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A REVIEW OF PREDICTIVE MAINTENANCE APPROACHES FOR CORROSION DETECTION AND MAINTENANCE OF MARINE STRUCTURES

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Abstract: Corrosion is a natural phenomenon that deteriorates and damages the surface of metallic material. Over time, the surface of the material deteriorates due to electrochemical reactions with the surrounding environment. If corrosion is not identified early on, it can become a major financial burden for industries, costing billions of dollars. Despite swift technological developments, preventing and maintaining corrosion progression with reactive maintenance remains difficult. Due to that, predictive maintenance has been developed to predict the deterioration, degradation, and fault over the remaining useful life of the material by using real-time data, historical data, simulation, modelling, and failure probability. Predictive maintenance allows inspectors to monitor the health and predict the corrosion level of the material. However, it is hard to predict the unexpected degradation of the material from the developed prediction model without considering the harsh environment and other external factors. Hence, there is a need to investigate these problems and their effect on predictive maintenance for corrosion detection and maintenance. Therefore, this paper reviews and compares the state-of-the-art predictive maintenance solutions developed to solve corrosion issues in various applications, industries, and academic research. The challenges and opportunities for the predictive maintenance application of corrosion detection and maintenance are also presented. This review will provide new and additional knowledge that can be used to develop prediction models for corrosion detection and maintenance, which will help prevent unexpected failures.

Keywords: Predictive maintenance, remaining useful life, health monitoring, corrosion detection, corrosion maintenance.
Abbreviations: PdM, IR4.0, IoT, RUL, CBM, WoS, ICCP, VLSFO, RAM, UDC, PCC, WDA, UHF RFID, EVA, AI, POT, BM, GEVD, EB, EWMA, PDF, RCM, CMMS, FE, ANN, RoI, LiDAR.

Introduction

Corrosion is a natural phenomenon that deteriorates and damages the surface of materials (Vazirinasab *et al.,* 2018). If corrosion is not identified early on, it can become a major financial burden for industries, costing billions of dollars (Baorong *et al.,* 2018). Corrosion is inevitable, but its progress can be reduced by employing substantial barriers to the material (Xia *et al.,* 2021). The nature of the environment can slow down or speed up the progress of corrosion. As a result, various methods have been created to decrease and lessen the impact of corrosion on the industry (Jamaludin *et al.,* 2016; Jamaludin *et al.,* 2017).

Predictive maintenance (PdM) is a maintenance approach that involves being proactive by identifying early signs and taking

action to prevent breakdowns (Selcuk *et al.,* 2017). In order to ensure smooth operations, it is important to address and resolve any of these breakdowns and failures, even if they are not major, as they can still cause disruptions. Because of that, PdM has been used in various industries to ensure the safety, reliability, efficiency, and quality of the equipment and materials. Moreover, recent advances in Industrial Revolution 4.0 (IR4.0) such as the Internet of Things (IoT) and artificial intelligence, help the industry players to embrace PdM since it has become more affordable, applicable and efficient (Guma *et al.,* 2019). PdM solutions are developed by involving abundant data from sensors and instruments. These data are incorporated with multiple approaches and then adopted into maintenance activities.

Despite technological advancements, preventing and maintaining corrosion with reactive maintenance remains difficult (Cheng *et al.,* 2020). Due to that, PdM has been adopted to predict the deterioration, degradation and fault over the remaining useful life (RUL) of a material to tackle corrosion issues by using real-time data, historical data, simulation, modelling and failure probability. PdM enables inspectors to monitor the health of materials and predict their corrosion levels. However, it is hard to predict the unexpected degradation of material from the developed prediction model without considering the harsh environment and other external factors. External factors, such as unwanted metal degradation and shock damage, can also impact corrosion levels. Hence, it is necessary to investigate these problems and their effects on PdM for corrosion detection and maintenance. As such, this paper reviews PdM methods used to solve corrosion issues in various real-time applications. Furthermore, challenges and opportunities for implementing PdM and corrosion maintenance are also presented.

Background

This section will explain the background of corrosion, the maintenance strategy used for corrosion detection and maintenance, predictive maintenance and the selection of the paper for this study.

Corrosion

Corrosion occurs when metal materials transform over time into unwanted substances because of their interaction with the surrounding environment through electrochemical and chemical reactions (Shaw *et al.,* 2006) as shown in Figure 1. Furthermore, corrosion is unavoidable and can cause deterioration in metal materials (Shi *et al.,* 2020). The fundamental nature of the corrosion phenomenon is to reduce Gibbs energy in a system. Metallic materials return to a low-energy oxide state, creating corrosion (Imran *et al.,* 2021). The corrosion process involves anodic and cathodic electrochemical reactions (Bitenc *et al.,* 2020). An electrochemical reaction at the anode will allow electrons to flow towards the cathode. The convergence of electrons at the cathode will create a reduction reaction. Therefore, it is critical to mitigate the metal dissolution from the surface of the oxide film formation.

Figure 1: Corrosions on ship structures, indicated by their morphological shape (Imran *et al.,* 2023)

Corrosion is classified based on the type of environmental exposure and the morphology of the attack (Imran *et al.,* 2023). The eight forms of corrosion are general or uniform attack, galvanic or two-metal corrosion, crevice corrosion, pitting, intergranular corrosion, selective leaching, erosion corrosion and stress-corrosion cracking (Goyal *et al.,* 2018). A general or uniform attack is a type of corrosion that occurs uniformly across the surface of a material due to electrochemical reactions. This form of corrosion is predictable and can be controlled. Galvanic or two-metal corrosion occurs when two different metals are in contact with each other in a corrosive solution, resulting in a potential difference (Ng *et al.,* 2020). The less resistant metal becomes the anode, while the more resistant metal becomes the cathode. Crevice corrosion is a localised form of corrosion in small stagnant solution areas, commonly affecting holes, gaskets and lap joints.

Pitting is the most severe form of corrosion, resulting in localised attacks that can create holes in the metal and are often difficult to detect due to the coverage of corrosion products. Intergranular corrosion occurs at the grain boundaries of metals, resulting in small areas of corrosion (Liu *et al.,* 2017). Selective leaching occurs when one element of an alloy is removed, typically involving iron, cobalt, chromium, zinc or aluminium. Erosion corrosion is caused by the rapid movement of corrosive fluids over a metal surface, accelerating the corrosion process and causing abrasion and mechanical wear. Stress-corrosion cracking is caused by the combination of corrosive mediums and tensile stress, leading to cracks in brass season, caustic embrittlement and steel. These eight forms of corrosion can occur in pipelines, metallic equipment, steel bridges, copper roofs, bronze statues, ship hulls and many other applications.

Regarding ship structures, fatigue and corrosion can weaken the strength of vessels and ships, ultimately leading to structural failures (Han *et al.,* 2019). The primary components that undergo corrosion in ship structures are the individual metal elements, such as those found in the ship's hull, two different metals, such as at the metallic coatings and rivets, and concentration elements such as the presence of electrolyte and metal. Ship structures are divided into the atmospheric zone and the immersed zone of stiffeners and plates. Several factors can influence the atmospheric zone, including chloride concentrations, sulphur dioxide, oxygen, sulfuric acid, carbon dioxide, pressure, ventilation, steel type, humidity and temperature. On the other hand, the main influencing factors for the immersed zone include hydrogen sulphide concentrations, sulfuric acid, carbon dioxide, salinity, seawater velocity, seawater pressure, pH value and temperature. Given these factors, it is crucial to have a reliable maintenance strategy in place for detecting and managing corrosion.

Maintenance Strategy

RUL is the basis of maintenance, where it is combined with performance, sustainability, reliability, productivity, automation, and the supply chain of tools or materials. The primary targets of maintenance are to minimise costs, increase productivity, and increase uptime/reliability by optimising the production process and output. Better maintenance analysis can allow us to understand the health of equipment and materials, as shown in Figure 2. However, the degradation of tools and materials is a common scenario in the industry. Hence, to ensure continuous production demand, cost estimation, repair time, production time, operation time, and RUL must be considered to create an efficient maintenance strategy. Any irregularities must be detected and analysed to ensure optimal performance.

Maintenance strategy can be classified into reactive maintenance and proactive maintenance. Reactive maintenance is a traditional method where necessary action is taken only when the tool or material is damaged due to corrosion. There is no need to do maintenance and fixing works as long as the tool or material is not broken. Management only has to perform and invest in maintenance when the failure arises. Meanwhile, proactive maintenance is a method

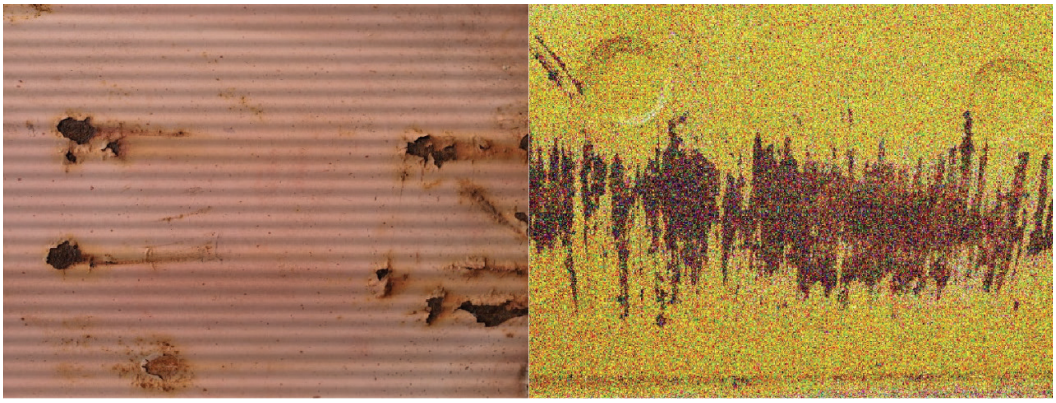

Figure 2: Health of equipment and materials affected by periodic noise (on the left) and Gaussian/motion blur noise (on the right) (Jan *et al.,* 2020)

where action is taken well before the damage occurs. Proactive maintenance can be divided into preventive, predictive, and prescriptive (Sakib & Wuest, 2018). Preventive maintenance is a time-driven or time-based maintenance where the maintenance work is scheduled earlier. The maintenance schedule depends on the cycle time or operation cycle of the given process. Maintenance activities are implemented periodically, even if the tool or material is still in good shape. However, the assumption that the tool or material will break down at a certain timeframe or cycle is inaccurate. Maintenance costs can be increased due to unnecessary maintenance activities, such as preventive maintenance. Predictive maintenance is efficient since this method uses advanced technology such as data analytics, artificial intelligence, modern manufacturing, information technology, and automation.

This maintenance strategy can predict failure states and maintenance activities are done accordingly. Developing a prediction model depends on real-time data, historical data, experience, and physics laws. Meanwhile, prescriptive maintenance is quite similar to predictive maintenance (Zonta *et al.,* 2020). However, it is only a part of predictive maintenance instead of an end-to-end strategy. An ineffective maintenance strategy can lead to inability, unreliability, and undesirable loss of assets, tools, and materials.

Predictive Maintenance

PdM, an abbreviation for predictive maintenance, is also commonly referred to as condition-based maintenance (CBM). It is a proactive maintenance strategy that uses data to detect anomalies and possible failures in tools and materials. Thus, maintenance action can be done immediately (de Jonge *et al.,* 2017). It monitors the performance and condition of the material from historical and real-time data and determines the necessary maintenance schedule. This maintenance strategy tries to minimise the frequency of unscheduled maintenance without compromising the condition of the material. PdM aims to achieve several primary goals, including decreasing the time needed for maintenance, minimising production downtime, and lowering the overall cost of component supplies. However, data misinterpretation is possible. Hence, it can produce a false maintenance schedule, RUL and material health.

PdM involves utilising mathematical or predictive models to identify when errors occur and determine the optimal time for maintenance (Luo *et al.,* 2020). The detected errors determine the basic, intermediate, or major maintenance actions. This maintenance strategy can predict the possibility of failure in the tool and material by scheduling maintenance programs to optimise performance and reduce false decision-making. Reliability and availability can be increased by optimising a

tradeoff between the cost of performance and maintenance. Any breakdown can be measured regarding productivity, RUL, and efficiency. The prognosis of future maintenance actions can extend RUL. Unexpected failures and breakdowns can be determined by analysing impending errors from maintenance indicators. These indicators are obtained from assessing many scenarios and conditions in the tool and material. Hence, production stoppage can be prevented with PdM and maintenance activity. All parameters are measured and recorded continuously, so real-time data are analysed to determine the appropriate maintenance action for each tool and material.

IR4.0 helps industries use more advanced technology in their systems (Jamaludin *et al.,* 2022). Advanced sensors, data analytics, signal processing, big data, and IoT emerge for corrosion prediction and detection from real-time data and system prognostics. A certain threshold is set according to the previous degradation level from the prediction model to obtain better accuracy and efficiency. Moreover, the future health of the tool and material can be predicted from the combination of real-time data and historical data, thus updating the threshold value. The proper judgment and timing for maintenance activity can be made and forecasted by analysing this data. PdM has also evolved from only breakdown and replacement cases to multiple failure rates in the multiple-state system degradation over time. PdM can work considerably well in the subsystem even when the parameters remain uncertain (Jamaludin *et al.,* 2020). Due to its ability to accurately predict and assess the degree of corrosion in affected materials, PdM has recently become increasingly popular for corrosion detection and maintenance. The classification of PdM models includes hybrid, data-based, physics-based, and knowledge-based models (Filom *et al.,* 2022).

Papers Selection

This paper reviews and compares the state-of-the-art PdM corrosion prediction models developed to solve corrosion issues in various applications, industries and academic research. The challenges and opportunities for PdM and corrosion maintenance are also investigated. The Web of Science (WoS), Scopus, Google Scholar, and IEEE websites were used to search for relevant journal papers. The initial search keywords were: "predictive + maintenance + corrosion" and "predictive + maintenance + corrosion + efficient". The search engines managed to search over 100 papers published from 2017 until 2022. Next, the keywords "artificial + intelligence" and "current + trends" were added to the search engines, reducing the number of relevant papers to 51. After sorting out, only 31 papers were relevant to PdM and corrosion maintenance.

These 31 papers were analysed to determine whether they can provide the most relevant PdM strategies for corrosion detection and maintenance in academic and industry applications. The future scopes of research were also investigated. The system's prediction models, theoretical ideas, and findings of these papers were evaluated so they could provide enthusiasm, motivation, and crucial contributions towards the optimal corrosion maintenance strategy.

Current Trends

This section will describe the state-of-the-art corrosion prediction models in PdM. The developed corrosion prediction models are divided into knowledge-based, physic-based, data-based and hybrid models.

PdM with Knowledge-Based Model

PdM knowledge-based model employs experiences, rules, facts and cases to create its prediction model (Jimenez *et al.,* 2020) as shown in Figure 3. Over the years, operation and maintenance data have been collected. With the advent of IR4.0, this model can be combined and automated with artificial intelligence, statistics and machine learning techniques.

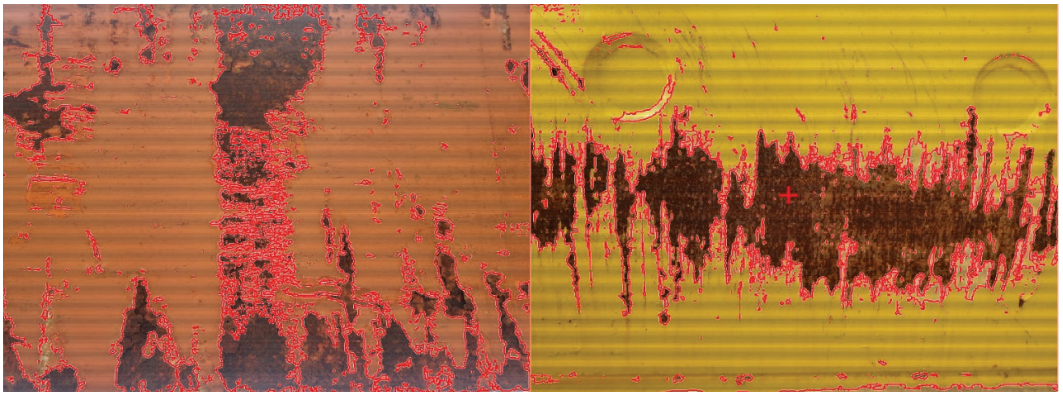

Figure 3: Corrosion prediction model from experiences and cases of inspectors with Chan-Vese active contour (on the left) and geodesic active contour (on the right) (Jamaludin *et al.,* 2020)

In 2021, a framework for an impressed current cathodic protection (ICCP) system was presented by Rossouw *et al.* (2021). This study utilised historical data and machine learning to forecast the downstream test post in the ICCP system. The effectiveness of this model was assessed using classification, regression and survival analysis to determine the progress of corrosion and the optimal time for maintenance based on the test post potential. The evaluation demonstrated that this model effectively prevented external corrosion and ensured efficient corrosion control. However, utilising multiple artificial intelligence techniques in this model may result in increased complexity of the prediction model.

Canca *et al.* (2020) utilised their extensive knowledge of sulphur to examine the current maintenance approaches employed in the maritime sector. Introducing a new marine fuel has presented a major challenge because of the constantly changing chemical and physical properties that can contribute to corrosion progression. This makes planned maintenance inadequate and can jeopardise ship operations. To reduce the potential critical risk, very low sulphur fuel oil (VLSFO) characteristics were monitored using PdM. This approach detected and provided corrective action for corrosion caused by sulphur emissions. However, this model was designed specifically to evaluate the Sulphur 2020 amendment.

Vu *et al.* (2020) utilised the hull girder rules to evaluate the impact of corrosion on bulk carriers. They investigated the flange and web sections of the vertical bending moment and cross-sectional properties to determine the ship's hull residual strength. Subsequently, they developed a model using probabilistic corrosion rate estimation and incremental-iterative methods. Parameters such as the vertical bending moment, neutral axis position, and cross-sectional property were measured to determine the required maintenance. The results indicated that this method could identify and mitigate the impact of corrosion on the ship's hull. However, the sensitivity of the prediction model for maintenance planning may be affected by a lack of historical data, and there is still a risk of unplanned and unexpected corrosion behaviour despite having an accurate prediction model.

Bicen *et al.* (2022) used reliability, availability and maintainability (RAM) analysis to forecast future maintenance planning trends. They gathered real-time data from a container ship's fuel injection valve to examine the impact of corrosion on the valve, which can reduce the ship engine's performance. The study showed that their developed prediction model could improve routine and non-routine maintenance activities on the ship engine. However, further model optimisation may be necessary to increase the reliability of maintenance planning.

Several PdM corrosion prediction models also focus on marine steel structures based on different cases, such as climatic conditions (Abbas *et al.,* 2020), ferrography lubricants (Bhat *et al.,* 2022), double hull girder tankers (Gong *et al.,* 2020), and random field approaches (Woloszyk *et al.,* 2020). These methods have shown improvement in terms of reducing maintenance activities, improving downtime, and reducing costs. However, production output can improve by optimising the model design with more accurate real-time and historical data. A summary of different PdM with knowledge-based models is illustrated in Table 1.

Table 1: Summary of PdM with knowledge-based models

Approach	Description	Limitation	Corrosion Parameter
ICCP (Rossouw *et al.,* 2021)	• Machine learning and historical data to predict downstream test post. • Evaluation with survival, regression and classification analysis. • Can estimate and detect corrosion progress and maintenance time.	• The model's complexity increased as many AI approaches were used.	• Mass loss
Rules of hull girder (Vu *et al.,* 2020)	• Can assess corrosion effect on a bulk carrier. • Can detect and reduce corrosion effect on ship hull.	• Lack of historical data can affect the sensitivity of the prediction model for maintenance planning. • Unplanned and unexpected corrosion behaviour can still occur.	• Mass loss
Vast knowledge in sulphur (Canca *et al.,* 2020)	• Investigate the existing maintenance strategy in the maritime industry. • VLSFO characteristics monitoring for a critical risk. • Corrective action and detection for corrosion from sulphur emissions.	• Only for the Sulphur 2020 amendment.	• Corrosion efficiency
RAM (Bicen *et al.,* 2022)	• Explicit rules for corrosion detection.	• Inflexible and cannot adapt to changing conditions or new information.	• Mass loss
Climatic conditions (Abbas *et al.,* 2020)	• Expert system to mimic the decision-making ability of human experts. • Reasoning engine to solve problems or make decisions.	• Difficulty in acquiring and representing expert knowledge. • High cost of developing and maintaining system.	• Mass loss
Double hull girder (Gong *et al.,* 2020)	• Based on fuzzy sets. • Fuzzy logic can be used to model complex systems.	• Difficult to understand and may require a large amount of data for training.	• Mass loss
Random field approaches (Woloszyk *et al.,* 2020)	• Represent complex relationships between variables. • Conditional probabilities to make predictions.	• Large amount of data. • Difficulty in obtaining accurate prior probabilities.	• Mass loss

PdM with Physic-Based Model

PdM physics-based model is a prediction model that utilises the fundamental laws of real-life situations, original equipment, physics, and the behaviour of equipment or material. Recently, the concept of a digital twin has emerged, which involves creating a virtual representation of the subject and comparing its behaviour with that of the physical equipment. This approach enables the digital twin to be calibrated to function and operate in a way that is consistent with the actual subject.

Pourabdollah (2021) investigated under-deposit corrosion (UDC) in the firetube of a three-pass seawater steam boiler to improve its predictive maintenance. The study was carried out over six years to collect relevant data. The results showed that carbonates and hematite minerals caused UDC. However, applying phosphate congruent control (PCC) and UDC propagation enhanced the model's accuracy. Nevertheless, it should be noted that the external environment and parameters in the workplace may differ for other types of boilers, making this model unsuitable for them.

Raadnui (2019) proposed using wear debris analysis (WDA) to evaluate the wear conditions of an industrial gearbox with multiple gear pitting and wear failure modes. To create a PdM prediction model, they simulated various forms of wear, including acid attack, contaminant-induced abrasive wear, and moisture corrosion on the gearbox. The results showed that the morphological analysis of wear debris effectively detected and predicted wear and its mechanism. However, it should be noted that the accuracy of the prediction model may be affected by factors such as the size, brand, and configuration of the gearbox since most industrial gearboxes are customised.

Additionally, Bouzaffour *et al.* (2021) introduced the UHF RFID (ultra-high frequency radio frequency identification) sensor for detecting corrosion in steel structures within marine environments. The corrosion occurs due to chloride, which causes the thin oxide film layer on steel to break down. The UHF RFID sensor detects the corrosion region by analysing the difference in moisture level between the steel layer and the surrounding concrete. The sensor can measure metallic film thickness up to a few micrometres. The method successfully monitored and controlled steel mass loss, although it did not employ PdM. The sensor network can potentially be used in developing a PdM physics-based model, as it provides accurate data on corrosion.

Melcherset (2019) conducted a study to determine the appropriate mathematical model for the marine corrosion of ships to support efficient maintenance decision-making. The study investigated the effects of long-term corrosion on physical infrastructure, such as crevice severity and pit depth, and empirically compared the degree of corrosion with available prediction models. However, collecting historical data on corrosion progression under oxygenated conditions can be time-consuming and complex, requiring several decades to obtain.

Lampe and Hamann (2018) proposed using the Weibull distribution as a prediction model to assess the corrosion of ageing ship structures. Their model was based on the degradation process of both stiffeners and plates and categorised ship structures by zone, compartment and structural type. These categories included deck longitudinal girders, side shells, bilge keels and many more. Historical and real-time data were used to develop the prediction models, which could be individually adjusted for each structural element. The models could also be fine-tuned by calculating the means of influencing factors. The authors found that their proposed method effectively predicted corrosion in ageing ship structures. However, the model required a large amount of data for fine-tuning each structural element. To address this, data can be analysed at the sensor nodes or edges and stored in the cloud to minimise transmission errors and costs.

The other PdM physics-based models include the prognostic model of physics-of-failure (Tinga *et al.,* 2017; Tinga & Loendersloot,

2019), the RUL model of ship hull structure profile (Ayyub *et al.,* 2022), and ship hull tanker profile (Gong *et al.,* 2020). These models were tested and evaluated by comparing them with their corresponding simulations. These methods showed improvements in terms of reducing maintenance activities and production outputs. However, it should be noted that these methods require a separate model for each physics-based implementation, which can be less efficient if the respective industry possesses many individual rigs. A summary of PdM with physics-based models is illustrated in Table 2.

PdM with Data-Based Model

PdM data-based models are prediction models that rely on data-driven approaches such as machine learning, statistics, and stochastic modelling, as shown in Figure 4. The accuracy of this model heavily relies on the quantity and quality of historical and real-time data (Jan *et al.,* 2020). However, noise and uncertainty in the data can impact its performance. Thus, validating the results with physics-based and knowledge-based models is essential. It should be noted that not all prediction models that use artificial intelligence (AI), statistics, and

Table 2: Summary of PdM with physic-based models

Approach	Description	Limitation	Corrosion Parameter
UHF RFID (Bouzaffour *et al.,* 2021)	• Detect corrosion steel in the marine environment. • Calculate the difference between the steel layer and concrete moisture degree. • Monitor and control mass loss of steel by detecting corrosion status.	• The developed sensor network must be suitable and accurate for developing prediction models.	• Mass loss
UDC (Pourabdollah, 2021)	• Enhance existing PdM. • Three-pass seawater steam boiler's firetube.	• Limit by external environment and parameters.	• Corrosion rate
WDA (Raadnui, 2019)	• Wear conditions of the industrial gearbox. • Can detect and predict wear.	• Accuracy can be affected by the size, brand, and configuration of the gearbox.	• Corrosion rate
Weibull distribution (Lampe & Hamann, 2018)	• Determine corrosion in ship structures. • Based on the degradation process. • Effective in predicting corrosion.	• Required large amounts of data.	• Depth dissipation

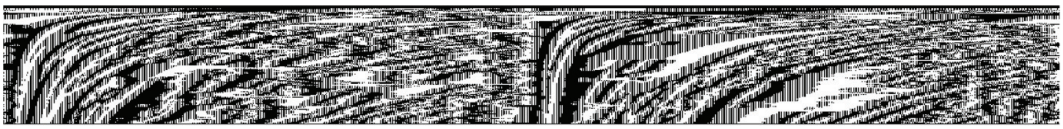

Figure 4: Data-driven corrosion prediction model where pixel values can be extracted. Black pixels represent corroded elements, while white pixels represent non-corroded elements (Jamaludin *et al.,* 2022)

machine learning are considered data-based models. The category of the developed model is determined by its core or fundamental methodology.

Yarveisy *et al.* (2022) proposed a data-based model using extreme value analysis (EVA) for predicting corrosion failure. The EVA technique was employed to predict the depth of pits that necessitated immediate maintenance. Real-time degradation data from inspection reports created the prediction model by considering the peaks over the threshold (POT). The block maxima (BM) approach validated the model's performance in assessing and detecting corrosion. The model performed well in assessing and detecting corrosion failures. However, it was not applied to multiple sections in the same workflow. Therefore, the model may need to be parameterised and fine-tuned to assess multiple sections of corrosion failure.

Kim *et al.* (2021) proposed a framework for predicting corrosion defects using Bayesian inference. The prediction model utilised historical and real-time data from a Generalised Extreme Value Distribution (GEVD). The model was frequently updated with new real-time data, while the historical data indirectly assisted in determining the corrosion defect distribution. This approach resulted in a highly reliable prediction model that can adapt to varying defect depth distributions. However, the accuracy of the model can be reduced if the historical data is unavailable, as the real-time data are sensitive to parameter estimation.

An approach combining the Exponentially Weighted Moving Average (EWMA) and Expected Behaviour (EB) model was proposed for shipboard corrosion systems (Cheliotis *et al.,* 2020). The study utilised recorded voyage data to explore the learning potential of the prediction model. The model was able to locate certain fault parameters, such as gas temperature and air pressure, which could be useful in developing a corrosion model. However, even with well-maintained ships, failures can still occur, leading to decreased energy reliability, safety and efficiency. These can contribute to fouling and corrosion in the nozzle ring and turbocharger of the vessel.

The study by Makridis *et al.* (2020) introduced a novel prediction model that combined machine learning and time-series anomaly detection to facilitate maintenance decision-making based on data collected from sensors on both the ship engine and hull. By utilising the available data sources, the lifetime of the hull could be extended with less cost. The results of the study indicated that it can accurately predict corrosion on specific parts of the ship engine. However, the placement of sensors on specific parts of the vessel may reduce the overall accuracy of the developed model. Therefore, it may be necessary to fine-tune and parameterise the model for different vessel parts to improve its accuracy.

The prediction model proposed by Kim *et al.* (2020) utilised a mathematical approach and real-time data from a ship's ballast tank to forecast corrosion damage on the ship structure. The researchers used the probability density function (PDF) method to derive time-dependent and nonlinear formulations, which were selected by comparing the real-time data to find the best fit. Sub-parameters were then determined using curve-fitting methods. The results showed that the prediction model accurately determined the corrosion damage over time and remaining useful life. However, the model may need to be parameterised and fine-tuned for different structures, including those onshore, offshore, nearshore, and on the ship itself.

Other PdM data-based models for corrosion prediction include historical data monitoring spanning 25 years of ship hull (Ivošević & Bauk, 2018), customised self-healing of a condition-based PdM system (Gautam *et al.,* 2021), spatial dependence of corrosion growth, geometric and material properties (Gong *et al.,* 2020), and a risk analysis framework of synthesised life-cycle (Liu *et al.,* 2019). These methods showed improvement in terms of reducing maintenance activities, improving downtime, and reducing cost. However, the respective models can still be improved by optimising more real-time

and historical data for model development. Furthermore, the number of samples for training, validating, and testing can be increased for accuracy improvement. A summary of different PdM with data-based models is illustrated in Table 3.

PdM with Hybrid Model

The PdM hybrid model is a prediction model that combines at least two PdM models, which may include data-based, physic-based and knowledge-based models. This model has unique configurations that distinguish it from multi-model PdMs, so not all multi-model PdMs can be classified as hybrid models as shown in Figure 5.

In Jimenez *et al.* (2020), machine learning and big data were utilised to solve hull corrosion in the shipping industry. This hybrid approach collected historical and real-time data through a sensor network to reduce operation disruptions. The results indicated that PdM could reduce the number of failures and breakdowns, with key parameters exhibiting strong correlations and influence between equipment. The accuracy and speed of maintenance decision-making were also improved. However, implementing this method may create disruptions because of

Table 3: Summary of PdM with data-based models

Approach	Description	Limitation	Corrosion Parameter
EVA (Yarveisy *et al.*, 2022)	• Predict the depth of pits for immediate maintenance. • Consider peaks over the threshold. • High performance.	• Not implemented to multiple sections in the same workflow. • Might require fine-tuning and parameterisation to assess multiple sections of corrosion failure.	• Depth dissipation
Time-series anomaly detection (Makridis *et al.*, 2020)	• Predict corrosion damages on ship structure. • Accurate for determining RUL and corrosion damage over time.	• Might require fine-tuning for each nearshore, offshore, onshore and ship structures.	• Mass loss
EWMA and EB (Cheliotis *et al.,* 2020)	• Can detect certain fault parameters. • Useful for developing corrosion models.	• Inevitable due to occurrence failures. • Contribute to corrosion and fouling in the turbocharger and nozzle ring of the vessel.	• Depth dissipation
PDF (Kim *et al.*, 2021)	• Time-series anomaly detection and machine learning. • Can detect and predict corrosion on specific parts of a ship's engine.	• Accuracy may have suffered. • Might need fine-tuning and parameterisation for different parts of the vessel.	• Corrosion rate
Bayesian inference (Kim *et al.,* 2021)	• Real-time data and historical data for employment of GEVD. • Can adapt to defect depth distribution.	• Real-time data is quite sensitive for parameter estimation. • Could reduce the accuracy of the prediction model if historical data is unavailable.	• Mass loss

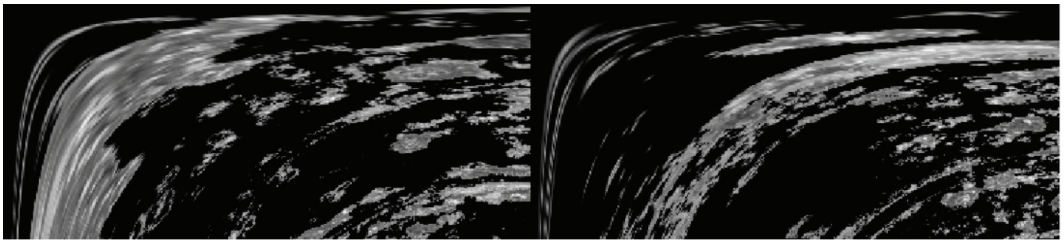

Figure 5: Hybrid corrosion prediction model by combining data-based and knowledge-based models. The corrosion rate of each corroded element is represented by grayscale values (Imran *et al.,* 2021)

its complexity. Additionally, it is necessary to define the potential failure identification and failure modes before developing the prediction model.

Silionis and Anyfantis (2023) developed a method for detecting thickness loss in the ship hull using a strain-sensing approach. The method involves a hybrid model that combines structural health monitoring with classical detection tools for corrosion detection and hull structure maintenance. Historical and real-time data were collected from in-situ sensors, and damaged hull conditions were estimated using Monte Carlo simulation. Mean-shifted and Gaussian methods were used to measure the deterministic signals from static strain. The results demonstrated that strain measurement is an effective means of detecting thickness loss in the ship hull. However, this method ignored the effect of noise in the historical data, which may challenge the signal dynamics.

Cullum *et al*. (2018) examined and applied a risk-based maintenance scheduling approach to vessels and ships. This method was previously used in other industries and involved probabilistic modelling and decision analysis for making predictions in the model. The prediction model was optimised using the corrosion scenario and fatigue crack propagation. Reliability-centered maintenance (RCM) was also integrated with the framework to evaluate the model regarding availability and maintenance cost. The proposed prediction model reduced maintenance costs and detected corrosion through risk-based scheduling. Despite this, the model has not yet been integrated with a sensor network and is still under development.

According to Simion (2020), the computerised maintenance management system (CMMS) was utilised as a framework for a prediction model aimed at maintaining all equipment and preventing corrosion on board ships. This model integrated various parameters such as the ship's structure corrosion, equipment, mission and constructive features, to make decisions regarding maintenance activities. The CMMS facilitated maintenance planning for all equipment and ship structures, optimised maintenance planning, improved maintenance resource allocation, and recorded data on maintenance activities. However, the model was only developed for a specific or customised ship, and it may be challenging to fine-tune and parameterise the model for other ships.

In a study by Anyfantis (2019), AI and digital twins were proposed for predicting ship hull structure damage and corrosion. The study utilised an optimisation method of finite element (FE) analysis to develop the model, which was then fitted and classified using an artificial neural network (ANN). The results showed that the prediction model could identify specific locations on the ship hull that were particularly sensitive to damage and corrosion, allowing for more focused monitoring. The study demonstrated the effectiveness of the hybrid approach of combining a data-based model of ANN and FE for the analysis of hull structure with a physics-based model of digital twins. A summary of different PdM with hybrid models is illustrated in Table 4.

Table 4: Summary of PdM with hybrid models

Approach	Description	Limitation	Corrosion Parameter
Digital twin and AI (Anyfantis, 2019)	• Specific corrosion locations can be determined.	• The sensitive area on the ship hull can be monitored closely.	• Corrosion efficiency
Machine learning and big data (Jimenez *et al*., 2020)	• For ship hull. • Real-time data was collected using the sensor. • Decision-making for precision and speed.	• May create disruptions because of its complexity.	• Corrosion efficiency, mass loss
Strain sensing (Silionis & Anyfantis, 2023)	• Thickness loss of ship hull. • Integrate structural health monitoring with conventional techniques for detecting corrosion and maintaining hull structures.	• Overlooked the impact of historical data noise, which could complicate signal dynamics.	• Mass loss
Risk-based maintenance scheduling (Cullum *et al*., 2018)	• For vessel and ship. • Able to reduce maintenance costs and detect corrosion.	• Not integrated with sensor network.	• Corrosion rate
Computerised maintenance management system (Simion, 2020)	• Predict corrosion onboard ships. • Effective.	• Only for one specific ship. The result can be different in other ships.	• Corrosion efficiency

Challenges and Opportunities

The implementation of PdM for corrosion detection and maintenance is fraught with challenges such as the lack of skilled workers, high upskilling costs, reliability issues, lack of regulation, industry adaptability, and high maintenance and installation costs. Finding and training skilled workers can be difficult due to the advanced technology used in PdM, requiring fundamental knowledge of artificial intelligence. Skilled workers also require specialised training before deployment, unlike unskilled workers. The high upskilling cost is also a challenge in PdM implementation, as highly trained workers are often task-specialised and require prolonged training. Reliability issues can also arise in the system, such as when the prediction model contains many errors and bugs.

Therefore, experts must develop and test the algorithm, and outdated firmware can contribute to reliability issues. Lack of regulation is also a challenge, as no regulatory body oversees PdM activities. Technical codes or regulations on software/hardware deployment and prediction model behaviour would be beneficial. Industry adaptability is still low, especially in underdeveloped countries, where industries heavily rely on low-cost, unskilled labour. The production output can be affected due to labour shortages. High maintenance and installation costs can contribute to low PdM adaptability in industrial operations, requiring a longer return on investment (ROI).

Despite these challenges, there are opportunities in PdM, such as introducing 5G communication, which can increase automation efficiency. Industries can also reduce their dependence on unskilled workers by training more skilled workers, and competition between training providers can increase the quality of training and assessment. As artificial intelligence becomes a trend, many students will enrol in AI courses, which can further reduce the cost of skilled worker training, upskilling, and installation.

One of the challenges of PdM is that the predictive model for corrosion detection is limited by the current technology's inability to integrate expert knowledge and physicality. This can affect the prediction of failure states and limit the ability to solve real-time corrosion issues. Additionally, the development of prediction models relies on limited data on failure modes, which can result in theoretical assumptions. However, combining data-based, physics-based, and knowledge-based models has shown positive results but requires more parameterisation and fine-tuning.

Data complexity remains a critical issue in the PdM implementation for corrosion studies. The data must be constructed and converted into time or frequency domains to obtain the relevant information. Then, the relevant and significant features can be extracted for the prediction analysis. On the other hand, PdM can be used as an optimisation tool, in addition to the other corrosion detection, maintenance and inspection methods. The pre-processing, segmentation and feature extraction can be optimised with PdM, thus increasing the RUL of a material. It also can be employed to offer segregation and resolution which can improve the performance of PdM. Moreover, the prediction of RUL and the health condition of metallic materials rely heavily on historical data and real-time data on the corrosion progress.

These data are pre-processed to reduce noise and interference before being fed into the prediction model. However, in terms of opportunity, the availability of historical data allows artificial intelligence and data mining to predict the RUL, life cycle and corrosion condition efficiently and accurately. Advanced data processing and big data can improve the prediction model for corrosion detection and maintenance, thus increasing the RUL and decreasing unexpected failures. The availability of advanced sensors, such as infrared and light detection and ranging (LiDAR), can also increase the detection sensitivity for hotspots in anode and cathode areas of metals. The summary of this section is included in Table 5.

Discussion

After searching and analysing 31 research papers, PdM can be considered a major topic in corrosion detection and maintenance and manufacturing, aeronautical, power and energy, food and beverage, waste management, and construction industries. Most papers were published on prediction models, corrosion models, and corrosion maintenance under PdM and corrosion studies. Complex methodologies, such as prediction modelling, are pressing issues and frequent research topics in PdM and corrosion. The summary can be observed in Table 6.

Industrial sectors have slowly migrated to PdM from traditional detection and maintenance concepts due to the urgency and necessity of minimising maintenance costs, maximising production output, and reducing equipment downtime. As mentioned, labour shortages and the pandemic have forced industries to migrate to PdM. High corrosion maintenance costs can be minimised and reduced through optimised maintenance activities. Corrective actions or activities are conducted only when maintenance is deemed necessary. The prediction model predicts and determines the specific corrosion element or region to be maintained or replaced. Repairing tools, components, or materials, such as epoxy and cement, can be ordered accordingly.

Thus, corrosion can be fixed before it becomes severely damaged. Regarding production output, maintenance activities

Table 5: Summary of challenges and opportunities in PdM

Description	Summary
Issue	
• Limited integration of expert knowledge and physicality	• Can affect the prediction of failure states and limit the ability to solve real-time corrosion issues
• Development of prediction models relies on limited data	• Can result in theoretical assumptions, requires more parameterisation and fine-tuning
• Data complexity	• Data must be constructed and converted into time or frequency domain, significant features must be extracted for prediction analysis
• Heavy reliance on historical and real-time data on corrosion progress	• Must be pre-processed to reduce noise and interference before being fed into the prediction model
Challenge	
• Lack of skilled workers	• Difficulty finding and training workers with fundamental knowledge of AI
• High upskilling costs	• Workers require prolonged and specialised training
• Reliability issues	• Contain errors and bugs, outdated firmware can contribute to reliability issues
• Lack of regulation	• No regulatory body to oversee PdM activities, technical codes or regulations would be beneficial
• Industry adaptability	• Low industry adaptability, especially in underdeveloped countries, where industries rely on low-cost unskilled labour
• High maintenance and installation costs	• Requires a longer ROI due to high costs
Opportunity	
• Introduction of 5G communication	• Can increase automation efficiency
• Training more skilled workers	• Reducing dependence on unskilled labour
• Trend of AI courses	• Many students will enrol in AI courses, which can reduce the cost of skilled worker training, upskilling, and installation
• Availability of historical data	• Allows for efficient and accurate prediction of RUL, life cycle, and corrosion condition through AI and data mining
• Advanced sensors	• Increase detection sensitivity for hotspots in anode and cathode areas of metals

can stop the operation of certain businesses. For example, a ship must be docked if heavy corrosion and pits are detected on the hull. This certainly reduces the productivity of the ship in fulfilling its shipping activities and obligations. However, PdM can predict the progress of corrosion, and earlier corrective actions can be taken. The ship no longer needs to dock since maintenance activities are minimal, and shipping activities can proceed. Thus, production outputs can be maximised, and logistic disruptions can be minimised.

Table 6: Discussion of PdM

Key Point	Summary
Importance of PdM	• Minimise maintenance costs, maximise production output and reduce equipment downtime • Labor shortages and the pandemic have forced industries to migrate
Corrosion maintenance	• Corrosion maintenance costs can be minimised and reduced • Corrective actions only when necessary • Model predicts and determines specific corrosion elements or regions to be maintained or replaced
Production output	• Can stop the operation of certain businesses • Production outputs can be maximised • Logistic disruptions can be minimised
Equipment downtime	• Reduce structures' downtime • RUL can be increased by proactive judgment • Residual life, failure rate, and ageing factors must also be considered to reduce unexpected failures
Importance of proper corrosion maintenance	• Ensure low downtime, continuous operation, and high efficiency • Vital to integrate expert knowledge and associated failure modes into the prediction model

On the other hand, equipment downtime can be minimised with PdM. For example, the most frequent corrosions on ships are on the ship hull plates, steerings, and propellers since they directly contact seawater. Corrosions on these structures can reduce the safety, speed, and strength of the ship. PdM can predict corrosion on these structures, and proper maintenance actions can be conducted earlier to reduce the structures' downtime. The RUL of the structures can also be increased by employing proactive judgment, whereby unexpected degradation can be detected. The effect of residual life, failure rate, and ageing factors must also be considered to reduce unexpected failures.

Furthermore, not all mathematical or prediction models are suitable for similar processes due to different components, environments, and corrosion detection and maintenance methodologies. The PdM knowledge-based model is entirely dependent on the heuristic knowledge of experts, such as corrosion inspectors. Examples of knowledge-based models are the condition-making method and fuzzy logic. However, expert knowledge cannot be converted into an algorithm without integrating it with data from the physics-based model.

Meanwhile, the PdM physics-based model requires a mathematical model from empirical and experimental data to create reliable predictions. Nevertheless, developing an accurate model from this method remains difficult as rigorous knowledge is required. Exhaustive experimentation is also required in the parameter identification of failure modes for developing the digital twin. The obtained failure modes might not be suitable for systems with complex architecture. Moreover, the PdM data-based model is easier to use since the mathematical model can be derived from historical data. Corrosion failures can be predicted in the current state with similarity, survival, and degradation models. However, actual failures in the current state cannot be fully determined since the physicality and knowledge of corrosion progress are not integrated.

This issue is crucial since similar material cannot be processed with the same prediction model in a similar environment. Hence, enormous parameterisation and fine-tuning are needed to recognise actual failure modes fully. Proper corrosion maintenance can ensure low downtime, continuous operation, and high efficiency of tools and materials. Therefore, it is vital to consider combining data-based, physics-based, and knowledge-based models into the prediction model. Integrating expert knowledge and associated failure modes can increase corrosion detection and maintenance accuracy and efficiency.

Conclusion

The authors have summarised the crucial topics in the PdM corrosion studies in this paper. The reviewed methods have improved corrosion detection and maintenance with PdM. PdM has been validated, as it can bring out the most advantages of proactive maintenance. The reviewed papers also considered harsh environments and other external factors that can contribute to the failure and inaccuracy of the developed prediction model for corrosion detection and maintenance. Furthermore, this paper has presented the challenges and opportunities in applying PdM for corrosion detection and maintenance, which could contribute a clearer direction for more practical research.

Industries and researchers continue to investigate the best prediction model, algorithm, or method to optimise the PdM application for corrosion detection and maintenance. Possible solutions are being considered, such as advanced signal processing, anomaly detection, health monitoring, RUL estimation and scheduling maintenance. Thus, the assets, tools, materials, and data can be safeguarded from the unforeseen failure or breakdown caused by the progression of corrosion. The review's findings can provide valuable insights into preventing unforeseen corrosion-related failures during maintenance by utilising corrosion prediction models, thereby adding to the existing knowledge base. For future recommendations, the recent advances in artificial intelligence and sensor networks allow the data-based, physic-based, and knowledge-based models to be more efficient and support e-maintenance and remote maintenance. Thus, PdM provides a safe working environment for corrosion inspectors, especially during the COVID-19 pandemic.

Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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