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Hydrogen station prognostics and health monitoring model

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HIGHLIGHTS

- Hydrogen station reliability is a key contributor to market success.
- Mean fills between failure and station availability are lower than conventional technologies.
- A prognostics health monitoring system can improve hydrogen station availability.
- Estimated remaining useful life of primary components assists in maintenance decisions.

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ABSTRACT

Hydrogen fuel has shown promise as a clean, alternative fuel aiding in the reduction of fossil fuel dependence within the transportation sector. However, hydrogen refueling stations and infrastructure remains a barrier and are a prerequisite for consumer adoption of low-cost and low-emission fuel cell electric vehicles (FCEVs). The costs for FCEV fueling include both station capital costs and operation and maintenance (O&M) costs. Contributing to these O&M costs, unscheduled maintenance is presently more costly and more frequent than for similar gasoline fueling infrastructure and is asserted to be a limiting factor in achieving FCEV customer acceptance and cost parity. Unscheduled maintenance leads to longer station downtime, therefore, causing an increase in missed fueling opportunities, which forces customers to seek refueling at other operable stations that may be significantly farther away. This research proposes a framework for a hydrogen station prognostics health monitoring (H2S PHM) model that can minimize unexpected downtime by predicting the remaining useful life for primary hydrogen station components within the major station subsystems. The H2S PHM model is a data-driven statistical model, based on O&M data collected from 34 retail hydrogen stations located in the U.S. The primary subcomponents studied are the dispenser, compressor, and chiller. The remaining useful life calculations are used to decide whether or not maintenance should be completed based on the prediction and expected future station use. This paper presents the background, method, and results for the H2S PHM model as for a means for improving station availability and customer confidence in FCEVs and hydrogen infrastructure.

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1. Introduction to hydrogen station status

Publicly available hydrogen fueling stations are essential infrastructure to support mass adoption of hydrogen fuel cell electric vehicles (FCEVs). Hydrogen-powered vehicles exhibit numerous benefits relative to conventional vehicles and other zero-emission vehicles [1–6], specifically related to their low life-cycle greenhouse gas emissions [7–9], long range and fast fueling [10–12], competitive market price [13–16], and durability [17,18]. As the demand for hydrogen-fueled vehicles has increased with advancements in fuel cell vehicle technologies, the number and variety of hydrogen stations has increased accordingly [19–22].

The hydrogen fueling station capital investment costs, and the O&M costs make up a significant fraction of the cost of hydrogen delivered to vehicles. For instance, in the fourth quarter of 2018, the average maintenance cost per kilogram hydrogen dispensed was $1.30 [23], which is likely incompatible with gasoline price parity target of less than $4 per kilogram. This estimate is based on the assumption that maintenance costs directly contribute to the dispensed hydrogen fuel price, but in many ways the non-monetized costs of hydrogen station maintenance—particularly unscheduled failures—are higher than the monetized cost of maintaining the fueling station.

When a hydrogen fueling station fails in its function to deliver hydrogen, this can have a detrimental effect on vehicle users' acceptance of hydrogen technology. For example, FCEV drivers fill up their vehicles when their tanks are 30% full on average [24,25]. This fueling behavior can be attributed in part to the range anxiety of FCEV drivers, which is different than gasoline vehicle fueling behavior [26] and is due in part to consumers' concern that the hydrogen station may not be available due to breakdown or unplanned maintenance [27–29]. Hydrogen station availability is so essential for consumers that both industry and government have developed software to communicate real-time station availability status to consumers as they drive [30,31]. At present, station operators are servicing hydrogen stations with dueling objectives. On one hand, they must service the system quickly to maintain the availability of the hydrogen station to meet consumers' reliability demands. On the other hand, they must take time to investigate the root cause of the failure to avoid future failures in what is a complicated hydrogen fueling system. The current frequency of hydrogen station component failures is too high—the mean fills between failures (MFBF) for the leading maintenance category (dispenser system) is less than 500 fills [10]. This is approximately one failure every 15 days, based on current fueling trends, and is lower than the mean time between corrective maintenance activities of 21.5 days for gasoline stations [32].

Based on this understanding of the challenges for the operation of hydrogen stations, there is a significant need to understand and improve the reliability of hydrogen fueling stations. This study seeks to apply reliability engineering concepts to hydrogen station O&M so as to reduce the cost of O&M and thereby reduce delivered hydrogen costs. This study presents the development of a hydrogen station prognostics health monitoring (H2S PHM) model, specific to the novel application of hydrogen refueling stations. The H2S PHM model includes steps to identify the needed data, observe operation, analyze the condition, and decide on actions, if any. This modeling seeks to enable a station operator to perform preventative maintenance instead of reactive maintenance to system failures, with real-time processing of information to predict failures and realize lower cost than conventional maintenance plans [33–36]. A primary value of PHM in this context is that it can inform O&M strategies that balance technical function and economic business decisions. In order to do that, PHM estimates remaining useful life (RUL) to determine future component functionality and to economically evaluate a course of action [33,37–41].

Hydrogen fuel as a clean energy vector in the transportation sector has gained significant interest in aiding the transition toward a low-carbon global economy. Hydrogen shows promise of continuing to further enhance its connection with the United Nations Sustainable Development Goals (SDGs). Specifically, this paper highlights hydrogen opportunities and improvements relevant to Goal 7 (Affordable and Clean Energy), Goal 9 (Industry, Innovation, and Infrastructure), Goal 11 (Sustainable Cities and Communities), and Goal 13 (Climate Action).

2. Review of hydrogen station systems and their reliability

2.1. *Hydrogen station overview*

A hydrogen station is a complicated system integrating numerous mechanical, electrical, chemical, safety, and structural subsystems [42–46]. A hydrogen station must seamlessly and safely manage the delivery of high-pressure, nearly-cryogenic hydrogen across varying ambient and throughput conditions with a user interface that is safe for the general public (see Fig. 1). There are numerous suppliers for hydrogen stations and their components, across the engineering specialties such as rotating equipment, cooling, pressure vessels and piping, safety, and electrical. Not all of the components are hydrogen-specific designs because the scale of hydrogen station deployment has not yet justified the

Fig. 1 – Fuel cell electric bus fueling at a hydrogen station (photo credit: NREL).

development of hydrogen-specific subsystems. To date, hydrogen station evaluation projects [47–50] have analyzed past events to study and report on station performance, economics, maintenance, and reliability. Through these projects, data is available to benchmark the challenge of reliability in these systems, along with some limited data to support targeted component reliability research [51,52].

2.2. *Reliability engineering and PHM overview*

At present, the individual operators of hydrogen stations are improving the reliability of hydrogen station operation on a relatively ad hoc basis. The published literature does not reveal any comprehensive research on hydrogen station system-level reliability engineering, although there is demonstrated potential to improve station reliability and availability, based on existing reliability engineering literature and an assessment of the current hydrogen station reliability [53–56].

Reliability Engineering methods aimed at improving reliability, decreasing unforeseen failures, and lowering operational costs have been in development and are applied in many analogous industries [57,58]. For example, the U.S. Army Material Systems Analysis Activity (AMSAA) published an AMSAA Reliability Growth Guide [59] that summarized benefits of reliability growth management to be finding unforeseen deficiencies, designing improvements, reducing risk, and increasing probability of meeting objectives. Reliability engineering is commonly applied to rotating equipment [40,60–62], and the wind industry is applying diagnostics and prognostics to improve wind farm reliability [63–67]. PHM, specifically, is also regularly applied to equipment and complicated systems to predict failure, as evident by many scholarly articles reviewing, researching, and applying prognostics and health management to engineering systems [68–70]. Just a few examples of these exemplar PHM systems include rotating equipment [71], wind turbines [37,66,67], fuel cells [72], batteries [73–75], and development of monitoring systems [76,77]. A recent review summarizes the benefits of PHM for system design, reliability prediction, logistics design, safety, quality control, extending service life, and cost [78].

Although there is no strong consensus on what the best methods for PHM modeling might be, or what metrics define success [79], there are some common classifications of methods (Fig. 2), which are applicable to a hydrogen fueling station. Generally, a PHM method is based on either a data-based, physics-based, or hybrid approach [34,39,80,81]. Options for a data-driven model are historical failure data and empirical operation lifetime data. The data-driven model is typically a statistical model or an artificial intelligence model. Options for a physics-driven model are theoretical or empirical models, with numerous model options that are specific to the equipment function and operation being modeled. The hybrid model combines historical data, available component models, and future loading conditions with the intent of a more accurate model than an either-or model [82–85]. Section 3 presents the PHM methods and propose options for application to hydrogen stations.

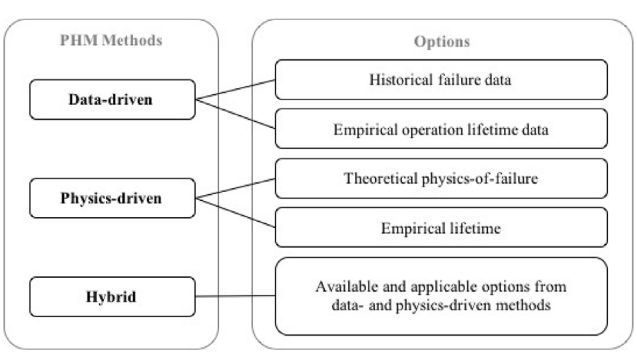

Fig. 2 – The three main PHM methods include data-driven, physics-driven, and a hybrid approach which combines both data- and physics-driven methodologies.

3. Hydrogen station PHM model methods

With the overarching objective of improving the reliability costs of hydrogen stations, this section presents the methods for developing the H2S PHM. The development of a hydrogen station-specific model is motivated by the fact that stations have attributes that complicate application of generic PHM approaches to operational improvement. For instance, complicated systems, like a hydrogen station, can be difficult to operate and maintain especially when one small component can have a large impact on system operation and function. Another challenge is that there are mixed failure modes. The real-world failure data for hydrogen stations is noisy and does not strictly control for identification of failure modes. Understanding the interconnections within complicated systems requires sophisticated models capable of handling multiple data inputs, technical/human decision making, and an understanding of uncertainties [86–88]. These high-fidelity, validation-rich models do not yet exist for many of the equipment and systems in hydrogen stations. For example, hydrogen embrittlement is a well-known issue [89–93] and an active area for research to find low-cost materials and designs that are safe for hydrogen use. Material failures, such as crack growth, may be accelerated in a hydrogen environment especially in high-fatigue operating conditions. Therefore, a physics-based or hybrid method is difficult to conceptualize and validate for the H2S PHM because there are no existing models of hydrogen balance-of-plant components at relevant operating conditions of high pressure (70 MPa) and cold gas temperatures (−40 °C).

The decision for which PHM method to use is therefore largely based on what inputs and datasets are available. In this case, hydrogen station operation data is more readily available than physics-based hydrogen equipment models. The primary source of data for hydrogen stations is the US Department of Energy's NFCTEC program, which gathers real-time data from 34 stations operational in the U.S. reporting O&M data that includes historical failure data and operation lifetime data. Therefore, a data-driven method is recommended for the H2S PHM at this initial stage, framed by a statistical regression model. The proposed Weibull statistical model (a well-established lifetime data analysis method) was selected instead of an artificial intelligence model because there was insufficient data to train an effective machine learning algorithm.

The proposed H2S PHM model has four main segments. The initial segment ("identify data") is added to the 3-part framework of Jouin et al., and includes development of instrumentation data, historical maintenance data, and data from model(s) [76]. The "observe" model segment includes data acquisition, data processing, and faults. The "model/analyze" segment includes condition assessment, diagnostics, and the calculation of prognostic metrics such as RUL. The final segment, termed "decide", includes decision support and human-machine interface that relies on technical expertise and understanding of the system. This architecture was used to break down the inputs and outputs of the H2S PHM model and defines means for implementation with hydrogen station operation to improve reliability. Each segment of the H2S PHM (shown in Fig. 3) feeds information to other segments, including feeding new lessons back to the segments for improvements as more operation data and physics of failure modeling becomes available.

3.1. *Step 1: Identify Data*

Datasets to inform the H2S PHM are available from the instrumentation, which is used to control every hydrogen station in the NFCTEC program. The subsystems with instrumentation include the hydrogen source (on-site production or delivery), compression, storage, dispensing (which includes chilling), and safety monitoring. These instruments are shown in the generic gaseous hydrogen station process and instrumentation diagram (P&ID), shown in Fig. 4. This P&ID is simplified to show typical instrumentation on hydrogen stations without extensive details on the multiples of components like valves and storage [94].

Typical instrumentation of hydrogen stations measures gas pressure and temperature. Pressure is monitored upstream and downstream of compression and dispensing, as well as at the storage system. Temperature is monitored at the chiller and dispenser. Other measurements include cycle counts on the storage system (e.g., depletion/fill), valves, and dispenser (e.g., fill count). On-board vehicle storage tank temperature, pressure, and volume are also recorded during every fill with communication between the station and the FCEV. Table 1 lists the component and subsystem measurements.

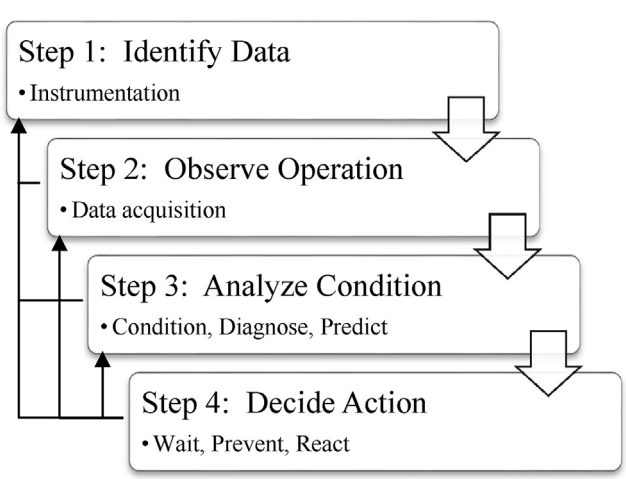

Fig. 3 – General H2S PHM model segments. Data and information from each step can update and influence previous steps as the model framework improves.

The frequency of data acquisition varies by signal and purpose. For instance, ambient temperature conditions and general station state information such as the quantity of stored hydrogen may be collected only once or twice a day. Other instrumentation could be stored every second while that subsystem is operating (e.g., high-pressure compression) or during a fill (e.g., dispenser gas temperature). Instrumentation costs for data acquisition contributes to capital and O&M costs, so not all instrumentation will be available for PHM purposes, especially given the capital and O&M cost challenges of hydrogen infrastructure that were discussed in the introduction. PHM must present a clear benefit in order to justify additional costs for PHM-specific instrumentation.

3.2. *Step 2: Observe Operation*

The station observation data stream for this study is based on two different sources of data: real-world hydrogen station data supplied by 34 stations across the U.S. (NFCTEC), and research data collected at NREL's Hydrogen Infrastructure Testing and Research Facility (HITRF), a research and demonstration hydrogen station located and maintained at the NREL campus [23].

The NFCTEC data stream includes data collected at every fill, at every maintenance event, and at every instance when the station transitions from available to unavailable for fill (and vice versa). At every fill, the stations report date, time, amount, rate, vehicle starting pressure, and vehicle ending pressure (example shown in Table 2). At every scheduled and unscheduled maintenance event, maintenance data is collected and tracked by component, subsystem, date, type, and action (example shown in Table 3). At every available/not available transition, the stations report time, date, and available/not available status through a Station Operating Status [30]. A limitation of this dataset is that it typically does not include second-by-second data for temperatures, pressures, and storage state of charge, or root-cause failure findings. Ideally for PHM purposes, assignment of all known component conditions prior to, or at, failure would be known and tracked for all maintenance events and equipment. In addition, typical parameters that contribute to failures like thermal, mechanical, chemical, physical, and electrical [41] should, ideally, be tracked.

The second data stream, from NREL's HITRF, has the level of data acquisition that could support more detailed causal analysis (Table 4), but it is operated for experimental purposes that often do not match the operational conditions of retail hydrogen stations.

By using both of these datasets together, this study seeks to understand the potential for improvement of hydrogen station PHM through the proposed methods.

3.3. *Step 3: Analyze Condition*

The goal of PHM is to reduce the frequency of reactive maintenance (i.e., unscheduled) after a failure occurs, and to increase the frequency of preventative maintenance (i.e.,

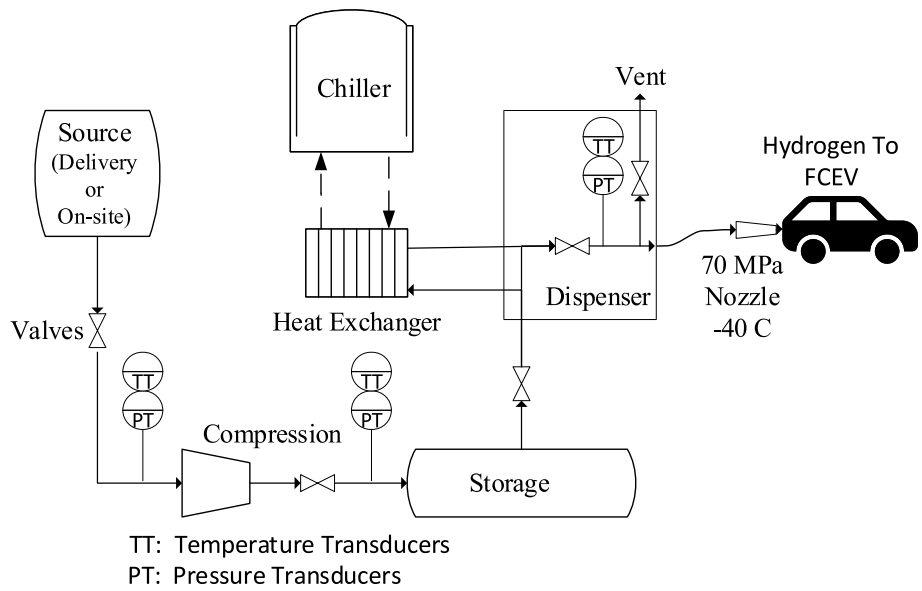

Fig. 4 – Simplified station (gaseous hydrogen storage) P&ID diagram illustrating typical components and instrumentation. Hydrogen is compressed into the storage system where it remains until needed for dispensing into FCEVs. Hydrogen gas is precooled by the chiller system prior to dispensing based on protocol [95].

condition-based) scheduled so as not to negatively impact customers who want to fuel their vehicle.

This proposed method asserts that the fueling state subsystem/component combination is the smallest model block for assessment and the aging parameter is the fill count (as opposed to the number of operation hours or days). There are many common parts (e.g., valves) across the subsystems yet each subsystem has significantly different operating conditions that are expected to influence the current condition and estimation for RUL (e.g., gas temperature at the storage system is approximately equal to the ambient temperature and gas temperature at the dispensing system is approximately −40 °C). The fill count was chosen as the aging parameter because it has not yet been determined that station subsystems/components deteriorate simply based on time. The system is considered a closed system, except for possible small hydrogen leaks to the environment, and operation is almost entirely controlled by the user's request to fill.

Fill data by subsystem/component is required to enable this approach. Failure data for complex systems is generally of two types: complete run-to-failure data or incomplete failure data from field systems. The complete run-to-failure data is preferred because it is controlled and thorough. This type of data is not yet publicly available for the hydrogen station subsystems and components included in this study. Run-to-failure for hydrogen equipment is an active area of research however, with more data expected to be available in the next 1–2 years [51]. The alternative is to use incomplete failure data derived from retail hydrogen stations. For this study, data is derived from this incomplete failure data from real-world station O&M. The incomplete failure data will be analyzed with a traditional lifetime data analysis, or Weibull [96–98] method. The traditional, three-parameter Weibull distribution function is shown in Equation (1).

$$F(t) = 1 - \exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{1}$$

where α is the scale parameter, β is the shape parameter, τ is the location parameter, and t is the aging parameter. A combination of α and β is sometimes represented as a combined parameter, $\lambda = \alpha^{-\beta}$. The Weibull distribution probability density function is shown in Equation (2).

$$f(t) = \beta\alpha^{-\beta}(t-\tau)^{\beta-1}\exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{2}$$

The available failure data will be used to fit key features (α, β, and τ), to assign the component condition, and thereby to predict RUL. With these key features, the Weibull survival function, or reliability function (Equation (3)), can be evaluated to model the probability that the component will successfully operate at time t.

$$R(t) = 1 - F(t) = \exp\left[-\left(\frac{t-\tau}{\alpha}\right)^{\beta}\right], t \geq \tau \tag{3}$$

The conditional survival function is shown in Equation (4), where the survival is calculated at time t based on the successful accumulation of operation time T. The component will be assessed (green, yellow, red) based on the conditional survival function (Equation (4)), as shown in the sample diagram (Fig. 5). The model will assign an approximate condition that is simply a basic assessment of the component survival probability to complete the next fill, while acknowledging that the component has survived through T [99].

Table 1 – Preferred measurements by hydrogen station parts for purposes of the H2S PHM.

Part	Function/Tag	Measurement(s)
Valves	Open/close valves	Open/close cycles, temperature (fluid and ambient), pressure, MFBF, valve position
Control valves	Control flow	Adjustment cycles, temperature (fluid and ambient), pressure, MFBF, valve position
Compressors	Compress to storage tanks (up to ~87 MPa)	Operation time, pressure (inlet/outlet), vibration, MFBF, ambient temperature, variable speed
Chiller	Cool hydrogen prior to fill	Operation time, pressure, MFBF, ambient temperature, operation set point, solar gain
Storage	Low-, medium-, and high-pressure hydrogen storage	State of charge, discharge cycle, discharge amount, ambient temperature, MFBF
Sensors	Temperature, pressure, leak	Operation time, ambient temperature, measurement output (sensor dependent), MFBF

Table 2 – Retail hydrogen station sample fill data from NFCTEC. Fill data includes total amount dispensed, dispense rate, and vehicle tank start and end pressures.

Date	Amount (kg)	Rate (kg/min)	Starting Pressure (MPa)	Ending Pressure (MPa)
1/4/2018 9:03 a.m.	3.1	0.83	28	70
1/4/2018 9:42 a.m.	2	0.85	35	71
1/4/2018 10:39 a.m.	3.7	0.83	21	70
1/4/2018 10:57 a.m.	3.2	0.83	17	70

$$R((t|T)) = \frac{R(T+t)}{R(T)} = \exp\left[-\left(\left(\frac{T+t-\tau}{\alpha}\right)^{\beta} - \left(\frac{T-\tau}{\alpha}\right)^{\beta}\right)\right] \tag{4}$$

Weibull distribution data can be plotted against t, especially for complete run-to-failure data. In the scenario of incomplete failure data from retail hydrogen stations, the Weibull hazard rate (or failure rate in Equation (5)) is recommended with the Weibull distribution data plotted against the cumulated hazard rate (Equation (6)).

$$h(t) = \frac{f(t)}{R(t)} = \frac{\beta}{\alpha}\left(\frac{t-\tau}{\alpha}\right)^{\beta-1} \tag{5}$$

$$H(t) = -\log R(t) = \left(\frac{t-\tau}{\alpha}\right)^{\beta} \tag{6}$$

The last step is to estimate RUL (Equation (7))

$$RUL = T_{eol} - T \tag{7}$$

where T_{eol} (depicted in Fig. 5 as "predicted failure fill count"), or the end-of-life, is the fill count corresponding to 10% survival probability, which will be considered the failure criterion for the purpose of this analysis. T is the current fill count. Another way to look at this is as a health indicator (i.e., survival probability), tracking the difference between the failure criterion and the latest observation [100]. The predicted failure fill count could be updated with additional failure data, root-cause failure results, and physics-based models to inform the precursors to component failure.

There are limitations with this method, as applied to hydrogen station reliability analysis. First, catastrophic (or sudden) failures would not be predicted using this method. Although these failures are not common in the dataset, there are instances of, for example, human error causing unpredictable failures. Second, the method is only as good as the available data, which is at present varied in source, frequency, and fidelity. The proposed method does not include physics-based failure models as the thresholds and times to fatigue failures are not yet known for many of the hydrogen components. The model uncertainty is not yet understood and should be quantified in future work when the comparison between predicted time to failure and actual time to failure can be considered as a function of both aging parameters and operating conditions. Despite these limitations, this proposed model sets the statistical framework, which can be adapted and learn from additional data and include operating

Table 3 – Retail hydrogen station sample maintenance data from NFCTEC. Maintenance logs utilize a picklist that helps technicians and operators keep consistent maintenance records.

Date	Category (system, subsystem)	Action	Duration (hours)	Cause/Effect	Mode
2/3/2018 4:43 p.m.	Compression, Compressor	Replace	8	Pressure loss, warning high	Failed part
3/28/2018 9:00 a.m.	Dispense, Valve	Replace	1	Failed part, hydrogen leak	Failed part
3/28/2018 9:00 a.m.	Dispense, Dispenser	Upgrade	1	NA, NA	Upgrade
4/9/2018 1:00 p.m.	Compression, Compressor	Repair	2	Communication error, lost functionality	Adjustment

Table 4 – Hydrogen station sample fill detailed data from HITRF. Additional dispensing temperature and pressure measurements are taken during the fill for the HITRF station as compared to the retail station data collecting in Table 2.

Date	Amount (kg)	Rate (kg/min)	Starting Pressure (MPa)	Ending Pressure (MPa)	Dispensing Temperature (°C)	Dispensing Pressure (MPa)
1/4/2018 9:03:26 a.m.	3.9	0.83	28	70		
1/4/2018 9:42:16 a.m.	Fill in progress	Fill in progress	35	Fill in progress	−10	35
1/4/2018 9:42:17 a.m.	Fill in progress	Fill in progress	35	Fill in progress	−12	35.3
1/4/2018 9:42:18 a.m.	Fill in progress	Fill in progress	35	Fill in progress	−15	35.6

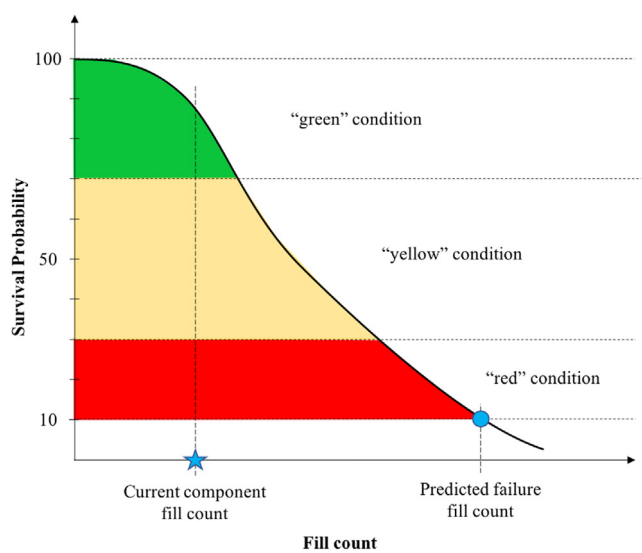

Fig. 5 – Example survival function estimate for components of the hydrogen station (excludes infant mortality failures). Predicted failure fill count occurs at 10% survival probability.

conditions or factors leading to failure as more root-cause failure data and physics-based models are available.

3.4. *Step 4: Decide Action*

The last step in the model is the presentation of information so that the station operator can make a data-driven decision (technical and economical) regarding O&M decisions and strategies. This step assumes that the conditional survival function and RUL will inform the operator, not automatically trigger an action, because at this early phase in commercial hydrogen station deployment, there is too much uncertainty in prediction to fully automate maintenance. Implementing the H2S PHM model at this early stage is advantageous though because the model can be validated and iterated on in parallel to the station technology development and deployment, allowing for a validated model ready in future commercialization phases.

Along with the H2S PHM outputs, the station operator will rely on other inputs such as technician availability and economic impact to determine the preferred actions, or no action at all. There is some guidance in the literature on assigning economic value to the decision to maintain or wait [54]. For example, the economic trade-offs would include consideration of cost avoidance (replace/repair costs of preventative and reactive maintenance as well as downtime penalty costs) and generated revenue. Cost avoidance is the difference between the cost of an unscheduled (failed) maintenance event and the cost of preventative maintenance per the recommendation of the H2S PHM or prior to a failure. There is value in a "wait-to-maintain" option and this value is dynamic, as both the predicted and actual end-of-life will change due to operation (or other aging parameters like calendar time), discrete maintenance intervals based on the logistics (scheduling maintenance technicians and part availability), risk tolerance, and model uncertainties.

An optimizer for the value of completing maintenance, with the input and decision power of trained/skilled hydrogen station operators, could be developed in future work to evaluate the real impact on the day-to-day hydrogen station O&M costs. In addition, preventative maintenance planning based on a reliability centered maintenance method [54] can be improved with additional logic like whether an overhaul is possible or a repair is needed and if a function test is needed for further diagnostics.

4. Hydrogen station PHM model results

The proposed H2S PHM model can be evaluated using currently available data, with the intention that the model will adapt with future data and technology advances. This is important because leading categories for station maintenance may change as reliability improvements are implemented at stations, new technologies are introduced, and early system development failures are designed out with experience and lessons learned. To demonstrate the initial framework and the iterations, Fig. 6, shows a general H2S PHM state diagram with the station O&M states (shown in black outline) integrated with the H2S PHM model steps (shown in green outline).

As a starting point, the station is initiated in a ready pseudo-state and then is available or unavailable to fill. If the station is available to fill, then the station state will move to the "Fill" state when requested. The fill is either successful, with data sent to the H2S PHM "Observe Operation" state, or unsuccessful, in which case the station moves into an "Unscheduled Maintenance" state. This state also supplies data to the H2S PHM "Observe Operation" state and the station may be unavailable for a period of time, depending on the issue. Another O&M state is "Preventative Maintenance," where the station may or may not be ready and able to fill, depending on the specific preventative maintenance event. This state is scheduled and also provides data to the H2S PHM model. The "Identify Data" state (described in Section 3.1) identifies what data signals are needed. The "Observe Operation" state (described in Section 3.2) uses all data inputs to inform the "Analyze Operation" state (described in Section 3.3). The last state in the model is the "Decide Action" state (described in Section 3.4).

4.1. *Step 1: Identify data for H2S PHM*

Available data for retail hydrogen stations is based on the NFCTEC O&M data template [34]. The NFCTEC data includes logs of hydrogen production, delivery, dispensing, costs, and second-by-second fueling data and maintenance/safety events. Heavily instrumented hydrogen stations (i.e., NREL's HITRF or Cal State Los Angeles's Hydrogen Research and Fueling Facility) can serve as a test bed for new hydrogen infrastructure instrumentation and precursors of component failures. This is expected for future study on the need and justification of additional instrumentation for an accurate and consistent set of failure data.

4.2. *Step 2: Observe operation for H2S PHM*

The primary data source is the NFCTEC retail hydrogen station dataset, with more than 465,000 hydrogen fills from more than 34 stations. Station operators typically supply new data every 1–3 months for NFCTEC analysis and reporting so this data could be used to update the H2S PHM regularly. The NFCTEC hydrogen station maintenance analysis shows that the dispenser, compressor, and chiller account for 90% of over

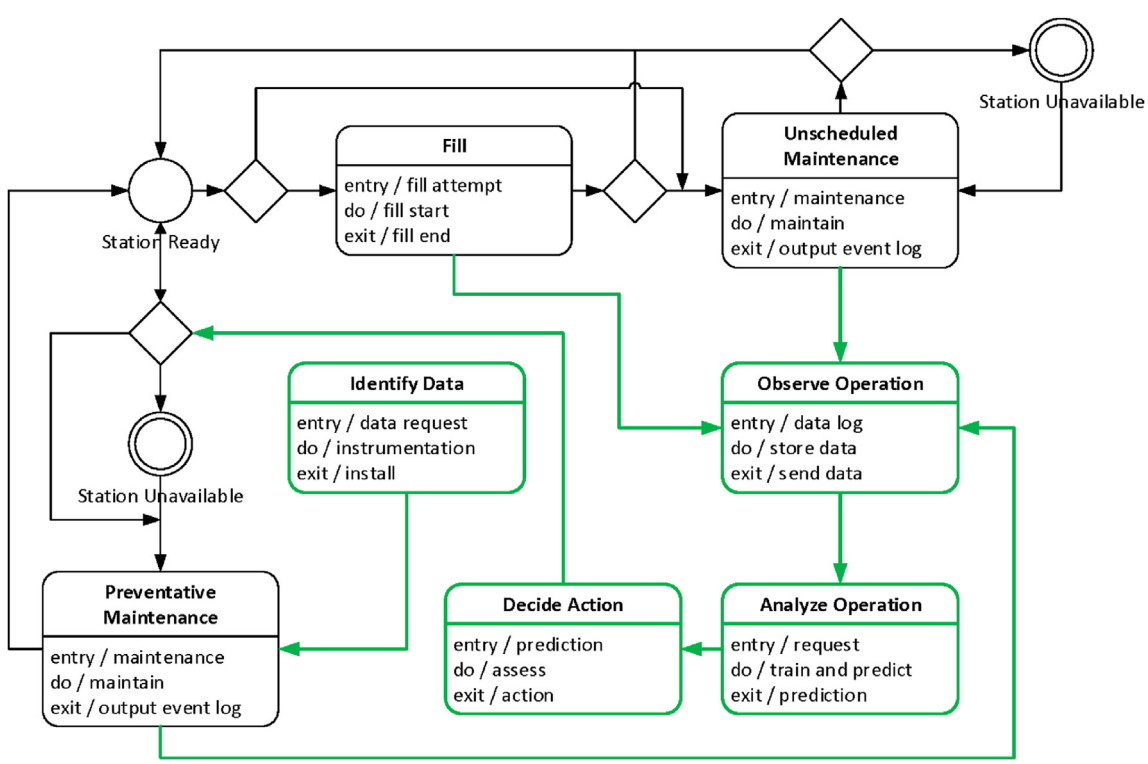

Fig. 6 – H2S PHM state model. Integrated H2S PHM model states are shown in green and station O&M states are shown in black. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

5,600 maintenance events [23]. Therefore, these subsystems are the top priority for observation. Fittings and valves are common failure points within these subsystems, where failures often result in lost functionality and warning alarms. This highlights a challenge with the data-driven PHM approach, where failure root cause and operation conditions are not often found in the station maintenance records because the goal of the technician is generally to get the station fixed as quickly as possible, and the effects (e.g., a hydrogen leak or an alarm warning) do not often point to a root cause of failure (e.g., vibration, installation error, or material degradation).

The observation continues, with the knowledge of this data gap, and correlates the number of fills to each maintenance event, assuming that a component is considered new up until the first time it is maintained. The condition after that maintenance event is then dependent on the specific action like inspect, repair, or replace. Individual component tag numbers are not in the current data, so the components are grouped by function (Table 1) and subsystem. Other gaps in the existing data include individual component identification, gas pressure and temperature cycles, and ambient temperature cycles. These data gaps are captured in the research dataset from HITRF and indicate that there are possible trends that could signal an impending failure.

4.3. *Step 3: Analyze condition for H2S PHM*

The training data for this process includes all relevant retail hydrogen station data at NFCTEC, which introduces a problem of mixing different station configurations and failure modes. This data is the best available however, so all data is categorized by subsystem and components. Stations do have various specifications, suppliers, operating conditions, designs, and utilization rates yet all have similar functional subsystems and components (like a dispenser with valves and nozzles). Data from all stations are aggregated in this to generate a shape and scale parameter for each subsystem/component category because of this common functionality. An expected advantage of using the H2S PHM at this early stage is that the aggregated statistics are a basis for comparison and iteration for station technology development when there is insufficient data for the ideal scenario.

With the aggregated reliability analysis of all applicable maintenance data (i.e., unscheduled maintenance), the parameters are found by fitting the maintenance data in the H2S PHM Step 2, as described Section 4.2. An example of these parameters from fitting the aggregated and categorized maintenance data, using a 2-parameter Weibull distribution (assuming $\tau = 0$) is shown in Table 5.

The shape and scale parameters are determined from the aggregated maintenance data, but the RUL estimate is calculated for each individual subsystem/component at a specific time for a specific station. Let us exemplify the calculations using the hypothetical example of a dispenser valve having completed $T = 92$ fills without a failure. The H2S PHM model first calculates the conditional survivability function, which estimates the probability that the component will continue operating without a failure, with the benefit of knowing that the component has already completed T fills. Fig. 7 presents both the survival function and the conditional survival function for comparison in this hypothetical example. The difference in the blue and orange lines show the increase in probability for a component that has completed 92 fills (blue line) instead of a component that has not completed any fills (orange line).

Table 5 – Example subsystem and component RUL estimates (not real data). When subsystem = component, it refers to the entire system being maintained vs. a specific component.

Subsystem	Component	Shape Parameter	Scale Parameters
Dispenser	Valve	0.58	32.8
Dispenser	Nozzle	0.66	830.8
Dispenser	Fitting	0.85	2851.0
Dispenser	Dispenser	0.62	2218.8
Compressor	Compressor	0.55	2414.6
Compressor	Valve	0.57	1362.5
Chiller	Chiller	0.43	1299.1
Chiller	Heat Exchanger	0.73	1361.6

The end-of-life criteria for this example is a survivability probability of 10%. As noted earlier, this criterion could be updated based on experience comparing the actual failures with predicted failures, the economic trade-off of wait-to-maintain, and the risk preference of individual station operators. In this hypothetical example, the $T_{eol} = 285$ fills and the RUL is 193 fills, based on the shape and scale parameters in Table 5.

4.4. *Step 4: Decide action for H2S PHM*

The H2S PHM can be used to estimate a RUL for each of the priority subsystem/components based on their real-time condition, for any particular hydrogen station. Combining the RUL with other decision factors like technician availability, part availability, predicted future fueling demand, and economics trade-offs, supports the O&M decisions like when to perform maintenance, order parts, or continue active monitoring.

Continuing with the hypothetical dispenser valve example, let us consider a longer period of approximately one month, or 3200 fills for a station averaging 2500 kg/week. The RUL changes as fills are completed until failure or proactive repair/replacement of the component is performed. Fig. 8 shows an example of how the RUL estimate changes over fill counts for the dispenser valve. This simple example has two scenarios for the same component. One scenario includes maintenance without PHM (black dashed lines) and the other scenario performs maintenance as informed by the H2S PHM (blue lines).

In the maintenance scenario without PHM, the dispenser valve fails and is replaced with a station downtime of three times the median labor repair hours [23]. This multiplier captures the time margin that would be necessary for maintenance logistics like notification, part availability, and technician availability. The downtime (assumed constant for each

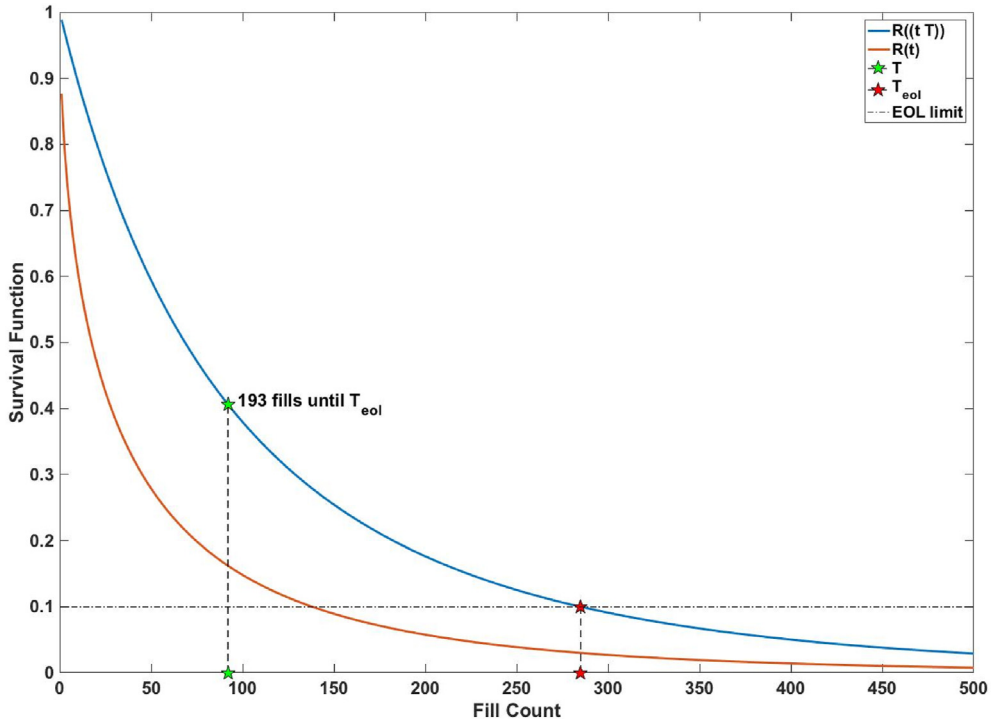

Fig. 7 – Sample RUL estimate for a dispenser valve. The conditional survival function (blue line) is the updated survival function based on the dispenser valve completing 92 fills. The orange line represents the survival function from component onset, T = 0 fills. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

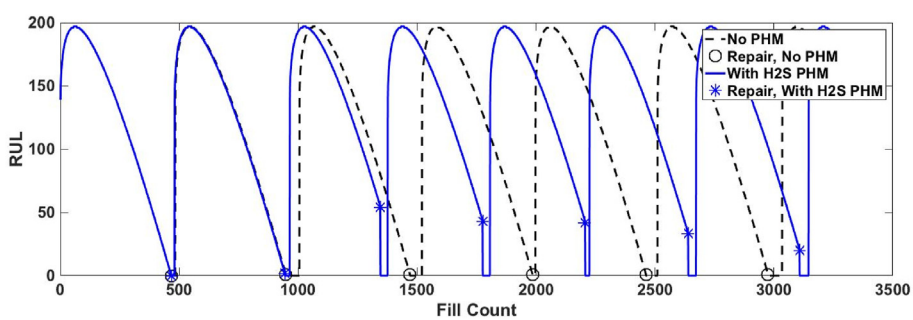

Fig. 8 – Time-series RUL example with variable repair schedules. The model begins to suggest repair prior to failure to minimize downtime. Improvements are made to allow the valve to reach lower RULs as time progresses.

reactive maintenance event accrued at each instance when RUL = 0) is translated into the metric of number of fills based on the predicted hourly demand for the hydrogen station, so that the number of fills varies based on the failure day and time of day. Note in this example the valve fails and is repaired at exactly the same fill count each time (identified by the black circle). This deterministic simulation is used for illustrative purposes only and is not intended to state that the failure is known and repeated exactly.

In the scenario with the H2S PHM, the dispenser valve is replaced at different intervals (identified by the blue *). These illustrative replacement intervals show one possible path of utilizing the H2S PHM with different repair criteria as more is learned and uncertainty is reduced in predicting the RUL. For example, at the cumulative fill count of 1,346, the valve is on its third replacement cycle, with 382 fills on the current valve. At this point of maintenance, the RUL estimate is 54 fills, so the replacement may have been too early, but the next replacement cycle is completed with a RUL less than 50 fills. This simplified example assumes the H2S PHM model shape and scale parameters are consistent therefore the RUL estimate is repeated with each repair cycle. In an actual implementation, the parameters may be updated regularly in order to incorporate learning and comparisons from the actual failures and predicted failures.

If the time period is extended to one year, or over 42,000 fills, the benefit of the H2S PHM can be quantified by the increased uptime compared with the no PHM scenario. Fig. 9 is

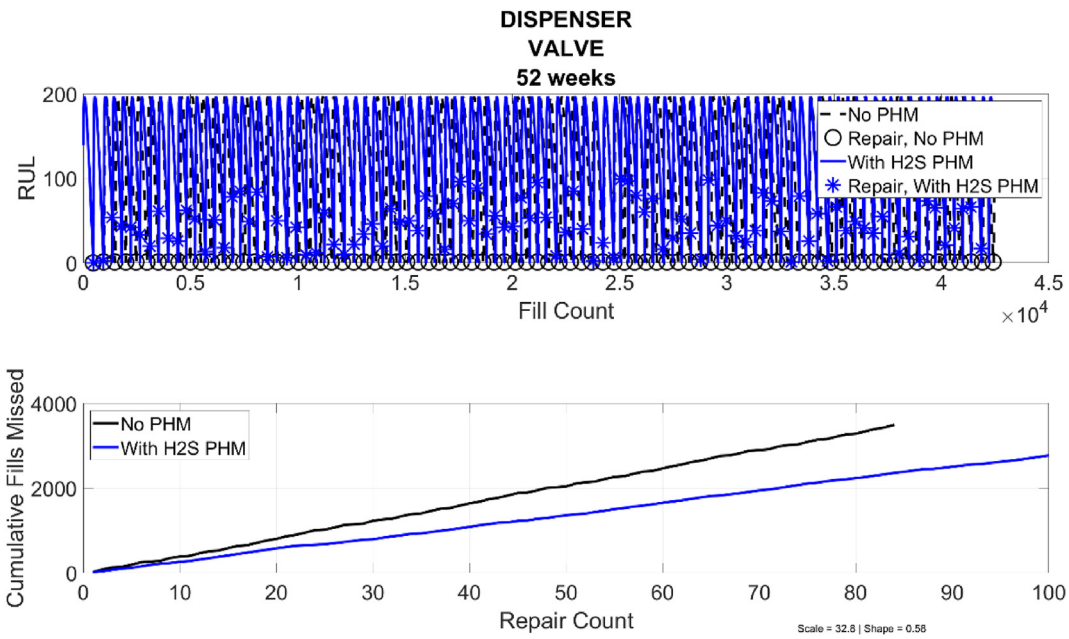

Fig. 9 – Time-series RUL example with variable repair schedules over an estimated 1-year fill profile. Overall cumulative missed fills are shown to demonstrate that less downtime results in more fills for stations, which improves station performance and sales.

an expanded view over one year, with an estimated fill profile. One impact measure is to study how many fills would have been missed because the station was not operation. The second subplot depicts a lost fills estimate versus the number of repairs completed. The number of missed fills is higher at each repair cycle for the scenario that does not have the H2S PHM.

The cost of unscheduled maintenance per kg of hydrogen delivered for a modern hydrogen station is $1.30/kg [10], on average. Preventative maintenance is expected to be lower cost than unscheduled maintenance by up to 30%, as informed by other industry estimates [101–103]. This study therefore anticipates that the H2S PHM will be able to increase uptime, along with lowering maintenance costs, resulting in station availability for more hydrogen fills and an economic advantage compared with status quo maintenance methods.

This is an overly simplified example meant to illustrate the factors influencing the decision step and what actions are taken. Future research is needed for an assessment on the return of investment of the H2S PHM and economic optimization that considers a full range of avoided O&M costs, revenue gain, and the PHM investment [104]. A future economic study of hydrogen fueling revenue, cost avoidance, and H2S PHM return on investment requires additional data on station maintenance costs by subsystem/component for both planned and unscheduled maintenance. So, in its initial iteration, the H2S PHM may provide the most value as a data input for the station operator's goal of high station availability, but it is not yet ready for full implementation until an economic analysis with more data on key variables like downtime per maintenance event and subsystem/category can be completed.

5. Discussion

The H2S PHM model presented here is a proposed framework meant to avoid frequent, unscheduled maintenance events that are costly and negatively impact the customer's trust in receiving hydrogen when it is needed. This model is entirely data-driven because physics-based models are not yet available for the components and subsystems operating in a hydrogen environment, which can have unique influences on failures like crack growth for steels, especially under stress [89–93].

The statistical model is constructed from incomplete failure data, without the ability to track failures of individual components because the data supplied to NFCTEC doesn't include that level of detail. As more maintenance data with higher fidelity is collected, improvements to the fitting parameters can be made, improving the overall functionality of the model framework as a whole. Implementation of the H2S PHM may be most effective with individual station operators because details like the component part numbers, and specific component configuration would be available. In this case, the individual components can be consistently tracked by part numbers, failure frequency, repair times, and maintenance costs that should enable a more meaningful interpretation of the Weibull distribution parameters and maintenance economics than with the generic parameters used for this study. For the purpose of illustrating how a station operator may use

the H2S PHM model, two hypothetical examples are provided below.

1. **Valve replacement scheduling**: Consider a dispenser valve which has a condition assignment of "yellow" indication, and that this valve is close to the lower threshold of survival probability. The yellow status highlights that the operator should monitor this component closely and be prepared for maintenance. The station operator reviews this with the predicted fill demand over the RUL estimate. The operator also factors in logistical items like technician and part availability. The station operator then determines the best time for replacement or repair based on all these considerations, ultimately minimizing the negative impact on the customer refueling capabilities. If the valve replacement or repair is scheduled, the total station downtime may be minimal because the station is only unavailable while the technician is actively working on the replacement or repair. If the valve fails without preventative maintenance, the station downtime could be significantly longer because a technician needs to arrive to the station site, make an assessment on the action required, complete the replacement or repair, which may not be possible if the part(s) are not readily available. The RUL estimate is valuable because it helps to balance the best time to do the replacement or repair so that costs aren't incurred maintaining a fully functional part and revenue is not lost due to an unscheduled failure resulting in missed fueling opportunities.
2. **Major equipment overhaul**: Let us assume that a full compressor overhaul requires the entire station to be unavailable for at least a full day. This is expensive and labor intensive, so it does not make economic sense to complete this maintenance too early in the compressor's operational life. The RUL estimate can be used to decide on the optimal time to complete the overhaul. For example, the compressor overhaul could happen during off-peak hours or when the station is closed for business, allowing for the station operator to mitigate any revenue loss or customer relationship risk. Forewarnings to customers and other methods like pushing the station storage state of charge to 100% before the overhaul can also help minimize station downtime while maintaining positive user experience. The primary difference with this scenario and a basic maintenance practice is that the RUL estimate informs the decision timing. A major component like a compressor is also an ideal candidate for integrating early warning signs (e.g., operation pressures), the statistical survival prediction, and a physics-based failure model.

In these and other near-term hypothetical examples, uncertainty may limit the utility of the H2S PHM model. Not every maintenance event can be predicted, and one-off, unforeseen failures are always a possibility with station equipment. In an early market phase, infant mortality failures may be difficult to predict and therefore the operator may not be confident in the RUL estimates. Any action initiated from the H2S PHM model outputs will also be influenced by uncertainty in the predicted fill demand and economic value. Another factor influencing uncertainty is whether the failures are systemic, simply because the market is new, or quality control issue for certain components. For instance, a particular component failure may only be an issue because the component has not been customized for the hydrogen environment. When the supply chain is more established than presently, the component will be replaced with a customized hydrogen-rated component with fewer failures and different failure modes.

There are a number of opportunities for improvements in the H2S PHM model, datasets, and data collection methods. Future work should study the assumption of a continuous failure model. If the failure behavior is more accurately described by a discrete model instead of a continuous one, the observations from the continuous model may be inaccurate [105]. Information from field data and continued study of the modeling will support the assessment of the data type and failures like burn-in or wear-out experienced by hydrogen station components. If the continued focus of the hazard rates shows variations in the traditional bathtub curve, the model should be adapted [106–109]. The model may also be customized as hydrogen station specific failure mechanisms are identified and used to inform the component condition as not all components may follow the typical aging phases as the traditional bathtub curve seen in other mechanical engineering applications [110].

6. Conclusion

Currently, hydrogen station O&M is primarily reactive, which has led to high O&M costs in this early stage of commercial development and deployment. Station system reliability is lower than needed for general consumer acceptance based on a comparison with gasoline station reliability, thereby identifying reliability as a key cost driver and an ideal area for research and development. Data collected from retail hydrogen stations is just now becoming available to provide a valuable data source for reliability engineering of hydrogen stations. However, hydrogen station data is currently sparse, inconsistent, and not yet standardized station to station. While prognostic health modeling and preventative maintenance scheduling using RUL is not a novel concept, it has yet to be tailored for hydrogen refueling stations and infrastructure. A promising option is the proposed data-driven H2S PHM. The H2S PHM framework serves as the initial building block to develop a way to increase station availability and improve O&M costs in an emerging field looking to gain widespread acceptance within the transportation and mobility sector. The H2S PHM could be adapted for an individual station or a network of stations, integrating a reliability survival analysis with economic trade-off of cost avoidance and revenue. Further reliability engineering methods, improved data collection, and failure modes for hydrogen systems should be an area of focus from the hydrogen community to help hydrogen become a competitive energy vector and as reliable as current refueling and transportation standards.

In order to be adopted by a station operator, a clear operational benefit must be identified, and model limitations addressed. The introduction of this H2S PHM framework

allows for validation and iteration as the number of hydrogen refueling stations increases and more, higher fidelity data is available. Other limitations of the data-driven H2S PHM can be mitigated with collection and integration of more data, and with advances in physics-based models of the physics of failure of hydrogen subsystems and components.

The H2S PHM model has been demonstrated with some example cases derived from real hydrogen operation and maintenance data to decrease the maintenance-related cost contributions to the cost per kilogram of hydrogen. The H2S PHM also demonstrates a decrease station downtime, resulting in higher station availability and customer acceptance, thereby increasing the confidence of FCEV drivers that the station will dispense hydrogen when requested. The application of these proposed reliability engineering methods to a new field (hydrogen station operation) is one means to address the reliability and cost challenges for future hydrogen stations, further improving the projected hydrogen landscape and outlook.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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