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RELIABILITY QUANTIFICATION OF PEM ELECTROLYSER STACK: A NOVEL FRAMEWORK INTEGRATING SIMILARITY ANALYSIS, FUZZY LOGIC, AND BAYESIAN NETWORKS

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Master's thesis in Hydrogen systems and enabling technologies

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ABSTRACT

The industrial scaling of Green Hydrogen production is currently hindered by a significant lack of long-term operational failure data for Proton Exchange Membrane (PEM) electrolyzers. To address this data gap and support thorough risk assessment, this research develops and validates an integrated, multi-layered reliability prediction framework for PEM electrolyser stacks. Unlike traditional statistical methods that need large historical datasets, this study employs a hybrid approach that combines top-down similarity analysis, fuzzy logic reasoning, and probabilistic modeling.

The methodology is structured in three progressive phases. First, Rahimi's similarity approach (adapted from subsea protocols) establishes baseline failure rates. Due to structural and electrochemical isomorphisms, the study utilized mature failure data from Proton Exchange Membrane Fuel Cells (PEMFCs) as a proxy for PEM electrolyzers. This data is adjusted using Reliability Influencing Factors (RIFs) such as water purity, operating conditions, and material selection. Second, to mitigate the epistemic uncertainty inherent in expert elicitation, a Fuzzy Failure Mode and Effects Analysis (FMEA) is integrated with the Fuzzy Best-Worst Method (FBWM). This phase employs triangular fuzzy membership functions in MATLAB to derive mathematically consistent weights for RIFs and calculate Fuzzy Risk Priority Numbers (FRPNs) that account for the vagueness of subjective expert inputs. Third, the framework incorporates Bayesian Networks (BNs) using GeNIe software. This probabilistic graphical model captures the causal dependencies among RIFs, Failure Causes (FCs), and Failure Modes (FMs), enabling dynamic updates to posterior failure probabilities as new evidence or operational scenarios emerge. The study targets explicitly three critical degradation mechanisms within the stack: Membrane Degradation (MD), Catalyst Degradation (CD), and Bipolar Plate Corrosion (BPC).

Finally, a Monte Carlo Simulation (MCS) is performed to conduct a rigorous sensitivity analysis. Running 40,000 iterations using Latin Hypercube Sampling, the simulation propagates input uncertainties to define confidence intervals and verify the stability of the predicted failure rates.

Keywords: PEM electrolyzer, reliability prediction, fuzzy FMEA, Bayesian belief networks, similarity analysis, failure rate estimation, green hydrogen, expert judgment, risk assessment.

SAMMENDRAG

Industriell oppskalering av produksjonen av grønt hydrogen hindres for tiden av en kritisk mangel på langsiktige data om driftsfeil for protonutvekslingsmembranelektrolysatorer (PEM). For å løse dette datamangelen og muliggjøre en robust risikovurdering, utvikler og validerer denne forskningen et integrert, flerlags rammeverk for pålitelighetsprediksjon for PEM-elektrolysatorstabler. I motsetning til tradisjonelle statistiske metoder som krever omfattende historiske datasett, benytter denne studien en hybrid tilnærming som syntetiserer top-down likhetsanalyse, fuzzy logikk og probabilistisk modellering.

Metodikken er strukturert i tre progressive faser. Først fastsetter en likhetsbasert Rahimi-tilnærming (tilpasset fra undervannsprotokoller) grunnleggende feilfrekvenser. På grunn av strukturelle og elektrokjemiske isomorfismer benytter studien modne feildata fra protonutvekslingsmembranbrenselceller (PEMFC) som en proxy for PEM-elektrolysatorer. Disse dataene justeres ved hjelp av pålitelighetspåvirkende faktorer (RIF) som vannrenhet, driftsforhold og materialvalg. For det andre, for å redusere den epistemiske usikkerheten som er forbundet med ekspertuttalelser, integreres en fuzzy feilmodus- og effektanalyse (FMEA) med fuzzy best-worst-metoden (FBWM). Denne fasen benytter triangulære fuzzy-medlemskapsfunksjoner i MATLAB for å utlede matematisk konsistente vektorer for RIF-er, og beregner fuzzy-risikoprioritetstall (FRPN) som tar hensyn til vagheten i subjektive ekspertinnspill. For det tredje inkorporerer rammeverket Bayesianske nettverk (BN-er) ved hjelp av GENIE-programvare. Denne probabilistiske grafiske modellen kartlegger de kausale avhengighetene mellom RIF-er, feilårsaker (FC-er) og feilmoduser (FM-er), og muliggjør dynamisk oppdatering av posterior feilsannsynligheter når nye bevis eller operasjonelle scenarier dukker opp. Studien retter seg spesielt mot tre kritiske nedbrytningsmekanismer i stabelen: membrannedbrytning (MD), katalysatornedbrytning (CD) og bipolar platekorrosjon (BPC).

Til slutt utføres en Monte Carlo-simulering (MCS) for å gjennomføre en grundig sensitivitetsanalyse. Ved å kjøre 40 000 iterasjoner ved hjelp av Latin Hypercube Sampling, sprer simuleringen usikkerhetene i inndataene for å definere konfidensintervaller og verifisere stabiliteten til de predikerte feilfrekvensene.

Nøkkelord: PEM-elektrolysør, pålitelighetsberegning, fuzzy FMEA, bayesianske troskapsnettverk, likhetsanalyse, feilrateestimering, grønn hydrogen, ekspertvurdering, risikovurdering

PREFACE

This thesis work was carried out in my second-year at Norwegian university of science and technology in the department of Mechanical and Industrial Engineering under the RAMS group and in collaboration with the Politecnico Di Torino, Italy, first year university, within the department of Energy and Nuclear engineering as part of the Erasmus Mundus Joint Master's in Hydrogen Systems and Enabling Technology (EMJM-HySET) During Autumn 2025.

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ABBREVIATIONS

List of all abbreviations in alphabetical order:

AEL Alkaline electrolyser

BN Bayesian Network

BOP Balance of Plant

BPC Bipolar Plate Corrosion

BPP Bipolar Plate

CAPEX Capital Expenditure

CD Catalyst Degradation

CCM Catalyst Coated Membrane

CI Contaminants and Impurities

CP Chemical Process

CPT Conditional Probability Table

DA Degradation and Ageing

EL Electrolyser

FBWM Fuzzy Best–Worst Method

FC Failure Causes

FM Failure Modes

FMEA Failure Mode and Effects Analysis

FRPN Fuzzy Risk Priority Number

GDL Gas Diffusion Layer

GP Gas Purity

GW Gigawatt

LCOH	Levelized Cost of Hydrogen
MD	Membrane Degradation
MEA	Membrane Electrode Assembly
MQ	Maintenance Quality
MS	Mechanical Stress
MTTF	Mean Time To Failure
MW	Megawatt
OC	Operating Condition
OPEX	Operational Expenditure
PEM	Proton Exchange Membrane
PEMEL	Proton Exchange Membrane Electrolyser
PEMFC	Proton Exchange Membrane Fuel Cell
PTL	Porous Transport Layer
RIFs	Reliability Influencing Factors
SMR	Steam Methane Reforming
SOEC	Solid Oxide Electrolyser Cell
TFN	Triangular Fuzzy Number
WP	Water Purity

SYMBOLS

CO₂ Carbon dioxide

H₂O Water

O₂ Oxygen

H₂ Hydrogen

Pt Platinum

IrO₂ Iridium dioxide

TiO₂ Titanium dioxide

SiO₂ Silicon dioxide

Ca Calcium

Cu Copper

Fe Iron

h hour

R_t Reliability function

$\lambda_{FC,i}$ PEMFC failure rate of a i failure mode C

P_i is the failure mode proportions

λ_{FC} PEMFC total failure rate

$\lambda_{EL,M1}$ Estimated PEMEL stack failure rate, Method 1

$\lambda_{EL,M2}$ Estimated PEMEL stack failure rate, Method 2

$\lambda_{EL,M3}$ Estimated PEMEL stack failure rate, Method 3

$Weight_{FL,i}$ Normalised fuzzy lofic weight of failure mode i

$Weight_{BN,i}$ Normalised Bayesian network weight of failure mode i

INTRODUCTION

The global reliance on fossil fuels has resulted in substantial environmental impacts, prompting the international community to adopt ambitious 2050 decarbonization targets. As countries gradually shift away from fossil-based energy systems toward low-carbon alternatives such as electric vehicles and green hydrogen, engineering efforts continue to prioritize safety, reliability, and maintainability. Yet, in contrast to well-established technologies supported by extensive historical datasets, the rapidly developing green hydrogen industry is constrained by the absence of standardized methodologies and a pronounced scarcity of operational and failure data.

This issue is particularly pronounced in the case of the PEMEL stack, which constitutes the core of the system and accounts for roughly 55% of its total cost [1]. The stack is also the component most prone to failure and, therefore, the central subject of ongoing research aimed at enhancing durability. Nevertheless, the lack of comprehensive failure data currently limits the accuracy of reliability assessments. This thesis addresses this gap by transferring and adapting reliability analysis techniques from more mature sectors to the context of PEMEL stacks, to establish a robust framework that supports the safe and sustainable scaling of green hydrogen technologies.

1.1 Green Hydrogen Production

Hydrogen is commonly categorized using a color-based classification system that indicates both the type of feedstock employed and the carbon intensity of its production pathway, as shown in Figure 1.1. Within this framework, green hydrogen is central to long-term energy transition strategies because its production results in zero CO₂ emissions, thereby enabling substantial decarbonization across multiple sectors [3].

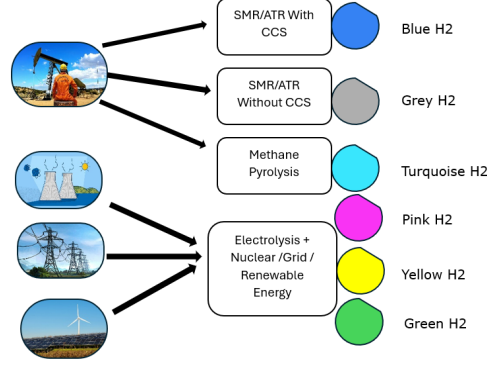


Figure 1.1: Classification of Hydrogen Production redrawn from[2]

Although there are several niche production routes for green hydrogen, it is predominantly produced via water electrolysis powered by renewable energy sources such as wind, solar, or hydropower. This route offers a clear advantage over conventional Steam Methane Reforming (SMR). While SMR is associated with considerable CO₂ emissions and an efficiency of only about 60%, electrolysis avoids direct emissions and can reach efficiencies of up to 85% [4], [5].

The primary electrolysis technologies currently implemented in industrial applications—AEL, SOEL, and PEMEL—are illustrated in Figure 1.2.

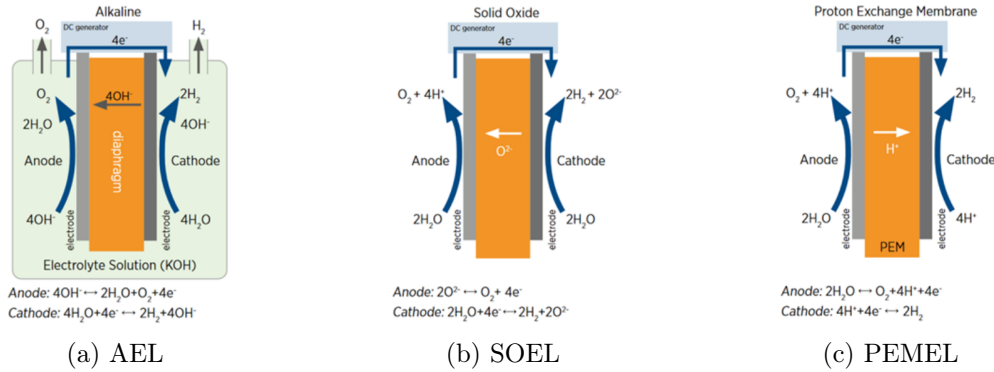


Figure 1.2: Three types of water electrolyser technologies reproduced from[1]

- (a) **Alkaline Electrolyser (AEL):** Among the electrolysis technologies considered, alkaline electrolysis (AEL) is the most traditional and thoroughly developed option, with a Technology Readiness Level (TRL) of 9, indicating a fully mature technology [6]. Owing to its long operational lifetime and relatively low capital expenditure—primarily due to the use of inexpensive nickel-based catalysts—it is widely adopted for large-scale installations [7]. Nevertheless, because AEL is already highly developed, the potential for substantial further economic or technical improvements is limited, and most cost reductions now stem from advances in cell and stack design [8].

Compared with other electrolysis technologies, AEL typically operates at lower current densities and pressures [9]. Furthermore, the presence of a liquid electrolyte restricts ion transport, which poses challenges for applications requiring rapid response, such as those associated with the integration

of renewable energy sources (RES) [9]. Commercial AEL systems generally exhibit efficiencies in the range of 51–60%, corresponding to a specific energy consumption of approximately $5.0 \sim 5.9 kWh/Nm^{-3}$ [10].

Given these characteristics, AEL is generally not the preferred option for RES-coupled applications, which are marked by fluctuations and fast dynamic behavior. Instead, this technology tends to deliver its most significant benefits in high-power, stationary installations continuously supplied by the electrical grid [6].

- (b) **Solid Oxide Electrolyser (SOEL):** Unlike PEMEL and AEL systems, Solid Oxide electrolyzers (SOEs) function at substantially higher temperatures, generally between 500 and 1000 °C. Operating at these elevated temperatures improves ionic conductivity and facilitates inherently rapid reaction kinetics, thereby enabling overall system efficiencies approaching 100%. Moreover, the possibility of coupling SOEs with external heat sources creates the opportunity to achieve electrical efficiencies exceeding 100% [9].

Despite these benefits, SOE technology is still at a comparatively early stage of development, with a TRL of only 3–5. When steam generation is performed without an external heat source, the efficiency advantage over PEMEL and AEL decreases significantly. Furthermore, although operating at elevated temperatures enhances efficiency, it also increases the likelihood of accelerated stack degradation caused by thermal stresses. Because SOEs are based on ceramic components, they require carefully controlled start-up and shut-down procedures, which complicates their straightforward integration with intermittent renewable energy sources for green hydrogen production [9].

- (c) **Proton Exchange Membrane Electrolyser (PEMEL):** PEM electrolyzers are more appropriate for small-scale applications than AEL. The operating power range can be expanded by simply connecting them in series to create a stack [7]. Industry favors PEM electrolyzers due to their thin, solid membranes, which allow higher current densities ($>1 Acm^{-2}$), resulting in more compact stacks [8], higher cell voltage efficiency, and improved reaction kinetics [7].

PEMEL has a significant TRL of 7–8, but there is still more room for advancement in both technology and cost [11]. Currently, standard alternatives have efficiencies ranging from 46 to 60% and operating pressures of 450 bar [11]. However, they cost more than their AEL equivalents. The possibility of a small stack and the anticipated 75% efficiency boost in commercial devices offer opportunities for cost improvement [7]. Cheaper components such as membranes, bipolar plates, and catalysts, along with increasing the cell area, could contribute to cost reduction [8].

Although green hydrogen provides significant environmental benefits, it still faces substantial economic challenges. Both its capital expenditures (CAPEX) and operational expenditures (OPEX) remain higher than those associated with conventional hydrogen production, resulting in a levelized cost of hydrogen (LCOH) that is currently less competitive and, consequently, hampers large-scale market

adoption [4] [5]. However, increasing global demand, combined with ongoing technological advancements, is expected to reduce these costs over time. According to IRENA, the extensive deployment of electrolyzers could reduce LCOH by as much as 60% by 2030 [1]. While early green hydrogen facilities typically operated at the megawatt (MW) scale, recent projects have expanded to gigawatt (GW) capacities, thereby necessitating more robust and efficient production technologies to meet projected energy demands [12].

PEMELs have been widely adopted in large-scale applications due to their compact design, high-purity hydrogen production, and compatibility with intermittent renewable energy sources. Industrial actors such as Nel Hydrogen are leading the development of this technology; for example, the commissioning of the world’s largest PEM electrolyser at Herøya, Norway, marks an important milestone in the large-scale deployment of green hydrogen production.[13].

1.1.1 PEM electrolyser

Proton exchange membrane water electrolyzers (PEMELs) represent the current state of the art for green hydrogen production. The first PEMEL system was reported in 1973 by Russell et al. at General Electric, and even these early devices achieved high current densities ($1\text{--}2\text{ A}\cdot\text{cm}^{-2}$ at $1.88\text{--}2.24\text{ V}$) with operating lifetimes longer than 15,000 hours [14]. Since that initial work, several companies—such as Giner Inc., Proton OnSite, Siemens, and Hydrogenics—have significantly advanced PEMEL technology toward commercial deployment. Despite the advantages of PEMELs, including compact system design, high energy efficiency (80–90%), and fast transient response suitable for fluctuating renewable power inputs, widespread industrial implementation is still limited. The primary barriers are the high costs associated with noble metal catalysts (Pt, IrO_2), titanium-based bipolar plates, and perfluorosulfonic acid membranes such as Nafion [14].

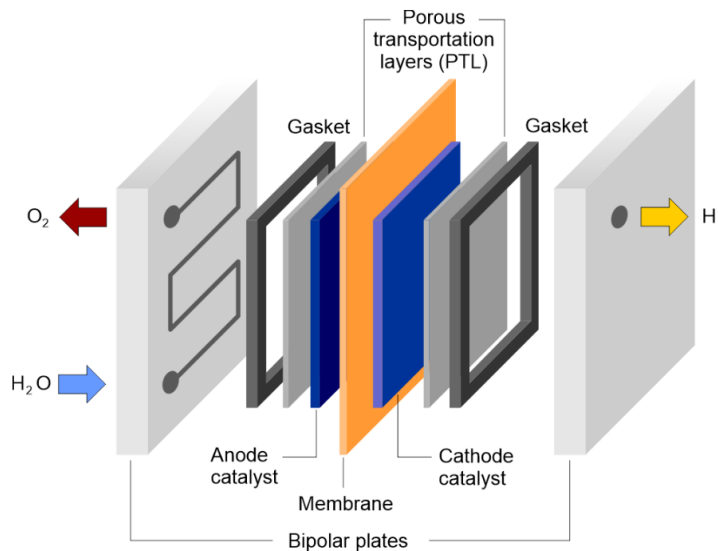
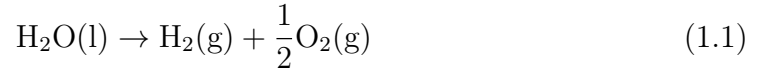


Figure 1.3: PEMEL Stack reproduced from[1]

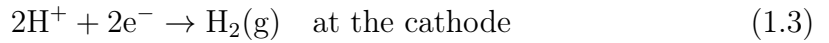
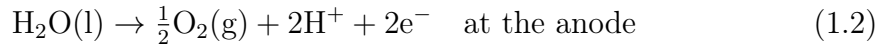
Technological innovation is therefore essential to accelerating the transition toward a sustainable hydrogen-based energy system. In the subsequent sections, we present the basic operating principles of electrolysis and examine the functions of its key cell components, including the membrane, electrocatalysts, membrane electrode assembly (MEA), gas diffusion layers (GDLs), and bipolar plates (BPPs). Special attention is devoted to the degradation mechanisms of these materials under realistic operating conditions, such as catalyst dissolution, membrane thinning, corrosion of bipolar plates, and the gradual deterioration of GDLs.

1.1.1.1 Fundamentals of PEMEL

PEMEL electrochemically splits liquid water into hydrogen and oxygen, producing the two gases at physically separated electrodes: hydrogen at the cathode and oxygen at the anode. In the electrolysis process, water is introduced on the anode side, where it is decomposed into oxygen (O_2), protons (H^+), and electrons (e^-), as represented by Equation (1.2):



Protons are transported through the proton-conducting membrane to the cathode side. At the same time, electrons depart from the anode via an external electrical circuit that provides the required cell voltage to sustain the reaction. At the cathode, these protons and electrons recombine to form hydrogen gas, as illustrated in Figure 1.3.



1.1.2 Stack Components

The stack comprises several key physical components, including bipolar plates, gaskets, porous transport layers, anode and cathode catalyst layers, and the membrane. These elements together form the structural and functional basis of the stack and are described in greater detail in the following sections.

- **Bipolar plates**

Bipolar plates provide the primary mechanical support for a PEMEL stack, while simultaneously conducting electrical current and distributing reactant gases and water. Titanium is often selected for its high corrosion resistance; however, it is costly and typically requires additional protective coatings, such as Pt or Au. Cost analyses suggest that bipolar plates may contribute to more than half of the total stack cost [15]. Previous review articles have also highlighted that passivation of bipolar plates represents a key degradation pathway that gradually reduces system efficiency [16]. More recent research underscores that the use of less expensive coated stainless steel or composite plates can substantially reduce overall costs [17].

- **Gasket Layers**

Gaskets and sealing layers are essential components in PEMEL stacks, as they prevent water and gas leakage. They maintain the mechanical integrity of the stack under compressive loads and contribute to operational safety by inhibiting hydrogen crossover. Failure of these seals can have serious consequences, because the resulting mixing of hydrogen and oxygen within the stack may lead to hazardous, potentially violent reactions [15]. Previous reviews on electrolysis have highlighted that gasket wear and degradation during pressure cycling constitute a significant reliability concern, particularly when stacks are operated dynamically with fluctuating renewable power inputs [18].

Degradation of sealing materials has also been linked to prolonged mechanical loading and to exposure to aggressive, acidic environments [16]. Recent studies further stress that improved gasket designs and more durable materials are necessary to ensure safe operation at elevated pressures and under intermittent operating conditions [17].

- **Porous Transport Layers**

Porous transport layers (PTLs), located directly adjacent to the catalyst layers, play a critical role in supplying water to the anode, removing oxygen, and providing electronic conductivity. They are typically fabricated from titanium sinters or perforated titanium sheets due to titanium's strong corrosion resistance under the acidic conditions characteristic of PEM systems [15]. However, titanium is expensive and can still undergo gradual corrosion during long-term operation, thereby increasing the overall stack cost and compromising durability [16]. The pore structure of PTLs is particularly crucial: tiny pores impede mass transport, whereas overly large pores allow catalyst ink to penetrate the PTL, diminishing the effective utilization of the catalyst [15].

Previous review studies have also emphasized that gas bubble formation within PTLs can obstruct active sites and degrade cell performance at high current densities [16]. More recent work further underscores the need to develop lower-cost, corrosion-resistant PTL materials to meet DOE cost targets [17].

- **Catalyst Layers** Catalysts play a central role in promoting the electrochemical reactions, with Pt typically employed at the cathode for the hydrogen evolution reaction (HER) and IrO₂ or RuO₂ used at the anode for the oxygen evolution reaction (OER) [15]. Nonetheless, these noble-metal-based catalysts are costly and are prone to dissolution and migration under strongly acidic operating conditions.

RuO₂ exhibits outstanding catalytic activity but suffers from rapid degradation, whereas IrO₂ provides superior durability at an even higher cost. Moreover, relatively high catalyst loadings are generally required (on the order of 2–3 mg·cm⁻² at the anode), which further contributes to the overall stack cost. To mitigate these issues, alloy catalysts such as Ir–Ru–Sn are

being explored to achieve an optimal trade-off between catalytic activity and long-term stability [16].

Advanced fabrication strategies, including nanostructured thin-film (NSTF) and direct membrane deposition (DMD), have been developed to improve catalyst utilization and reduce noble-metal consumption. Recent review articles also highlight that minimizing catalyst loading is a critical requirement for meeting the DOE cost targets for hydrogen production [17].

• Membrane

The Membrane serves two primary functions: separating the reactant gases and facilitating proton conduction. Nafion is among the most widely employed PEM materials due to its high proton conductivity and favorable mechanical properties. However, its conductivity decreases above 100°C, and it is susceptible to gas crossover. To overcome these drawbacks, composite membranes incorporating inorganic fillers such as TiO_2 or SiO_2 have been developed to improve water retention and enhance overall membrane stability. In addition, hydrocarbon-based membranes, for example, polybenzimidazole (PBI) doped with phosphoric acid, can operate at temperatures above 100°C. Despite this, ensuring their long-term durability remains a significant challenge [15]. Earlier investigations identified membrane thinning and gas crossover as the main degradation mechanisms [3]. More recent studies also emphasize that membranes account for a considerable fraction of the total cost of PEMFC stacks [17] [4].

1.1.2.1 Comparison between PEMFC and PEMEL

PEM fuel cells and electrolyzers are fundamentally related technologies, as they share a very similar physical design, despite operating in opposite directions. A PEMFC generates electrical energy from hydrogen, whereas a PEMEL uses electrical energy to produce hydrogen. In both cases, the devices employ a conventional stack-based configuration.

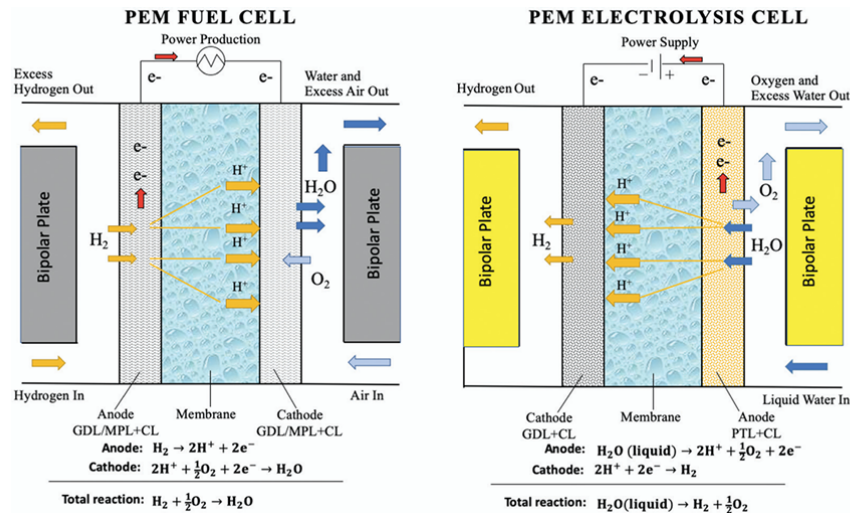


Figure 1.4: PEM Fuel cell and electrolyser , reproduced from [17]

PEMFCs and PEMELs serve as complementary technologies within the broader field of electrochemical systems. They are structurally identical in terms of their proton exchange membrane, catalyst layers, porous transport layer, bipolar plates, and sealing gasket components.[15].

The functional distinction between the two systems is evident in their respective reaction pathways. In a PEMFC, hydrogen is fed to the anode, where it is oxidized to form protons and electrons. The protons traverse the membrane, while the electrons flow through an external circuit before recombining with oxygen at the cathode to form water, which is the only byproduct of the process [19]. In contrast, PEMELs operate by reversing this thermodynamic sequence. Liquid water is supplied to the anode, where it undergoes the Oxygen Evolution Reaction, producing oxygen, protons, and electrons. The protons then migrate across the membrane and are reduced at the cathode, resulting in the formation of hydrogen gas [17].

From a materials standpoint, the two systems share a comparable foundational design but diverge in regions where their chemical environments differ. Both make extensive use of Nafion or similar perfluorosulfonic acid membranes owing to their superior proton conductivity and mechanical robustness [20]. However, their catalyst arrangements vary in terms of the most expensive components in each device: fuel cells typically employ platinum at both electrodes. At the same time, electrolyzers use platinum solely at the cathode and depend on iridium- or ruthenium-based oxides at the anode [16]. Similarly, although carbon-based materials are suitable for transport layers and bipolar plates in fuel cells, the highly oxidative environment at the electrolyser anode instead demands titanium-based components [17][20].

Because of these design parallels, the two systems exhibit similar degradation patterns. Both are susceptible to membrane thinning, gas crossover, catalyst dissolution, and component corrosion [21]. Consequently, reliability evaluation methodologies originally developed for fuel cells—specifically FMEA, FTA, and quantitative risk assessment—can be readily applied to electrolyzers. Just as these approaches have been used to detect catalyst agglomeration, pinhole development, and corrosion in fuel cells [22], they can similarly be used to characterize corresponding failure modes in electrolyzers, such as iridium dissolution, titanium passivation, and gasket fatigue [15][20].

Despite their shared technological foundation, the two systems exhibit substantially different operational requirements. PEMFCs are developed primarily for automotive propulsion and backup power, with typical durability targets of 8,000 to 30,000 operating hours. In contrast, PEMELs serve as industrial production units. They are expected to run for 40,000 to 90,000 hours, often at elevated pressures and under highly dynamic load profiles driven by variable renewable energy sources cite FOPEM4. A comprehensive comparison of these operational parameters is provided in Table 1.1.1. The cost structure likewise differs significantly: in fuel cells, platinum catalysts constitute the primary cost driver, whereas in electrolyzers, overall system costs are dominated by iridium-based catalysts and the titanium stack cite FCvsEL3.

Table 1.1.1: Comparison of PEMFC and PEMEL, Adopted from [17]

Aspect	PEMFCs	PEMELs
Function	Converts hydrogen into electricity	Uses electricity to split water into hydrogen and oxygen
Overall Reaction	$H_2 + \frac{1}{2}O_2 \rightarrow H_2O$	$H_2O \rightarrow H_2 + \frac{1}{2}O_2$
Operating Temperature	Typically $\sim 80^\circ\text{C}$ but the range: -40 to 120°C	Typically ~ 60 – 90°C but the range: 25 to 120°C
Operating Pressure	1–2 atm	1–50 atm
Durability Target	8,000–30,000 hours	40,000–90,000 hours
Cost Target	\$30/kW (light-duty); \$60/kW (heavy-duty)	\$1–2 per kg H_2 (DOE Hydrogen Shot goal: \$1/kg)
Membrane Thickness	10–50 μm (Nafion commonly used)	100–200 μm (Nafion same as PEMFC)
Catalyst Layer	Platinum-based (0.1–0.4 mg/cm ²) for both electrodes	Iridium-based (anode, 0.2–2 mg/cm ²); Pt-based (cathode)
Porous Transport Layer	Carbon fiber GDL + MPL (20–50 μm pores)	Titanium PTL (20–100 μm pores, corrosion-resistant)
Bipolar Plates	Metallic/graphite/composite; flow fields for gas distribution	Metallic/composite; corrosion-resistant; flow fields for liquid water + O_2 removal

1.1.2.2 Durability Challenges of PEMEL

The long-term stability of proton exchange membrane electrolyzers (PEMELs) is limited by degradation mechanisms that closely parallel those observed in proton exchange membrane fuel cells (PEMFCs). Within the stack, bipolar plates are susceptible to corrosion and coating failure, which in turn increases electrical resistance [23]. Porous transport layers deteriorate through oxidation and pore blockage, thereby hindering fluid transport [24]. Catalyst layers experience dissolution of iridium or platinum (Ir/Pt) and particle agglomeration, while carbon supports at the cathode are vulnerable to corrosion [25][26]. The membrane is subjected to both mechanical and chemical stresses, leading to thinning and gas crossover, raising safety concerns [27]. Furthermore, gaskets degrade as elastomer components lose elasticity under compression and undergo chemical breakdown in acidic environments [28].

System-level (Balance-of-Plant) malfunctions also have a pronounced effect on stack reliability. Contaminants originating from degraded water purification systems, such as chlorides, can markedly accelerate stack corrosion [29]. Operational safety is further compromised by sensor drift and mechanical wear in pumps, while downstream performance is diminished by blocked filters or inadequate gas separation. Additional reliability concerns arise from fouling in the cooling circuits and hydrogen embrittlement in storage tanks [30]. Collectively, these BoP challenges highlight that achieving long-term durability requires solutions that extend beyond the stack itself.

Long-term aging investigations [31] have revealed key degradation mechanisms: under high anodic potentials, platinum dissolves as Pt^{2+} , migrates, and subsequently precipitates within the membrane as an electrochemically inactive layer, producing voltage spikes. At the same time, the membrane is susceptible to chemical degradation; contaminants such as calcium, potassium, and silicon can promote radical formation, resulting in a reduction in membrane thickness of up to 75% within only 5,500 hours. These degradation pathways often lead to short circuits, underscoring the importance of both catalyst stability and impurity control for long-term durability.

In conclusion, failure arises from the combined action of multiple mechanisms rather than from single, isolated defects. While PEMELs exhibit degradation pathways similar to those of fuel cells (e.g., gasket fatigue and catalyst degradation), they operate under more severe conditions, including high voltages and aqueous environments. Addressing these challenges requires a two-pronged strategy: the development of advanced material systems—such as radical-scavenging membranes and protective coatings—alongside enhanced BoP engineering. The integration of these advances is essential to attaining the reliability needed for large-scale, industrial hydrogen production.

1.2 Reliability and safety for green hydrogen

Emerging green hydrogen infrastructure—encompassing production, storage, distribution, and end-use—faces distinct safety and reliability challenges stemming from hydrogen’s physical properties and the intermittency of renewable power sources. Due to its wide flammability limits, high diffusivity, and low minimum ignition energy, even seemingly minor faults in equipment such as electrolyzers or compressors can rapidly develop into hazardous events [32]. As a result, ensuring reliable performance throughout the full life cycle of these systems is critical, as shown in Figure 1.5. Reliability shortcomings often act as precursors to safety incidents, underscoring the need for an integrated treatment of safety and reliability to secure both technical robustness and societal acceptance [33].

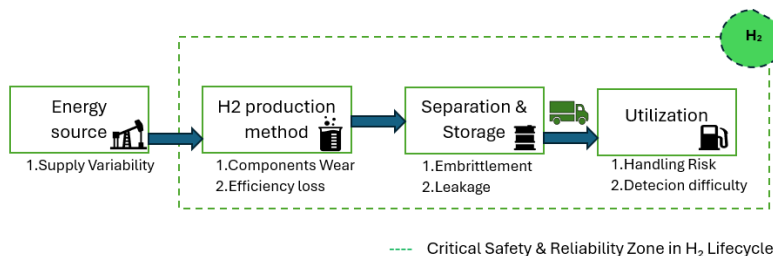


Figure 1.5: Green Hydrogen value chain

The most significant risks concentrate around leakage, material degradation, and delays in fault detection. Hydrogen embrittlement compromises the structural

integrity of metallic components, and high-pressure operation increases the vulnerability of seals and valves to leakage [34]. Within the electrolyser, membrane deterioration not only reduces efficiency but also elevates the likelihood of gas crossover; at the same time, sensor or control system malfunctions can prevent operators from recognizing emerging issues [35]. Collectively, these weaknesses highlight the necessity of thorough reliability evaluations, as an undetected leak or sluggish response can directly precipitate ignition [36].

To mitigate these risks, the industry relies on a combination of systematic analysis and multi-layered defense strategies. Analytical methodologies such as FMEA, FTA, and QRA provide the critical data needed to optimize system design and inform strategic decision-making [37]. On the operational front, safety is ensured through component redundancy, continuous real-time monitoring, and physical containment. These practices are further reinforced by condition-based maintenance programs that span the facility’s life cycle [38]. By linking these predictive reliability measures with tangible safety outcomes—most especially reducing the likelihood of leaks and ignition—operators can help ensure that green hydrogen systems are both technically resilient and socially acceptable [39].

1.2.1 Literature Review

PEMELs are central to green hydrogen production, but their reliability and safety remain key barriers to large-scale deployment. The literature has approached these challenges mainly through qualitative failure analysis, degradation studies, and system-level modeling.

Long-term degradation: metallic cation contamination from feed water and system hardware can markedly increase both ohmic and charge-transfer resistances, leading to voltage decay over prolonged operation. Sun et al. reported that a nine-cell stack operated for 7800 hr showed an average degradation rate of $35.5 \mu\text{V hr}^{-1}$ per cell, attributed to the impurities Ca, Cu and Fe occupying the ion-exchange sites within the membrane and catalyst layers; in particular, the performance was largely recoverable by dilute acid treatment, underscoring the reversible character of this contamination [40]. Investigations of catastrophic failures have also revealed significant safety risks. Millet [41] demonstrated that local perforation of the polymer electrolyte membrane can permit hydrogen and oxygen to mix and subsequently ignite, leading to the destruction of the entire stack within seconds. They characterized this behavior as a two-stage failure process:[41]

- the membrane is mechanically or chemically damaged [41]
- hydrogen and oxygen spontaneously react on catalyst surfaces, causing intense heat release that leads to destruction. [41].

The dynamic operating conditions associated with the integration of renewable energy sources introduce additional challenges for system reliability. In this regard, Papakonstantinou [42] investigated performance degradation under potential cycling between 1.4 and 1.8 V for more than 800 hours. The study showed that resistive losses—especially those at the anode–membrane interface—were substantially more significant than kinetic losses. Based on these findings, the authors

concluded that, although IrOx catalysts can withstand variable load profiles, the main factor contributing to the increase in irreversible resistance during dynamic operation is the chemical degradation of the membrane, which remains the principal reliability concern. [42].

Reliability modeling methodologies extend and reinforce these experimental findings. Vasilyev [21] constructed hybrid Petri net models for PEM systems that couple deterministic physical parameters (such as temperature, pressure, and voltage) with stochastic representations of component failures. Their dynamic reliability analysis showed that load cycling and purging have a pronounced impact on system lifetime, underscoring the importance of probabilistic frameworks for representing multistate degradation and maintenance behavior. More recent studies have also examined hydrogen crossover and associated safety hazards through advanced modeling techniques. Norazahar [43] introduced a Bayesian structural equation model to forecast membrane degradation and hydrogen permeation, pinpointing current density and anode-side water supply as key influencing factors. Their results demonstrated that membrane thinning and gas crossover can generate explosive H_2/O_2 mixtures, underscoring the need for reliable quantitative predictions to ensure safe operation.

Building on earlier analyses focused primarily on the fuel cell stack, recent studies have extended reliability evaluations to the balance-of-plant (BoP) and auxiliary subsystems. Ubale [44] identified 30 distinct failure modes in the water subsystem, with water quality deterioration and supply interruption exhibiting unavailability probabilities of 0.49 and 0.68, respectively. Complementary RAMS 2025 analyses characterized BoP failures, reporting unavailability values of 0.6134 for the water purification unit and 0.8784 for uncontrolled H_2/O_2 mixing, highlighting significant safety concerns [45]. Applying HAZOP and FTA to a 7 kW PEMFC installation, Gerbec [46] estimated an occurrence rate of three failures per year and an availability of approximately 98%, while also identifying potential hydrogen release and explosion hazards.

From a methodological perspective, Yuan [47] introduced a hierarchical Bayesian degradation model for PEMFC stacks that captures nonlinear voltage decay and yields probabilistic distributions of failure time. Tanrioven and Alam [48] applied Markov state-space models to PEMFC plants, incorporating derated operating states caused by failures in cooling, humidification, and hydrogen supply, and used fuzzy logic to characterize aging phenomena. Schuderer [49] examined the reliability of a 30 kW power converter, demonstrating that ICs, connectors, and MOSFETs are the primary contributors to failure rates. In contrast, lifetime-limited components such as fans and IGBTs require scheduled replacement.

Despite substantial prior research, validated failure rate data at the individual component level for PEMEL stacks remain unavailable. Addressing this data gap is the critical next step for enabling accurate, quantitative reliability assessments.

Gap and Thesis Contribution

In summary, most existing studies have examined PEMEL reliability using qualitative approaches and experimental degradation tests. While these investigations have been valuable for understanding the mechanisms of failure, they do not provide sufficient information on how often individual components fail. This

lack of quantitative, component-level failure data represents the main gap that this thesis seeks to address. This work aims to develop a framework for quantifying these failure rates. By filling this gap, the thesis advances beyond qualitative assessments to enable robust quantitative prediction, thereby facilitating safer system designs, more accurate reliability models, and more effective maintenance planning for the hydrogen industry.

1.3 Motivation and Research goals

The primary objective of this work is to establish a robust framework for predicting the reliability of PEMEL stacks that overcomes the widespread shortage of component-level failure data in the industry. Because green hydrogen technologies are still emerging, conventional reliability assessment approaches are constrained by limited field data. To address this limitation, the thesis proposes a framework that integrates two key data sources: employs Rahimi’s similarity-based approach to draw on existing PEMFC datasets, and utilizes the Fuzzy best worst method (FBWM) in combination with Bayesian Networks (BN) to translate qualitative expert judgments into quantitative reliability inputs.

The resulting failure rate predictions are critical for managing industrial-scale operations. They provide the necessary data to optimize maintenance schedules, ensure production efficiency, and mitigate severe safety risks, including the risk of stack destruction from gas crossover.

The overall goal is achieved through the following specific objectives:

1. Failure Mode Identification: Define and categorize the failure modes and root causes inherent to PEMEL stacks.
2. Data Adaptation: Develop a methodology to transfer relevant reliability data from PEMFCs to PEMELs using Rahimi’s similarity approach - New Sub-sea pump reliability prediction
3. Quantification: Utilize FBWM and BN to transform qualitative assessments into quantitative failure rate predictions.
4. Validation: Perform sensitivity analyses to compare and verify the accuracy of the predicted baseline failure rates.
5. Assessment: Determine the suitability and scalability of this integrated framework for future green hydrogen facilities.

1.4 Scope and Limitations

Given that this work establishes a reliability prediction framework in the absence of comprehensive failure records, the following boundaries and limitations apply:

1. **Reliance on Adapted Data:** Because long-term operational data for green hydrogen systems are limited, this study relies on expert judgment and data adapted from fuel cells. These predictions serve as a baseline and must be validated against actual field measurements as the industry matures.
2. **Qualitative Uncertainty:** The process of converting qualitative expert inputs (such as RIF scores and weighting factors) into quantitative data inevitably carries a degree of subjectivity.
3. **Technology Transfer:** Adapting data from PEMFCs to PEMELs rests on the assumption of structural similarity. Although effective, this method has limitations due to the distinct operating modes and degradation pathways of the two technologies.
4. **Partial Reliability:** The study is scoped to the PEM stack and select critical components. Therefore, the predicted values represent a specific subset of reliability, rather than a total system failure rate, which is the sum of all component failure rates.

1.5 Structure of the report

The thesis is structured as follows.

- **Chapter 2: Methodology** – Presents an overview of existing reliability prediction techniques, describes the specific methods employed in this work, and outlines the proposed approach for the PEMEL Stack.
- **Chapter 3: Results and Discussion:** The qualitative and quantitative findings obtained from the calculations are presented and examined in this section.
- **Chapter 4: Conclusion and Future Work**

METHODOLOGY

2.1 Reliability Engineering

Fundamentally, reliability engineering is the discipline of calculating the likelihood that a product will operate without failure under set conditions for a specific period [50]. This concept is defined by the following equation 2.1:

$$R(t) = P(T > t) = 1 - F(t) \quad (2.1)$$

Where,

$R(t)$ Reliability function at time t .

T Random variable for time to failure.

$P(T > t)$ Probability that failure occurs after time t .

$F(t)$ Cumulative distribution function (CDF) of T .

To achieve accurate predictions, the field synthesizes statistical analysis with physics-of-failure models. These methods are indispensable in industries ranging from consumer electronics to complex subsea and aerospace systems, where ensuring safety and minimizing warranty liabilities are primary operational goals [50].

2.1.1 What Reliability prediction ?

Reliability prediction is the practice of forecasting product performance in the absence of comprehensive field data. Because traditional statistical techniques struggle with sparse data—often resulting in unusable confidence intervals—engineers turn to Bayesian methods. These techniques reduce uncertainty by combining limited new data with prior knowledge from experts or historical records [51], [52]. This approach provides a necessary framework for managing uncertainty, allowing manufacturers to optimize warranty planning and anticipate design flaws early in the life cycle [51].

This predictive capability is supported by physics-of-failure analysis, which connects statistical probabilities to actual physical degradation (e.g., component fatigue), and by the inclusion of environmental covariates that influence durability [50] [53].

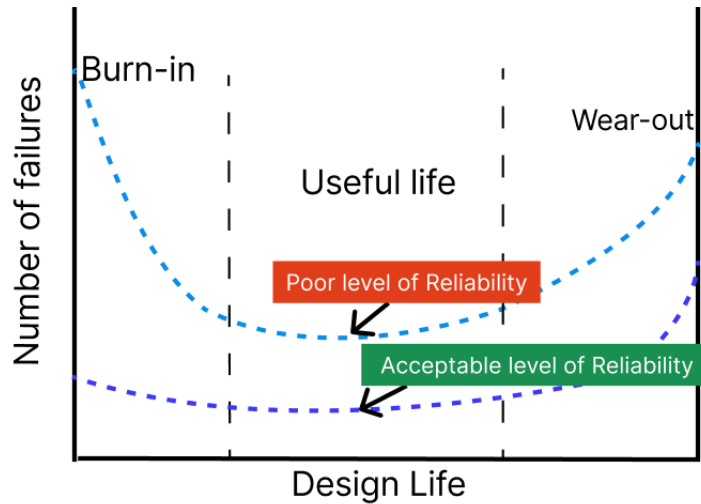


Figure 2.1: Bathtub curve and recreated from [54]

Mechanical products are often assumed to follow the bathtub curve of failure rate 2.1:

- Burn-in (Infant Mortality): A period of decreasing failures caused by early defects,
- Useful life: A period of stable, nearly constant failure rate,
- Wear-out: A final period of increasing failures due to age [50].

A solid grasp of these phases is essential for conducting data analysis. In the subsea sector, for example, components are typically replaced proactively before significant degradation occurs. Consequently, widely used reliability data sources such as OREDA [55] focus mainly on the "useful life" phase, where failures are modeled by an exponential distribution [51]. This allows engineers to anticipate wear-out mechanisms before they appear in operational settings [53]. In this way, reliability prediction provides both a statistical underpinning and a practical tool to control product performance under uncertainty.

At the heart of this field lies the concept of the "Bathtub curve," illustrated in Figure 2.1, which depicts how failure rates change over time. This model identifies three distinct operational stages: an initial "infant mortality" period marked by elevated failure rates arising from manufacturing or design flaws; a "useful life" stage during which the failure rate remains low and approximately constant; and a final "wear-out" stage, where failure rates increase again as components deteriorate with age [50]. This graphical model serves as a crucial resource for engineers and

managers, as it shows how reliability evolves across the product life cycle and clarifies why prediction techniques must be tailored to the product's current stage of use.

2.1.2 Prediction methods

Reliability prediction methods can be broadly classified into three categories [56]:

- **Bottom-up statistical methods** – rely on historical failure data, field statistics, or analytical modeling at the component level. Examples include MIL-HDBK-217F, Telcordia SR-332, IEC 61709, Siemens SN 28500, and OREDA, which provide baseline failure rates and adjustment factors for environmental and operational conditions.
- **Top-down similarity analysis methods** – estimate reliability by adjusting failure rates from predecessor or similar systems. Differences in environment, operation, or design are accounted for using reliability-influencing factors (RIFs), which may be continuous, categorical, or binary variables.
- **Physics-of-failure (PoF) methods** – use physical models of degradation mechanisms such as fatigue, corrosion, or thermal cycling. These are particularly useful for novel materials or applications where empirical data are limited [56]:

Machine learning/AI methods: Data-driven approaches, such as artificial neural networks, may supplement or replace conventional models, particularly when complex non-linearities or sparse data are present [57].

2.1.2.1 Prediction With Data

When sufficient field or test data are available, statistical and regression models are applied. The proportional hazards (PH) model is widely used [56]:

$$\lambda(t | X) = \lambda_0(t) \cdot \exp \left(\sum_{i=1}^n \beta_i X_i \right) \quad (2.2)$$

Where $\lambda_0(t)$ is the baseline failure rate, X_i are covariates (RIFs such as temperature, humidity, manufacturer), and β_i are parameters estimated from data. MIL-HDBK-217F can be seen as a special case of the PH model, where the predicted failure rate is :

$$\lambda = \lambda_0 \cdot \prod_{j=1}^m \pi_j \quad (2.3)$$

with π_j representing multiplicative adjustment factors for stress conditions.

The accelerated failure time (AFT) model assumes that covariates act multiplicatively on time:

$$T = T_0 \cdot \exp \left(\sum_{i=1}^n \gamma_i X_i \right) \quad (2.4)$$

where T is the failure time, T_0 is the baseline and γ_i are the covariate effects. Parametric life distributions such as exponential, Weibull, log-normal, or extreme-value distributions are often used in this framework.

2.1.2.2 Prediction Without Data:

In the early stages of a product's life cycle, there is usually little empirical information available. In these situations, Bayesian approaches are often favored [51], [52]. Bayes' theorem provides a way to integrate prior knowledge with a small amount of new data.

$$P(h | E) = \frac{P(E | h) P(h)}{P(E)} \quad (2.5)$$

Where,

h Hypothesis.

E Evidence (observed data).

$P(h)$ Prior probability of the hypothesis.

$P(E | h)$ Likelihood; probability of the evidence given the hypothesis.

$P(h | E)$ Posterior probability of the hypothesis given the evidence.

$P(E)$ Marginal probability of the evidence.

In the context of Weibull-distributed lifetimes, Ameri [51] introduced a Bayesian estimator for the scale parameter.

$$\alpha : \hat{\alpha} = \frac{\text{BesselK}_{-1+n}(v/2)}{\text{BesselK}_{-2+n}(v/2)} \quad (2.6)$$

where α and $\hat{\alpha}$ are scale parameters, BesselK_k denotes the modified Bessel function of the second kind of order k , n is the order index, and v is the argument of the Bessel functions, and the updated reliability function becomes:

$$R(t) = e^{-(t/\hat{\alpha})^\beta} \quad (2.7)$$

where $R(t)$ denotes the reliability at time t , t represents time, $\hat{\alpha}$ is the scale parameter and β is the shape parameter of the Weibull distribution. This approach reduces uncertainty when only a limited number of failures have been observed, leading to more realistic warranty forecasts than those derived using conventional methods [51], [52]. These works demonstrated that Bayesian updating progressively improves prediction accuracy as additional field data are collected.

2.2 Overview of Proposed Approach

In novel deployments where operational data are scarce, comparing diverse reliability prediction approaches builds confidence in failure rate estimates. Comparing multiple reliability prediction approaches provides validation and confidence bounds for failure rate estimates, addressing uncertainty in data-scarce reliability assessment while identifying the most suitable techniques for emerging technologies.

This study adapts three established methodologies to predict the reliability of the PEMEL Stack. Combining both qualitative and quantitative approaches to address the challenge of reliability assessment under data-scarce conditions. The First method is adapted from Rahimi's new system reliability prediction-based similarity approach, developed initially to predict failure rates of new subsea systems (pump) by comparing them with similar topside systems using reliability-influencing factors (RIFs) and expert judgment. However, their work identified this as an area requiring further development and validation [56]. The other two methods represent well-established approaches successfully applied in various engineering domains: fuzzy Best Worst Method (FBWM) and FMEA with risk-based weight allocation [58], [59]. (applied in manufacturing and process industries) and Bayesian networks for probabilistic reliability modeling [60].

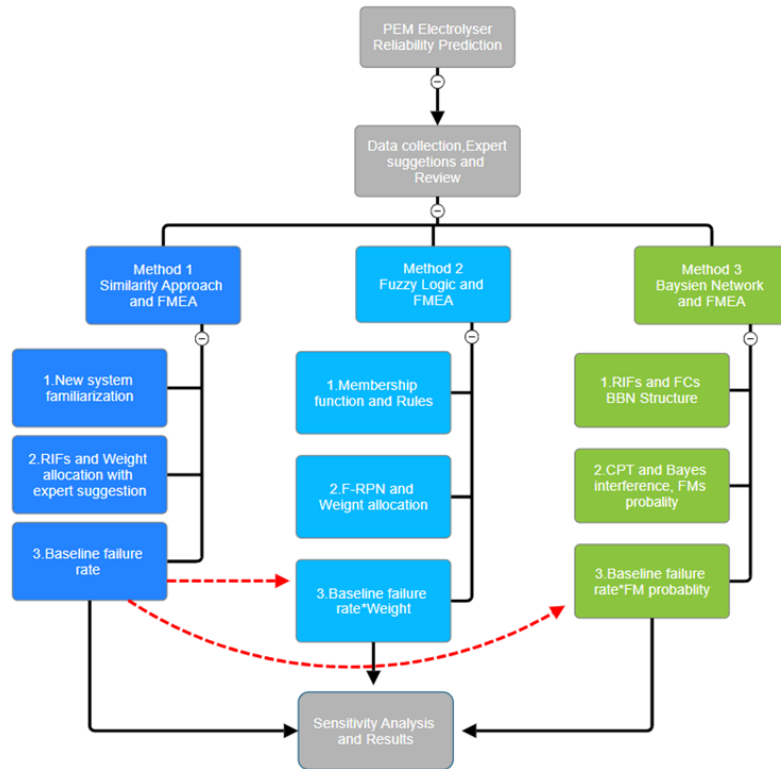


Figure 2.2: Proposed reliability quantification flowchart

2.2.1 Methodological sequence

The framework is sequential. Method 1 establishes a quantitative baseline using Rahimi's new system reliability prediction-based similarity approach as the found-

dational method to generate baseline failure rates. Methods 2 and 3 then use this baseline as input, applying fuzzy and probabilistic logic, respectively, to improve the prediction's accuracy.

- **Method 1: Rahimi's Similarity Approach**

A top-down, similarity-based approach is applied to adapt failure data from analogous systems (e.g., subsea pumps compared with similar offshore pumps) to the electrolyser context, particularly PEMEL, by leveraging methods previously used for PPEMFCs. Similarity factors such as differences in operating environment, load conditions, and material properties are taken into account. Using the FMEA of a PEMEL and PEMFC system, failure modes, causes, and reliability influence factors (RIFs) are identified. RIFs and weighting factors for the failure causes are then assigned to determine scaling factors for the various failure modes. Subsequently, the failure rates for the PEMEL stack are calculated using PEMFC failure-mode failure-rate data. The failure-mode rates are aggregated across the stack to obtain an overall system estimate, after which the baseline failure rate of the PEMEL stack is established.[56]

- **Method 2: FBWM and FMEA**

The Fuzzy Best–Worst Method (FBWM) is integrated with FMEA using the MATLAB Fuzzy Logic Designer. FBWM is employed to handle uncertainty and imprecision in expert evaluations by producing consistent and dependable weights for reliability-influencing factors (RIFs) based on pairwise comparisons between the best and worst criteria. These derived RIF weights are then fed into the fuzzy logic system, which computes Fuzzy Risk Priority Numbers (FRPNs) for each failure mode. This process yields a weighting factor that modifies the baseline failure rate, leading to a more refined, risk-adjusted reliability metric. The FMEA and the reliability influence diagram are identical to those used in Method 1.[58], [59].

- **Method 3: Bayesian Networks**

This approach maps FMEA causal chains into a probabilistic graphical model using GeNIe software. Expert probabilities are propagated through Conditional Probability Tables (CPTs). The model calculates the probability of specific failure scenarios and then determines their weights. Those weights are then multiplied by the baseline rate to determine scenario-specific failure rates. The third method maps causal dependencies via directed links. Probabilities assigned to RIFs are propagated through Conditional Probability Tables (CPTs) to update failure mode probabilities [60]. The model employs a scenario-based logic: if any single scenario is valid, the output failure mode is triggered. This allows complex expert reasoning to be integrated into the calculation. Finally, the updated probability derived from the network is multiplied by the baseline failure rate to generate a specific, scenario-based failure rate.

For the computational analysis, MATLAB's Fuzzy Logic Designer was used to calculate FRPN values, GeNIe (academic license) was employed to construct

Bayesian networks, a Monte Carlo simulation was carried out to ensure robustness of the three methods, and Microsoft Excel was used to generate bar charts for comparative analysis of the failure modes.

This multi-layered framework integrates empirical evidence with adaptive probabilistic and fuzzy reasoning to improve prediction accuracy. The method employs three complementary methods to estimate the reliability of the PEMEL stack. Method 1 - Rahimi's Similarity approach, to derive baseline failure rates from comparable systems, thereby providing a robust empirical foundation. Method 2 applies FMEA in combination with the Fuzzy Best–Worst Method to incorporate expert uncertainty and to obtain consistent weights for each reliability factor, thus refining the initial failure rate estimates. Method 3 develops an FMEA-based Bayesian network to model dependencies among failure modes and to update their probabilities as new data become available. Collectively, this layered strategy ensures that reliability predictions are grounded in real-world observations while remaining flexible and responsive to evolving operational information.

However, this layered approach enhances accuracy by combining empirical data with expert reasoning, but it also increases complexity. Key challenges include the intensive effort required to populate Bayesian CPTs and the potential bias inherent in defuzzification choices. Furthermore, the accuracy of the baseline depends heavily on the relevance of the PEMFC materials data.

As depicted in Figure 2.2, the study aims to cross-reference the results of these three techniques. Alignment between the methods provides the necessary validation for reliability estimates in data-scarce environments, responding to Rahimi's call for the practical testing of similarity-based models in new energy sectors [54]. [56].

In the following subsections, three methods are explained individually to highlight their specific principles and applications.

2.3 FMEA

Failure Mode and Effects Analysis (FMEA) is a systematic reliability and risk assessment tool that was first introduced in U.S. military standards in 1949 and later refined by Boeing in 1956 for aerospace applications. Since then, it has been widely adopted across industries such as automotive, aerospace, and energy systems as a structured methodology to identify potential failure modes, their causes, and their effects on system performance. By documenting these risks early in the design and development process, FMEA enables preventive actions that improve product dependability and operational safety throughout the life cycle [61], [62].

Traditional FMEA evaluates each failure mode using three parameters: Severity (S), Occurrence (O), and Detection (D). The product of these values yields the Risk Priority Number (RPN), which is used to rank and prioritize risks for mitigation. High RPN values (shown in Figure 2.3) indicate critical risks that require immediate attention, while lower values represent less urgent issues. Despite its widespread use, conventional FMEA has limitations, including reliance

on subjective expert judgment, equal weighting of risk parameters, and inability to capture dependencies between failure events [61], [62].

Failure Mode and Effects Analysis (FMEA)

System / Item / Process Step	Potential Failure Mode	Potential Failure Effects	Severity	Causes	Occurrence	Current Controls	Detection	RPN	Recommended Actions
Name, ID number, etc.	How could the system / item / process potentially fail?	Consequential impact on other systems, departments, etc.		All contributing factors		Prevention / Detection		Risk Priority Number	Steps required to reduce severity, occurrence, and detection

Figure 2.3: FMEA Template reproduced from [63]

Types of FMEA commonly applied in engineering include:

- Design FMEA (D-FMEA): Focuses on product reliability during the design phase.
- Process FMEA (P-FMEA): Examines potential failures in manufacturing and assembly processes.
- System FMEA (S-FMEA): Considers interactions among subsystems to ensure overall system dependability [64].

Despite its widespread application and structured approach, conventional FMEA faces distinct limitations. It relies heavily on subjective expert judgment, weighs all risk parameters equally, and often fails to account for the complex dependencies between different failure events. In this thesis, the reliability modeling approach is specifically adapted from Rahimi et al. [54]. While their original framework compared topside and subsea pumps, this study applies their exact procedural steps and equations to transfer reliability data from PEM fuel cells to PEM water electrolyser systems

2.4 Rahimi's Similarity Approach

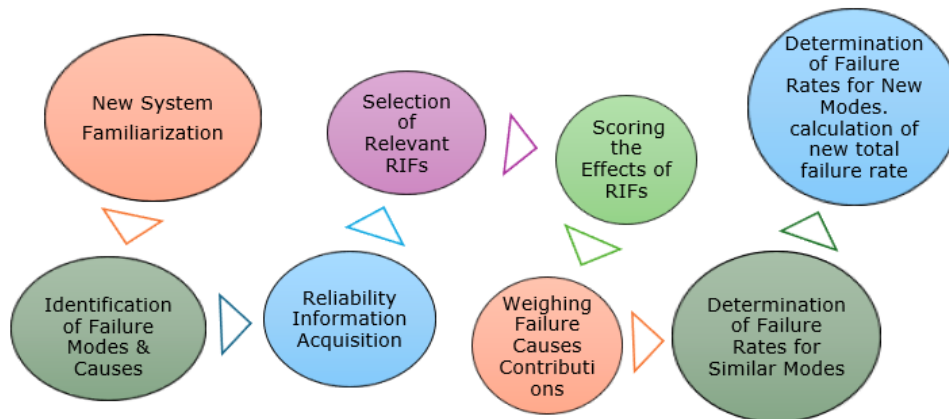


Figure 2.4: Similarity-Based Rahimi's method - steps

The Reliability prediction approach used in this PhD thesis is adopted from Rahimi[56], who initially developed a stepwise method to predict the failure rate of a new subsea pump system. In this thesis, the detailed step-by-step methodology and associated equations are employed and implemented for both PEMFC and PEMEL systems.

2.4.1 Familiarization of a New system

The new study of the system must be clearly worked out, considering its physical constraints, operational requirements, and environmental factors. It should be structured hierarchically, with subsystems and maintainable components; maintainable items can be repaired or replaced over time. Following the standards guidelines, which emphasize the identification of critical elements and the documentation of key characteristics such as materials, load capacity, and other essential data through drawings and reports.

2.4.2 Identification of failure modes and causes

A Failure Modes and Effects Analysis (FMEA) should be performed to identify potential failure modes and their causes for the new system and its components. If an FMEA study already exists for the new system components, it should be reviewed to determine further the failure modes and causes associated with each new component. Once these have been identified, the next step is to determine the reliability-influencing factors (RIFs) that contribute to each cause. One or more RIFs may lead to a given failure cause, and likewise, multiple causes may contribute to a specific failure mode.

Finally, the overall failure rate is determined based on the contribution of each failure mode to the total failure. This allows the identification of which potential failure modes should be analyzed in detail, together with their corresponding causes and mechanisms, across all operating conditions. The detailed methodology is illustrated in Figure 2.4 (a).

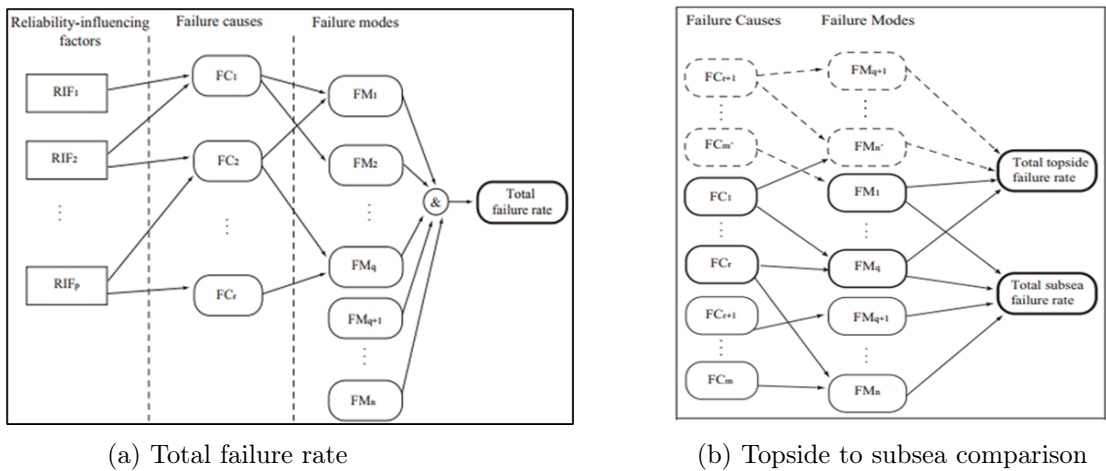


Figure 2.5: RIFs to Total failure rate reproduced from [56]

2.4.3 Comparison of the new and known system

Similar known system data from established systems are required to determine the failure rates, modes, and mechanisms of the new system. In addition, the database is used to identify the maintainable items and subsystems of the new system. In this study, because the system under consideration is a subsea pump, the author employed topside system data from the OREDA database [55]. Other data sources are also available, such as MechRel, and extensive data exist for electronic components.

Failure modes can differ between the new and similar systems used for comparison. All data must be recorded. The solid thick-bordered lines are standard for both systems, while the dashed and light-bordered lines belong to topside and subsea, respectively.

total failure, it denoted as $\lambda^{(T)}$.

Where $\lambda^{(T)}$ is the constant failure rate for failure mode FM_i

FM_i for $i = 1, 2, \dots, n$, so when failure modes are disjoint

$$\lambda^{(T)} = \sum_{i=1}^n \lambda_i^{(T)} \quad (2.8)$$

Introducing vector a_i is n failure modes

$$\lambda^{(T)} = a_i \lambda^{(T)} \quad (2.9)$$

2.4.4 RIF's selection and scoring

Scale	Perceived Effect
-3	Much lower effect
-2	Significantly lower effect
-1	Slightly lower effect
0	No difference
1	Slightly higher effect
2	Significantly higher effect
3	Much higher effect

Table 2.1: Scale for evaluating perceived effect differences

Category	RIFs
Design and manufacturing	System structure
	Materials
	Dimensions
	Loads and capacities
	Quality (manufacturing process, installation, logistics, assembly, ...)
Operational and maintenance	Functional requirements
	Time in operation
	Mechanical constraints
	Frequency of maintenance
	Maintenance policy
	Accessibility for maintenance
	Type and quality maintenance
Environmental External	Temperature
	Location of operation
	Pressure
	Corrosive environment
	Pollution
Environmental Internal	Pressure
	Sand particles in the fluid
	Chemical content

Figure 2.6: RIF selection Example

Table 2.1 and Figure 2.6 reproduced from [56] In short evaluating the different RIFs leading to one or more causes (FC_j)

RIFs are the key to identifying the system reliability, where in the system the reliability of the systems is affected, taking into account the generic RIFs, which gives insights about all levels, from design, manufacturing, operation, maintenance, to environmental. Kind of the whole value chain of the product, to system, then to operation.

For the new system, the RIF are selected by experts, and they rank according to their criticality for each because that leads to failure. each failure causes a comparison of all pairs of RIFs, e.g. $[\text{RIF}]_{i,K1}$ and $[\text{RIF}]_{i,K2}$ then assign the weight ε_{kj} regarding how RIFs influence to a specific failure

$$\sum_{k=1}^p \varepsilon_{kj} \quad (2.10)$$

Influenced RIFs must be overtly identified when comparing with both systems. For the topside is $\nu_{kj}^{(T)}$ and subsea is $\nu_{kj}^{(S)}$

$$\nu_{kj}^{(T)} = \begin{cases} 1, & \text{if RIF}_k \text{ has effect on (topside) failure cause FC}_j \\ 0, & \text{if RIF}_k \text{ has no effect on (topside) failure cause FC}_j \end{cases} \quad (2.11)$$

$$\nu_{kj}^{(S)} = \begin{cases} 1, & \text{if RIF}_k \text{ has effect on (subsea) failure cause FC}_j \\ 0, & \text{if RIF}_k \text{ has no effect on (subsea) failure cause FC}_j \end{cases} \quad (2.12)$$

The influence score $\eta_{kj}^{(S)}$ indicates how strongly the RIFs influences the failure cause $[FC]_j$

The number of RIFs influencing the subsea is

$$\sum_{k=1}^p \nu_{kj}^{(S)} \quad (2.13)$$

2.4.5 Weighting the contribution of FCs to FMs

Assumed that the failure causes are as “disjoint” as possible, which means that the different effects of two or more failure causes in a failure mode should not be dominated by the combined effect of the failure causes. The failure mode might carry different weights than the topside system.

$$w_{ji}^{(T)} \quad (2.14)$$

The causes of failure are mapped to their corresponding failure modes in the topside system. Using data obtained from OREDA and applying expert judgment, the associated weights for the new subsea system can be determined. These are represented as the sum of the weights assigned to each failure mode.

$$\sum_{k=1}^p w_{ji}^{(S)} = 1 \quad \text{for } i = 1, 2, \dots, q \quad (2.15)$$

2.4.6 Similar mode failure rate estimation

The final failure rate of the subsea system is expressed as the topside failure rate and the quantified parameter calculated in the previous steps.

$$\lambda_i^{(S)} = \nu_i^{(T)}(1 + k_i) \text{ for } i = 1, 2, 3, \dots, q \quad (2.16)$$

Where $k_i > -1$ is a consonant scaling factor that is calculated in the next steps. As $\lambda_i^{(S)}$ depends independently on the failure causes of the failure mode FM_i and their weights $w_{ji}^{(S)}$, the scaling factor must also depend on the weights

$$w_{ji}^{(S)} = \Pr(\text{the failure is caused by } FC_{ji} \mid FM_i \text{ has occurred}) \quad (2.17)$$

k_i also depends on the various failure-causing effects on the failure modes compared with the topside system. This is quantified as a weighted average of scores of the RIFs that effect $[FC]_j$

$$\bar{\eta}_J = \sum_{k=1}^p \varepsilon_{k_j} \nu_{k_j}^{(s)} \frac{\eta_{k_j}}{3} \quad \text{for } j = 1, 2, \dots, r \quad (2.18)$$

The scaling factor is calculated as:

$$k_i = c_i \cdot \sum_{j=1}^r w_{ji}^{(S)} \bar{\eta}_j \quad \text{for } i = 1, 2, \dots, q \quad (2.19)$$

it is first assumed that the failure rate, $\lambda_i^{(S)}$ can be delimited with respect to failure mode $[FM]_i$

$$\lambda_i^{(S)} = \left[\lambda_{Low,i}^{(S)} \lambda_{High,i}^{(S)} \right] \quad (2.20)$$

The boundary values are based on topside failure rate $\lambda_i^{(T)}$ for failure mode $[FM]_i$

$$c_i = \begin{cases} 1 - \theta_{\min,i}, & \text{when } \sum_{j=1}^{v_i^{(S)}} w_{ij}^{(S)} \eta_j < 0, \\ 0, & \text{when } \sum_{j=1}^{v_i^{(S)}} w_{ij}^{(S)} \eta_j = 0 \quad \text{for } i = 1, 2, \dots, q, \\ \theta_{\max,i} - 1, & \text{when } \sum_{j=1}^{v_i^{(S)}} w_{ij}^{(S)} \eta_j > 0. \end{cases} \quad (2.21)$$

$c_i = 1 - \theta_{\min,i}$ and for maximum case $c_i = \theta_{\max,i} - 1$. The expression for c_i is then written as Finally, the equation becomes

$$\lambda_i^{(S)} = v_i^{(T)}(1 + k_i) \text{ for } i = 1, 2, 3, \dots, q \quad (2.22)$$

2.4.7 New failure mode rate estimation

The total failure rate is calculated as the sum of all failure rates for the failure modes given as

$$\lambda_{\text{Total}}^{(S)} = \sum_{i=1}^n \lambda_i^{(S)} \quad (2.23)$$

2.5 FBWM and FMEA

2.5.1 Fuzzy Logic as a Foundation

Fuzzy logic provides a mathematical framework to handle imprecision and uncertainty in human reasoning. Unlike classical binary logic, which forces decisions into rigid true/false categories, fuzzy logic allows partial truth values between 0 and 1. This makes it particularly suitable for the prediction of the reliability of new components, where historical data are scarce and expert judgments are expressed in linguistic terms such as “low,” “moderate,” or “high” rather than precise numerical values.

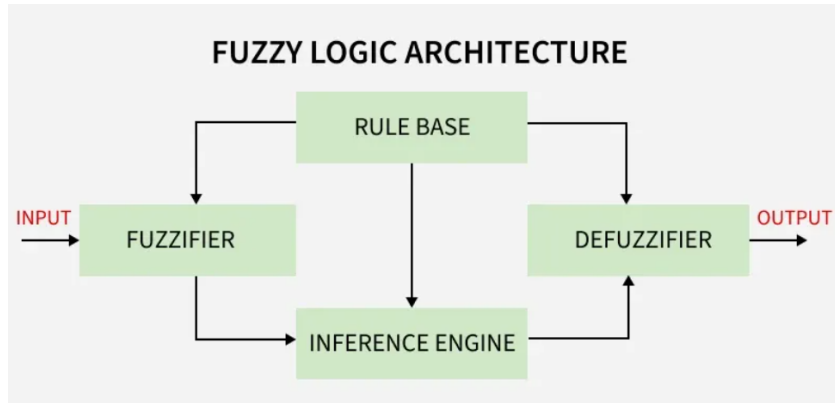


Figure 2.7: Fuzzy Logic reproduced from [65]

In reliability engineering, fuzzy rule-based systems have been widely applied to emulate expert reasoning and to improve the prioritization of failures in complex systems [66]. More recent studies confirm that fuzzy logic remains a powerful tool for modeling subjective evaluations in FMEA, allowing decision-makers to capture the vagueness inherent in severity (S), occurrence (O) and detection (D) ratings [67]. Formula (example for severity as fuzzy set):

$$S = \text{Triangular}(a, b, c) \quad (2.24)$$

Where represent the lower, modal, and upper bounds of severity.

The fuzzy Risk Priority Number (RPN) is then derived by combining fuzzified inputs through fuzzy inference rules and defuzzification

$$RPN_{\text{fuzzy}} = f(S, O, D) \quad (2.25)$$

2.5.2 Fuzzy-BWM

The Best Worst Method (BWM) is a multi-criteria decision-making technique that determines the relative importance of criteria by comparing the “best” and “worst” attributes. Its fuzzy extension (FBWM) integrates fuzzy logic into the weighting process, allowing experts to express judgments in linguistic terms rather than in crisp numerical terms. This enhances flexibility and accuracy when dealing with uncertainty in complex decision environments, especially in predicting the reliability of new components, where expert input is the primary source of knowledge and is represented by triangular fuzzy numbers (TFN).

Table 2.2: Linguistic terms and their corresponding TFNs

Linguistic Term	TFN (l, m, u)
Equal importance	$(1, 1, 1)$
Slightly more important	$(2, 3, 4)$
Moderately more important	$(4, 5, 6)$
Strongly more important	$(6, 7, 8)$
Very strongly more important	$(8, 9, 9)$

FBWM has been highlighted as an effective way to reduce inconsistency in pairwise comparisons and to reflect better human reasoning in risk prioritization [68]. Recent developments emphasize that FBWM strengthens transparency and robustness in decision-making, particularly when applied to engineering and supply chain risk contexts [69]. Formula (weight optimization problem):

$$\min_{\mathbf{w}} \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \quad (2.26)$$

where w_j are the weights of the criteria, w_B and w_W denote the best and worst criteria

subject to:

$$\text{subject to: } \sum_{j=1}^n w_j = 1, \quad w_j \geq 0 \quad (2.27)$$

2.5.3 Integrating FBWM with FMEA

Failure Mode and Effect Analysis (FMEA) is one of the most widely used techniques to identify and prioritize potential failure modes in engineering systems. Traditionally, FMEA calculates a Risk Priority Number (RPN) as:

$$RPN = S \times O \times D \quad (2.28)$$

However, conventional FMEA has been criticized for several limitations: it assumes the same importance of the three parameters, produces identical RPN values for different risk scenarios, and struggles to incorporate uncertainty into expert judgments [66], [68].

By integrating FBWM with FMEA, these shortcomings can be addressed. FBWM provides a structured way to assign relative weights to severity, occurrence, and detection, reflecting their actual importance in specific contexts. When combined with fuzzy logic, this hybrid approach allows incorporating subjective expert knowledge while modeling uncertainty more effectively. As demonstrated in engineering and maritime risk studies, the fuzzy-Bayesian and fuzzy-rule-based extensions of FMEA improve the accuracy of failure prioritization while maintaining transparency and usability [66]–[68]. Weighted fuzzy RPN formula:

$$RPN_{fuzzy} = w_S \cdot S + w_O \cdot O + w_D \cdot D \quad (2.29)$$

This hybrid approach is particularly useful for the prediction of the reliability of new components, where empirical failure data is limited and expert-driven assessments must be systematically incorporated.

2.5.4 Advantages and Disadvantages

Advantages and Disadvantages Combining the FBWM with FMEA provides several important benefits. By using fuzzy logic, it can better handle the uncertainty and vagueness that are naturally present in expert opinions. Through pairwise comparisons, it also allows for more consistent and objective weighting of the factors that affect system reliability, leading to more accurate and transparent prioritization of failure modes compared with standard FMEA. This makes the method especially useful for new or emerging technologies, such as PEM electrolyzers, where there is limited historical failure data.

On the other hand, the approach also has some limitations. It requires more advanced mathematical modelling and greater computational effort than conventional FMEA. Moreover, it still relies strongly on the quality and consistency of expert judgments, which may introduce subjective bias. In addition, the method can encounter scalability issues as the number of fuzzy rules increases combinatorially with the number of input parameters.[66]–[69]

2.6 Bayesian Network and FMEA

A Bayesian Network (BN), that uses Bayes' theorem to model relationships between variables and compute prior and posterior probabilities. A prior probability is the initial belief about the occurrence of an event, while a posterior probability is the updated probability after observing new evidence. This dynamic update capability makes BNs effective for reasoning under uncertainty.

Each node in the network contains a Conditional Probability Table (CPT), which defines the probability distribution of the variable given the states of its parent nodes.

Bayesian Networks (BNs) are probabilistic graphical models that capture cause-and-effect relationships among system variables. In a reliability context, each node in the network represents a factor, such as a reliability driver, failure cause, or failure mode. At the same time, the directed edges describe how these variables influence one another. The strength of these dependencies is expressed through conditional

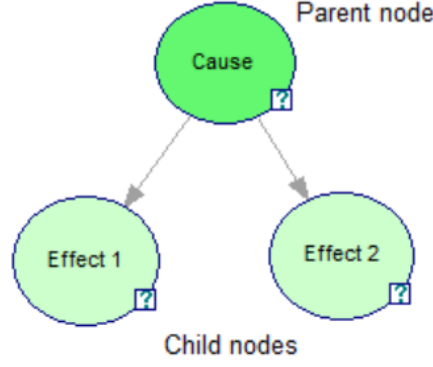


Figure 2.8: Bayesian Belief Network redrawn based on [70]

probability distributions, which together form the joint probability of the system.[52], [71]

The overall distribution can be written as:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i \mid Pa(X_i)) \quad (2.30)$$

where X_i is a variable in the network and $Pa(X_i)$ denotes its parent nodes. This formulation allows complex reliability problems to be broken down into smaller conditional relationships that are easier to analyze.[71]

2.6.1 Data-driven BNs

When historical or experimental data are accessible, conditional probabilities can be inferred directly from observed failure records. For example, given degradation measurements for a new component operating under different conditions, these probabilities may be derived through statistical analysis. Bayes' theorem then provides a systematic framework for revising these probabilities as additional evidence or data are collected [52], [71].

$$P(H \mid E) = \frac{P(E \mid H) \cdot P(H)}{P(E)} \quad (2.31)$$

Here, H represents a hypothesis (e.g., component failure), while E represents observed evidence (e.g., abnormal operating conditions).

2.6.2 Expert-driven BBNs

For novel components, historical data are often limited or absent. In these situations, probabilities are derived from expert opinion or sourced from published studies. Qualitative descriptors such as “low,” “medium,” or “high” can be mapped to numerical probability values, enabling reasoning under uncertainty even when data are sparse [66], [67].

Bayesian techniques offer a systematic framework. The general procedure is as follows with expressions.

Define prior distributions for the probability of component failure based on expert judgment or similar equipment. For example, the probability of component failure θ can be modeled as a Beta distribution:

$$\theta \sim \text{Beta}(\alpha, \beta) \quad (2.32)$$

where α and β are parameters reflecting previous belief [72].

Model system scenarios using annotated diagrams (e.g., UML or sequence diagrams) to capture usage profiles and component interactions [71]. 3. Calculate the probability of system failure by combining component priors with scenario probabilities. For a system with (N) components and (K) scenarios:

$$P_{sys} = 1 - \sum_{j=1}^K p_j \prod_{i=1}^N (1 - \theta_i)^{bp_{ij}} \quad (2.33)$$

Where p_j is the probability of scenario (j), (θ_i) is the probability of failure of component (i) and bp_{ij} is the number of busy periods for component (i) in scenario (j) [71].

Update the reliability prediction as test data becomes available. If (n) tests yield (r) failures, the posterior distribution becomes:

$$\theta \mid \text{data} \sim \text{Beta}(\alpha + r, \beta + n - r) \quad (2.34)$$

This Bayesian updating reduces uncertainty over time and refines reliability estimates [52].

Bayesian networks capture uncertainty in expert judgments and limited data, allow dynamic updating of reliability predictions as new evidence emerges, and integrate qualitative FMEA parameters into a probabilistic framework [66], [71]

The application of Bayesian networks requires expert input for prior probabilities, which may introduce bias into the model; it can also become computationally intensive when dealing with large systems containing many nodes, and the underlying assumptions of independence and regularity may not always hold in practice [67], [71]

RESULTS AND DISCUSSION

3.1 Proposed Model for quantification

Rahimi's top-down, similarity-based approach [56] represents an initial step toward familiarizing a new system, which they applied specifically to a novel subsea pump system using data from a topside pump in the OREDA database [55]. Similarly, this thesis focuses on the green hydrogen production system, with particular attention to the PEMEL stack, and assesses its similarity to a PEMFC stack. The unit diagrams for both systems are presented below in Figures 3.1 and 3.2

PEMFCs were selected as the reference system primarily for comparison, as they exhibit material, structural, and stress similarities with PEM electrolyzers. Despite operating in opposite electrochemical modes, both stacks employ Nafion membranes, Pt catalysts, and titanium/carbon bipolar plates, and are subject to analogous mechanical, electrochemical, and thermal loads. This strong isomorphism, confirmed in multiple studies, supports [17], which provides a basis for considering PEMFC reliability insights in the PEMEL context. Therefore, this study examines whether such a comparative approach can be applied meaningfully in the absence of PEMEL-specific reliability data.

Based on the pump inventory diagram from OREDA, analogous inventory diagrams were developed for PEM Fuel cell and electrolyser units. [55]

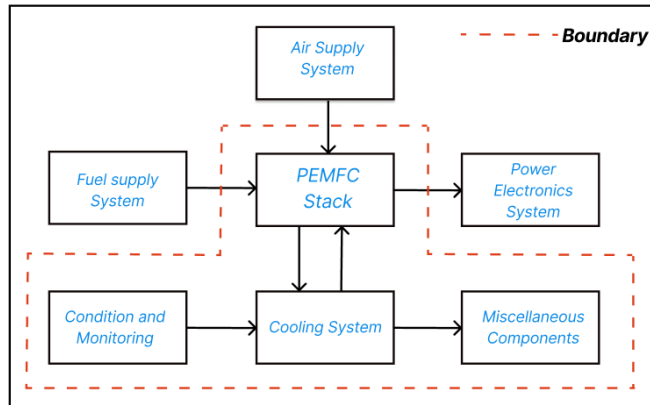


Figure 3.1: PEM Fuel cell unit

A simplified block diagram of a typical PEM Fuel Cell unit is presented in Figure 3.1, which defines the system boundary commonly adopted in reliability analyses. The purified hydrogen from the fuel supply subsystem and the filtered air from the air supply subsystem are fed into the PEMFC stack, where the electrochemical reaction occurs: hydrogen is oxidized at the anode and oxygen is reduced at the cathode, generating electricity, water, and heat. Within the system boundary (dashed red line), the stack is supported by a cooling system for thermal management, condition monitoring for operational oversight, and miscellaneous auxiliary components. The power electronics subsystem processes the electrical output before delivery to the external load, while components outside the boundary are classified as Balance of Plant (BoP)

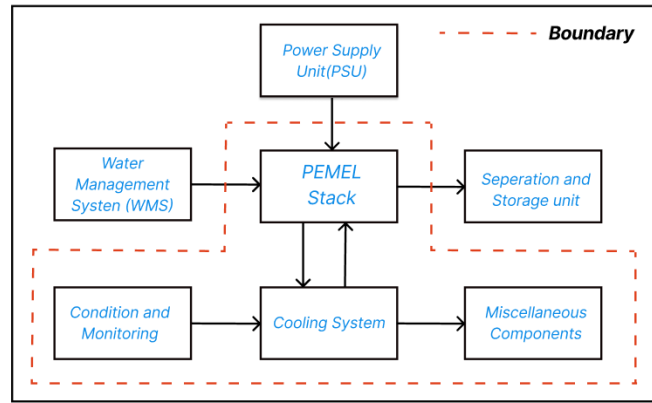


Figure 3.2: PEM electrolyser unit

Figure 3.2 Simplified block diagram of a PEM electrolyser unit with the system boundary typically used in reliability studies. Deionized water from the water management system (WMS) and electrical power from the power supply unit (PSU), usually sourced from renewables, are fed to the PEMEL stack. Inside the dashed boundary, water is split into hydrogen (cathode) and oxygen (anode) by electrolysis. The stack is supported by cooling, condition monitoring, and auxiliary components, while product gases are sent to the downstream separation and storage unit for hydrogen purification and compression. Components located outside the system boundary are referred to as the balance of plant (BoP).

3.2 FMEA of a PEM stack

Electrolyzer and fuel cell FMEA analysis mainly focused on the balance of plant and electrolyser, particularly. From that, and various degradation mechanism literature sorted out specifically for the PEM Stack. Traditional FMEA focused on identifying failure modes, causes, and RPN. This study, by [56], focused only on failure modes and causes. Then, adding to those, what reliability-influencing factors affect the failure causes of the failure modes? The three most important failure modes among the fuel cell and electrolyser stacks were taken from various literature related to degradation studies (membrane, catalyst, etc) [27] [42] [35] [41][26] , FMEA of PEMEL and PEMFC [38] [31] [19] finally the comparison

studies of both [17] summarized and failure modes of PEMFC and PEMEL are tabulated in 3.1 and relevant failure causes, and RIFs are in the Table 3.2

Table 3.1: Comparative failure modes in PEMFC vs PEMEL stack components

Failure Mode (FM)	PEMFC[19]	PEMEL [27]
Membrane Degradation (MD)	Membranes are highly sensitive to humidity fluctuations and thermal cycling, which weaken mechanical stability. Contaminants and metal-ion migration further reduce proton conductivity, promoting pinhole formation and thinning. Thus, membrane performance is strongly governed by operating conditions and feedwater/gas purity.	Membrane degradation is driven by thinning under compressive and vacuum stresses, cation contamination from feedwater, and accelerated chemical attack at high current densities. These factors underscore the critical role of operating load and water/gas purity in preserving membrane integrity.
Catalyst Degradation (CD)	Catalysts undergo Pt dissolution, migration, and agglomeration during voltage cycling, while contaminants from humidifiers or gas impurities reduce activity. Thus, operating conditions and gas purity critically determine the long-term reliability of the catalyst.	IrO ₂ and Ru catalysts dissolve under strong oxidative conditions, with degradation accelerated by water impurities. Dynamic loading further destabilizes the catalyst layer, underscoring the critical influence of the operating profile and stream purity.
Bipolar Plate Corrosion (BPC)	Bipolar plates corrode when oxide films deteriorate, releasing multivalent cations. Poor material choice or manufacturing flaws exacerbate this vulnerability, highlighting material selection, process quality, and operational stresses as key determinants of reliability.	Titanium bipolar plates are vulnerable to hydrofluoric acid formed during ionomer degradation; harsh conditions and weak coatings accelerate passivation and corrosion. Thus, water purity, coating durability, and operating environment emerge as key reliability risk factors.

Failure mode (FM)	Failure cause (FC)	RIFs
MD – Membrane degradation	DA – Degradation & ageing	OP – Operating conditions
	MS – Mechanical stress	WP – Water purity
	CT – Contaminants & impurities	OP, WP, GP – Gas purity
CD – Catalyst degradation	DA – Degradation & ageing	OP – Operating conditions
	CP – Chemical processes	GP – Gas purity, MS
	CT – Contaminants & impurities	OP, WP, GP
BPC – Bipolar plate corrosion	CP – Chemical processes	MS – Material selection
	MD – Manufacturing defects	MQ – Manufacturing quality
	CT – Contaminants & impurities	OP, WP, GP

Table 3.2: Identified FMs, FCs, and RIFs

3.3 Expert inputs and assumptions

Expert inputs

1. Proportion (P_i) of failure modes that lead to the stack failure of PEMFC
2. RIF's scoring for the effects cause to failure modes, ($RIF_{FC,j}$)
3. Failure causes proportions for the failure modes, ($FC\%$)
4. TFN allocation of fuzzy Best-Worst Method for RIFs, in table (3.6)
5. Bayesian belief network input probability of RIFs (true,false), in (3.9)

Assumptions

1. Rules of fuzzy membership functions attached in the appendices Pages:61 - 66
2. CPT tables of the Bayesian network are attached in the appendices page: 68

3.3.1 Proportion-based allocation of the total failure rate

Based on the literature for automotive applications, where fuel cell stacks operate in a dynamic environment, the operating hours range from 5000 to 8000 hours. For a stationary application, 20000-40000 hours are the target. In this thesis, a conservative value is chosen for 20000 hours [73], [74] to find the failure rate of the fuel cell stack according to Expert, given the proportions of the identified failure modes shown in table 3.3

A detailed step-by-step calculation of the baseline stack failure rate of the electrolyser is presented below.

Failure Modes	Proportion P_i
Membrane Degradation	40%
Catalyst Degradation	30%
Bipolar Plate Corrosion	15%
Others	15%

Table 3.3: Proportional allocation of failure modes – Expert recommended

$$\lambda_{FC} = \frac{1}{MTTF_{FC,Stack}} h^{-1} \quad (3.1)$$

where,

- λ_{FC} is Total failure rate of PEMFC
- $MTTF_{FC,Stack}$ is the Mean time to failure of PEMFC.

$$\lambda_{FC,i} = \lambda_{FC} \cdot P_i \quad (3.2)$$

$$\begin{aligned} \lambda_{FC,MD} &= 2 \times 10^{-5} h^{-1} \\ \lambda_{FC,CD} &= 1.5 \times 10^{-5} h^{-1} \\ \lambda_{FC,BPC} &= 7.5 \times 10^{-6} h^{-1} \\ \lambda_{FC,others} &= 7.5 \times 10^{-6} h^{-1} \end{aligned}$$

$$\lambda_{FC} = \sum_{i=1}^n \lambda_{FC,i} \quad (3.3)$$

Where $\lambda_{FC,i}$ denotes the PEMFC failure rate of i failure modes and P_i is the failure mode proportions

The Fuel cell failure rate is $5 \times 10^{-5} hr^{-1}$, this with four failure modes. Since the study carries out the three main failure modes, MD,CD, and BPC ,except for others. The calculated baseline failure rate below will be used as input for the similarity-based Rahimi Method.

$$\lambda_{FC,Stack} = 4.25 \times 10^{-5} h^{-1}$$

3.4 Similarity-based Rahimi approach for PEM Stack

- **Step 1:** New system familiarization.

A detailed description of the PEMEL and PEMFC is discussed in Section 3.1

- **Step 2:** As documented in Section 3.2, the FMEA was applied to identify the relevant failure causes and modes. In Step 4, the critical Reliability Influencing Factors (RIFs) were selected, and subsequently a RIF diagram 3.3 was modeled to capture their interdependencies.

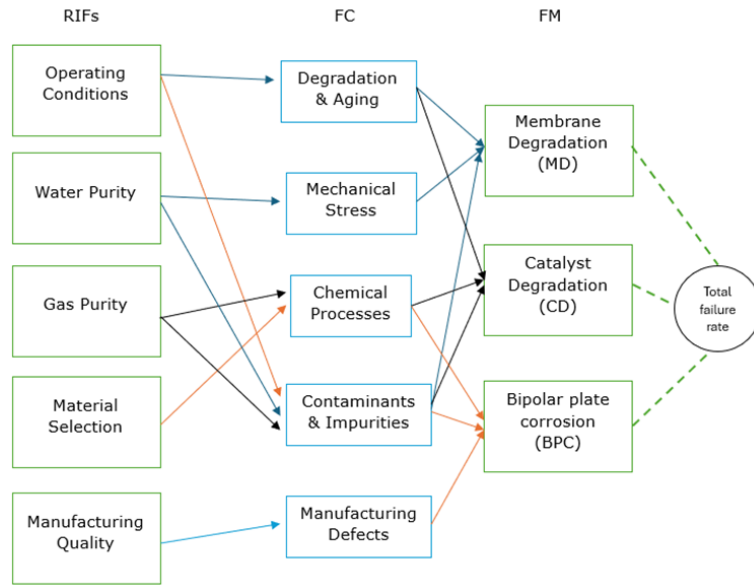


Figure 3.3: Reliability influence(RIF) diagram adopted from [56]

- **Step 3:** Obtaining Reference Failure Rate Data : the target failure rates of the modes were calculated in Section 3.3.1 .Here is presented the stack failure rate of the fuel cell shown below (reference)

$$\lambda_{FC,Stack} = 4.25 \times 10^{-5} \text{ h}^{-1}$$

- **Step 4:** Selection and Scoring of RIFs

Expert suggestions Relevant RIFs are shown together with the FM and FC in the table 3.2

The expert suggested scoring the effects of reliability on the causes of failure and the relevant failure modes shown in Table 3.4. Scores typically range from -3 (strongly reduced impact) to +3 (strongly increased impact), 0 meaning no difference.

Table 3.4: Failure modes, causes, connected RIFs, and expert scores

Failure mode (FM)	Failure cause (FC)	Connected RIF	Expert score
MD – Membrane degradation	DA – Degradation & ageing	OP – Operating conditions	3
	MS – Mechanical stress	WP – Water purity	2
	CT – Contaminants & impurities	OP,GP And WP	1.33
CD – Catalyst degradation	DA – Degradation & ageing	OP – Operating conditions	3
	CP – Chemical processes	GP – Gas purity	3
	CT – Contaminants & impurities	OP,GP And WP	1.33
BPC – Bipolar plate corrosion	CP – Chemical processes	MS – Material selection	3
	MD – Manufacturing defects	MQ – Manufacturing quality	3
	CT – Contaminants & impurities	OP,GP And WP	1.33

Calculating the weighted average RIF Score for Failure Cause.

$$RIF_{FC,j} = \frac{1}{n_j} \sum_{k=1}^{n_j} s_{j,k} \quad (3.4)$$

where $s_{j,k}$ are expert suggested scores and n_j Number of scores

- **Step 5:** Assign the weights (w_j) to each Failure cause (n_{FC}) contributing to the Failure Mode - expert suggested

$$\sum_{j=1}^{n_{FC}} w_j = 1 \quad (3.5)$$

- **Step 6:** Weighted Average RIF Score for each Failure Mode.

$$RIF_{FM,j} = \sum_{j=1}^{n_{FC}} w_j RIF_{FC,j} \quad (3.6)$$

where $RIF_{FC,j}$ are the weighted Average RIF score for each Failure cause and W_j assigned weights of a failure cause contributing to the failure mode. Both are expert-suggested values shown in table 3.5

- **Step 7:** Computing the Scaling Coefficient K_s :

$$K_{FM,j} = 1 + \frac{RIF_{FM,j}}{3} \quad (3.7)$$

- **Step 8:** New system failure rate for the FM in the PEMEL Stack

$$\lambda_{FM_j,M1} = \lambda_{FCStack} \cdot K_{FM_j} \quad (3.8)$$

$\lambda_{FM_j,M1}$ Failure rate of FM_j failure modes of Method 1 , $\lambda_{FCStack}$ fuel cell stack failure rate (estimated Reference) and K_{FM_j} is the scaling factor of the failure modes.

Estimated PEMEL stack failure rate ($\lambda_{EL,M1}$) of Method 1 - similarity based Rahimi approach

$$\lambda_{EL,M1} = \sum_{FM} \lambda_{FM_j,M1} \quad (3.9)$$

where $\sum_{FM} \lambda_{FM_j,M1}$ sum of failure modes rates FM_j

$$\lambda_{EL,M1} = 7.165 \times 10^{-5} h^{-1}$$

Table 3.5: Method 1: Quantified Values

FM_s	$RIF_{FC,j}$	W_j	$RIF_{FM,j}$	$K_{FM,j}$	$\lambda_{FM_j,M1} h^{-1}$
MD	3	30	2.076	1.692	3.384×10^{-5}
	1.44	40			
	2	30			
CD	3	30	2.076	1.692	2.538×10^{-5}
	2	30			
	1.44	40			
BPC	2	40	1.976	1.658	1.243×10^{-5}
	1.44	40			
	3	20			

3.5 FBWM

The Fuzzy Best–Worst Method (Fuzzy BWB) is an advanced MCDM approach that integrates the Best–Worst Method with fuzzy logic. In this fuzzy-based analysis, FMEA and the RIFs from Method 1 are employed.

Best and Worst RIFs are selected for this study based on expert judgment.

Best (most important): Water Purity, Worst (least significant): Manufacturing Quality are considered.

After identifying the most relevant Reliability Influencing Factors (RIFs), a comparative evaluation was conducted between the best-performing RIFs and the complete set of factors. Triangular Fuzzy Numbers (TFNs) were assigned to capture the relative importance of each RIF. In this framework, the TFN reflects the degree to which a factor contributes to system reliability, with water purity emerging as the most critical.

To ensure consistency, each RIF was also compared with the least significant factor, thus establishing a comprehensive scale of importance—the assignment of TFNs based on expert judgment, which was systematically converted into quantitative values. Using the linguistic conversion matrices presented in Table 3.6, qualitative expert assessments were transformed into TFNs, providing a transparent and reproducible representation of subjective evaluations. Stepwise calculation as follows:

(a) Best(B) vs RIFs				(b) RIFs vs Worst(W)			
Comparison	TFN	Average	Final Value	Comparison	TFN	Average	Final Value
WP (B) vs OC	2,3,4	(2+3+4)/3	3	OC vs MQ (W)	4,5,6	(4+5+6)/3	5
WP vs GP	1, 1,2	(1+1+2)/3	2	GP vs MQ	5,6,7	(5+6+7)/3	6
WP vs MS	6,7,8	(6+7+8)/3	7	MS vs MQ	2,3,4	(2+3+4)/3	3
WP vs MQ	8,9,9	(8+9+9)/3	8.6	WP vs MQ	8,9,9	(8+9+9)/3	8.6

Table 3.6: Triangular Fuzzy Number(TFN)

Step 1: FBWM Weight calculation

IF $w_{WP} = 1$ (Best) then $w_{MQ} = x$ (Worst).

Each remaining RIF (OC, GP, MS) is assigned a weight w_i .

Best-to-Others:

$$\frac{w_{WP}}{w_i} = D_i \quad (3.10)$$

Others-to-Worst:

$$\frac{w_i}{w_{MQ}} = D_i \quad (3.11)$$

Step 2: Finding Consistent Weights

Best-to-Others, approximate weights were calculated, and from Others-to-Worst, weights were expressed as multiples of w_{MQ} . These values should be consistent, so adjustments may be applied if necessary.

$$w_{WP} = 1, \quad w_{OC} \approx 0.333, \quad w_{GP} \approx 0.5, \quad w_{MS} \approx 0.142, \quad w_{MQ} \approx 0.115$$

Step 3: Normalize Weights.

$$\sum_{i=1}^n w_i = w_{WP} + w_{OC} + w_{GP} + w_{MS} + w_{MQ} = 2.09$$

The normalized weights are then:

$$w_i^{\text{norm}} = \frac{w_i}{\sum_{i=1}^n w_i} \quad (3.12)$$

Table 3.7: Normalized weights of RIFs

RIF	Raw Weight, w_i	Normalized Weight , w_i^{norm}
w_{WP}	1.000	0.478
w_{OC}	0.333	0.160
w_{GP}	0.500	0.240
w_{MS}	0.142	0.068
w_{MQ}	0.115	0.055
Sum	2.090	1.000

3.5.1 Fuzzy Logic Modeling

The modeling process was carried out using MATLAB within the fuzzy logic modular tool. The first step involved constructing the Fuzzy Inference System (FIS) tree diagram, as illustrated in Figure 3.3, while maintaining the logical flow of interactions between Reliability Influencing Factors (RIFs), Failure Causes (FCs), and Failure Modes (FMs). A Mamdani type-1 system was adopted, which applies standard fuzzy-logic operations—namely, fuzzy AND and OR—to combine input conditions. The system incorporates a rule base that links input RIF levels to the corresponding risk outputs, followed by centroid defuzzification to derive a single crisp failure risk priority number (fRPN). In this manner, expert knowledge of the influence of RIFs on failure modes is encoded in linguistic rules and systematically translated into a quantitative risk indicator. The developed model consists of five input variables (RIFs) and eleven output variables (FCs and FMs), as shown in Figure 3.4

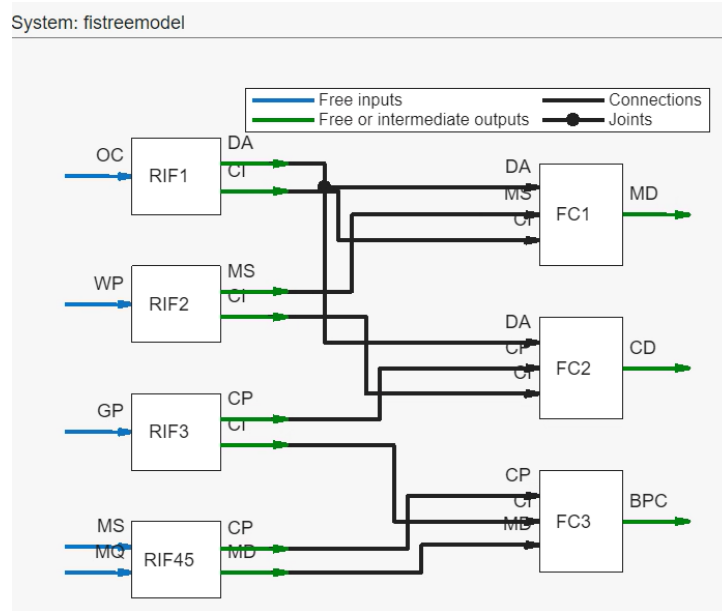


Figure 3.4: FIS tree model interference diagram

Step:4 Range and Membership function

The fuzzy range was set to the universal domain [0,1], ensuring that all inputs and membership functions (Low, Medium, High) were normalized to a standard scale. Figure 3.5

Step:5 Fuzzy Rules

In this study, five input variables and eleven output variables were considered. Each input was represented by three membership functions: Low, Medium, and High. The maximum number of possible rules is given by 3.5.

$$\text{Rules}_{\max} = \prod_{i=1}^n m_i \quad (3.13)$$

Where n denotes the number of inputs and m_i the number of membership functions for each input, accordingly, the total number of rules is $3^5 = 243$. How-

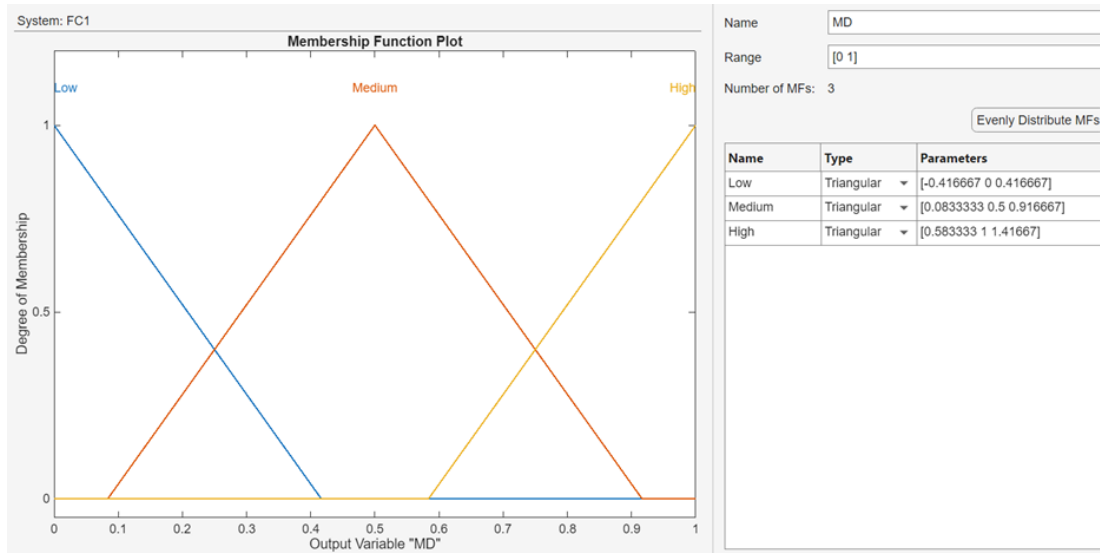


Figure 3.5: Membership plot and range

ever, the software environment is not optimized to handle such a large rule base efficiently. Therefore, in consultation with experts, the rule set was reduced by focusing only on the High and Medium membership levels. In this way, only the most significant rules—those that strongly influence the Failure Causes (FCs) and Failure Modes (FMs)—were retained, resulting in a final set of 126 rules.

The fuzzy rules were not derived from a generic standard. Still, they were formulated based on the author's assumptions about how each failure cause is expected to influence the corresponding failure mode. Subsequently, these assumptions were discussed with domain experts to ensure that the selected rules reflect plausible and meaningful cause-and-effect relationships within the system.

For example, when both relevant causes are at the medium level, the output associated with membrane degradation (MD) is classified as High. The complete set of fuzzy rules employed in this study is located in the Appendices Pages: 67-71.

For the DA, MS, and CI effects on the MD, the rules include:

- If DA is Low and MS is Medium and CI is Low, then MD is Low
- If DA is Medium and MS is Medium and CI is Low, then MD is High
- If DA is High and MS is Medium and CI is Low, then MD is High

DA - Degradation & Aging,

MS - Mechanical Stress,

CI - Contaminants& Impurities

Step:6 FRPN calculation

The Table of FBWM normalized weights 3.7 is the input for the RIFs The quantified output value of the fuzzy RPN for the three failure modes was calculated in Fuzzy logic designer in MATLAB and is shown in Figure 3.6. Fuzzy rule interference of the MD attached in appendices pages : 72-73

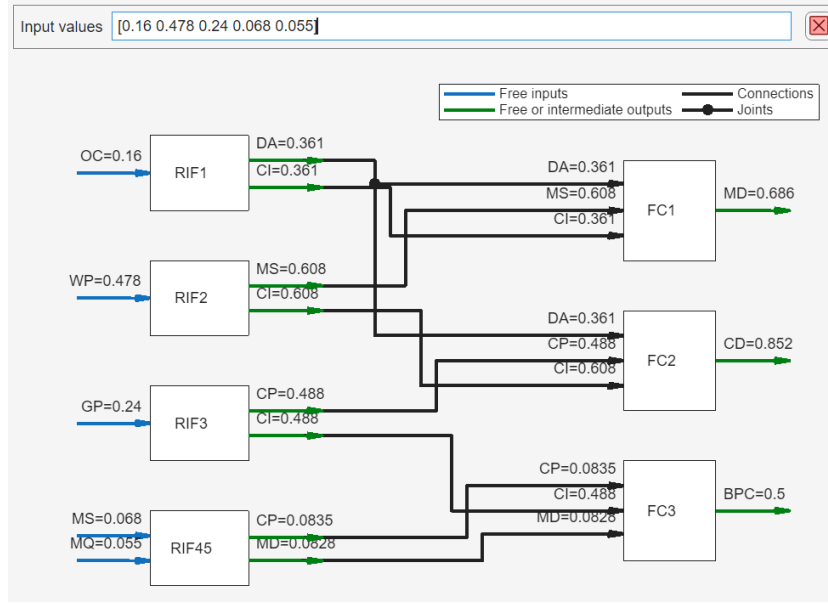


Figure 3.6: FIS Tree

Step:7 Normalizing the Fuzzy RPN

Fuzzy evaluation of failure modes yields the corresponding risk priority numbers (RPNs). Based on these results, catalyst degradation exhibits the highest fRPN 0.852 and therefore represents the highest risk. Catalyst degradation is the most critical failure mode, closely followed by membrane degradation, which also has a high fuzzy RPN of 0.685 and thus a similarly high risk. In contrast, bipolar plate corrosion is associated with a low RPN and consequently a lower risk level.

$$CD > MD > BPC$$

The FRPN output cannot be used for failure rate calculation. need to follow the reliability allocation [59] to Normalizing the output.

$$FRPN_{tot} = \sum_j FRPN_j \quad (3.14)$$

$$W_{FL,i} = \frac{FRPN_j}{FRPN_{tot}} \quad (3.15)$$

Step:8 Fuzzy Logic (FL) risk-associated failure rate calculation

Method 1 - Estimated PEMEL stack failure rate $\lambda_{EL,M1}$ used to calculate the fuzzy risk associated with the failure rate of the individual failure modes, with the fuzzy risk associated $Weight_{FL,i}$

$$\lambda_{FM_j,M2} = \lambda_{EL,M1} \cdot Weight_{FL,i} \quad (3.16)$$

Step:9 Estimated PEMEL stack failure rate ($\lambda_{EL,M2}$) of Method 2

$$\lambda_{EL,M2} = \sum_{FM} \lambda_{FM_j,M2} \quad (3.17)$$

$\lambda_{FM,M2}$ is used to calculate the independent failure rate of the failure modes for Method 2

$$\lambda_{EL,M2} = 7.145 \times 10^{-5} h^{-1}$$

Table 3.8: Method 2: Quantified values

FM_j	$FRPN_j$	$Weight_{FL,i}$	$\lambda_{FM_j,M2} h^{-1}$
MD	0.686	0.336	2.4×10^{-5}
CD	0.852	0.418	2.99×10^{-5}
BPC	0.500	0.245	1.755×10^{-5}

3.6 BN

The Bayesian inference diagram was modeled in the same manner as Figure 3.3, maintaining the logical flow of interactions between Reliability Influencing Factors (RIFs), Failure Causes (FCs), and Failure Modes (FMs) within the GeNIe academic software. Probability distributions were defined for each RIF, with values assigned based on expert judgment under the same conditions as Method 2 - scenario conditions. These distributions reflect how RIFs influence the probability of error causes in general. Alternatively, the weights obtained from the FBWM analysis of RIFs can be incorporated to represent their relative contributions.

Table 3.9: RIF Proportions

RIF	TRUE (%)	FALSE (%)
OC (Operating Conditions)	30	70
GP (Gas Purity)	20	80
WP (Water Purity)	40	60
MS (Material Selection)	10	90
MQ (Material Quality)	15	85

Table 3.9 provides the input values used to calculate the failure mode factors. The Conditional Probability Tables (CPTs) were not derived from a standard dataset but were assumed by the author based on the specific scenario under

study. These assumptions reflect how the Reliability Influencing Factors (RIFs) are expected to affect the likelihood of failure causes and modes. While the CPTs were primarily based on the author's interpretation, they were discussed with experts to ensure the assigned values reflect plausible dependencies within the system.

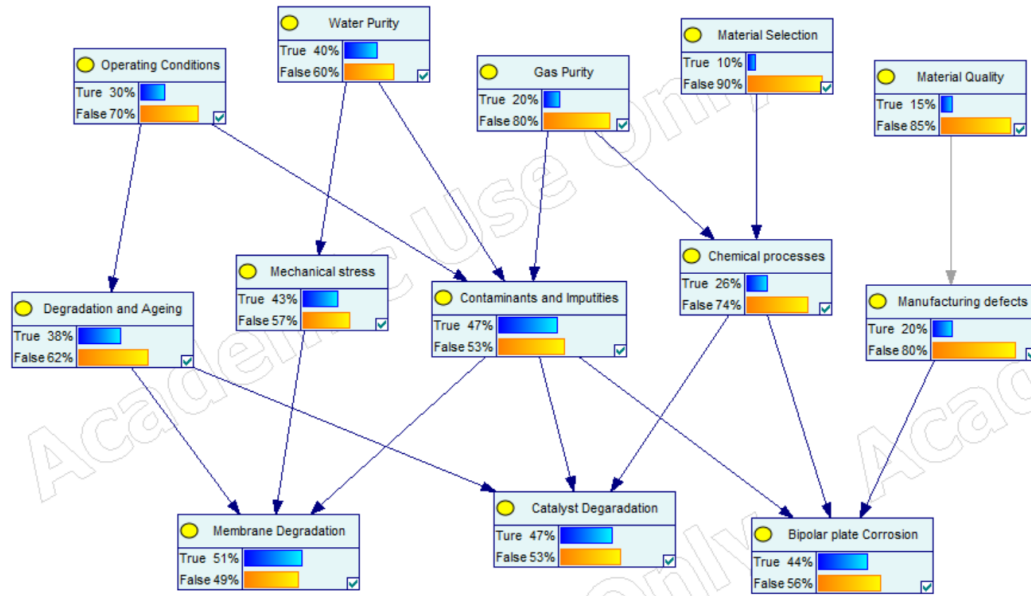


Figure 3.7: Bayesian Network Model

This diagram illustrates the RIF diagram as a Bayesian Network where each node represents a factor that contributes to system degradation, such as operating conditions, material quality, or membrane degradation.

- Parent nodes (RIFs like Water Purity or Gas Purity) influence intermediate causes such as Contaminants and Impurities or Mechanical Stress.
- These child nodes then propagate their effects to failure modes like Membrane Degradation, Catalyst Degradation, or Bipolar Plate Corrosion.
- The arrows show cause-and-effect relationships, meaning that the probability of a failure mode depends on the state of its parent causes.

3.6.1 Normalizing the Bayesian Network(BN) FMs factor

These normalized values were then used as weighting factors and multiplied by the baseline failure rates from the Method 1 - Rahimi SIMILARITY approach to produce adjusted reliability measures. The posterior probabilities obtained from the Bayesian Network were first normalized to ensure they formed a valid distribution.

$$BN_{tot} = \sum_j BN_j \quad (3.18)$$

$$Weight_{BN,i} = \frac{BN_j}{BN_{tot}} \quad (3.19)$$

where BN_j is the probability of independent failure modes of the Bayesian Network and BN_{tot} is the sum of the probability of the failure modes

3.6.2 Calculation of Posterior Failure Rate

The posterior failure rate of each failure mode is obtained by multiplying the stack failure rate of the electrolyser from Method 1

$$\lambda_{FM_j,M3} = \lambda_{EL,M1} \cdot Weight_{BN,i} \quad (3.20)$$

$$\lambda_{EL,M3} = \sum_{FM} \lambda_{FM_j,M3} \quad (3.21)$$

Method 3- Estimated PEMEL stack failure rate ($\lambda_{EL,M3}$)

$$\lambda_{EL,M3} = 7.087 \times 10^{-5} h^{-1}$$

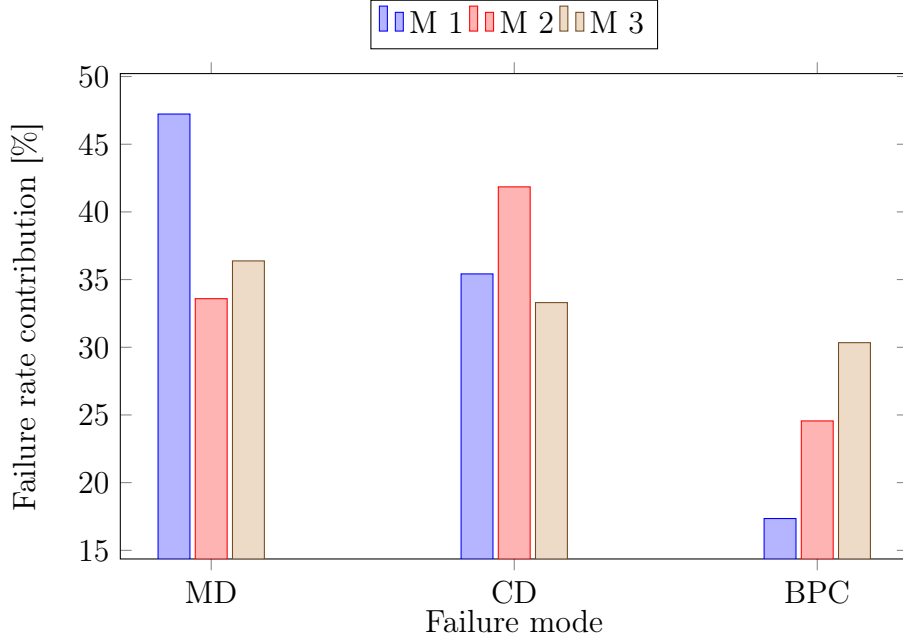
Table 3.10: Method 3 : Quantified Values

FM_j	BN_j	$Weight_{BN,i}$	$\lambda_{FM_j,M3} h^{-1}$
MD	0.51	0.36	2.578×10^{-5}
CD	0.47	0.33	2.36×10^{-5}
BPC	0.44	0.309	2.15×10^{-5}

3.7 Sensitivity analysis

3.7.1 Comparison of failure modes

The main aim of this study was to assess the reliability of a PEMEL stacks using three different approaches. As shown in the bar chart below 3.7.1, for the various failure modes, the individual methods and the overall failure rates derived from them exhibit strong agreement.



Estimated PEMEL stacks failure rate as follows:

- Method 1: Similarity-based Rahimi's approach (M1)

$$\lambda_{EL,M1} = 7.165 \times 10^{-5} h^{-1}$$

- Method 2: Fuzzy Best-worst and FMEA (M2)

$$\lambda_{EL,M2} = 7.145 \times 10^{-5} h^{-1}$$

- Method 3: Bayesian Network and FMEA (M3)

$$\lambda_{EL,M3} = 7.087 \times 10^{-5} h^{-1}$$

The standard deviation across these three results is minimal, which shows that the selected frameworks are mathematically in agreement with one another. The Rahimi Approach (M1) produced the highest failure rate and therefore serves as a conservative upper limit. This outcome is reasonable, since Method 1 applies a linear scaling factor ($K_{FM,j}$ derived from Reliability Influencing Factors, RIFs) and does not account for probabilistic mitigation effects arising from complex system interactions.

In contrast, the Bayesian Network model (M3) showed the lowest failure rate. This improvement can be explained by its capability to represent conditional dependencies. Unlike linear scaling, the BN can handle situations where a RIF is present (such as low water quality) but does not automatically lead to failure, because probabilistic safeguards are incorporated in the Conditional Probability Tables (CPTs).

Component-Level Contribution

Across the three approaches, the relative contribution of each failure mode stayed essentially the same, supporting the experts' original evaluation of how the risks were distributed:

Catalyst Degradation (CD) : This failure mode showed the highest criticality in the Fuzzy analysis (FRPN = 0.852) and continued to play a significant role in the overall failure rate. This is consistent with the FBWM weighting, where Water Purity ($w_{WP} = 0.478$) and Gas Purity ($w_{GP} = 0.240$) were identified as the most influential RIFs. Because the catalyst layers are highly sensitive to chemical impurities, the model appropriately highlights this aspect as the main source of vulnerability.

Membrane Degradation (MD) : It ranks as the second most critical mode. The Rahimi's method showed that MD is especially sensitive to "Operating Conditions," which is linked to the mechanical stress exerted on the membrane under varying pressure differentials.

Bipolar Plate Corrosion (BPC) : It showed the lowest contribution (around $1.2\text{--}1.7 \times 10^{-5} h^{-1}$). Although this factor remains important, the use of titanium components helps reduce this risk, especially compared with the kinetic and chemical stresses acting on the membrane and catalyst.

The difference between the baseline method (M1) and the most advanced method (M3) is under 1.1%. This indicates that, in early-stage technology assessments where no field data are yet available, the Similarity-Based Approach (Rahimi's method) can serve as a sufficiently accurate "worst-case" baseline. Nevertheless, Methods 2 and 3 provide a higher level of detail for sensitivity analysis, enabling engineers to identify which specific RIFs (such as Water Purity) should be prioritized for design improvements in order to reduce the overall impact.

3.7.2 Monte carlo Simulation

To validate the stability of the proposed reliability framework, a high-precision Monte Carlo simulation (N=40,000 iterations) was executed. This large-scale stochastic analysis aimed to generate robust reliability curves ($R(t)$) for the PEMEL stack and to compare the outputs of three methods under parameter-uncertainty conditions.

Statistical Convergence and MTTF Estimates The simulation results demonstrate strong statistical convergence across all three methodologies, reinforcing the internal consistency of the hybrid framework. The variance in Mean Time To Failure (MTTF) between the methods is minimal:

Method 1 (Rahimi's similarity Approach): Serves as the conservative baseline with an estimated MTTF of 13,950 hours.

Method 2 (FBWM): Represents the optimistic upper bound with an estimated MTTF of 14,100 hours.

The narrow differential of approximately 150 hours between the conservative and optimistic models indicates that the epistemic uncertainty inherent in the different mathematical approaches does not significantly alter the operational prognosis of the stack.

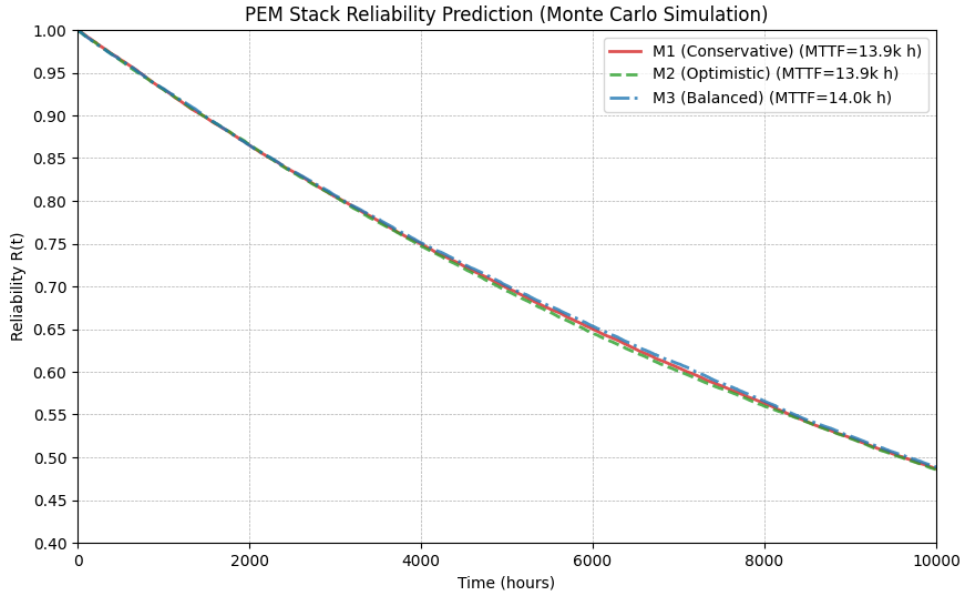


Figure 3.7: Monte carlo plot

The reliability curve exhibits a characteristic exponential decay, initiating at $R(t)=1.0$ and degrading smoothly over time. This trajectory confirms that the stack is modeled within its "useful life" phase, governed by a constant random failure rate rather than early-life infant mortality or late-stage wear-out cliffs.

Key reliability milestones identified from the simulation include:

- $t = 5,000$ hours: The probability of survival of the stack remains high, at approximately 70%.
- $t = 10,000$ hours: The reliability drops to approximately 49%. In particular, the "median life" of the stack (where reliability falls below 0.50) is observed at approximately 9,700 hours.

Visual Interpretation and Operational Implications Visually, the reliability trajectories for the three methods are virtually indistinguishable. The superposition of the curves indicates that the choice of modeling technique (Rahimi's similarity approach vs. FBWM vs. Bayesian) yields negligible differences in practical outcomes.

From an operational perspective, this convergence is a critical finding. It suggests that the predicted failure dynamics are primarily driven by the physical input parameters (Reliability Influencing Factors) rather than by artifacts of the modeling algorithms. Consequently, plant operators can utilize these predictions

Table 3.11: Comparative Data Table ($N = 40,000$)

Method	MTTF (hours)	R @ 5,000 hours	R @ 10,000 hours
M1 (Conservative)	13,934	69.9%	48.8%
M3 (Balanced)	14,115	70.3%	49.3%
M2 (Optimistic)	14,082	70.1%	49.1%

with high confidence for maintenance scheduling, regarding the inputs as a unified representation of operational reality rather than conflicting theoretical models.

- M1 (Conservative) Minimizes the risk of over-promising performance.
- M2 (Optimistic) represents potential performance under ideal conditions.

3.8 Discussion

This study evaluated the reliability of PEMEL stacks using three proposed approaches: Rahimi’s similarity method, FBWM, FMEA, and Bayesian networks. Each technique was used to identify and quantify the dominant failure modes and relevant RIs, namely catalyst degradation, membrane degradation, and corrosion of the bipolar plates. By first establishing a baseline failure rate through method 1, the work assessed the relative contribution of each failure mode to the overall stack reliability.

The resulting baseline stack failure rate was approximately $7.1 \times 10^{-5} \text{ h}^{-1}$, corresponding to a mean time to failure (MTTF) on the order of 14,000–20,000 hours. Although this estimate is more conservative than the 60,000–80,000 hours indicated in EPRI industry surveys, it aligns with Sun [40], who reported an average cell degradation rate of $35.5 \mu\text{V h}^{-1}$ over 7800 hours, and with Kimmel [75] measured a 0.88 V voltage loss at 1 A cm^{-2} in an aged stack. These comparisons demonstrate that Rahimi’s similarity-based approach effectively characterizes realistic degradation behavior under dynamic operating conditions. In this study, the PEMFC failure modes were first assessed on a proportional basis. Then a scaling factor was applied to estimate the PEMEL stack failure rate, even though the resulting lifetime predictions are shorter than the more optimistic values commonly assumed in industry.

From a design perspective, the FBWM method provided a deeper understanding of how reliability-influencing factors (RIFs)—such as water purity, operating parameters, and material quality—affect stack performance. The fuzzy risk priority numbers indicated that catalyst degradation is the dominant concern, with an fRPN of 0.82, followed by membrane degradation at 0.74 and bipolar plate corrosion at 0.41. These outcomes underscore the strong sensitivity of CCM durability to both water purity and current density. Kimmel [75] observed that replacing only the CCM can restore more than 60% of the original cell voltage, while Hao [76] showed that Ru/IrOx catalysts experience rapid dissolution above 1.5 V vs RHE, with dissolution rates increasing by a factor of five in the presence of 10 ppm chloride contaminants. Taken together, these studies support our fuzzy weighting

results and suggest that future design improvements should focus on improving catalyst stability and implementing more effective water-management strategies to counter impurity-driven degradation.

The Bayesian network framework introduced a probabilistic perspective, clarifying how the joint effects of poor water quality and dynamic operating profiles increase the likelihood of failure. Using the similarity-based baseline as prior information, the Bayesian model estimated a probability of 0.62 for CCM degradation under poor water conditions, 0.55 for membrane contamination, and 0.28 for bipolar plate oxidation.

Monte Carlo simulations further indicated that membrane and catalyst degradation are the primary contributors to overall risk, with aggregate failure probabilities exceeding 0.75 in high-current-density regimes. Ubale [44] reported system unavailability probabilities of 0.49 for water quality deterioration and 0.68 for water supply interruption in balance-of-plant subsystems, which is consistent with our Bayesian estimates and underscores the critical role of maintenance planning. In practical applications, Bayesian modeling facilitates condition-based maintenance by explicitly linking operational data to reliability outcomes.

Sensitivity analyses across all three methods showed that reliability predictions are most strongly influenced by water purity, operating profile, and CCM quality. When the water purity in the model was reduced, the overall failure rate increased from $7.1 \times 10^{-5} \text{ h}^{-1}$ to $1.2 \times 10^{-4} \text{ h}^{-1}$, corresponding to a 70% increase. Although the predicted failure rate of the PEMEL stack is higher than that of a comparable PEMFC Stack, this conservative estimate is intentional and advantageous for practical use. The purpose of reliability prediction is not only to estimate the time to complete stack failure but also to enable predictive, condition-based maintenance measures before a catastrophic shutdown. In real operation, the stack continues to produce hydrogen. It enters a high-risk regime once performance has dropped to 85–90% of the nominal value (due to membrane thinning, catalyst poisoning, or increased cell resistance). Prolonged operation under these conditions can quickly lead to the formation of pinholes, gas crossover, or even explosion hazards [31]. The increased failure rate determined in this study, therefore, serves as a conservative early-warning margin, promoting planned maintenance during operation and thereby reducing unplanned downtime, improving safety, and lowering the levelized cost of hydrogen production [1].

Overall, the three methods together yield a multi-layered perspective on PEMEL reliability. The similarity-based approach established a baseline failure rate, the fuzzy method ranked failure modes based on expert assessments, and the Bayesian framework linked RIFs to probabilistic operating scenarios. In all three analyses, catalyst and membrane degradation were identified as the primary reliability concerns, with bipolar plate corrosion as a secondary issue. The discussion indicates that reliability can be enhanced through design strategies—such as employing more durable CCMs and corrosion-resistant PTLs—and through operational measures, including water quality management and scheduled cleaning. Taken together, these findings underpin reliability-oriented design and maintenance strategies for PEMEL in green hydrogen production [40], [44], [75]–[77].

CONCLUSION AND FURTHER WORK

4.1 Conclusion

The transition to a hydrogen-based economy faces a critical epistemological barrier: the paucity of longitudinal operational data for PEMEL. As the industry scales from Megawatt to Gigawatt capacities, the inability to accurately predict system lifespan poses severe risks to both safety and financial viability. This thesis bridges this gap by engineering a novel Hybrid Reliability Prediction Framework. This methodological innovation successfully synthesizes deterministic similarity analysis with stochastic reasoning to quantify reliability in data-scarce environments.

4.1.1 Methodological Innovation and Robustness

The primary contribution of this research is the development of a multi-layered analytical architecture that overcomes the limitations of traditional, data-intensive statistical methods. By integrating Similarity Analysis (to establish a baseline from analogous PEMFC technology), Fuzzy Logic ,FBWM with FMEA (to neutralize expert subjectivity), and Bayesian Networks (to model causal inter dependencies), the framework provides a comprehensive "digital reliability twin" for the electrolyser stack.

The robustness of this model was rigorously validated through a high-precision Monte Carlo Simulation (N=40,000). The simulation demonstrated a remarkable statistical convergence across all three methodologies, with a negligible deviation between the conservative and optimistic models. This convergence confirms that the framework is mathematically stable and that the predicted failure dynamics are driven by physical reliability drivers rather than modeling artifacts.

4.1.2 Quantitative Insights and Operational Reality

The study yielded specific, actionable quantitative data on the current state of PEMEL technology:

1. **Baseline Failure Metrics:** The analysis established a total stack failure rate of approximately $7.1 \times 10^{-5} h^{-1}$. The Monte Carlo analysis refined the Mean Time To Failure (MTTF) to a tight confidence interval of 13,950-14,100 hours.
2. **Characteristics of the life cycle:** The reliability curve revealed a "median life" (the point at which the reliability drops below 50%) of approximately 9,700 hours. Although this reflects the performance of commercial early-stage stacks operating under variable loads, it highlights the technological distance remaining to meet the durability target of 40000-80000 hours [17] in coming years .
3. **Critical Reliability Drivers:** Through the application of the Fuzzy Best-Worst Method (FBWM), the purity of the water was mathematically isolated as the single most critical factor influencing reliability (Normalized Weight = 0.478). This finding statistically demonstrates that failures in upstream water management are more detrimental to stack longevity than manufacturing defects or material selection.

Strategic Impact and Industrial Relevance The implications of these findings extend beyond academic theory into industrial application: **De-risking Green Hydrogen Investments:** By providing a defensible, quantitative basis for failure prediction, this framework reduces perceived risk for investors and insurers, thereby enhancing the bankability of large-scale hydrogen projects. **Safety and Maintenance Optimization:** Identifying the exponential decay curve enables operators to transition from reactive to predictive maintenance. Knowing that the probability of survival remains high (70%) at 5,000 hours but degrades significantly by 10,000 hours allows for precise scheduling of stack refurbishment, preventing catastrophic failure modes such as hydrogen-oxygen crossover. **Economic Efficiency (LCOH):** The dominance of water purity as a failure driver dictates a clear design priority: maximizing the reliability of the Balance of Plant (BoP) water purification subsystem is the most cost-effective strategy to extend the stack life and reduce the Levelized Cost of Hydrogen (LCOH).

In conclusion, this thesis provides the hydrogen sector with a validated, scalable tool for reliability quantification. It transforms qualitative expert knowledge into rigorous quantitative data, laying the foundation for safer, more efficient, and economically viable green hydrogen production.

4.2 Further Work

Although this thesis establishes a robust framework for the reliability of the PEM stack, the complexity of hydrogen production systems suggests several avenues for future research to refine the accuracy and applicability.

1. **Integration of Field Operational Data (Bayesian Updating)** The current model relies on priors derived from expert elicitation and similarity analysis. Future work should focus on the "Posterior Update" phase of the Bayesian Network. As pilot PEMEL plants (EX. MW-scale installations) accumulate operational hours, these real-world failure data should be fed back into the GeNIe model. This would transition the framework from a predictive tool to a living reliability model, narrowing the confidence intervals of the failure rates.

2. **Balance of Plant (BoP) Reliability Quantification** This study focused exclusively on the PEM Stack. However, literature indicates that up to 45% of system failures originate in the Balance of Plant (power electronics, water purification, gas separation, circulation pumps). A comprehensive "System-Level" reliability model is required. Future studies should apply the same hybrid framework (Similarity/Fuzzy/BN) to the BoP components to calculate a global l_{System} . Special attention should be paid to the Power Electronics (Rectifiers/Buck Converters), as they are subjected to high thermal cycling in renewable applications.

3. **Dynamic Reliability Modeling (Markov Chains)** The current framework assumes a constant failure rate (λ) during the useful life phase (exponential distribution). However, PEMEL coupled with wind or solar sources operate under highly transient loads. This cycle induces fatigue not captured by static models. Future work should implement Markov Chain modeling to simulate different operational states (e.g., Standby, Rated Power, Overload). By assigning state-dependent failure rates, the model could quantify the degradation penalty of coupling electrolyzers directly to intermittent renewables versus grid-connected steady-state operation.

4. **Economic Impact Analysis (LCOH Optimization)**

Reliability is directly related to economics. Future research should integrate these reliability outputs into a techno-economic model. By quantifying the cost of downtime caused by the calculated failure rates (e.g., revenue loss from stopped hydrogen production + replacement costs of catalyst coated membranes), researchers can optimize the redundancy of the system. For example, is it more cost-effective to invest in higher-grade water purification (reducing l_{CD}) or to install a redundant stack? 5. **Physics-of-Failure (PoF) Hybridization** To reduce reliance on the "Similarity" assumption between PEMFC and PEMEL, future work could incorporate Physics-of-Failure models. Specifically, equations describing Iridium dissolution rates (anode) or fluoride emission rates (membrane thinning) could be used as deterministic nodes within the Bayesian Network. This "Hybrid Causal Logic" would combine the physical laws of degradation with the probabilistic framework developed in this thesis.

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APPENDICES

A - FIGURES

A - Figures

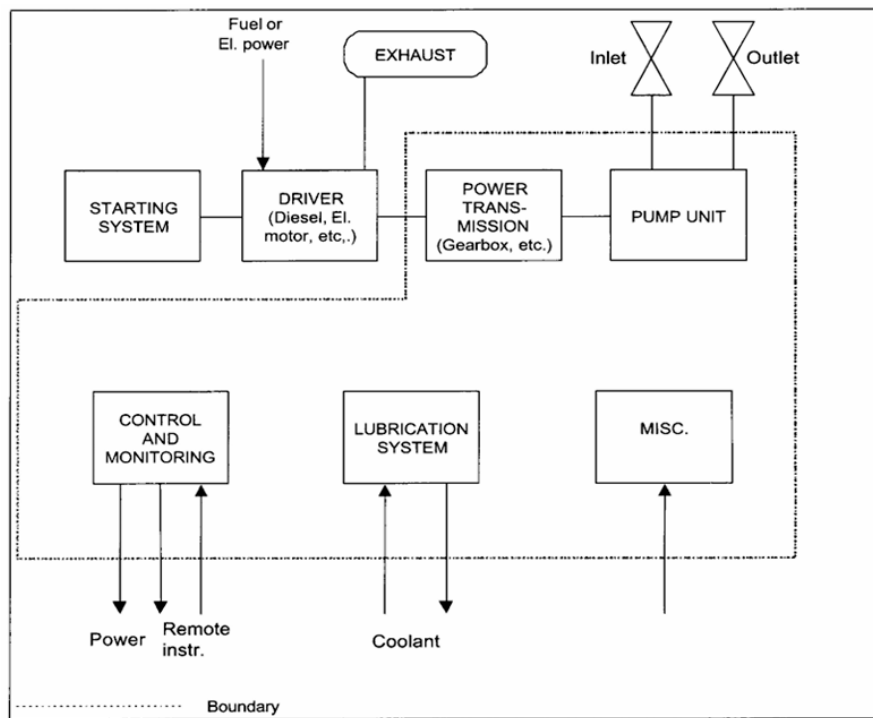


Figure A.1: OREDA Pump

Fuzzy Logic designer - MATLAB

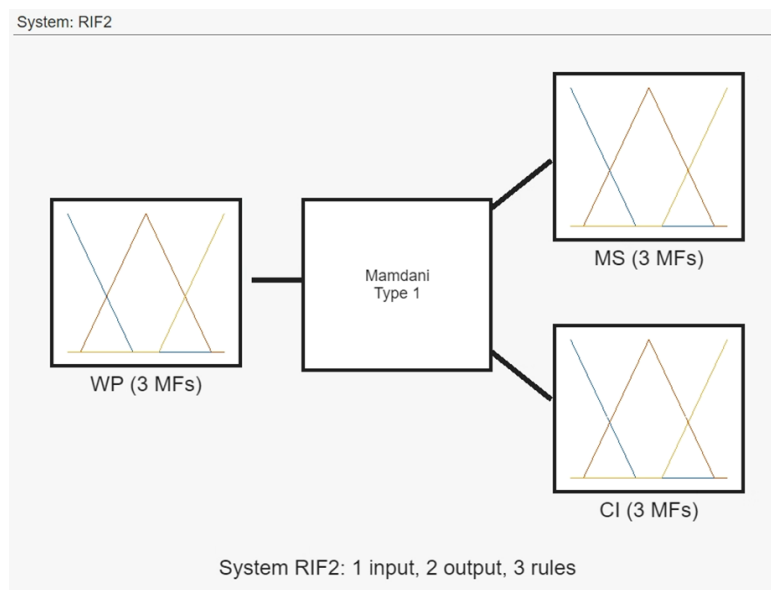


Figure A.2: Fuzzy Interference system RIFs-FC

Where WP - Water Purity , MS - Mechanical stress , CI - contaminants and Impurities

	Rule	Weight	Name
1	If OC is Low then DA is Low, CI is Low	1	rule1
2	If OC is Medium then DA is Medium, CI is High	1	rule2
3	If OC is High then DA is Medium, CI is High	1	rule3
4	If OC is Medium then DA is Medium, CI is Medium	1	rule4
5	If OC is Medium then DA is High, CI is Medium	1	rule5
6	If OC is High then DA is Medium, CI is Medium	1	rule6
7	If OC is High then DA is High, CI is High	1	rule7
8	If OC is High then DA is High, CI is Medium	1	rule8
9	If OC is Medium then DA is High, CI is High	1	rule9

Figure A.3: Rules : RIFs - FC1

RIFs to Failure Causes

OC - Operating conditions, DA - Degradation and aging , CI - contaminants and Impurities.

	Rule	Weight	Name
1	If WP is Low then MS is Low, CI is Low	1	rule1
2	If WP is Medium then MS is Medium, CI is High	1	rule2
3	If WP is High then MS is Medium, CI is High	1	rule3
4	If WP is Medium then MS is Medium, CI is Medium	1	rule4
5	If WP is Medium then MS is Medium, CI is Medium	1	rule5
6	If WP is High then MS is Medium, CI is Medium	1	rule6
7	If WP is High then MS is High, CI is High	1	rule7
8	If WP is High then MS is High, CI is Medium	1	rule8
9	If WP is Medium then MS is High, CI is High	1	rule9

Figure A.4: Rules: RIFs - FC2

Where WP - Water Purity , MS - Mechanical stress , CI - contaminants and Impurities

	Rule	Weight	Name
1	If GP is Low then CP is Low, CI is Low	1	rule1
2	If GP is Medium then CP is High, CI is High	1	rule2
3	If GP is High then CP is High, CI is High	1	rule3
4	If GP is Medium then CP is Medium, CI is Medium	1	rule4
5	If GP is Medium then CP is High, CI is Medium	1	rule5
6	If GP is High then CP is Medium, CI is Medium	1	rule6
7	If GP is High then CP is High, CI is High	1	rule7
8	If GP is High then CP is High, CI is Medium	1	rule8
9	If GP is Medium then CP is High, CI is High	1	rule9

Figure A.5: Rules : RIFs - FC3

GP - Gas purity, CP - Chemical process , CI - contaminants and Impurities

Fuzzy rules for mapping RIFs to FC for the three RIFs discussed in this section

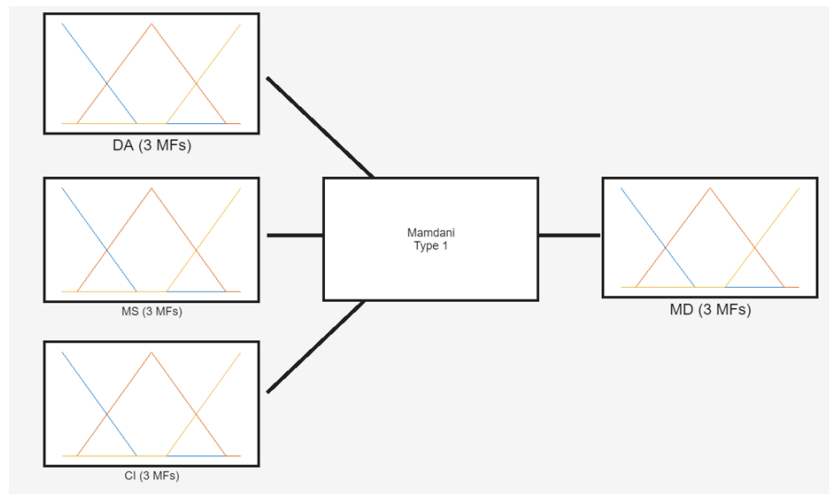


Figure A.6: fuzzy inference diagram FC-FM

	Rule	Weight	Name	
1	If DA is Low and MS is Low and CI is Low then MD is Low	1	rule1	▲
2	If DA is Medium and MS is Low and CI is Low then MD is Low	1	rule2	
3	If DA is High and MS is Low and CI is Low then MD is Medium	1	rule3	
4	If DA is Low and MS is Medium and CI is Low then MD is Low	1	rule4	
5	If DA is Medium and MS is Medium and CI is Low then MD is High	1	rule5	
6	If DA is High and MS is Medium and CI is Low then MD is High	1	rule6	
7	If DA is Low and MS is High and CI is Low then MD is Medium	1	rule7	
8	If DA is Medium and MS is High and CI is Low then MD is High	1	rule8	
9	If DA is High and MS is High and CI is Low then MD is High	1	rule9	
10	If DA is Low and MS is Low and CI is Medium then MD is Medium	1	rule10	
11	If DA is Medium and MS is Low and CI is Medium then MD is High	1	rule11	
12	If DA is High and MS is Low and CI is Medium then MD is High	1	rule12	
13	If DA is Low and MS is Medium and CI is Medium then MD is Medium	1	rule13	
14	If DA is Medium and MS is Medium and CI is Medium then MD is High	1	rule14	
15	If DA is High and MS is Medium and CI is Medium then MD is High	1	rule15	
16	If DA is Low and MS is High and CI is Medium then MD is High	1	rule16	
17	If DA is Medium and MS is High and CI is Medium then MD is High	1	rule17	
18	If DA is High and MS is High and CI is Medium then MD is High	1	rule18	
19	If DA is Low and MS is Low and CI is High then MD is High	1	rule19	▼
20	If DA is Medium and MS is Low and CI is High then MD is High	1	rule20	
21	If DA is High and MS is Low and CI is High then MD is High	1	rule21	
22	If DA is Low and MS is Medium and CI is High then MD is High	1	rule22	
23	If DA is Medium and MS is Medium and CI is High then MD is High	1	rule23	
24	If DA is High and MS is Medium and CI is High then MD is High	1	rule24	
25	If DA is Low and MS is High and CI is High then MD is High	1	rule25	
26	If DA is Medium and MS is High and CI is High then MD is High	1	rule26	
27	If DA is High and MS is High and CI is High then MD is High	1	rule27	▼

Figure A.7: Rules for Membrane Degradation

	Rule	Weight	Name	
1	If DA is Low and CP is Low and CI is Low then CD is Low	1	rule1	▲
2	If DA is Medium and CP is Low and CI is Low then CD is Medium	1	rule2	
3	If DA is High and CP is Low and CI is Low then CD is High	1	rule3	
4	If DA is Low and CP is Medium and CI is Low then CD is Medium	1	rule4	
5	If DA is Medium and CP is Medium and CI is Low then CD is High	1	rule5	
6	If DA is High and CP is Medium and CI is Low then CD is High	1	rule6	
7	If DA is Low and CP is High and CI is Low then CD is High	1	rule7	
8	If DA is Medium and CP is High and CI is Low then CD is High	1	rule8	
9	If DA is High and CP is High and CI is Low then CD is High	1	rule9	
10	If DA is Low and CP is Low and CI is Medium then CD is High	1	rule10	
11	If DA is Medium and CP is Low and CI is Medium then CD is High	1	rule11	
12	If DA is High and CP is Low and CI is Medium then CD is High	1	rule12	
13	If DA is Low and CP is Medium and CI is Medium then CD is High	1	rule13	
14	If DA is Medium and CP is Medium and CI is Medium then CD is High	1	rule14	
15	If DA is High and CP is Medium and CI is Medium then CD is High	1	rule15	
16	If DA is Low and CP is High and CI is Medium then CD is High	1	rule16	
17	If DA is Medium and CP is High and CI is Medium then CD is High	1	rule17	
18	If DA is High and CP is High and CI is Medium then CD is High	1	rule18	
19	If DA is Low and CP is Low and CI is High then CD is High	1	rule19	
20	If DA is Medium and CP is Low and CI is High then CD is High	1	rule20	
21	If DA is High and CP is Low and CI is High then CD is High	1	rule21	
22	If DA is Low and CP is Medium and CI is High then CD is High	1	rule22	
23	If DA is Medium and CP is Medium and CI is High then CD is High	1	rule23	
24	If DA is High and CP is Medium and CI is High then CD is High	1	rule24	
25	If DA is Low and CP is High and CI is High then CD is High	1	rule25	
26	If DA is Medium and CP is High and CI is High then CD is High	1	rule26	
27	If DA is High and CP is High and CI is High then CD is High	1	rule27	▼

Figure A.8: Rules for Catalyst Degradation

	Rule	Weight	Name	
1	If CP is Low and CI is Low and MD is Low then BPC is Low	1	rule1	▲
2	If CP is Medium and CI is Low and MD is Low then BPC is Medium	1	rule2	
3	If CP is High and CI is Low and MD is Low then BPC is High	1	rule3	
4	If CP is Low and CI is Medium and MD is Low then BPC is Medium	1	rule4	
5	If CP is Medium and CI is Medium and MD is Low then BPC is High	1	rule5	
6	If CP is High and CI is Medium and MD is Low then BPC is High	1	rule6	
7	If CP is Low and CI is High and MD is Low then BPC is High	1	rule7	
8	If CP is Medium and CI is High and MD is Low then BPC is High	1	rule8	
9	If CP is High and CI is High and MD is Low then BPC is High	1	rule9	
10	If CP is Low and CI is Low and MD is Medium then BPC is Medium	1	rule10	
11	If CP is Medium and CI is Low and MD is Medium then BPC is High	1	rule11	
12	If CP is High and CI is Low and MD is Medium then BPC is High	1	rule12	
13	If CP is Low and CI is Medium and MD is Medium then BPC is High	1	rule13	
14	If CP is Medium and CI is Medium and MD is Medium then BPC is High	1	rule14	
15	If CP is High and CI is Medium and MD is Medium then BPC is High	1	rule15	
16	If CP is Low and CI is High and MD is Medium then BPC is High	1	rule16	
17	If CP is Medium and CI is High and MD is Medium then BPC is High	1	rule17	
18	If CP is High and CI is High and MD is Medium then BPC is High	1	rule18	
19	If CP is Low and CI is Low and MD is High then BPC is High	1	rule19	
20	If CP is Medium and CI is Low and MD is High then BPC is High	1	rule20	
21	If CP is High and CI is Low and MD is High then BPC is High	1	rule21	
22	If CP is Low and CI is Medium and MD is High then BPC is High	1	rule22	
23	If CP is Medium and CI is Medium and MD is High then BPC is High	1	rule23	
24	If CP is High and CI is Medium and MD is High then BPC is High	1	rule24	
25	If CP is Low and CI is High and MD is High then BPC is High	1	rule25	
26	If CP is Medium and CI is High and MD is High then BPC is High	1	rule26	
27	If CP is High and CI is High and MD is High then BPC is High	1	rule27	▼

Figure A.9: Rules for Bipolar plate corrosion

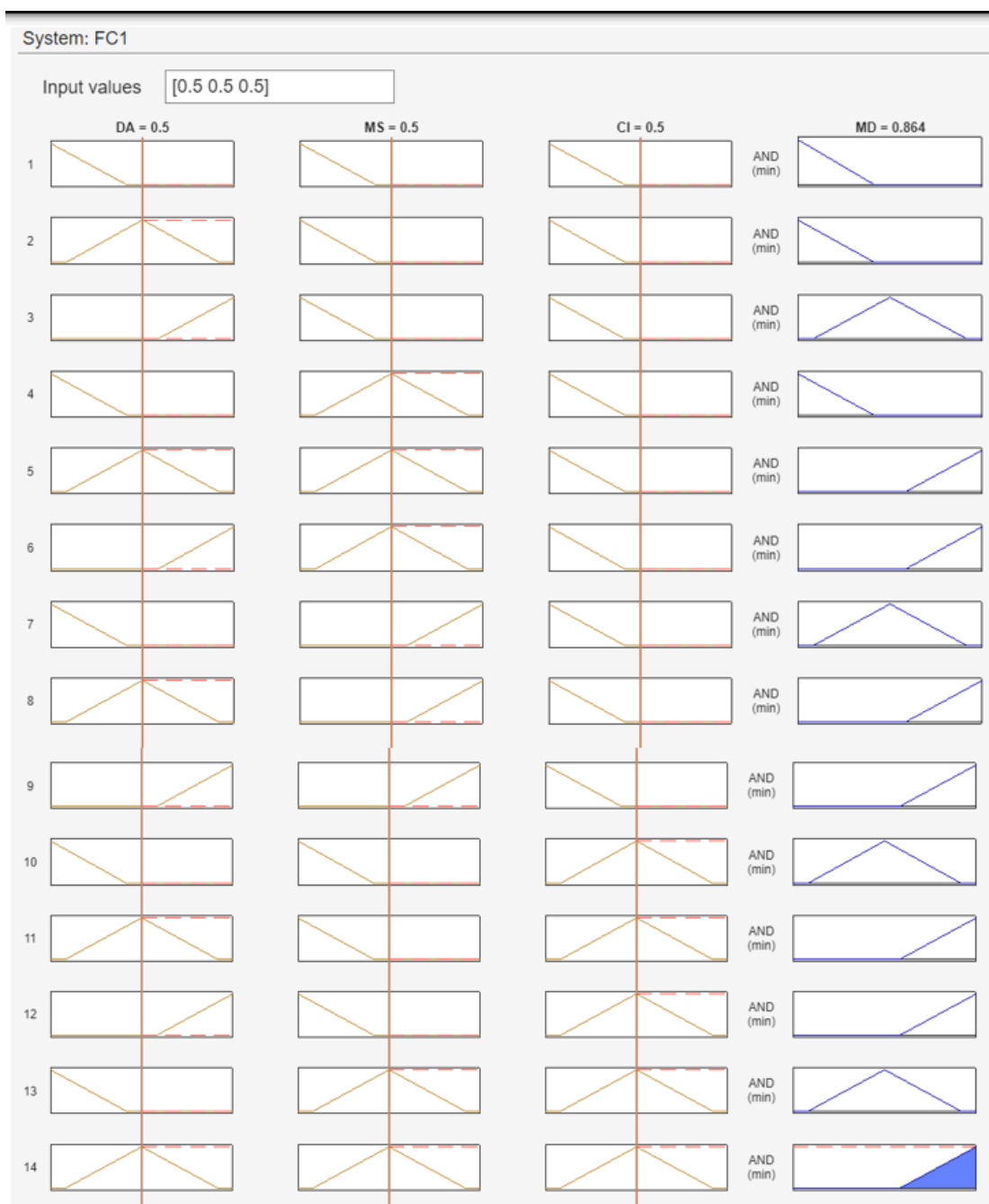


Figure A.10: Rule Interference of Membrane Degradation -1

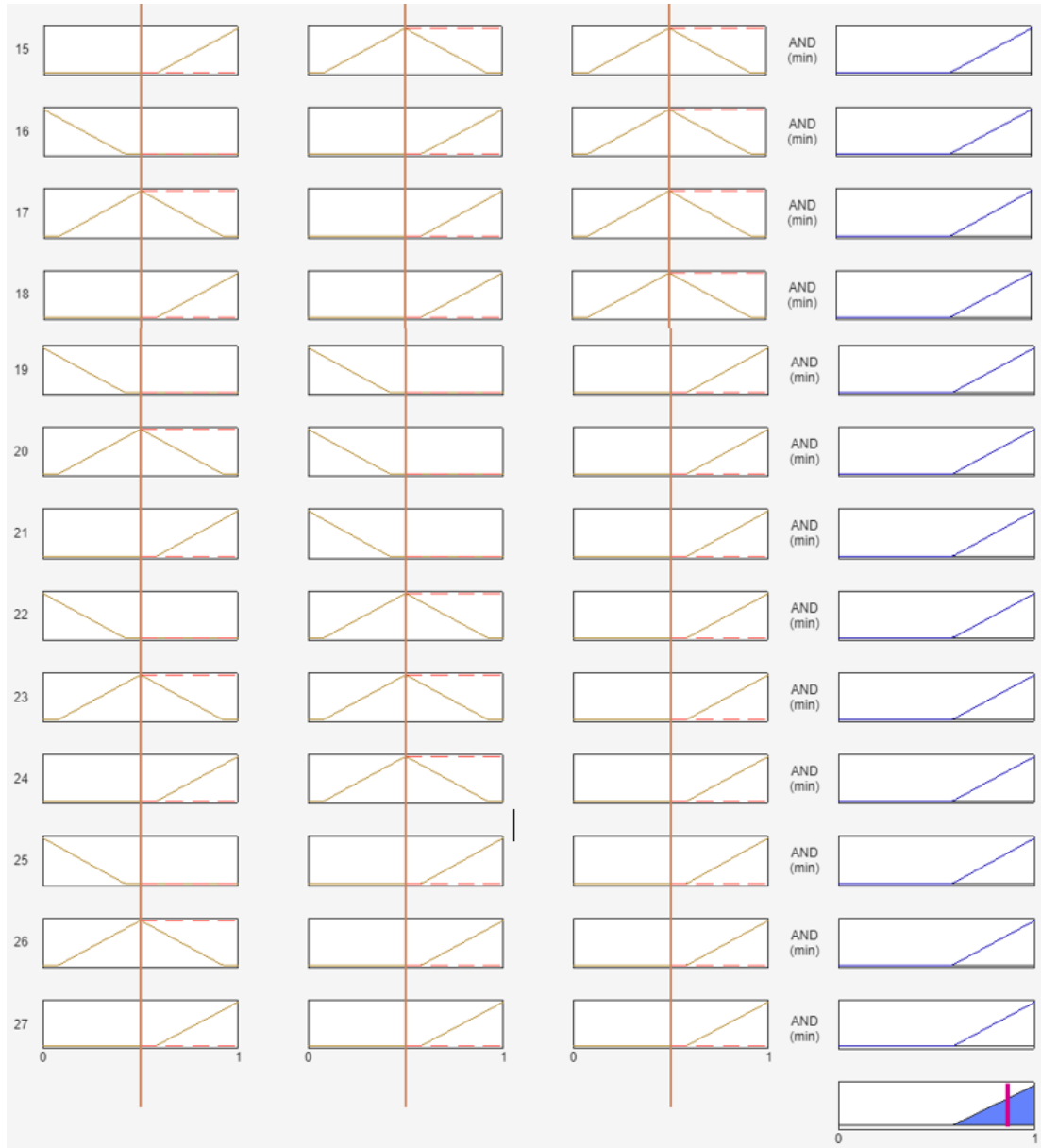


Figure A.11: Rule Interference of Membrane Degradation -2

Bayesian Network

Bayesian conditional probability tables for important Failure causes and all three failure modes.

Node properties: Contaminants and Impurities

General Definition Format User properties Value

Operating Cond. ☐ True ☐ False

Water Purity ☐ True ☐ False

Gas Purity ☐ True ☐ False

	True				False			
	True	False	True	False	True	False	True	False
True	0.9	0.8	0.8	0.5	0.9	0.6	0.6	0.1
False	0.1	0.2	0.2	0.5	0.1	0.4	0.4	0.9

Figure A.12: BN - Contaminants and Impurities

Node properties: Membrane Degradation

General Definition Format User properties Value

Degradation and Ageing ☐ True ☐ False

Mechanical stress ☐ True ☐ False

Contaminants and Impurities ☐ True ☐ False

	True				False			
	True	False	True	False	True	False	True	False
True	0.9	0.7	0.8	0.5	0.7	0.4	0.6	0.1
False	0.1	0.3	0.2	0.5	0.3	0.6	0.4	0.9

Figure A.13: BN - Membrane Degradation

Node properties: Catalyst Degradation

General Definition Format User properties Value

Chemical processes ☐ True ☐ False

Contaminants and Impurities ☐ True ☐ False

Degradation and Ageing ☐ True ☐ False

	True				False			
	True	False	True	False	True	False	True	False
True	0.9	0.8	0.7	0.6	0.7	0.4	0.3	0.2
False	0.1	0.2	0.3	0.4	0.3	0.6	0.7	0.8

Figure A.14: BN - Catalyst Degradation

Node properties: Bipolar plate Corrosion

General Definition Format User properties Value

Chemical processes ☐ True ☐ False

Contaminants and Impurities ☐ True ☐ False

Manufacturing defects ☐ True ☐ False

	True				False			
	True	False	True	False	True	False	True	False
True	0.9	0.8	0.6	0.5	0.7	0.6	0.3	0.1
False	0.1	0.2	0.4	0.5	0.3	0.4	0.7	0.9

Figure A.15: BN - Bipolar plate corrosion

Python code for Monte Carlo reliability simulation

```

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import os

# Data: failure rates (lambda) in failures/hour
data = {
    "M1": {"MD": 3.38e-5, "CD": 2.54e-5, "BPC": 1.24e-5},
    "M2": {"MD": 2.40e-5, "CD": 2.99e-5, "BPC": 1.76e-5},
    "M3": {"MD": 2.58e-5, "CD": 2.36e-5, "BPC": 2.15e-5},
}

NUM_SIMULATIONS = 40000
TIME_HORIZON = 10000 # hours
TARGET_TIMES = [2500, 5000, 7500, 10000]

results = []

print(f"Starting Monte Carlo Simulation (N={NUM_SIMULATIONS})
    ...")

plt.figure(figsize=(10, 6))

styles = {
    "M1": {"color": "#d62728", "style": "-", "label": "M1 (
        Conservative)"},
    "M2": {"color": "#2ca02c", "style": "--", "label": "M2 (
        Optimistic)"},
    "M3": {"color": "#1f77b4", "style": "-.", "label": "M3 (
        Balanced)"},
}

for method, components in data.items():
    # Total failure rate for the series system (stack)
    lambda_total = sum(components.values())

```

```

# Simulate Time To Failure (TTF) ~ Exponential(1/
    lambda_total)
ttf_samples = np.random.exponential(scale=1 /
    lambda_total,
                                     size=NUM_SIMULATIONS)

# Mean TTF
mttf_sim = np.mean(ttf_samples)
mttf_theo = 1 / lambda_total

print(f"\n--- Method {method} ---")
print(f"Total Lambda: {lambda_total:.2e}")
print(f"MTTF (Theoretical): {mttf_theo:.0f} hours")
print(f"MTTF (Simulated): {mttf_sim:.0f} hours")

rel_data = {"Method": method, "MTTF": mttf_sim}

# Reliability at target times:  $R(t) = P(T > t)$ 
for t in TARGET_TIMES:
    R_t = np.sum(ttf_samples > t) / NUM_SIMULATIONS
    print(f"Reliability @ {t}h: {R_t:.4f}")
    rel_data[f"R@{t}h"] = R_t

results.append(rel_data)

# Plot reliability curve from empirical CDF
sorted_ttf = np.sort(ttf_samples)
y_vals = 1.0 - np.arange(1, NUM_SIMULATIONS + 1) /
    NUM_SIMULATIONS

s = styles[method]
plt.plot(
    sorted_ttf,
    y_vals,
    label=f"{s['label']} (MTTF={mttf_sim/1000:.1f}k h)",
    color=s["color"],
    linestyle=s["style"],
    linewidth=2,
    alpha=0.8,
)

plt.yticks(np.arange(0, 1.05, 0.05))
plt.ylim(0.4, 1.0)
plt.title("PEM Stack Reliability Prediction (Monte Carlo
    Simulation)")
plt.xlabel("Time (hours)")
plt.ylabel("Reliability  $R(t)$ ")
plt.xlim(0, TIME_HORIZON)
plt.grid(True, which="both", linestyle="--", linewidth=0.5)
plt.legend()

```

```
output_dir = os.path.dirname(os.path.abspath(__file__))
plot_path = os.path.join(output_dir, "reliability_plot.png")
plt.savefig(plot_path)
print(f"\nPlot saved to: {plot_path}")

# Summary table
df = pd.DataFrame(results)
print("\nSummary Table:")
print(df)
```

