences that may happen without protective measures and identifying measures to mitigate the risks. To complement the failure mode identification process, several other Failure Mode and Effect Analysis (FMEA) done on hydrogen fueling stations and hydrogen vehicles were consulted (Groth et al. 2024; Groth, LaChance, and Harris 2012; Stephens et al. 2009). The resulting failure modes obtained are presented in Table 3 in the discussion section. The failure mechanisms for each failure mode were also identified, obtaining with it a taxonomy to be used in HyCReD.

2.3 Data sources from the station

Several data types have been identified for QRA in hydrogen systems, like gas data (chemical information), system data (component count and configuration), system operating conditions, observed failures, and consequence data (Moradi and Groth 2019). However, as the station for this case study is currently under construction, there is no historical dataset available with the system operating conditions nor its failures.

Nevertheless, the PCS of the station has already been set up and is currently collecting simulated data for testing purposes. In total, 109 features are being collected for the hydrogen fueling experimental site, which are the following:

- 19 pressure sensors (throughout the station)
- 21 temperature sensors (throughout the station)
- 9 H_2 gas detectors (specific location in station is yet unknown)
- 23 valve statuses (throughout the station)
- 21 weather station sensors
- 16 other testing signals

2.4 Current methods for fault diagnosis

We conducted a scientific literature survey to find the suitable methods that could be employed for this framework. In particular, the search focused on studies that developed an automatic failure detection and diagnosis (FDD) methodology in engineering applications. Achieving a correct diagnosis by this framework provides the critical information necessary to log into HyCReD.

Current FDD methodologies are categorized as model-based, knowledge-based and data-driven methods (Chen et al. 2023). Analytical model FDD employ mathematical models representing the real system to identify faults by comparing their outputs with the real system. When a detailed mathematical model is not available, knowledge-based FDD is an option. A knowledge-based approach uses a knowledge base built with facts of the system, and an inference engine that applies reasoning methods to the known facts (Chi et al. 2022). Reasoning methods can be rule-based (expert systems) or ontology-based.

In regards to data-driven approaches, fault detection can be categorized as supervised, semi-supervised or unsupervised (Chen et al. 2023). All these methods require fault-free data to train the detection models, which learn to identify the normal operation of the system, while supervised and semi-supervised models also require fault data to learn the specific behaviors during a failure event. The data-driven diagnosis of a fault involves identifying or localizing the root cause of the failure, which is considered more challenging than detecting the fault given that different faults can lead to the same symptoms (Mirnaghi and Haghighat 2020).

Bayesian Networks (BN) are one particular data-driven model that has become popular for fault diagnosis given their properties to incorporate system information through structured probabilistic conditional relations and for performing diagnostic inference based on a set of observations (evidence) (Cai, Huang, and Xie 2017). A BN consists of a directed acyclic graph (DAG) with nodes and edges, where nodes represent a random variable to assess and edges modeling the probabilistic relationship between nodes. Each node has associated a conditional probability table (CPT) representing the probabilities given the state of the parent nodes. Nodes without parents are called root nodes their CPT is simply the probability distribution of the node.

In the context of hydrogen fueling stations, a study by Lee et. al (Lee, Cho, and Choi 2021) developed a data-driven approach for fault detection using process variables (sensors) and status variables (component's operational states). Their model could assess normality or abnormality during operation by assessing the likelihood of a target observation, however the diagnosis of the detected abnormal states was not further discussed.

3. Failure event logging into HyCReD

3.1 HyCReD digital logging tool

The methodology for an automatic failure detection and logging into HyCReD needs to be divided into 3 stages: 1) collect the process data from the station, 2) detect failure events from the process data and identify the component or equipment that caused that fault, and 3) log the information regarding the event into HyCReD.

For this purpose, a software package is developed with the aims to be used as a digital tool for the station. This tool is designed to be executed once per day, following the 3 stages defined in the methodology, for the data collected over a complete day of operation. Figure 1 summarizes the flowchart of the digital tool.

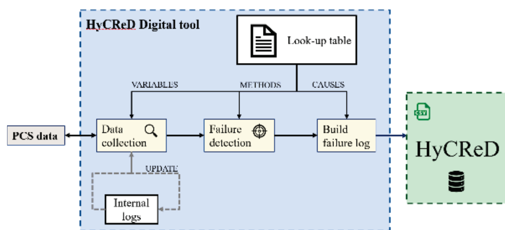

Figure 1: Flowchart of the HyCReD logging tool

3.2 PCS data collection

The data collection is done by requests to the API (Application Programming Interface) integrated into the PCS of the station, which is accessible only through a secure virtual private network (VPN). The requested data corresponds to the daily recordings of each relevant sensor for detecting failures, which are stored in the backup database of the PCS. This collected data is only used for analysis and it gets discarded after the tool has detected and diagnosed events.

3.3 Failure detection, diagnosis, and logging

For the first implementation of this tool, the approach for failure detection is done by monitoring the process variables and assessing if they are outside the normal ranges defined by the station design. A process variable deviating from its expected range is recognized as a failure event to be diagnosed and logged into HyCReD. Only the pressures and temperatures measured throughout the station are analyzed in this first version of the tool.

The detection of failure events is done through a lookup table which lists all the failures detectable, the process variable used to identify them and the range that defines that failure event. Using that information, the tool analyses the daily data and searches for any period within the limits that define a failure. Each entry in the table also summarizes the information needed to diagnose the event, which corresponds to the component that is most likely responsible to have caused that event, as well as its failure mode and failure mechanism.

The current version of the tool can detect 16 different failure events in the station: 13 corresponding to pressure relief valves failing to operate, the overpressure or overtemperature of the hydrogen gas compressor, and insufficient heat transfer by the heat exchanger. Several other failure modes were recognized as detectable but would require more complex methods for detection. This is further discussed in Section 4.

3.4 HyCReD logging procedure

The full procedure for the automatic failure detection and logging done by the digital tool is the following:

Step 1: Collect the daily data for the process variables.

Step 2: For every potential failure listed in the lookup table, analyze if the process variable responsible for that failure is within the specific failure ranges.

Step 3: If a failure is detected, retrieve from the lookup table the failure mode, mechanism and ID of the component that caused it. Use that to populate HyCReD fields #17 and #18 with the event failure mode and mechanism.

Step 4: Collect the details of the failed component from an internal table listing the technical information of the components. Use that to populate HyCReD fields #6 to #16 for the log.

Step 5: If the failure event corresponded to a hydrogen leak, complete fields #21 to #25, and answer field #26 if it involved at hydrogen ignition (not addressed in current tool version).

Step 6: Finally, populate fields #1 to #5 with the details of the facility, which are the same for every event in the hydrogen fueling station.

Step 7: Upload log to HyCReD and internally log the execution to avoid the tool repeating the analysis.

4. Discussion

The HyCReD logging tool developed can detect failure events in the hydrogen fueling station and log that information under the HyCReD format. This tool will be implemented once the hydrogen fueling test site enters commission, after which a verification period is to be followed to assess its validity.

This development will help to build a reliability database necessary for improving the accuracy of risk and reliability assessments of hydrogen infrastructure, particularly for hydrogen fueling stations. Furthermore, the automatic identification done by this tool of the component that caused a failure could improve the efficiency of corrective maintenance by providing information on the component that failed and the failure mode it encountered. Nevertheless, the automation achieved by the tool is limited only to the failure detection and diagnosis and it is not able to automate the logging of the maintenance service details asked in HyCReD, which will need to be manually added after it was completed.

An important metric to consider for this tool is completeness of its detection and diagnosis capabilities, meaning how many of all possible failure events can be addressed by the tool. To assess this, the detectability and diagnosability of every failure mode were estimated based on the station system layout and the data available from the PCS, presenting this information in Table 3. This table also summarizes the number of component types (# C. type) that present each failure mode.

Table 3: Failure modes and their estimated detectability and diagnosability

Failure modes	# C. types	Detectable	Diagnosable
Abnormal output-high	6	Yes	Yes
Abnormal output-low	5	Yes	Yes
Bent/warped/ damaged	16	No	No
Contamination	15	No	Partial
Drift	2	Partial	Partial
Erratic output	5	Yes	Partial
External leak hydrogen	15	Partial	Partial
External leak utility medium	2	Partial	Partial
External rupture hydrogen	15	Partial	Partial
External rupture utility medium	1	Partial	Partial
Fail closed	2	Yes	Yes
Fail open	3	Yes	Yes
Fail to close	5	Yes	Yes
Fail to operate	11	Yes	Partial
Fail to stop	2	Yes	Yes
Insufficient heat transfer	1	Yes	Partial
Internal leak hydrogen	8	Partial	Partial
Internal leak utility medium	2	Partial	Partial
Internal rupture hydrogen	8	Partial	Partial
Internal rupture utility medium	2	Partial	Partial
Noise	2	Yes	Yes
Overheating	4	Yes	Yes
Overspeed	1	Yes	Yes
Plugging	4	Yes	Yes
Restrict flow	9	Yes	Partial
Spurious operation	3	Yes	Yes
Spurious stop	2	Yes	Partial
Underspeed	1	Yes	Yes
Vibration	2	Yes	Yes

Currently, 16 failure events coming from 4 different failure modes on 3 different components are addressed by the tool. Most of the other failure modes are deemed to be detectable or partially detectable from the control logic of the PCS. Leak events of every kind are considered to be only partially detectable because the accurate localization of their origin is challenging, despite that the station is equipped with hydrogen gas detectors. This problem is becoming a growing research topic for hydrogen fueling stations (Zhao et al. 2021). The structural damage of components and contamination are the only failure modes that are considered to not be detectable from process data.

5. Future work

While this work has proposed a tool to address the lack of reliability data for hydrogen components, its scope is still limited to just a few failure events while critical failure modes are not yet considered. This may lead to an unbalanced representation of failure events in HyCReD, and its usefulness would be limited. Future work to expand the capacity and complexity of the failure event detection is a must for the digital tool.

As presented in Table 3, the number of all possible failure events to address in the station may be too large to achieve in the short-term future. To prioritize the failure modes and components to be detected, the insights obtained from past reliability studies on hydrogen fueling station (Kurtz et al. 2020; Groth et al. 2024) could be used to focus first on highly unreliable components and on failure modes with an inherently high-risk.

However, the detection and diagnosis of complex failure modes and mechanism would require a more complex approach. This could be done with BN models, as several properties make them ideal for this objective; they are able to integrate data from different sources under causal relationships, perform diagnostic inference with limited observations, and enable uncertainty analysis on its predictions. The identification of the failed component and characterization of the failure event can be done through backward inference on the BN using as evidence the data collected and additional information from the system components like operational setpoints and states. A BN model could also be developed to help localize the origin of a detected hydrogen release and potentially extend it to estimate the magnitude of the hydrogen release, which is necessary information to be recorded in HyCReD for events of this nature. Employing a model like this for real-time monitoring could also help with the operation of the station by reducing false alarms, particularly fire alarms which are subject to a high degree of false alarms (Festag 2016).

Two challenges for the development of these causal models are structuring the BN and quantifying its parameters. As in previous works, the structure of the BN can be based on the expert knowledge or by structure learning based on data (Cai, Huang, and Xie 2017). The former option is preferable in this case as it can be developed on the known system control procedure, component configuration and the cause and effect relationships between failure modes, symptoms, and failure mechanism. This approach has been demonstrated successfully in similar applications (Moradi et al. 2022; Lewis and Groth 2020; Hazra et al. 2024). On the other hand, the BN parameter modeling corresponds to quantifying the CPT of the nodes in the networks, which can be estimated from expert elicitation or by learning from process data. A combination of both may be required to fully quantify the BN models.

Another aspect to consider for the development of BN models is the possibility for concurrent failures. Jun and Kim (Jun and Kim 2017) defined five fault types able to be represented on a BN: catastrophic, degraded, common cause to faults (or symptoms), multiple causes to fault (or symptom), and cascading fault. To address this, they proposed a procedure with which to identify each type of failure.

6. Conclusion

In this paper we developed a digital tool that detects failure events in a hydrogen fueling station and automatically logs that information into the hydrogen component reliability database (HyCReD). Currently the tool can potentially detect 16 different failure events, and it is set to be implemented and validated in the hydrogen fueling test platform at the H2Safety@BAM Competence Center for safe hydrogen technologies. The total set of failure modes in the hydrogen station were identified and the methods available to address more complex failure events were discussed. Future work will include gathering an historical dataset and building and integrating more complex detection and diagnosis algorithms into the tool.

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