Impacts of Sensor Degradation on Measurement Uncertainty in Prognostics and Maintenance Decision-making: State of the Art and Challenges

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ABSTRACT

Prognostics and maintenance decision-making rely heavily on accurate and reliable measurements derived from sensors. However, sensor degradation introduces measurement uncertainties that compromise the precision of fault detection, remaining useful life estimation, and overall maintenance strategies. This paper provides a comprehensive review of the multifaceted impacts of sensor degradation on measurement uncertainty and its subsequent influence on prognostics and maintenance. The paper synthesizes various sensor degradation mechanisms and existing modelling techniques, emphasizing the growing research focus on developing accurate degradation models. The review also provides an in-depth analysis of how sensor degradation affects measurement uncertainty, exploring both qualitative and quantitative impacts through various modelling approaches and tools. Furthermore, this review examines the implications of this uncertainty on prognostics and maintenance decision-making methodologies, showcasing current mitigation methods and models. Finally, the review identifies key challenges and research gaps, outlining promising directions for future research in sensor degradation and its impact on prognostics and maintenance. By addressing these critical issues, this paper contributes to the advancement of more reliable, adaptive, and efficient Prognostics and Health Management (PHM) systems across various industrial and technological domains.

https://doi.org/10.36001/IJPHM.2025.v16i4.4306

Keywords: Sensor Degradation, Measurement Uncertainty, Prognostics, Maintenance Decision-Making

1. INTRODUCTION

Sensors are devices that detect and monitor physical phenomena (Wilson, 2004; Algamili, Khir, Dennis, Ahmed, Alabsi, Ba Hashwan and Junaid, 2021). They convert composition variations of the phenomenon (such as electrical conductivity, hydrogen potential, etc.) into a particular form that can be utilized (Basuwaqi, Khir, Ahmed, Rabih, Mian and Dennis, 2017), typically electrical signal (Wilson, 2004; Su, Ma, Chen, Wu, Luo, Peng and Li, 2020). They form part of the interface between the physical world and electronic devices such as computers, with actuators representing the other part by converting electrical signals into physical actions (Wilson, 2004).

Sensor degradation is a well-known phenomenon that impacts the accuracy and reliability of measurements, as sensors degrade over time, the data they provide become less precise and more uncertain (Abid, Sayed Mouchaweh and Cornez, 2019; Elattar, Elminir and Riad, 2016; Javed, Gouriveau and Zerhouni, 2017). The quality of measurements provided by sensors is a critical factor impacting the performance of prognostics, maintenance decision-making and optimization, and it can be compromised by sensor degradation (Liu, Do, Iung and Xie, 2019). Lukens, Rousis, Baer, Lujan and Smith (2022) echoed that poor data quality can lead to incorrect assessments of equipment health, resulting in unnecessary maintenance or unexpected failures. As a result, low-quality data can lead to increased maintenance costs and operational disruptions, as organizations may either over-maintain or under-maintain their equipment based on flawed data interpretations. The degradation of sensors can introduce systematic errors in the data they collect. Many existing references in the literature note that sensor degradation causes increased measurement error (Mukhopadhyay, Liu, Bedford and Finkelstein, 2023; Ohsuga & Ohyama, 1988; Zhang, Si, Du and Hu, 2018; He, Sun, Xie and Kuo, 2022) and error rates over time (Zhang, Xin, Yin, Wang and Wang, 2016). Thereby, it worsens error metrics such as Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) (Hachem, Vu and Fouladirad, 2024). Consequently, it weakens the correlation between sensor output and actual conditions (Li, Price, Stott and Marshall, 2007) leading to reduced measurement reliability (Wanga, Al Atata, Ghaffaria, Leea and Xib, 2008; Li & Dai, 2020). Several methods designed to deal with uncertainty face various difficulties due to sensor degradation. Filtering methods encounter filtering error dynamic instability (He, Wang and Zhou, 2008), indicating difficulty in deriving exact values of filtering error covariance (FEC) which tends to be increasing (Huang & Shen, 2021). Similarly, Wen, Wang, Yang and Ma (2023) showed increased estimation error covariance due to sensor degradation. Calibration methods suffer from a reduction in accuracy (Sun & Xiong, 2020; Yu & Wu, 2009), possible errors in the calibration coefficients (Kamei, Nakamura, Yamamoto, Nakamura, Tsuchida, Yamamoto and Wu, 2012), and increased frequency of recalibration (Aldrin, Medina, Allwine, QadeerAhmed, Fisher, Knopp and Lindgren, 2007).

Several decades ago, maintenance decisions were primarily made in response to failures, however, today, making maintenance decision is widely acknowledged as a vital business function and a key component of asset management (De Jonge & Scarf, 2020). It is the process of selecting the most appropriate maintenance strategy or action to ensure the optimal performance, reliability, and cost-effectiveness of equipment, systems, or assets (Liu, Lv and Yang, 2016; Cao, Zhang, Gong, Jia and Zhang, 2021; Zandiyehvakili, Aminnejad and Lork, 2022). This process involves considering various factors such as the assets' conditions, failure modes, maintenance costs, resource constraints, and operational requirements (Đuric, Josimovic, Adamovic, Radovanovic, Jovanov, Adamovic and Jovanov, 2012; Ding, Goh, Tan, Wee and Kamaruddin, 2012; Tee & Ekpiwhre, 2020). Several factors have been considered for inclusion in the process to improve effectiveness, including the impacts from sensor degradation (Liu et al., 2019; Kaiser & Gebraeel, 2009; Salehpour-Oskouei & Pourgol-Mohammad, 2017). Many maintenance models assume that sensor performance remains constant, which is often not the case in reality (Mukhopadhyay et al., 2023; van Oosterom, Maillart and Kharoufeh, 2017). Condition monitoring systems that rely on sensor data are used to identify changes in machinery conditions and inform maintenance decisions (Li, Jiang, Carroll and Negenborn, 2021). However, the uncertainties caused by sensor degradation and limitations in degradation mechanisms can lead to inaccurate determination of machinery condition, which in turn affects the reliability of maintenance decisions (Li et al., 2021; Huynh, Barros and Bérenguer, 2012; Hegedus & Kosztyán, 2011). Liu et al. (2019) highlighted that sensor degradation results in distorted measurements, causing observations to deviate significantly from true values, which can mislead Condition-Based Maintenance (CBM) strategies.

Achieving predictive maintenance, prognostics is required, which is an emerging science of predicting the health condition of systems. A typical definition of prognostics is found in the International Organization for Standardization [ISO] 13381-1; its goal is to provide the user with the ability to predict the remaining useful life (RUL) with a satisfactory level of confidence. The accuracy of prognostics is affected by multiple sources of uncertainties, including input uncertainty such as initial state estimation; model uncertainty such as misspecified methods, unexplained features, unmodelled phenomena; operational uncertainty such as operating and environmental conditions; and measurement uncertainty such as sensor errors, estimation error (Goebel, Saxena, Daigle, Celaya, Roychoudhury and Clements, 2012; Saxena & Goebel, 2012; Sankararaman & Goebel, 2015; Huang, Gardoni and Hurlebaus, 2012). Accurate prognostics requires reliable measurement on the states of the system, which can be compromised by sensor degradation and the resulting measurement uncertainty (Zhao, Zhang, Liu and Qiu, 2019; Sun, Zuo and Pecht, 2011; Tao, 2012). Addressing the challenges of sensor degradation is crucial for developing reliable and effective prognostics systems, as degradation-related features extracted from the sensor data can dramatically improve the accuracy of RUL prediction (Qin, Cai, Gao, Zhang, Cheng and Chen, 2022).

Despite the critical impact of sensor degradation on prognostics and maintenance decision-making, no comprehensive review on this topic has been conducted to date. This study aims to fill that gap by providing an in-depth analysis of the multifaceted impacts of sensor degradation on measurement uncertainty and its influence on prognostics and maintenance decision-making. This review explores sensor degradation mechanisms, existing modelling techniques, application domains, and their impact on measurement uncertainty, emphasizing both qualitative and quantitative effects. It also examines how this uncertainty influences prognostics and maintenance decision-making while highlighting methods to mitigate its impact. Finally, the review identifies key challenges and research gaps, outlining promising directions for future research in sensor degradation and its impact on prognostics and maintenance optimization.

This article is organized as follows. Section 2 describes the methodology used for the systematic review. The bibliometric results and analysis are also presented. Section 3 focuses on the literature review of various degradation processes and their modelling techniques. Section 4 discusses the impact of sensor degradation on measurement errors and examines different approaches to quantify and model the measurement uncertainty induced by sensor degradation. Sections 5 and 6 explore the existing works considering the sensor degradation impacts on prognostics and maintenance, ultimately leading to more robust maintenance optimization. Section 7 discusses the issues, challenges, and research gaps identified through the review, providing insights into areas requiring further investigation. Finally, Section 8 concludes by presenting the main results of our study and future perspectives, summarizing the key findings and suggesting directions for future research.

2. METHODOLOGY

The review protocol followed in this paper adheres to the Kitchenham guidelines (Keele, 2007), ensuring a thorough and systematic literature review. This approach structures the articles around specific questions that align with the study's objectives, thereby focusing the analysis on key topics of interest. We formulated the following main research questions to guide our analysis:

1. What is sensor degradation and how to model the sensor degradation processes?
2. What are the impacts of sensor degradation on measurement uncertainty?
3. How have impacts of sensor degradation on measurement uncertainty been considered in prognostics and maintenance decision-making?

With these research questions, we address in detail the impacts of sensor degradation on measurement uncertainty within the context of prognostics and maintenance optimization.

2.1. Keywords and Search String Definition

To achieve comprehensive coverage, some widely used scientific databases were explored, including Web of Science (WOS), Scopus, IEEE Xplore, and ACM Digital Library. These databases are typically considered sufficient for a literature search. The articles sourced from Scopus and WOS are published by well-known publishers such as Elsevier, Springer, Taylor & Francis Online, IEEE, among others, thereby enhancing the thoroughness of this research. Defining the search string was conducted, described in Section 2.1.2. Then, filtering criteria were defined, described in Section 2.1.3.

To effectively identify articles relevant to the research questions, specific keywords were carefully formulated to construct the search string. Synonyms and alternative spellings were included to ensure comprehensive coverage. The keywords were categorized into search topics, sensor degradation, measurement uncertainty, and their implications for prognostics and maintenance, which were connected using Boolean operators. Within each topic, keywords were linked with the OR operator, while the topics themselves were combined using the AND operator, resulting in the following query:

(“sensor degradation” OR “sensor deterioration” OR “sensor impairment” OR “sensor decline” OR “sensor wear” OR “degradation of sensor” OR “deterioration of sensor” OR “impairment of sensor” OR “degrading sensor” OR “deteriorating sensor” OR “impairing sensor” OR “degraded sensor” OR “deteriorated sensor” OR “impaired sensor”)

AND (“error” OR “uncertainty” OR “reliability” OR “accuracy” OR “precision” OR “consistency” OR “quality” OR “prognostics” OR “maintenance” OR “structural health monitoring”)

To ensure a systematic review, the primary search relied on article metadata. They included titles, abstracts, authors, and keywords, providing a structured framework for the identification of relevant articles, as these metadata are meticulously curated by authors and editors to reflect the core content of the article. Table 1 shows the total number of articles retrieved from each scientific database from the search string. Those retrieved articles were then filtered according to the criteria explained in the next section.

Databases	Number of papers
Web Of Science	245
Scopus	369
IEEE Xplore	147
ACM	63
Total	824

Table 1. Number of papers by databases

2.2. Article Filtering

Gathering all primary articles from the keyword-based search within scientific databases, a two-phase filtering process was conducted to assess their relevance. The first phase involved a thorough examination of the metadata of each article to determine their initial suitability. In the second phase, a more in-depth evaluation of the full-text content of the articles was investigated.

The keyword-based search yielded 824 references from digital libraries. A series of exclusion criteria were applied to identify relevant studies. They were formulated based on the research objectives investigated, as detailed in Table 2. First, duplicate and non-English papers were excluded, reducing the count to 477. Next, the relevance of the remaining papers was assessed by examining their metadata, including titles, abstracts, and keywords, further narrowing the number to 223. After excluding inaccessible papers and thoroughly analysing the full text of the remaining papers and additional papers identified during the process to avoid bias, resulting in 85 papers being selected. Two statistical analyses of these selected papers are discussed in the following sections.

Phases	Nº papers
Total Nº papers retrieved from digital libraries	824
Nº papers remained after removing duplications	486
Nº papers remained after removing non-English	477
Nº papers remained after revising metadata	223
Nº papers remained after reading full text	71
Nº papers to be reported	85

Table 2. Summary of article filtering process

2.3. Growth Trend of the Research Topic

Figure 1 shows that the number of selected publications shows a trend of being low in the early years but shows a significant increasing trend from 2018 onwards. In addition, it is worth mentioning that the contribution of journal articles has substantially increased in recent years. This can indicate that the literature witnessed a growing interest related to the relationship between sensor degradation and measurement uncertainty and prognostics and maintenance.

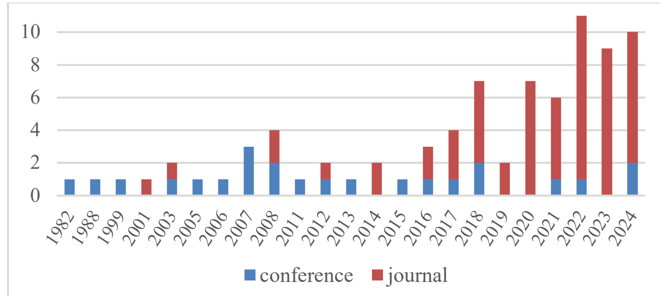

Figure 1. Number of publications by publication years

2.4. Keyword Occurrence Analysis

Conducting keyword occurrence analysis, the interconnections among various terms associated with sensor degradation are visualized through a multi-coloured network visualized in Figure 2. At the centre of the network, "sensor degradation" emerges as the most prominent and interconnected keyword, signifying its central role in this thematic landscape. Surrounding it are clusters of related concepts, such as "remaining useful lifetime", "maintenance", "uncertainty analysis", and "degradation modelling". The clusters are color-coded, revealing thematic groupings such as reliability analysis, maintenance and health monitoring, and estimation techniques. This network reveals how research topics interrelate, with frequent co-occurrences suggesting strong conceptual ties, aiding in the identification of notable themes within the field.

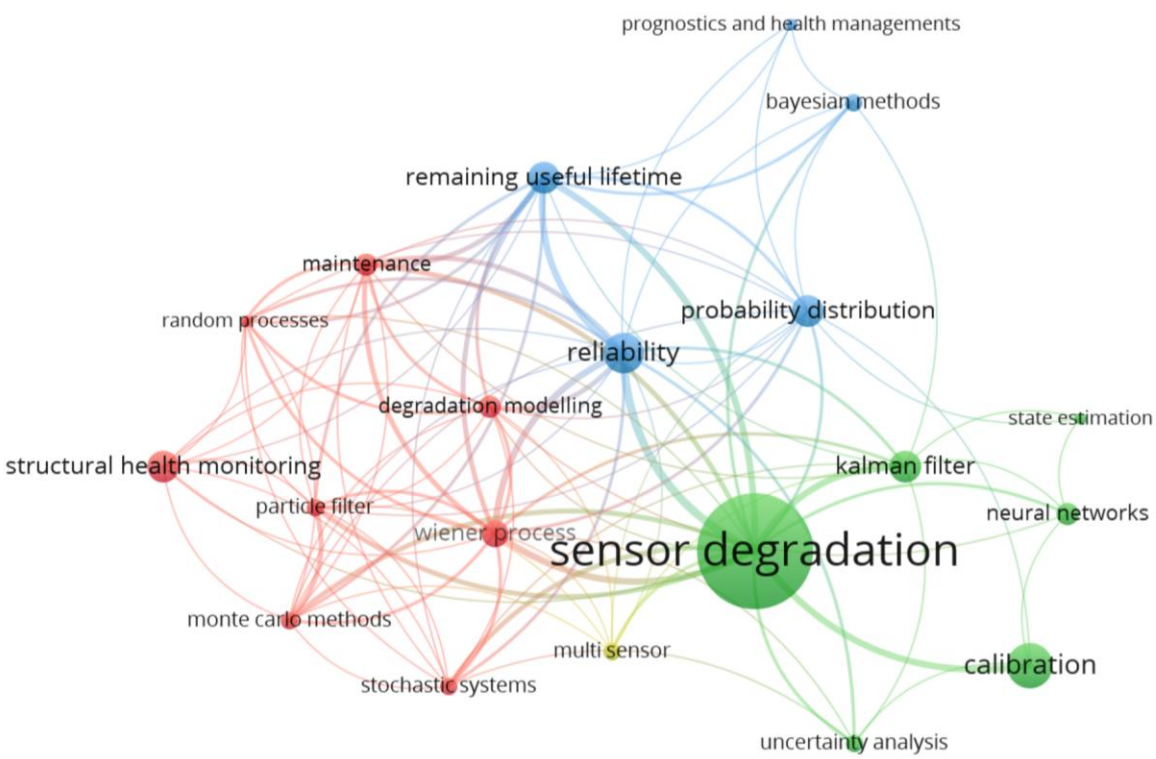

Figure 2. Keyword co-occurrence analysis

3. Review on Sensor Degradation

In this section, the root causes of sensor degradation across various domain applications are first reviewed. This foundational understanding of how sensors degrade is crucial, as it directly informs the appropriate development of quantification models, which are standard in the literature to manage this phenomenon. Subsequently, several modeling techniques for sensor degradation processes are discussed in this section.

3.1. Sensor Degradation Process

The degradation of sensors is a complex phenomenon driven by a variety of physical and chemical conditions, and are highly dependent on the sensor type and its operational environment. For example, sensors face degradation under extreme operating conditions, such as high pressures and temperatures, scaling, or erosion (Abdel-Jaber & Glisic, 2016; Bikmukhametov, Stanko and Jäschke, 2018). For instance, magnetostrictive sensors degrade through cyclic relaxation and ambient temperature variations affecting the FeCo strip and epoxy layers (Chen, Yang, Liu and Liu, 2021) and causing interlayer diffusion (Bonhote, Chang, Judy, Kitamoto, Krongelb, Romankiw and Zangari, 2006), or piezoelectric sensors experience fiber breakage from fatigue loading and electrode misalignment from fiber breakage and mechanical stress (Mehdizadeh, John, Wang, Ghorbani and Rowe, 2012). To further illustrate the diversity of these processes across various sensor types, Table 3 categorizes a range of reported degradation mechanisms based on their common characteristics.

Sensor types	Reported degradation processes
Temperature sensors	physicochemical degradation (Zhang et al., 2018; Li, Zhang, Thayil, Chang, Sang and Ma, 2021); contamination accumulation (Sakurai, Yamaguchi, Hiura, Yoneshita, Kimura and Tamura, 2008); mechanical degradation (Mandal, Sairam, Sridhar and Swaminathan, 2017)
Optical and imaging sensors	noise-induced (Khanam, Aslam, Saha, Zhai, Ehsan, Stolkin and McDonald-Maier, 2021); electro-optical degradation (Yin, Shi, Peng, Zhang and Guo, 2022; Yang, Wen, Zhao, Liu, Feng, Li and Guo, 2024); contamination accumulation (Li et al., 2007; Kamstrup & Hansen, 2003); mechanical degradation (Kim, Cao and Liang, 2013)
Acoustic and ultrasonic sensors	mechanical degradation (Aldrin et al., 2007; Shu, Wang, Yan, Fan and Wu, 2019; Li, Peng and Yu, 2017); physicochemical degradation (Shu et al., 2019; Li et al., 2017; Johnson, Kim, Zhang, Wu and Jiang, 2014; Quattrocchi, Alizzio, Martella, Lukaj, Villari and Montanini, 2022); contamination accumulation (Li et al., 2017)
Motion sensors	mechanical degradation (Li et al., 2007; Wanga et al., 2008); contamination accumulation (Ohsuga & Ohyama, 1988; Wanga et al., 2008)
Pressure sensors	mechanical degradation (Park, Jung, Ko, Park and Cho, 2021); physicochemical degradation (He et al., 2022)
Chemical sensors	physicochemical degradation (Xu, Meng and Yang, 2022); contamination accumulation (Anil, 2020; Moriya & Sako, 2001; Bai, Huang, Wang, Ying, Zheng, Shi and Hu, 2020; Liu, Diao, Hu, Zhao, Shi, Wang and Li, 2023)
Power electronics sensors	mechanical degradation (Hu, Zhang, Liu, Lin, Dey and Onori, 2020; Xia, Xu and Gou, 2020) electromagnetic interference (Hu et al., 2020)

Table 3. A classification of sensor degradation mechanisms by measurement characteristics

Studies have shown that thermistors subjected to thermal shock cycles exhibit significant changes in their resistance characteristics, which can compromise their accuracy and reliability (Li et al., 2021). Thermocouples experience ageing due to natural wear and tear, mechanical issues leading to loss of sensor component contacts, environmental factors, and physicochemical reactions (Zhang et al., 2018; Mandal et al., 2017). Resistance thermometers experience oxidation processes of sensing wires, which lead to instabilities in their readings, as highlighted with platinum resistance thermometers by Sakuraï et al. (Sakurai et al., 2008).

Medium-resolution spectral imagers are affected by changes in the reflectivity of scan mirrors caused by vibrations during launch and the harsh conditions of space, along with the ageing of the instrument (Kim et al., 2013). Complementary Metal-Oxide-Semiconductor (CMOS) image sensors degrade due to gamma-ray-induced photo-signal processes, radiation-induced noise (Khanam et al., 2021), or proton-induced displacement damage (Yang et al., 2024). Thematic mappers face issues such as sensor outgassing leading to decreased responsivity (Kamstrup & Hansen, 2003). Brightness sensors exhibit defects such as dark current tolerance, open circuit faults, low insulation resistance, and large reverse currents in light-emitting tubes, which are exacerbated by weather conditions, vibration, sand, and temperature rise, leading to data distortion (Yin et al., 2022). Solar radiation sensors accumulate deposits on their transparent external casings from environmental exposure (Li et al., 2007).

Acoustic and ultrasonic sensors commonly use piezoelectric materials, which are sensitive to temperature fluctuations and can experience changes in their mechanical properties. Acoustic sensors often lose their piezoelectric properties at high operating temperatures, typically above 500°C to 700°C, which eventually results in sensitivity degradation (Johnson et al., 2014). Similarly, surface acoustic wave

(SAW) sensors are highly sensitive to environmental changes such as temperature and humidity, surface scratching, oxidation, and chemical degradation, which can lead to irreversible material degradation and functional failure (Shu et al., 2019; Li et al., 2017). Low-cost ultrasonic transducers face rapid sensor ageing caused by temperature and humidity, leading to critical issues in metrology and reliability that can compromise their functionality and safety (Quattrocchi et al., 2022). Acoustic emission transducers and ultrasonic current sensors in structural health monitoring can be degraded by several processes such as sensor bond breakdown, thermal loading, and dynamic stress (Aldrin et al., 2007).

Motion sensors are prone to mechanical degradation, which can lead to failures, for instance, anemometers may become stuck in fixed positions as a result of such wear and tear (Li et al., 2007). Wheel speed sensors face issues such as air gap problems, wear on toothed rings, wiring problems, and failures in internal IC components due to extreme temperatures, high humidity, chemical attacks, strong vibrations, electromagnetic interference, and pollution (Wanga et al., 2008). Hot-wire type air flow meters degrade due to dust deposition from airborne particles, and gas diffusion layer type air-fuel ratio sensors suffer performance issues from contaminants accumulating in exhaust gas components (Ohsuga & Ohyama, 1988).

Pressure sensors often degrade under harsh conditions such as mechanical fatigue, environmental factors, and material limitations. For instance, high temperature can accelerate degradation by altering the coefficients in piezoresistive pressure sensors in reliability tests (He et al., 2022). Park et al. (2021) also highlighted that existing pressure sensors, specifically polyurethane-based, exhibit insufficient durability when subjected to a wide pressure range.

One of the primary factors contributing to the degradation of chemical sensors is the gradual accumulation of contaminants on the sensor's surface. Continuous exposure to target gases can lead to surface contamination degrading the sensor performance in gas sensors (Anil, 2020). Antimony-based pH sensors degrade through the formation of an antimony oxide layer during use due to oxidation processes (Liu et al., 2023). Oxygen sensors degrade as silicon oxide deposits accumulate from the decomposition of seal rubber (Moriya & Sako, 2001). Aerosol particulate matter sensors are prone to ageing of the electric components and dust accumulation on optical components due to insufficient maintenance (Bai et al., 2020). In addition, degradation can be caused by physicochemical interactions between the sensor materials and the analytes they are designed to detect. For instance, in metal oxide semiconductor gas sensors, irreversible chemical reactions over time exacerbated by high humidity and temperature fluctuations, can degrade the sensing material's properties (Xu et al., 2022).

Degradation in power electronics sensors is susceptible to internal and external influencing factors. Hu et al. (2020) highlighted that mechanical stress from component disruptions, vibrations, thermal stress from operational losses, and electromagnetic interference can degrade voltage-current sensors, affecting the operation of closed-loop control systems. Similarly, Xia et al. (2020) emphasized that environmental factors such as mechanical vibration and equipment ageing can lead to faulty in current sensors, which can severely affect control performance and potentially lead to system shutdowns.

In other articles, sensor degradation has been described as a generalized process. It can be categorized into three classes, as shown in Table 4.

Degradation types	References
Gradual, continuous degradation	Li & Dai, 2020; Lu, He, Liang and Zhang, 2021; Gao & Liu, 2022; Murthy, 1982; Zhang, Song, Zhao and Deng, 2021
Abrupt, catastrophic degradation	Murthy, 1982; Hachem, Vu and Fouladirad, 2021
Stochastic degradation	He et al., 2008; Huang & Shen, 2021; Wen et al., 2023; van Oosterom et al., 2017

Table 4. Generalized degradation processes

Some studies have described sensor degradation using gradual and continuous processes. The gradual and continuous radiometric sensor degradation process has been observed in panchromatic and multispectral sensors, highlighting the consistent decline in sensor performance over time (Lu et al., 2021). Additionally, various sensors have exhibited additive and multiplicative degradation, indicating a combination of steady deterioration and proportional changes in sensor output (Gao & Liu, 2022). Furthermore, in chemical processes involving soft sensors, time-varying chemical impacts have been noted as influencing sensor degradation (Li & Dai, 2020).

In addition to gradual processes, sensor degradation can occur abruptly or catastrophically. Other studies have identified general processes that include continuous degradation alongside abrupt changes caused by external shocks, suggesting a complex interplay between gradual and sudden deterioration mechanisms (Hachem et al., 2021). The degradation patterns also encompass gradual deterioration, catastrophic deterioration, and combinations thereof, reflecting a broad spectrum of degradation behaviours in various sensors (Murthy, 1982).

Stochastic degradation presents another important category of sensor degradation processes. This type of degradation is inherently random and can be described by probabilistic models. Various sensors have been observed to undergo stochastic degradation, reflecting the unpredictable nature of their performance decline over time (He et al., 2008; Huang & Shen, 2021). Instantaneous and delayed sensors alike have been subject to stochastic degradation, suggesting that this random degradation behaviour is prevalent across different sensor types (Wen et al., 2023). Additionally, the probabilistic relational degradation has been analysed to understand and model the stochastic nature of sensor degradation (van Oosterom et al., 2017).

The detailed exploration of diverse sensor degradation mechanisms in this section underscores the multifaceted nature of sensor deterioration. Understanding these degradation pathways is a crucial prerequisite for effectively managing and predicting sensor degradation over time. This comprehensive overview of how sensors degrade naturally leads to the next critical step: developing robust models to quantify these degradation, which will be the focus of subsection 3.2.

3.2. Sensor Degradation Modelling

Modelling of sensor degradation provides essential insights for advancing the acquisition of reliable measurements as it translates the understanding of degradation mechanisms into quantitative frameworks, thereby enabling predictive analysis of sensor performance and reliability. These modelling methods, examined in the literature, can be categorized into various approaches as presented in Table 5.

Categories	Some modelling techniques	Some implicit and explicit representations
Calibration	Calibration coefficients (Sun & Xiong, 2020; Aldrin et al., 2007; van Oosterom et al., 2017; Kamstrup & Hansen, 2003; Kim et al., 2013; Lu et al., 2021; Gao & Liu, 2022; Detsch, Otte, Appelhans and Nauss, 2016)	$D(t) = \{calibCoefficients(t)\}$
Normalization	Normalization to undamaged condition (Michaels, Michaels, Mi, Cobb and Stobbe, 2005)	$D(t) = f(X(t), X_{initial})$
	Belief rule base (Yin et al., 2022)	$Rule_k$: If x_1 is A_1^k, x_2 is A_2^k..., x_M is A_M^k then $D(t)$ is D_j with belief β_j^k
	Fitness function (Arosh, Nayak and Duttagupta, 2015)	$D = \frac{1}{N}\sum_{t=0}^{N-1}\left[\hat{Z}^2_{non-degraded}(t) - Z^2(t)\right]$
Deterministic	Linear model (Zhang et al., 2016; Kim et al., 2013)	$D(t) = D_0 + \alpha t + \beta$
	Accumulation model (Zhang, Qin, Lu, Liu and Faber, 2023; Su, Huang, Liu and Wang, 2024)	$D(t) = D_0 + \sum_{t_i=0}^{t}\Delta D(t_i)$
	Power law model (Kamstrup & Hansen, 2003; Hua, Al-Khalifa, Hamouda and Elsayed, 2013)	$D(t) = D_0 + at^c$ (Kamstrup & Hansen, 2003) $D(t) = D_0 + at^c + \delta\sqrt{at^{c-1}}B(t)$ (Hua et al., 2013)
	Exponential growth model (Aldrin et al., 2007; Saha, Goebel, Poll and Christophersen, 2007)	$D(t) = f\left(e^{g(t)}\right)$
	Explicit empirical/physics-based equations (Bonhote et al., 2006; Carrino, Nicassio and Scarselli, 2018; Carratù, Gallo, Iacono, Sommella, Ciani and Patrizi, 2024; Yang et al., 2024)	$D(t) = f(\theta(t))$, $\theta(t)$ are parameters of sensor changing overtime
Stochastic Process	Wiener process (Mukhopadhyay et al., 2023; Zhang et al., 2018; He et al., 2022; Hachem et al., 2024; Liu et al., 2019; Hachem et al., 2021; Hua et al., 2013; Hossain, Kobayashi and Alam, 2024; Liu, Wang, Liu, Coombes and Chen, 2022; Dinh, Do, Hoang, Vo and Bang, 2024)	$D(t) = D_0 + \alpha t + \sigma B(t)$ $D(t) = D_0 + \alpha t + \beta X(t) + \sigma B(t)$ (Dinh et al., 2024)
	Gamma process (Mukhopadhyay et al., 2023; Hachem et al., 2024; Hachem et al., 2021; Hua et al., 2013)	$D(t) \sim Gamma(\alpha, \beta)$
	Gaussian process (Zhang et al., 2021)	$D(t) \sim Gaussian(\mu, \sigma)$
	Weibull process (Wu, Cantero-Chinchilla, Prescott, Remenyte-Prescott and Chiachío, 2024)	$D(t) \sim Weibull(\eta, \beta)$
	Uniform distributions (Huang & Shen, 2021; Wen et al., 2023)	$D(t) \sim Uniform(\kappa_{min}, \kappa_{max})$
	Stochastic matrix transformation (van Oosterom et al., 2017)	$D(t) = D(t-1) \cdot StochasticMatrix(t)$

Table 5. Sensor degradation process modelling technique categorizations

One approach to model sensor degradation is through calibration, where degradation is accounted for by continuously updating calibration coefficients to maintain measurement accuracy. Calibration coefficients were used to indicate degradation in additive and multiplicative degradation processes (Gao & Liu, 2022). Gradual and continuous radiometric sensor degradation was effectively identified using monthly updated calibration coefficients, highlighting the necessity of timely cross-calibration to ensure reliability (Lu et al., 2021). Self-calibration methods were proposed to record degradation process of sensor bonds over time, demonstrating their utility in prolonging sensor lifespan (Aldrin et al., 2007). Similarly, Sun and Xiong (2020) calculated hybrid F-factors for solar diffuser (SD) processes. Some statistical post-analysis methods were applied such as Theil-Sen and Mann-Kendall Test to identify degradation trends (Detsch et al., 2016). This approach offers the advantage of managing sensor accuracy over time, as it adapts the model to real-world conditions. It is straightforward and allows for continuous improvement based on data observation, however, can heavily relies on the availability of stable and reliable reference data for frequent recalibration, which can be costly challenging to obtain.

Normalization approaches offer the integration of expert insights into sensor degradation phenomena. Normalization to undamaged conditions, such as the normalized energy ratio method used by Michaels et al. (2005), accounts for transducer degradation by addressing the fact that damaged sensors record varying measurement levels under different conditions, while consistent levels are observed in no-degradation scenarios. Yin et al. (2022) used belief rule base, characterized by expert knowledge encoding for the modelling of mixed sensor degradation processes. Estimating sensor degradation levels using fitness functions was also discussed, comparing the current conditions with estimated non-degraded conditions, specifically the case of H-infinity filter (Arosh et al., 2015). A key strength of this method is its ability to model complex, nonlinear degradation patterns that may be difficult to capture with purely data-driven techniques. However, the approach is fundamentally limited by its reliance on expert knowledge, which can be subjective, and the challenge of defining an accurate non-degraded baseline for comparison.

Deterministic models offer empirical insights into sensor degradation phenomena. Measures such as slope, y-intercept, and correlation coefficient have been used to analyse sensor ageing (Zhang et al., 2016), or simple linear regression models are applied to assess changes in reflectivity of scan mirrors (Kim et al., 2013). The accumulation model was used (Zhang et al., 2023; Su et al., 2024), which treats the degradation process as independent increments, a specific type of discrete Markov process. The power law model, frequently observed in practice, is used for various degradation processes (Kamstrup & Hansen, 2003; Hua et al., 2013), which is considered the best function describing gain changes over time (Kamstrup & Hansen, 2003). Exponential growth models can be applied to model specific degradation processes such as plate sulfation, passivation, and corrosion (Saha et al., 2007). Bonhote et al. (2006) utilized Fick’s law to model interdiffusion processes and temperature-dependent time to failure fitted with the Arrhenius equation. Carrino et al. (2018) implemented a physics-based approach, specifically Rayleigh’s quotient, to calculate the natural bending frequency of a partially debonded piezoelectric sensor, which helps identify degradation by analysing frequency shifts caused by debonding. Yang et al. (2024) modelled sensor degradation due to proton radiation using an equation describing how factors such as temperature, defect energy levels, and carrier concentrations influence the defect generation rate over time. Carratù et al. (2024) proposed a Health Index for MEMS (Micro-Electro-Mechanical Systems) sensors, derived from time-domain and frequency-domain features using Principal Component Analysis, effectively capturing the sensor's degradation trend over time. The primary advantage of this approach lies in its high interpretability, as the models are based on well-understood physical laws and empirical evidence. However, these models often struggle to capture the inherent randomness and variability of real-world degradation processes, and their accuracy is highly dependent on precise knowledge of physical parameters that can be difficult to obtain.

Using stochastic processes to model sensor degradation offers the advantage of capturing the probabilistic nature of degradation over time, allowing for a dynamic representation that reflects the inherent randomness of the phenomena. Wiener process parameters (Mukhopadhyay et al., 2023; Zhang et al., 2018; He et al., 2022; Hachem et al., 2024; Liu et al., 2019; Hachem et al., 2021; Hua et al., 2013; Hossain et al., 2024; Liu et al., 2022; Dinh et al., 2024), Gamma process parameters (Mukhopadhyay et al., 2023; Hachem et al., 2024; Hachem et al., 2021; Hua et al., 2013), Gaussian process parameters (Zhang et al., 2021), and Weibull process parameters (Wu et al., 2024) provide frameworks for understanding random degradation patterns. A uniform distribution was also used to model sensor degradation process (Huang & Shen, 2021; Wen et al., 2023). Additionally, stochastic matrix transformation (van Oosterom et al., 2017) offers additional tools for capturing the probabilistic nature of sensor degradation. The limitation of this approach lies in the significant mathematical complexity and the requirement for substantial historical data to accurately select the appropriate stochastic process and estimate its parameters.

In summary, this review section provides an overview of the various mechanisms underlying sensor degradation and the methods used for its modelling. Degradation processes can be broadly categorized into two main types: time-dependent degradation, which may occur either gradually (continuous) or abruptly (catastrophic), and stochastic degradation, which follows a probabilistic nature. Time-dependent degradation is typically modelled using either discrete approaches, such as calibration-based methods, or continuous approaches, including normalization techniques and deterministic models. On the other hand, stochastic degradation is analysed using probability distributions or matrix transformations to capture the inherent randomness of the process. Building upon this foundation, the following section will explore in detail, how sensor degradation influences measurement uncertainty, ultimately affecting the precision, reliability, and consistency of sensor measurements. Meanwhile, section 7 will delve into the existing research gaps and challenges that remain in the field.

4. REVIEW ON IMPACTS OF SENSOR DEGRADATION ON MEASUREMENT UNCERTAINTY

This section provides a comprehensive review of how sensor degradation impacts measurement uncertainty. As sensors age and their performance deteriorates, the reliability and accuracy of the data they produce are compromised, directly affecting the precision and credibility of measurements derived from them. We will first delve into the various forms and implications of sensor degradation on measurement uncertainty, identifying and categorizing the critical effects observed in different sensor systems. Following this, we will explore the diverse modeling approaches employed to quantify and predict these impacts, offering a systematic overview of techniques used to account for degradation in measurement uncertainty assessments.

4.1. Impact of Sensor Degradation on Measurement Uncertainty

As sensors age and their accuracy diminishes, the reliability of the data they produce is compromised as the complex nature of degraded measurements makes it difficult to accurately capture system states (Wen et al., 2023), directly affecting the precision and credibility of measurements. By examining the relationship between sensor degradation and uncertainty, several critical implications of sensor degradation on measurement uncertainty can be seen, summarized with categorizations presented in Table 6, followed by their interpretations.

Impacts	References
Gain degradation	He et al., 2008; Michaels et al., 2005; Liu, Wang, He, Ghinea and Alsaadi, 2016; Yoo, Kim, Yoon, Kim, Kim and Youn, 2020; Jiang, Djurdjanovic, Ni and Lee, 2006
Bias	He et al., 2022; Liu et al., 2019; Bai et al., 2020; Chughtai, Tahir and Uppal, 2022; Li & Ying, 2017
Sensitivity degradation	Kamei et al., 2012; Aldrin et al., 2007
Noise	van Oosterom et al., 2017; Bikmukhametov et al., 2018; Khanam et al., 2021; Murthy, 1982; Liu et al., 2022; Chughtai et al., 2022; Loo, Ding, Baskaran, Nurzaman and Tan, 2022; Feng, Hajizadeh, Samadi, Sevil, Hobbs, Brandt and Cinar, 2018; Guo, Li, Xue and Zhang, 2024
Drift	Sun & Xiong, 2020; Bikmukhametov et al., 2018; Mandal et al., 2017; Liu et al., 2023; Murthy, 1982; Loo et al., 2022; Feng et al., 2018; Jordan, Deline, Kurtz, Kimball and Anderson, 2017; Phan, Kim, Islam, Kim and Lee, 2024
Shift	Hickinbotham & Austin, 1999
Increased latency	Kamstrup & Hansen, 2003; Liu et al., 2023
Sensor failure	Li et al., 2007; Bikmukhametov et al., 2018; Murthy, 1982

Table 6. Major impacts of sensor degradation on measurement uncertainty

Gain degradation is a common impact in sensor systems and can be caused by factors such as ageing, intermittent failure, and transmission congestion (Liu et al., 2016). When sensor deterioration occurs, estimating the exact gain reduction becomes challenging, complicating maintenance and prognostics processes (He et al., 2008). Another form, which is normalized gain, shows a decreasing trend (Jiang et al., 2006). A specific gain degradation, which is the reduction in the through-transmission ultrasonic signal amplitude, occurs due to changes in the coupling of transducers to the specimen or the degradation of the transducers themselves (Michaels et al., 2005). It was also reported that gain degradation frequently occurs in rotary speed-R sensors (Yoo et al., 2020).

Bias in sensor measurements can cause data distortion (Liu et al., 2019). Mean normalized bias tends to increase, associated with the ageing of electric components and the accumulation of dust on optical components (Bai et al., 2020). Ultra-wide Band (UWB) sensors suffer from bias when transceivers face physical obstructions during transmission (Chughtai et al., 2022). Measurement biases can be complex, as reported in (Li & Ying, 2017) and might not follow a Gaussian distribution.

Sensitivity degradation affects the responsiveness of sensors. It was mentioned to be associated with optical sensors (Kamei et al., 2012). Additionally, strain-gauge acoustic emission transducers and ultrasonic eddy current sensors suffer from sensor bond degradation processes and can result in inconsistent sensitivity (Aldrin et al., 2007).

Noise is a pervasive issue in sensor systems and is exacerbated by degradation processes. Ageing processes further increase noise levels, affecting sensor accuracy (van Oosterom et al., 2017). Additionally, distributed optical fibre sensors exposed to radiation can experience increased noise intensity (Guo et al., 2024; Khanam et al., 2021). Degradation-induced noises were reported to cause the system to become non-Gaussian (Liu et al., 2022). UWB sensors often encounter outliers and missing data (Chughtai et al., 2022). The presence of noise can cause significant fluctuations in estimated task space coordinates and other measurements (Loo et al., 2022). Mechanical degradation in pressure and temperature sensors leads to increased measurement noise (Bikmukhametov et al., 2018). Continuous glucose monitoring and energy expenditure sensors may experience missing signals, stuck signals, spikes, and other noise-related issues (Feng et al., 2018).

Drift in sensor readings is a synthesised impact, can result from long-term use or improper storage. For instance, antimony-based sensors exhibit such performance characteristics, causing potential drift (Liu et al., 2023). Mechanical degradation processes and ageing also contribute to drift, as shown in pressure and temperature sensors (Bikmukhametov et al., 2018; Mandal et al., 2017). In continuous glucose monitoring sensors, the sensors experience drift over time (Feng et al., 2018). It was mentioned that sensor data records may show long-term and erroneous drift due to a non-uniform degradation process (Sun & Xiong, 2020). Additionally, drift increases were also mentioned as being associated with a gradual deterioration process (Murthy, 1982). Drift can lead to error in the estimation algorithm, as seen in Recurrent Neural Network Direct (RNN-Direct) estimations (Loo et al., 2022). Membrane dissolution and oxidative ageing process in intraocular pressure sensors contribute significantly to zero drift over time, which is a common issue in long-term implantation scenarios (Phan et al., 2024). Sensor degradation also causes a shift in sensor measurements; for instance, it can alter the gradient of the load-response regression relationship, which distorts the distribution of measurement data (Hickinbotham & Austin, 1999).

Increased latency is another measurement impact of sensor degradation. Long-term use of antimony-based sensors leads to the formation of an antimony oxide layer, resulting in decreased response sensitivity and longer response times (Liu et al., 2023). Thematic mapper sensors show decreasing response times over periods of use (Kamstrup & Hansen, 2003).

Finally, sensor failure is an inevitable outcome of severe degradation. Sensor failure was linked with catastrophic deterioration process (Murthy, 1982). Mechanical degradation in pressure and temperature sensors can lead to sensor failure (Bikmukhametov et al., 2018). Anemometers and wind speed indicators suffer from failure due to sticking in a fixed position due to mechanical failure (Li et al., 2007).

The various manifestations of sensor degradation contribute to increased measurement uncertainty. Recognizing these distinct impacts is crucial, as it provides the necessary insights for developing effective strategies to quantitatively model these effects. The following subsection 4.2, will delve into the diverse methodologies and techniques used to achieve this, bridging the gap between identifying the problem and finding quantifiable solutions.

4.2. Modelling Impact of Sensor Degradation on Measurement Uncertainty

Understanding the effects of sensor degradation on measurement uncertainty is essential for evaluating system performance and reliability. To systematize the various approaches found in the literature, Table 7 provides a comprehensive summary and categorization of key modelling techniques. The table outlines the main categories of these techniques, presents representative examples for each, describes the specific degradation impacts they model, and details how measurement uncertainty is represented, either implicitly or explicitly.

Technique categories	Representative modelling techniques	Types of impacts to be modelled (Θ)	Uncertainty representation
Filtering technique-based	modified likelihood functions within the filters (Chughtai et al., 2022)	Noise (Chughtai et al., 2022); Sensor Failure (Chughtai et al., 2022)	$p(y_k \| x_k, \Theta_k) = \mathcal{N}(y_k \| h(x_k), (R_k^{-1} diag(\Theta_k))^{-1})$
	integrating sensor degradation as part of measurement model within the filters (Mukhopadhyay et al., 2023; He et al., 2022; Hachem et al., 2024; He et al., 2008; Huang & Shen, 2021; Liu et al., 2019; Liu et al., 2022; Liu et al., 2016; Loo et al., 2022; Feng et al., 2018; Li & Ying, 2017; Wu & Yan, 2022; Zhang, Song, Zhao, Xu and Deng, 2022; He, Zheng, Jin and Li, 2025; Mayilsamy, Lee, Joo, and Jeong, 2025)	Noise (Mukhopadhyay et al., 2023; Hachem et al., 2024; Liu et al., 2019; Liu et al., 2022; Loo et al., 2022; Feng et al., 2018; Dinh et al., 2024; Wu & Yan, 2022; Wu & Liu, 2024; He et al., 2025; Mayilsamy et al., 2025); Drift (Mukhopadhyay et al., 2023; He et al., 2022; Hachem et al., 2024; Liu et al., 2019; Liu et al., 2022; Loo et al., 2022; Feng et al., 2018; Cao, Niazi, Barreau and Johansson, 2024); Bias (He et al., 2022; Liu et al., 2022; Feng et al., 2018; Li & Ying, 2017; Dinh et al., 2024; Zhang et al., 2022; Cao et al., 2024; Mayilsamy et al., 2025); Gain Degradation (He et al., 2008; Huang & Shen, 2021; Liu et al., 2016; Liu et al., 2022; Dinh et al., 2024; Zhang et al.,	$Z(t) = C(t)X(t) + \Theta(t) + v(t)$ (Mukhopadhyay et al., 2023; He et al., 2022; Hachem et al., 2024; Liu et al., 2019; Li & Ying, 2017; Feng et al., 2018; Dinh et al., 2024; Zhang et al., 2022; Cao et al., 2024; He et al., 2025; Mayilsamy et al., 2025) $Z(t) = \Theta(t)C(t)X(t) + v(t) + S(t, X(t), \varsigma(t))$ (He et al., 2008; Huang & Shen, 2021; Liu et al., 2016; Zhang et al., 2022; Wu & Liu, 2024) $Z(t) = C(t)[X(t), \Theta(t)] + v(t)$ (Liu et al., 2022) $Z(t) = f(W_\Theta^T, X(t))$, W_Θ^T is a neural network (Loo et al., 2022)

		2022; Wu & Liu, 2024); Sensor Failure (Zhang et al., 2022)	
Statistical and probabilistic	random variables/ probabilistic models (Wen et al., 2023; Yoo et al., 2020; Hickinbotham & Austin, 1999; Zhang, Wang, Ma and Alsaadi, 2019; Wu et al., 2024)	General/Not Explicit Impact (Wu et al., 2024), Gain Degradation (Wen et al., 2023; Zhang et al., 2019); Bias (He et al., 2022); Noise (Hickinbotham & Austin, 1999); Shift (Hickinbotham & Austin, 1999); Sensor Failure (Yoo et al., 2020)	$\Theta(t) \sim Distribution(params)$; $Z(t) = \Theta(t)C(t)X(t) + v(t)$ (Wen et al., 2023; Zhang et al., 2019); $Z(t) = C(t)X(t) + \Theta(t) + v(t)$ (Hickinbotham & Austin, 1999) Uncertainty of $Z(t) \propto ResilienceMeasure = f(\Theta(t))$, $\Theta(t) = [0,1]$ indicating failure probability (Yoo et al., 2020) Uncertainty of $Z(t) \propto InformationGain = f(p_\Theta(\theta, Z(t), C_n)$, θ indicate system parameters, C_n indicate sensor configuration (Wu et al., 2024)
	ARMAX model (Jiang et al., 2006)	Gain Degradation (Jiang et al., 2006); Increased latency (Jiang et al., 2006)	$A(q)z(t) = \Theta(q)u(t - nk) + D(q)v(k)$, q present shift (delay) operator
	Markov decision process (van Oosterom et al., 2017)	Noise (van Oosterom et al., 2017)	Uncertainty of $Z(t) \propto Q(t) = [p_{ik}(t \mid \Theta(t))]$
	descriptive statistics (Li et al., 2007)	Noise (Li et al., 2007)	
Empirical	explicit empirical/physics-based equations (Ohsuga & Ohyama, 1988; Yu & Wu, 2009; Aldrin et al., 2007; Kim et al., 2013; Lu et al., 2021; Singh & Shanmugam, 2018; Zhan, Shen, Mao, Shu, Shen, Yang, ... and Lu, 2025)	General/Not Explicit Impact (Kim et al., 2013; Lu et al., 2021); Sensitivity Degradation (Aldrin et al., 2007; Singh & Shanmugam, 2018); Drift (Ohsuga & Ohyama, 1988; Chughtai et al., 2022; Zhan et al., 2025)	$Z_k(t) = f(X(t), \Theta(t))$ (Ohsuga & Ohyama, 1988; Yu & Wu, 2009; Aldrin et al., 2007; Kim et al., 2013; Lu et al., 2021; Singh & Shanmugam, 2018)
	conditional rules (Li et al., 2007)	Sensor Failure (Li et al., 2007)	$Rule_k$: If $Z_k(t)$ is $A_k(t)$ then $\Theta(t)$ marked as failure (Li et al., 2007)
Machine learning	weights and biases in neural networks (Bai et al., 2020; Li, Gou, Li and Liu, 2023; Wu & Yan, 2022); transfer learning/domain adaptation (Zhang et al., 2021)	Noise (Bai et al., 2020; Wu & Yan, 2022); Drift (Bai et al., 2020; Zhang et al., 2021); Sensor Failure (Li et al., 2023)	$X(t) = f(W_\Theta^T, Z(t))$ (Bai et al., 2020; Li et al., 2023; Wu & Yan, 2022) $X(t) = \mathcal{GP}(f(W_\Theta^T, Z(t)), \delta)$ (Zhang et al., 2021)

Table 7. Modelling techniques for impacts of sensor degradation on measurement uncertainty

Filtering technique-based models, commonly explored in the literature, are prominently recognized within the frameworks of filtering methods. This approach enhances adaptability and provides robust uncertainty quantification by leveraging inherent structures of filtering algorithms. In (Chughtai et al., 2022), noise (outliers) and sensor failures (missing data) are modelled as special cases of outliers using a measurement likelihood function within Selective Observations-Rejecting Unscented Kalman Filter (SOR-UKF). This is achieved by incorporating an indicator vector as a parameter in the measurement likelihood function, which takes a value of 1 when the measurement is valid (no outlier) and a value of ϵ, a number close to zero, when the measurement is considered an outlier or corrupted. In addition, most methods incorporate measurement uncertainty from sensor degradation, specifically gain degradation, bias, drift, sensor failure, into the measurement model within filters, specifically, local recursive filter (Huang & Shen, 2021), particle filter (Hachem et al., 2024; Liu et al., 2022), Kalman filter (Mukhopadhyay et al., 2023; Liu et al., 2019; Loo et al., 2022; Feng et al., 2018; Dinh et al., 2024; Wu & Liu, 2024; He et al., 2025; Mayilsamy et al., 2025), distributed resilient filter (Liu et al., 2016), H-infinity filter (He et al., 2008), Bayesian framework (He et al., 2022), Gaussian data reconciliation (Li & Ying, 2017), Probabilistic Local Maximum Mean Discrepancy (PLMMD) framework (Zhang et al., 2022), Neural Network-based Kazantzis-Kravaris/Luenberger observer (NN-KKL) (Cao et al., 2024). The performance of these filtering approaches is critically dependent on the accuracy of the underlying system model and the statistical assumptions made about the process and measurement noise.

Statistical and probabilistic models are founded on the principles of statistics and probability, focusing on deterministic relationships while incorporating elements of uncertainty. Wen et al. (2023) incorporated random variables representing gain degradation directly into the measurement model, while Zhang et al. (2019) employed set-membership estimation, treating gain degradation as a probabilistic factor characterized by random variables bounded within a specific interval. Yoo et al. (2020) modelled sensor failure by defining “sensor fault” as a gain reduced to 70% of its normal value and measuring resilience under such conditions. Noise and sensor failure (loss of informativeness) are modelled by van Oosterom et al. (2017) using a Partially Observable Markov Decision Process (POMDP) with an observation matrix that evolves with sensor age. He et al. (2022) integrated bias and noise into the measurement model through a Bayesian framework that incorporates sensor degradation. In (Hickinbotham & Austin, 1999), noise is modelled using a Gaussian distribution, then sensor shifts are detected via the eigenface algorithm, leveraging Principal Component Analysis of sensor responses. Wu et al. (2024) quantified measurement uncertainty through the Information Gain (EIG), calculated using Relative Entropy to capture the loss of information and an increase uncertainty due to sensor network degradation processes. Jiang et al. (2006) captured gain degradation and increased latency (time constant) in throttle position sensors by using Autoregressive Moving Average with Extra Input (ARMAX) model. Wanga et al. (2008) modelled “synthetic” gain by combining multivariable measurements into a Confidence Value. In (Li et al., 2007), noise was modelled by the standard deviation, such that an increase in the standard deviation is interpreted as a sign of sensor degradation. The strength of this approach lies in its remarkable versatility, offering a diverse toolkit of statistical methods to model a wide array of degradation effects. A notable challenge, however, lies in the selection and validation of the appropriate statistical model, as an improper choice can lead to non-descriptive results and/or inaccurate predictions.

Empirical models are constructed using data observed from experiments or real-world measurements, providing data-driven insights into system behaviour. In measuring Top-of-Atmosphere radiance, implicit impact, which could be a synthesis, e.g., drift, shift, bias, … was modelled by updating calibration coefficients monthly with cross-calibration using observed data (Lu et al., 2021), or under a mathematical model followed by a Bidirectional Reflectance Distribution Function (BRDF) and fitted using linear regression analysis (Kim et al., 2013). Aldrin et al. (2007) modelled sensor sensitivity degradation in a variety of sensors used in Structural Health Monitoring (SHM) through flaw size, as sensors degrade, it becomes less sensitive, requiring a larger flaw size to detect the same flaw with a given probability, as determined by a Probability of Detection (POD) model. Zhan et al. (2025) modelled sensor drift through the use of Hessian matrix and the analysis of its eigenvalues for positioning systems, "when sensors become degenerate, the corresponding eigenvalues become much smaller. Yu and Wu (2009) modelled drift by a degradation rate using formulas using a time series of observations. Ohsuga and Ohyama (1988) described “drift” by a correction coefficient K_{grad}. Li et al. (2007) modelled implicit impact using correlation coefficients between two related sensor readings, such that a decrease in this correlation over time suggests that one or both measurements indicate increasing uncertainty, additionally, they modeled sensor fault using rules that the sensor was identified as stuck when its measurement meets specific conditions. A principal benefit of this approach is its practicality, as these models can often be developed and implemented straightforwardly from available data. However, a major weakness of empirical models is their limited ability to extrapolate, as their predictive accuracy can degrade when applied to varying conditions outside of the original observed operating points.

Machine learning methods leverage training processes to learn from data with complex patterns, enabling the development of models that can adapt and generalize to diverse scenarios. Bai et al. (2020) modelled noise and drift by considering multiple input parameters, including sensor outputs and environmental factors, and then adjusting the weights and biases through training to account for measurement errors caused by sensor degradation over time. Li and Dai (2023) proposed a physics-guided neural network model for detecting sensor faults in aeroengine control systems. Wu and Yan (2022) addressed the challenge of bounded noise in measurement data by proposing a novel autoencoder-based model designed to effectively capture and mitigate the impact of such noise. Zhang et al. (2021) modelled drift with Domain Adaptation Mixture of Gaussian Processes (DA-MGP) model, which integrates Gaussian Processes and domain adaptation techniques. The most significant advantage of this approach is its ability to automatically learn and represent highly complex and nonlinear degradation patterns directly from data. However, these models often act as “black boxes” with low interpretability, and their performance is critically dependent on the availability of large, representative training datasets.

In summary, it is clearly demonstrated that sensor degradation has discernible impacts on measurement quality, affecting both qualitative and quantitative aspects. These effects can be systematically analysed and modelled using a variety of techniques, ranging from empirical models based on observations and experimental data to more advanced filtering methods employed within state estimation frameworks. Additionally, theoretical and data-driven methodologies, including statistical, probabilistic, and machine learning-based approaches, offer insights into degradation patterns and their consequences. The complexity of sensor degradation necessitates a multifaceted approach, incorporating domain expertise, computational techniques, and real-world validation to ensure robustness and reliability. This introduce into prognostics and maintenance decision-making strategies, the necessity of effectively adapting and mitigating these challenges to safeguard the system reliability. These strategies will be discussed in the next sections. While substantial progress has been made in this domain, certain research gaps remain, which will be further explored in Section 7.

5. REVIEW ON PROGNOSTICS WITH MEASUREMENT UNCERTAINTY FROM SENSOR DEGRADATION

This section delves into reviewing the topic of prognostics in the presence of measurement uncertainty arising from sensor degradation. Investigating sensor degradation in prognostics is crucial, as accurate measurements are essential for predicting system health and sensor degradation is a significant source of measurement uncertainties that undermine the accuracy of the prognostics process (Mukhopadhyay et al., 2023; Zhang et al., 2018; Liu et al., 2019). Sensor degradation impacts prognostics by reducing the availability of effective monitoring data and making it difficult to distinguish adjacent health states, leading to inaccurate predictions of health conditions and increased risk of failure in critical systems (Yin et al., 2022).

Prognostics approaches can be classified into three categories: data-driven, physics-based, and hybrid methods (Guo, Li and Li, 2019). Data-driven approaches leverage techniques such as artificial intelligence and statistical methods. Physics-based methods rely on principles such as physics of failure and system modelling. Hybrid approaches combine data-driven techniques with knowledge of degradation mechanisms to enhance prediction accuracy. These classifications are illustrated in Figure 3.

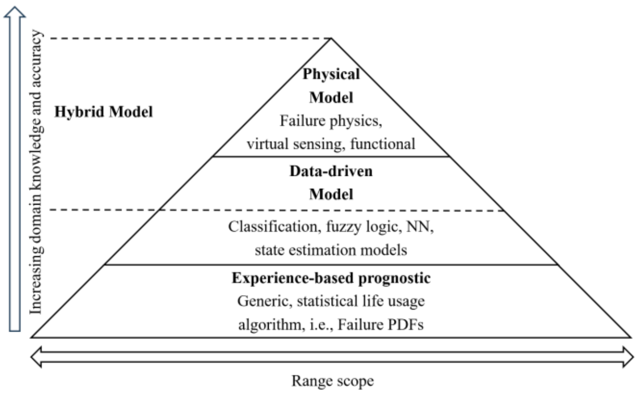

Figure 3. Applications of various prognostics approaches (Guo et al., 2019)

Studies have highlighted a range of methods for addressing sensor degradation and measurement uncertainty in prognostics. They can be categorized, as shown in Table 8.

Experience-based methods rely on historical data and expert knowledge to inform predictions and decision-making, drawing insights from observations and professional expertise. Yin et al. (2022) proposed a Belief Rule Base (BRB) model to encode expert knowledge about the sensor's degradation and failure mechanisms, represented by probabilities of failure at each time step of data, which accommodate uncertainties and inaccuracies in the data caused by sensor degradation, and subsequently use fuzzy logic under Membership Functions (MF) to predict the sensor's future health state, categorizing it into different states with a high accuracy and a reasonable state based on the probabilities of failure. The proposed BRB-MF model demonstrated high accuracy in predicting sensor health states; a case study using brightness sensors showed that BRB-MF has clear advantages in effectively utilizing comprehensive expert knowledge when dealing with limited data availability, naturally, when a full range of data is available, the results would not be different from other data-driven methods such as neural networks, as stated by the authors. A primary benefit of such methods is their high degree of interpretability, as the explicit encoding of expert rules allows for clear insight into the model's decision-making logic. The approach's main vulnerability, however, lies in its potential for subjectivity and bias, as the model's accuracy is fundamentally constrained by the quality and completeness of the expert knowledge it is built upon.

Categories	Description	References
Experience-based	relies on historical data and expert knowledge to make predictions	Yin et al., 2022
Data-driven	utilizes statistical methods for prognostics (when no or rare physical understandings are available)	Zhang et al., 2018; Wanga et al., 2008; Yuan, Xu, Adjallah, Wang, Liu and Xu, 2024; Carratù et al., 2024

Physical-Based	incorporates parameters about sensor degradation into prognostics estimation models	Mukhopadhyay et al., 2023; Hachem et al., 2024; Liu et al., 2019; Hossain et al., 2024
Hybrid	combining physical-based models of prognostics with data-driven models of sensor degradation	Michaels et al., 2005; Bonhote et al., 2006
	combining physical-based models of sensor degradation with data-driven models of prognostics	He et al., 2022; Aldrin et al., 2007; Yoo et al., 2020

Table 8. Categorizations of prognostics methods with measurement uncertainty from sensor degradation

Data-driven methods employ statistical techniques for prognostics, particularly in scenarios where physical understanding of the system is limited or unavailable. Zhang et al. (2018) effectively quantified the influence of sensor measurement errors on RUL prediction in a blast furnace system by modelling system degradation with a Wiener process that incorporated deteriorating sensor measurement errors quantified using Relative Entropy, and estimated failure time using an Inverse Gaussian distribution, numerical results indicate that controlling the measurement error within specified permissible ranges significantly improves the accuracy of lifetime estimates. Wanga et al. (2008) used a Statistical Pattern Recognition model to estimate a Confidence Value (CV) as the RUL for automotive sensors by training with data during the offline phase to recognize the normal behaviour of the sensor based on historical data, and then to be used in online phase to calculate a CV that quantified the similarity between the current sensor behaviour and the normal behaviour observed during training, which showed that as the sensors degrade, the CV clearly showed a declining trend, effectively detecting even small and early-stage degradation in the sensor's performance. Yuan et al. (2024) presented a data-driven method for predicting the remaining useful life of sensors, considering the impacts of sensor degradation on measurement uncertainty, by employing statistical models such as the Weibull distribution to estimate failure probabilities over time based on historical sensor failure data. Carratù et al. (2024) proposed a data-driven method for predicting the RUL of MEMS sensors, that utilized a neural network trained to forecast RUL based on degradation trends captured by the Health Index. The core strength of this approach is its ability to build effective prognostic models directly from operational data, even in the absence of a detailed first-principles understanding of the system's failure physics; however, the quality and quantity of historical data directly govern the model's predictive accuracy and generalizability.

Physics-based methods integrate sensor degradation parameters into prognostics estimation models to enhance accuracy and reliability in predicting system performance over time, requiring a deep understanding of the system's and sensor's physical degradation processes. Hachem et al. (2024) incorporated parameters about sensor degradation into state estimation models in the case of wastewater treatment using stochastic processes such as Gamma and Wiener, with state estimation carried out through particle filters, and RUL is predicted by simulating the future degradation path based on the current state estimation-based particle filter, specifically, for each particle, the future degradation is simulated by advancing the stochastic process forward in time, resulting in a significant reduction in MSE and RMSE when sensor degradation is considered in estimating system's degradation state. Liu et al. (2019) presented a physics-based approach that uses a Wiener process to model both system and sensor degradation of wastewater treatment plants and employed the Kalman filter to incorporate sensor degradation parameters into the system's state estimation for accurate RUL prediction through its cumulative distribution function. The same approach was also used by Hossain et al. (2024) for the case of nuclear reactor pressure vessels. Mukhopadhyay et al. (2023) proposed a methodology for estimating the RUL of an offshore wind system where both the system and the sensor degrade over time, by modelling the degradation processes of both the system and the sensor, and then estimating them using a Kalman filter, RUL was estimated by simulating the future trajectory of the system degradation using the updated state probability distribution, with results that finally showed that accounting for sensor degradation leads to more accurate predictions, without accounting for degradation, deviations were evident; whereas with the proposed method, estimations closely matched actual degradation.

Hybrid methods in prognostics and health management represent a powerful approach by integrating physics-based models with data-driven techniques, either by combining physical models of prognostics with data-driven insights into sensor degradation or vice versa, enabling more accurate and robust system health predictions. Michaels et al. (2005) contributed to prognostics of aluminium components by monitoring their progression of damage using affixed ultrasonic sensors by physics-based monitoring fatigue crack growth using through-transmission ultrasonic signals, while addressing measurement uncertainty from sensor degradation through pulse echo corrections and Energy Ratio methods that effectively compensate for the impacts of sensor degradation. In addition, Chunping et al. (2006) used the Arrhenius model to predict time to failure of giant magnetoresistance (GMR) sensor heads $TFF = Ae^{\frac{E_a}{kT}}$ fitted with historical data. Yoo et al. (2020) presented a hybrid prognostics method that integrates physics-based models of sensor degradation accounting for faults such as bias, gain, and drift, and with linear discriminant analysis to estimate system resilience demonstrated with the electro-hydrostatic actuator (EHA) system, resulting in a more precise resilience estimation that reveals a 6% drop in resilience due to sensor degradation. Aldrin et al. (2007) presented an approach for assessing aircraft system reliability that integrates a physics-based, time-dependent POD model for sensor degradation with a data-driven probabilistic risk assessment framework to evaluate the impact of sensor degradation on SHM performance and system prognostics, and concluded that sensor degradation leads to an increased probability of failure over time in the POD model compared to a fixed POD model. He et al. (2022) predicted the RUL through reliability metrics, including lifetime quantiles and system reliability, which is used to quantify how long a system will function before failure, by modelling the degradation of both the system and the sensor using Wiener processes and dynamically updating these models through an Approximate Bayesian Computation (ABC) algorithm, which incorporates measurement uncertainty arising from sensor degradation during sequential Accelerated Degradation Tests (ADT), numerical studies on a gas turbine system achieved a significantly lower asymptotic variance in RUL prediction metrics compared to the benchmark sequential model that ignored sensor degradation. The strength of hybrid philosophy is its ability to leverage first-principles models while using data-driven techniques to capture complex interactions or correct for unmodelled effects. Still, the development of such integrated models can be more complex to properly fuse the different modelling paradigms.

This section provides insights into how prognostic techniques have evolved to manage the challenges posed by sensor degradation. Several approaches and techniques have been applied to address the challenges, ranging from encoding expert experience or physics of sensor degradation into the approach, to data-driven methods with the capability for generalization for various applications, or hybrid methods to utilize the strengths of both. Given the critical role of prognostics as an input for many maintenance decision-making processes, the next section will review maintenance decision-making, with a focus on the effects of sensor degradation. Remaining research gaps will be discussed in Section 7.

6. REVIEW ON MAINTENANCE DECISION-MAKING WITH MEASUREMENT UNCERTAINTY FROM SENSOR DEGRADATION

Condition-Based Maintenance (CBM) and Predictive Maintenance (PdM) are popular concepts in maintenance decision-making. CBM is a proactive approach that utilizes real-time monitoring of equipment conditions to assess and determine the necessity for maintenance (Golmakani, 2022; Kroculick, 2014; de Meyer, Goosen, van Rensburg, du Plessis and van Laar, 2021). Meanwhile, PdM leverages data through the prognostics process, enabling proactive predictions of future health based on current and historical data (Roehrich & Raffaele, 2023; Assagaf, Sukandi, Abdillah, Arifin and Ga, 2023). The relationship between them can be visualized in Figure 4, where the data acquisition process directly informs the maintenance decision-making process or is further utilized for predictive capability.

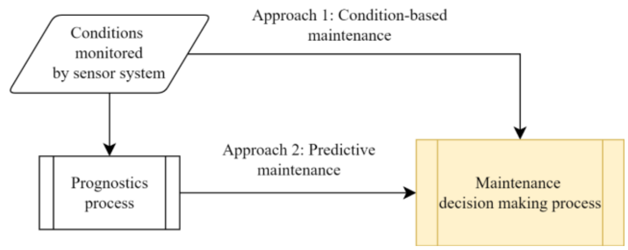

Figure 4. Maintenance decision-making approaches considering measurement uncertainty from sensor degradation

Building upon the insights provided in the previous sections that explored impacts on measurement uncertainty and the adaptation of prognostics in managing uncertainty arising from sensor degradation, this section delves into maintenance decision-making under these factors. Considering measurement uncertainty resulting from sensor degradation, the maintenance decision-making process has been adapted. Table 9 summarizes the approaches outlined by the following interpretations.

Sensor degradation increases the probability of undetected failures and unnecessary repairs due to false alarms. To address this, Aldrin et al. (2007) employed a probabilistic risk assessment and cost-benefit analysis to evaluate how sensor degradation affects the reliability of SHM systems. Inputs include time-dependent sensor degradation characteristics, capturing how sensor performance deteriorates over time, and the relationship between the actual damage state and the detected damage state, ensuring accurate damage assessments. Essential parameters such as the 50% detectable flaw size and the random missed flaw rate are dynamically modelled as functions of time to reflect ongoing sensor reliability changes. Maintenance outputs are actionable recommendations for sensor replacement when degradation compromises system reliability, ensuring consistent monitoring effectiveness. Additionally, cost evaluations and maintenance interval decisions are optimized by assessing reliability and associated costs under varying degradation scenarios. The results show that sensor degradation significantly increases the probability of failure (e.g., an increase in random missed detection rate to 10% or detectable crack size to 0.07 inches leads to higher failure risks), while slightly reducing total maintenance costs due to fewer repairs, highlighting the critical need for sensor replacement or recalibration to balance safety and cost.

Categories	Description	References
Condition-Based Maintenance	*Characteristics*: involves monitoring the actual condition of equipment in real-time to determine whether maintenance is needed, minimizing unnecessary repairs by performing work only when justified by equipment health. *Inputs*: system states, sensor measurements, belief states, degradation states, …	Aldrin et al., 2007; Liu et al., 2019; van Oosterom et al., 2017; Murthy, 1982; Li & Ying, 2017; Zhang et al., 2023
Predictive Maintenance	*Characteristics*: involves predicting the future health of a system or component by estimating RUL based on current and historical data, requires investment in prognostic models and historical data for accurate predictions *Inputs*: prognostics information	Zhang et al., 2018; Dinh et al., 2024; Yuan et al., 2024

Table 9. Maintenance decision-making approach considering measurement uncertainty from sensor degradation

Disregarding sensor degradation significantly increases the risk of inaccurate system state estimation, leading to suboptimal maintenance decisions with ineffective actions and increased costs. Liu et al. (2019) proposed a maintenance policy utilizing estimated system and sensor states as key maintenance inputs, derived through a stochastic filtering approach using the Kalman filter, applicable to systems operating in harsh environments, such as wastewater treatment plants, manufacturing systems, chemical plants, and pharmaceutical factories. This method effectively accounts for both system degradation and sensor degradation, ensuring accurate state estimation despite measurement uncertainties. Maintenance actions are dynamically determined at each inspection, offering two primary responses: corrective replacement is performed if the system is found to have failed, while preventive replacement is initiated when the predicted system reliability is projected to reach a critical threshold before the next inspection. The method achieves a near-optimal maintenance policy effectively addressing sensor degradation and achieving a long-run cost rate that is lower than 36% compared to when sensor degradation is disregarded.

Considering degrading sensors allows for the optimization of maintenance strategies, balancing the trade-off between sensor performance (minimizing variance in estimation) and the costs of maintenance. Murthy et al. (1982) developed maintenance for deteriorating sensors guided by degradation indicators, specifically, signal intensity, noise intensity, and drift quantification, which can be applied broadly to industries relying on sensor-based systems for real-time monitoring and control. Indicators reflect the gradual or catastrophic deterioration of sensor performance over time. Maintenance actions are optimally chosen between full maintenance and no maintenance during specific periods, depending on the sensor's degradation level. The decision-making process aims to balance reducing the measurement variance caused by sensor degradation and controlling maintenance costs. This balance is achieved through optimization methods that determine the most effective maintenance strategy, specifying when and how much maintenance should be applied to achieve this balance. The results showed that the optimal maintenance strategy often involves either full maintenance during a portion of the operational time or no maintenance, with maintenance improving the mean time to failure and reducing the variance of the signal estimation error.

Oosterom et al. (2017) presented a maintenance strategy that integrated sensor degradation into its decision-making process utilizing a belief state that quantifies the probability that the system is in an out-of-control state, applied in safety-critical systems, such as chemical plants, hospitals, and nuclear power reactors. This belief is dynamically updated using Bayes' rule as new, potentially imperfect, observations from the deteriorating sensor are received. The maintenance actions derived from this model include: (1) continuing operation when the system is deemed stable, (2) conducting a full inspection to perfectly determine the system's condition, (3) replacing the system if the inspection confirms it is out-of-control, and (4) replacing the sensor when its degradation surpasses a defined threshold to restore measurement reliability. These decisions are systematically guided by a Markov decision Process framework, which incorporates both the updated belief state and the sensor's age. The model employs a threshold-based policy, wherein actions are triggered when the belief and/or the sensor age exceed thresholds, ensuring optimized coordination between system inspections and sensor replacements. The model is highly effective, with numerical results showing the optimal policy achieving significantly lower total costs compared to heuristic policies, with examples showing optimality gaps of 1.0% for a heuristic policy using a simplified threshold and up to 11.9% for a less coordinated policy.

Li and Ying (2017) presented an enhancement to gas turbine reliability by addressing measurement inputs affected by sensor degradation. Over time, gas-path sensors can produce biased measurements due to degradation or failure, compromising the accuracy of diagnostic results. To mitigate this, the proposed method outputs critical maintenance actions, including the detection of degraded sensors, isolation of faulty sensors, and quantification of the degradation rates of both gas-path components and sensors. This is achieved through an advanced maintenance decision-making process utilizing an extended nonlinear Gas Path Analysis (GPA) method. The approach integrates Gaussian data reconciliation to identify and correct suspicious sensor data and employs multiple operating points to distinguish between sensor faults and actual component degradation. This comprehensive process ensures accurate fault detection, effective isolation of faulty components, and precise assessment of degradation severity, thereby improving maintenance decisions and overall engine performance. The proposed method significantly improves diagnostic accuracy, enabling the correct identification and quantification of components across five test cases.

Zhang et al. (2023) developed maintenance decision-making in the context of SHM systems, specifically addressing how measurement uncertainty caused by sensor degradation impacts the reliability of maintenance strategies. The study incorporates the effects of time-varying sensor performance, including random measurement errors and systematic biases, which influence the accuracy of structural condition assessments. Maintenance decisions are guided by key information such as the monitored structural damage condition, SHM measurement outcomes affected by degradation, and diagnostic reliability indicators such as the Probability of Detection and the Probability of False Indication. Based on this information, the framework supports critical maintenance activities, including determining when to conduct inspections, triggered when monitoring data exceed specific thresholds, and deciding on repairs when detected damage surpasses safety limits. Additionally, the approach considers the need to renew or recalibrate SHM systems as their performance deteriorates over time. The study proposes two maintenance strategies: the first initiates inspections based on real-time monitoring data exceeding a damage threshold, while the second relies on the annual failure probability inferred from SHM data to trigger inspections when it exceeds a predefined limit. The results demonstrate that the impact of ignoring SHM performance degradation significantly elevates the lifecycle cost (LCC) of structures, underscoring the necessity of incorporating time-varying measurement uncertainties into maintenance strategies. Specifically, the results from degradation scenarios show that neglecting sensor degradation can significantly increase the expected LCC compared to strategies that account for measurement uncertainty.

Sensor degradation leads to inaccuracies in lifetime estimation due to measurement errors, which can cause suboptimal maintenance decisions, increased costs, and elevated safety risks. Zhang et al. (2018) revolved around the critical role of accurate lifetime estimation in guiding maintenance decisions, which can be applied in complex industrial systems such as blast furnaces. This estimation is notably influenced by measurement errors stemming from sensor degradation over time. Such errors can bias lifetime predictions, impacting the effectiveness of maintenance policies. Specifically, maintenance outputs include the development of replacement policies and the determination of optimal maintenance intervals to avoid unscheduled maintenance events and minimize associated costs. A degraded sensor is scheduled for replacement either when its degradation trajectory intersects a defined failure threshold or when it reaches a predetermined age. This decision-making process is deeply rooted in lifetime estimation models that account for potential measurement errors. Consequently, maintenance decisions, primarily following an age-based replacement strategy, are informed by evaluating lifetime predictions while incorporating sensor measurement errors, which ensures a more robust maintenance framework. The numerical results demonstrate that controlling measurement errors reduces maintenance costs significantly, specifically, in test cases, when measurement errors are controlled within permissible ranges, the long-run average maintenance cost per unit can be minimized, whereas uncontrolled measurement errors lead to substantial cost increases.

Yuan et al. (2024) introduced a risk-based PdM method that quantifies the impact of sensor degradation on decision-making risks to optimize maintenance schedules. This method relies on inputs such as historical sensor failure data, sensor lifespan distribution models (e.g., Weibull distribution), and risk assessment metrics that link sensor failure probabilities to operational risks, including financial losses and customer complaints. The outputs/actions involve determining the optimal timing for sensor replacements or inspections based on predicted risk thresholds, allowing for proactive interventions before failures cause significant disruptions. The maintenance method employs mathematical models that calculate both individual and combined risks of sensor failures, integrating failure probabilities with risk values to assess how degradation affects system performance. This approach also accounts for the compounded effects of multiple sensor failures, enabling a more comprehensive risk evaluation. Numerical results from case studies demonstrate the method's effectiveness, showing that without predictive maintenance, the risk of financial loss can reach 336.13 per day when critical sensors fail simultaneously, while the proposed method significantly reduces both financial risks and the frequency of customer complaints compared to traditional periodic maintenance strategies that do not consider the impacts of sensor degradation on measurement uncertainty.

Dinh et al. (2024) introduced an adaptive PdM strategy specifically designed for manufacturing systems where measurement uncertainty arises from the degradation of health monitoring devices (HMDs). The decision-making process is driven by several critical factors, including estimated degradation levels of both the system and the HMDs, prediction of the reliability of the system at future inspection intervals, and data collected during regular monitoring activities. Additionally, maintenance-related cost parameters, such as inspection expenses, costs of preventive and corrective actions, HMD replacement or calibration costs, and potential downtime losses are integral to the decision framework. Based on these factors, maintenance actions are determined through a structured approach: corrective maintenance is triggered if the estimated system degradation exceeds the failure threshold, preventive maintenance is scheduled when system reliability drops below a critical level while the HMD remains reliable, and HMD replacement or calibration is initiated if its degradation undermines the accuracy of condition monitoring. If the system's reliability remains high, maintenance actions are deferred to optimize resource usage. This decision-making process operates within an adaptive framework, where system and HMD conditions are continuously evaluated using Kalman filter techniques. By integrating real-time data with predictive modelling, the approach ensures that maintenance decisions are both cost-effective and responsive to the dynamic interplay between system degradation and sensor performance, ultimately enhancing system reliability while minimizing unnecessary maintenance interventions. The proposed method achieved an optimal maintenance cost rate; compared to the conventional method, which had a higher cost rate, it reduced costs by approximately 12.5%. Further analysis showed that the maintenance cost rate is sensitive to the sensor replacement threshold: compared to the optimal value, lower thresholds increase costs due to frequent sensor replacements, while higher thresholds reduce replacements but raise costs from system failures or poor maintenance timing caused by degraded sensor accuracy.

In brief, the performance of CBM and PdM fundamentally depends on measurement quality, which can be compromised by sensor degradation. Various approaches have been developed to mitigate this issue, incorporating sensor degradation into maintenance frameworks through additional indicators, state estimation, and filtering. New policies define maintenance actions for both sensors and systems, supported by optimization algorithms. Despite these advancements, significant gaps remain. The next section will explore several challenges and potential research opportunities.

7. DISCUSSION AND RESEARCH OPPORTUNITIES

7.1. Modelling Sensor Degradation and Impacts in Measurement Uncertainty

The challenge of developing precise models that represent sensor degradation processes persists. Most current models rely on oversimplified assumptions and fail to capture the complexity of real-world dynamic operating conditions. These conditions include a range of stochastic factors such as variable operational loads, thermal cycling, intermittent power-on/off cycles, and exposure to sudden shocks and vibrations, which are often ignored in laboratory settings. For instance, current studies frequently overlook shocks or assume their effects are constant (Hachem et al., 2021), failing to capture the stochastic nature of these events. Therefore, a key research direction involves creating more robust, multifaceted degradation models. Future work should focus on integrating sensor-specific parameters with models that can dynamically account for these real-world conditions. This includes advanced techniques such as probabilistic modelling for shock events, hybrid simulations, and real-time anomaly detection.

Furthermore, performance under a wide range of operating conditions has also received insufficient attention (Mehdizadeh et al., 2012). Existing approaches often fail to model degradation across different operating points. This is evident in the case of the Solar Diffuser Stability Monitor (SDSM), which cannot track degradation uniformly across its full sensing range (Sun & Xiong, 2020). Addressing these limitations requires models that can account for the full spectrum of operational variabilities encountered in real-world scenarios.

Traditional degradation modelling methods such as the Wiener process, though widely used, may not be sufficient to capture the nonlinear and complex nature of sensor degradation (Liu et al., 2019). Although root-cause analysis of the nonlinear physical mechanisms of sensor degradation can provide more accurate modelling; however, this can be hard and costly due to the multi-factor complexity of degradation phenomena. This limitation hinders the generalization of models to real-world data, where degradation conditions vary significantly across different sensors. Recent research highlights the need for models that incorporate nonlinear and non-stationary degradation processes to better capture the diverse nature of sensor degradation (Hachem et al., 2021). There is a recognized gap in the integration of physics-based and stochastic models for sensor degradation, while both approaches have been explored separately, combining them could provide more comprehensive and accurate degradation models (Hua et al., 2013). While physics-based models excel at describing degradation through well-defined mechanisms, stochastic models effectively capture the probabilistic and uncertain nature of degradation processes. By developing hybrid frameworks integrating physics-based terms with a stochastic approach, researchers can create models capable of capturing both deterministic and probabilistic degradation trends. Data-driven approaches, such as machine learning, can support modelling degradation patterns by leveraging historical sensor data. Unlike traditional methods that rely on predefined degradation models, machine learning techniques can uncover complex, nonlinear relationships and patterns directly from the data that can be highly adaptable to various applications. Physics-Informed Machine Learning (PIML) can be a standout approach to modelling sensor degradation, by integrating physical terms with the data-driven adaptability power of machine learning, which ensures predictions remain consistent with real-world physical behaviours, especially in scenarios where training data may be sparse or noisy, that eventually improve model accuracy and explainability.

Multi-dimensional correlated sensor degradation remains underexplored (Mandal et al., 2017; Hua et al., 2013). Real-world systems often experience complex interactions between multiple degradation factors, such as operational stress or environmental influences. Current research typically focuses on isolated degradation mechanisms, failing to capture the interdependence among these dimensions. In addition, there is a lack of research on the simultaneous degradation of both the monitored system and the sensor, which may require decoupling their dynamics for effective degradation detection (Jiang et al., 2006). Moreover, distinguishing between sensor degradation and system degradation is critical, especially for applications such as SHM, yet advanced techniques to differentiate between these two phenomena are still lacking (Mehdizadeh et al., 2012). These gaps present significant research opportunities, particularly in developing advanced modelling algorithms capable of analysing multi-dimensional degradation processes.

Integration of sensor degradation modelling into analysis of measurement uncertainty takes a pivotal role in the domain of estimation and filtering. Although sensor measurement degradation can be conveniently detected, challenges persist in quantifying the consequent uncertainty, for example, the difficulty in estimating the detected gain degradation (He et al., 2008). Research opportunities could focus on developing more sophisticated modelling and estimation methods to better evaluate sensor performance reduction. Currently, measurement errors are often treated as time-independent random variables; however, in reality, sensor errors tend to change over time due to degradation (Zhang et al., 2018). An important focus is the development of dynamic models that account for sensor degradation time-varying errors. This opens a wealth of research opportunities focused on developing augmented state modelling techniques that account for the dynamics of degraded sensors by incorporating degradation-related parameters, integrating these into estimation frameworks such as adaptive Kalman or particle filters. In addition, the integration of physics with data-driven approaches can significantly improve modelling performance. Furthermore, there is a need for investigations into probabilistic models to consider robustness (He et al., 2008). Data-driven approaches depend on datasets, which are currently limited, and their construction is often resource-intensive and laborious, particularly due to conditions such as environmental variability during the data acquisition process (Qiu, Shen, Yue and Zheng, 2023). Future research could focus efforts on introducing more data collection for future development and benchmarking. Furthermore, less attention has been given to fusing degradation data from multiple sensors, multiple sensor data, and data fusion algorithms can be implemented for multi-sensor degradation systems (Arosh et al., 2015). Another prominent research gap is the need for more comprehensive indicators to capture measurement uncertainty caused by sensor degradation. Future work can focus on developing resilience measures that accommodate the time-dependent degradation dynamics of sensors (Yoo et al., 2020). Moreover, further development of advanced simulation methods could support data augmentation and precision (Kamei et al., 2012).

To summarize the current limitations and highlight the avenues for future research in modelling sensor degradation and its impacts on measurement uncertainty, Table 10 provides a concise overview of key research gaps, their current limitations, and promising future directions.

Current Limitations	Possible Research Directions
Simple assumptions, ignore dynamic/stochastic factors (shocks, loads).	Develop robust, multifaceted models; account for real-world conditions; probabilistic shock modelling, hybrid simulations, real-time anomaly detection
Fail to model degradation uniformly across operating points	Develop models for full spectrum of operational variabilities.
Traditional degradation models insufficient for nonlinear/complex degradation; high cost for root analysis.	Incorporate nonlinear/non-stationary processes; hybrid physics-stochastic models; Physics-Informed ML (PIML).
Focus on isolated mechanisms; lack of interaction analysis, simultaneous system/sensor degradation, and differentiation techniques.	Develop algorithms for multi-dimensional degradation analysis; decouple system/sensor dynamics.
Difficulty quantifying measurement uncertainty; errors often treated as time-independent.	Develop sophisticated modelling for performance reduction; dynamic models for time-varying errors; augmented state modelling; probabilistic models.
Datasets are scarce, resource-intensive; environmental variability issues.	Increase data collection/benchmarking; develop resilience measures for time-dependent degradation; advanced simulation for data augmentation.
Less focus on fusing degradation data from multiple sensors.	Implement multi-sensor data fusion algorithms for degradation systems.
Lack of comprehensive indicators for degradation-induced uncertainty.	Develop resilience measures for time-dependent sensor degradation dynamics.

Table 10. Research Opportunities in Modelling Sensor Degradation and Measurement Uncertainty

7.2. Managing Impacts of Sensor Degradation in Prognostics

Sensor degradation introduces additional uncertainty in RUL predictions. Most existing studies have largely overlooked how sensor deterioration affects RUL predictions, necessitating more focused research in this area

(Mukhopadhyay et al., 2023; Hachem et al., 2024). Prognostic algorithms must incorporate sensor degradation more effectively through the development of sensor-aware prognostic frameworks. These frameworks must dynamically adjust to varying levels of sensor reliability.

Developing adaptive prognostic algorithms represents a critical area of research. These algorithms must adjust their behaviour based on changes in sensor performance, ensuring improved accuracy when considering sensor degradation. The focus has been primarily on simple systems; however, prognostic frameworks must also account for more complex engineering systems, consisting of multiple sensors and components with interdependent degradation processes, which require further study (Mukhopadhyay et al., 2023). Multi-rate systems (MRSs) with sensor degradation have received particularly little attention, despite the clear need for robust fusion estimation methods tailored to handle degradation effects (Huang & Shen, 2021). Research can focus on developing prognostic algorithms that integrate data from multiple sensors while accounting for their interaction and individual degradation patterns.

Another promising avenue is explainable AI (XAI) in prognostics. Many advanced data-driven algorithms, such as deep neural networks, are often seen as “black boxes,” which limits their applicability in safety-critical industries (Nor, Pedapati, Muhammad and Leiva, 2021). By integrating explainability into prognostic algorithms, researchers can ensure that the models not only provide accurate predictions but also offer insights into the underlying reasons for those predictions; included the impacts of sensor degradation, a crucial source of measurement uncertainty within prognostics implementations (Guo et al., 2019). The ability of XAI to explain diagnostic and prognostic activities by discovering features and unusual patterns responsible for system and sensor degradation can assist in managing these impacts and provide more descriptive prognostic results.

Current prognostics methods also struggle with the challenge of limited useful data. Extensive monitoring data and expert knowledge are often required, but effective sensor health data can often be scarce (Yin et al., 2022). This opens up research opportunities to develop innovative techniques that can function effectively under data-constrained conditions. This points to a need for innovative approaches that combine limited data with expert insights, such as employing fuzzy evaluation techniques for more precise prognostics outcomes (Yin et al., 2022). Moreover, exploring methods integrating data augmentation, transfer learning, or synthetic data generation may provide a pathway to overcome these limitations and enhance the reliability of prognostics systems.

Another key related area is the development of digital twins, which are virtual representations of physical systems. Digital twins continuously ingest real-time data from sensors and can incorporate sensor degradation models to monitor system health. The integration of digital twin technology in prognostics presents a significant opportunity for enhancing PdM and operational efficiency. By continuously assimilating data from various sensors, digital twins can provide insights into the potential degradation issues, allowing for timely interventions (Liu, Blasch, Liao, Yang, Tsukada and Meyendorf, 2023; Li, Wang, Fan, Zhang and Gao, 2023). By simulating the effects of sensor degradation on system behaviour, digital twins can provide better predictions of RUL and identify critical components requiring attention. This real-time synchronization between the physical and digital environments allows for proactive and precise maintenance strategies.

Experimental validation and real-world case studies are indispensable for advancing the field of prognostics and understanding the impacts of sensor degradation. Research can focus on creating benchmark datasets that include controlled degradation patterns and corresponding system failures. Such datasets are critical for developing and testing models that can robustly handle degraded sensor data. Real-world case studies are equally important for bridging the gap between theory and practice. For instance, in the aerospace sector, sensors play a critical role in monitoring engine health and flight systems. Case studies on how degraded sensor data affect RUL predictions can yield valuable insights for enhancing algorithmic robustness. Another opportunity lies in the development of cross-domain case studies that compare sensor degradation and prognostics in different industries. This approach can help identify universal principles and best practices that apply across domains. Furthermore, collaborative studies with industry partners can ensure access to operational data, which is often proprietary but critical for validating models in real-world contexts. Research can also focus on long-term monitoring projects, where systems are observed over their lifecycle to collect continuous data on sensor performance and system health. These projects provide a unique opportunity to study degradation as they unfold in real time, offering insights that static datasets cannot capture. For instance, monitoring an industrial robot’s sensors over several years can reveal patterns of degradation that inform maintenance schedules and predictive models.

To summarize the current limitations and highlight the avenues for future research in managing the impacts of sensor degradation on prognostics, Table 11 provides a concise overview of key research gaps, their current limitations, and promising future directions.

Current Limitations	Possible Research Directions
Most studies overlook sensor deterioration's effect on RUL.	Develop sensor-aware prognostics frameworks; dynamically adjust to varying sensor reliability.
Focus on simple systems; complex multi-sensor systems	Develop adaptive algorithms for complex multi-sensor systems

and MRSs underexplored.	(interactions, individual degradation); robust fusion for MRSs.
Advanced data-driven algorithms are "black boxes".	Integrate XAI to provide insights into predictions and degradation causes.
Effective sensor health data are often scarce; extensive monitoring is needed.	Develop techniques for data-constrained conditions; combine limited data with expert insights (fuzzy evaluation); data augmentation, transfer learning, synthetic data.
Emerging integration; full potential not yet realized.	Integrate digital twins for enhanced PdM; assimilate real-time sensor data, incorporate degradation models for timely interventions, RUL prediction.
Need for benchmark datasets and bridging theory/practice.	Create benchmark datasets with controlled degradation; conduct cross-domain/industry case studies; collaborate with industry; long-term monitoring projects.

Table 11. Research Opportunities in Managing Impacts of Sensor Degradation in Prognostics

7.3. Managing Impacts of Sensor Degradation in Maintenance Decision-Making

Future research could delve deeper into how variations in data quality resulting from sensor degradation, influence maintenance decision-making processes. A promising direction is the study of frameworks that more effectively incorporate uncertainty quantification due to sensor degradation. This includes understanding how operators perceive and react to uncertain data, how trust in the system evolves, and how cognitive biases might affect maintenance prioritization under uncertain conditions. A CBM framework accounting for sensor degradation presents research opportunities. There is a need to investigate the integration of sensor degradation models into the framework that capture sensor abnormal behaviours, and failure patterns of sensors. The integration of adaptive filtering and sensor fusion techniques to mitigate the impact of degraded or faulty sensors on data reliability represents a critical area for exploration. The development of a robust PdM decision-making framework with deeper utilization of prognostics under the influence of sensor degradation also introduces numerous research opportunities. A significant area of focus could be the integration of advanced prognostics models that can explicitly incorporate sensor degradation parameters into the RUL predictions, ensuring more reliable forecasts despite noisy or incomplete data. Another promising opportunity is the development of predictive analytics capable of distinguishing between actual system degradation and erroneous sensor readings. Additionally, integrating proactive sensor health monitoring into the PdM framework could help ensure the reliability of predictive models over time. Research into decision-making algorithms considering multi-objective optimization that balances maintenance costs, downtime, and the risk of uncertainty from sensor degradation using techniques such as robust optimization, Bayesian inference, or reinforcement learning can improve maintenance decision-making.

Maintenance policies considering sensor degradation can also be introduced. For example, research can focus on developing dynamic maintenance policies that incorporate sensor recalibration and adjustment to mitigate the effects of sensor degradation (van Oosterom et al., 2017). In addition, when the true state of a system is considered unknown due to sensor degradation, the maintenance decision-making process can rely on a combination of indirect indicators, probabilistic models, and historical data to assess risks and prioritize actions. The policies can involve observable parameters (e.g., vibration, temperature, or performance metrics), using predictive algorithms to infer the system's condition, and leveraging Failure Modes, Effects, and Criticality Analysis (FMECA) to estimate the likelihood and impacts of potential issues. Maintenance cost analysis can also be conducted to provide more details on the trade-offs. Another innovative approach is the integration of self-healing mechanisms in sensors, enabling automated repairs or calibrations when degradation is detected. The use of digital twins to simulate sensor performance and anticipate degradation scenarios can also enhance maintenance planning by creating adaptive maintenance policies capable of dynamically revising plans based on sensor performance. Additionally, implementing redundancy in critical systems by deploying backup sensors or adaptive algorithms that compensate for faulty readings can significantly improve system reliability in the face of sensor wear and tear.

The development of standards and guidelines for managing sensor-related uncertainties is also a pressing need. Research can contribute to standards for uncertainty quantification and propose maintenance guidelines for robust systems that account for sensor degradation. For example, there is a gap in the research on quantifying how much sensor degradation can be tolerated while still ensuring reliable prognostics and maintenance decisions. By establishing clear metrics and classification schemes, researchers can lay the groundwork for standardized uncertainty management practices. Another vital area for exploration is the integration of these standards into sensor design and maintenance strategies. Research could focus on embedding sensor uncertainty management principles into the lifecycle of sensor systems, from design and manufacturing to deployment and maintenance. For instance, guidelines could specify calibration routines, validation techniques, and redundancy strategies to mitigate uncertainty in sensor data. Furthermore, collaboration between academia, industry, and regulatory bodies would be essential to ensure that these standards are practical, widely applicable, and capable of addressing the diverse needs of industries relying on sensors in safety-critical applications.

To summarize the current limitations and highlight the avenues for future research in managing the impacts of sensor degradation on maintenance decision-making, Table 12 provides a concise overview of key research gaps, their current limitations, and promising future directions.

Current Limitations	Possible Research Directions
Data quality variations from degradation influence decisions; operator perception of uncertain data, trust, and cognitive biases underexplored.	Develop frameworks for comprehensive uncertainty quantification; understand operator response to uncertain data, system trust evolution, and cognitive biases in maintenance prioritization.
CBM lacks integrated models for sensor abnormal behaviours/failure patterns.	Integrate sensor degradation models; incorporate adaptive filtering and sensor fusion to mitigate degraded/faulty sensors.
Challenges in integrating explicit sensor degradation into RUL; distinguishing system degradation from erroneous readings.	Integrate advanced prognostics models with degradation parameters; develop predictive analytics to distinguish system vs. sensor degradation; integrate proactive sensor health monitoring.
Balancing maintenance costs, downtime, and degradation risk is complex.	Research decision-making algorithms using multi-objective optimization (costs, downtime, uncertainty risk) via robust optimization, Bayesian inference, or reinforcement learning.
Policies often lack dynamic recalibration/adjustment; maintenance for unknown system states is challenging.	Develop dynamic policies (recalibration, adjustment); rely on indirect indicators, probabilistic models, historical data; utilize FMECA; conduct cost analysis.
Limited self-healing mechanisms or advanced redundancy strategies.	Integrate self-healing sensors; use digital twins for adaptive maintenance planning; implement redundancy (backup sensors, adaptive algorithms).
Lack of clear standards for managing sensor uncertainties; need to quantify tolerable degradation.	Develop standards for uncertainty quantification; propose maintenance guidelines for robust systems; establish metrics/classification schemes.
Insufficient integration of uncertainty management principles across sensor lifecycle (design, manufacturing, deployment, maintenance).	Embed uncertainty management principles into sensor design/maintenance (calibration, validation, redundancy); foster academia/industry/regulatory collaboration.

Table 12. Research Opportunities in Managing Impacts of Sensor Degradation in Maintenance Decision-Making

8. CONCLUSION

This article provided a comprehensive review of the impact of sensor degradation on measurement uncertainty and its implications for prognostics and maintenance decision-making. A structured methodology was adopted, encompassing the identification of relevant studies, classification of key themes, and synthesis of critical findings. The literature review focused on sensor degradation mechanisms, their influence on measurement uncertainty, and how this uncertainty propagates through prognostics and maintenance strategies. The review highlighted that sensor degradation significantly affects measurement reliability, potentially compromising the accuracy of fault detection, remaining useful life estimation, and maintenance optimization. Various modelling techniques have been employed to address these challenges, ranging from empirical models based on experimental data to advanced filtering methods within state estimation frameworks. Additionally, theoretical and data-driven approaches, including statistical, probabilistic, and machine learning-based methods, offer deeper insights into degradation patterns and their impact on system performance. Incorporating measurement uncertainty into prognostics and maintenance frameworks has become a crucial strategy for improving system health predictions and optimizing maintenance decisions. Effective solutions have emerged, integrating sensor degradation into predictive maintenance and condition-based maintenance frameworks. These approaches often utilize expert knowledge, physical degradation models, and data-driven or hybrid methods to enhance generalization across diverse applications. Furthermore, mitigation strategies such as state estimation, filtering techniques, and revised maintenance policies have been developed to account for sensor degradation and sustain system reliability. Many of these approaches leverage optimization algorithms to enhance decision-making efficiency, ensuring that both sensor maintenance and overall system performance are effectively managed.

In addition, the research opportunities underscore the need for ongoing exploration of methodologies to quantify sensor degradation-related uncertainties and develop robust prognostics and uncertainty-aware maintenance decision-making frameworks.

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