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Role of artificial intelligence (AI) and machine learning (ML) in the corrosion monitoring processes

ABSTRACT

When it comes to the upkeep of engineering structures in a variety of industries, corrosion monitoring systems are an extremely important components. In particular, applications such as storage tanks for hazardous chemicals and weight-bearing structures of large engineering constructions are at the forefront of providing attention to relevance. This is due to the fact that failures experienced by these applications can potentially result in catastrophic consequences. As a result, contemporary methods make use of the application of concepts connected with machine learning and artificial intelligence in order to efficiently monitor and identify corrosion related damges. As a consequence of this, the monitoring system is able to provide the control of the industrial structures with minute-by-minute updates. Therefore, the catastrophe is prevented to a significant degree, and there is a significant possibility of lowering the costs associated with technical procedures that require maintenance. Within the scope of this paper, a comprehensive analysis is conducted on the applications of artificial intelligence and machine learning techniques that are utilized in corrosion monitoring systems across a wide range of industries. Through this assessment, the solutions and efficient corrosion monitoring methods that are specific to the domains made available. Consequently, the purpose of this work is to determine the appropriate technique of monitoring systems for each and every corrosion-related disorder.

Keywords: *Artificial Intelligence, machine learning, corrosion monitoring system, oil and gas industries*

1. INTRODUCTION

It is possible to make effective use of artificial intelligence and machine learning in the maintenance of engineering structures such as bridges, heavy buildings, and water pipelines, among other types of structures [1-3]. The construction industry has begun to implement artificial intelligence and machine learning in order to optimize and automate the production processes, which are essential for the completion of a project in a shorter amount of time. Consequently, for the purpose of optimizing the production phases and the construction activities that came before them, artificial intelligence analysis is used to the numerous processes that are involved in construction projects [4,5]. Some examples of corrosion monitoring systems include the monitoring of pipeline corrosion, the monitoring of heavy engineering structures utilized in the oil and gas industries, and the monitoring of the health of chemical storage tanks. A combination of artificial intelligence and machine learning is utilized by these systems in order to determine the important components that correspond to the failure modes of structures [6,7]. When it comes to structural applications, aluminum alloys are gradually replacing steel structures. Furthermore, corrosion-resistant applications require specialized aluminum alloys in order to function effectively. Through the application of artificial intelligence and machine learning techniques, it is possible to conduct an analysis of the corrosion behavior of aluminum alloys that are utilized in the construction of engineering structures [8-10].

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2. REVIEW ANALYSIS

A research work presents a methodology for evaluating maritime pipelines based on corrosion. The existing testing approaches impose limitations on the reuse of root cause analysis. This study uses artificial intelligence to convey failure informations to the control unit during the Inspection and failure prevention analysis. In addition, This work employs experimental and modelling techniques to generate a test that can be executed in real time conditions. These tests provide clarification on the elemental makeup, hardness, and tensile strength and the properties of metals and the substances formed during corrosion. Utilizing a scanning electron microscope to examine the sample and analyze its energy characteristics it is possible to predict the abnormal variation on the surface of structures. The evaluation of corrosion was conducted using scanning electron microscopy with energy-dispersive X-ray spectroscopy and X-ray diffraction. The rusting mechanism is revealed by the examination of products and morphologies. The Gauss Pearson multicollinear matrix-supported mixed model anticipate the mechanism of coil damage and offer solutions to mitigate it [11]. Applying machine learning techniques to detect atmospheric corrosion by using Strain-based sensors enhance the precision of thinning assessment. This work relates to Safeguarding low-carbon steel plate against atmospheric corrosion. The monitoring data for this investigation comprised a study on corrosion products utilizing active pseudo strain gauges. Pre-corrosion instrument measurements were obtained from subjecting the specimen to salt water treatment. Data from standard test pieces with reduced thickness was utilized for the purpose of learning. Training methods are employed to reduce errors in machine learning. The model exhibited a reduced size of data analsysis compared to previous models used for data evaluation [12]. Soil erosion degrades the environment, making this crucial to be considered in health monitoring of structures established on soils. Geological-environmental relationships in corrosion monitoring must be established. Limited methods exist for identifying pipeline corrosion regions. A research work explains steel corrosion reinforcement and its non-destructive consequences by detailing how to spot and avoid common steel rust and to minimise reinforcing steel corrosion by design, structure, and material optimisations. By opting to enhance submerged structure life, this work utilized artificial intelligence to predict pipe line corrosion [13].

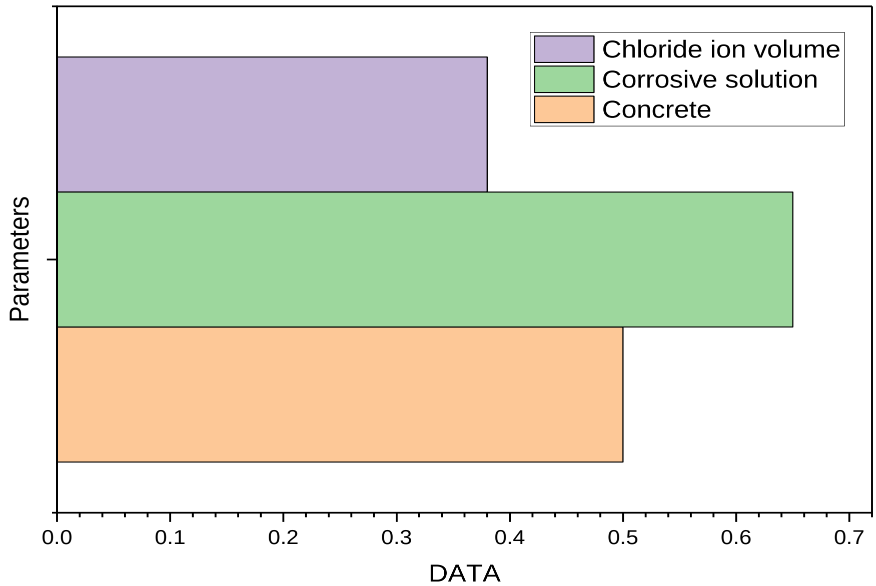

Figure 1. Data variation with parameters utilized in Artificial intelligence data feed [13]

Figure 1 shows the corresponding data variation with paparmeters in AI analaysis. Another work presents a comprehensive review of the existing literature and patents on corrosion monitoring, as well as the utilization of artificial intelligence in this sector. Additionally, it includes a case study that demonstrates a unique approach to monitoring corrosion in tower legs using a closely monitored remote process. A decision-making method for predictive maintenance programs was established by developing a predictive computer model. This model utilized artificial neural network criteria to get and suggest a corrosion index for the tower leg foundations of electric transmission lines.

The data was collected in situ mode using electrochemical corrosion monitoring of eighty tower legs from twenty transmission line towers, encompassing diverse environmental conditions [14]. Electromagnetic technology is extensively employed for the purpose of detecting corrosion and assessing performance. Corrosion testing is well recognized and firmly established. Nevertheless, there has been a scarcity of research conducted in this domain, The advancement and dependability of intelligent corrosion monitoring devices designed to detect and monitor internal or buried structures experiencing corrosion. When observed from afar, the thickness is diminished as a result of corrosion. A novel magnetic corrosion transducer with advanced intelligence capabilities has been created. Continuous surveillance of the reduction in thickness caused by corrosion at crucial sites are carried out. Reliability of utilizing an alternative active redundancy strategy enhances the performance of the transducer [15]. Another research examines the comparison between conventional computer vision techniques and a deep learning approach for the automated detection of metal corrosion, specifically rust. The typical approach involves classifying images based on the proportion of pixels that contain specific red components. The Python code utilized OpenCV libraries to do image computation and classification [16]. The supply of water networks, particularly the subsystems designed for the purpose of detecting and pinpointing leaks. Water supply network breaches, including concealed leaks are of focus at recent times. These leaks are the primary source of significant issues in water supply networks. Water loss in networks, particularly in older systems characterized by significant variations in age and material composition. The suggested subsystem concept comprises an iclusion of geographic information system. This work discusses the use of hydraulic models in SCADA systems and water supply networks, as well as a technique that utilizes MLP neural networks for leak identification and localization [17]. Figure 2 shows the learning and testing cycle errors in Python coding.

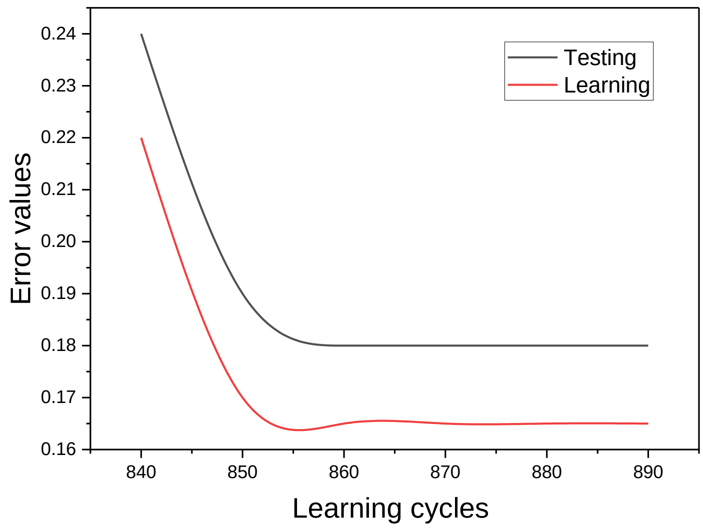

Figure 2. Learning cycle error values utilized in Python coding [17]

When it comes to the protection of health, safety, and the environment, having a thorough understanding of the possibility of corrosion in a pipeline is absolutely necessary. For the purpose of predicting the increase in corrosion defect depth in ageing pipelines, this study made use of a data-driven machine learning methodology that applied Principal Component Analysis Feed-Forward Artificial Neural Network. A number of different Machine Learning models were developed and assessed for the X52 grade of pipeline. This was accomplished by modifying the hyperparameters of the FFANN algorithm through the use of PSO and employing principal component analysis (PCA) to transform the operating variables [18]. Corrosion is the costliest factor contributing to the degradation of metal and concrete structures on a global scale. This can result in substantial financial losses and unforeseen fatalities in industries. Hence, corrosion monitoring is crucial for evaluating and determining the effectiveness of structural elements. Initial phase of asset predictive maintenance for illness detection are very crucial. Due to the high cost, only corrosion monitoring devices that are currently available will be used solely for monitoring the structural features. Applications, particularly in the field of identifying corrosion in civil structures are of utmost importance in recent times [19]. Anticipating corrosion and implementing effective monitoring techniques helps mitigate financial losses.

Conventional methods for predicting and detecting corrosion are characterized by a lengthy processes. These procedures are challenging to execute in remote or hard-to-reach areas. Artificial intelligence relies on algorithms, which have emerged as the preferred tools for researchers in simplifying the data nalaysis. This study focuses on advanced artificial intelligence (AI) techniques used to anticipate and detect seawater corrosion. Specifically, it explores two methods: predictive maintenance approaches with machine vision and computational image processing approaches.

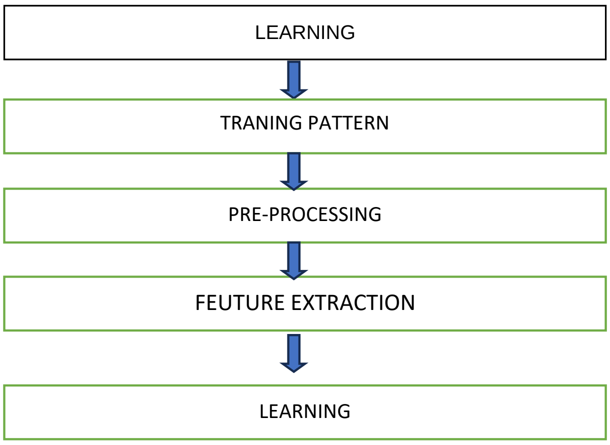

Figure 3. Pattern recognition steps in feature extraction from imaging [20]

Corrosion is a significant challenge that the maritime sector is now grappling with. It results in both immediate and long lasting dmages. Timely forecasting and effective corrosion surveillance can aid in minimizing financial losses. Conventional methods for predicting and detecting corrosion are characterized by a significant investment of time. Artificial intelligence Algorithms have emerged as the preeminent tools for academics in this domain [20]. Figure 3 show the pattern recognition in image analysis.

An investigation examines the elements that contribute to the deterioration of exterior components in monitoring underwater oil and gas pipelines that have been fitted with autonomous underwater systems (AUS). The responsibility of AUS is to gather and conduct in-depth analysis of picture data and utilizes advanced artificial intelligence algorithms for data analysis. The potential for corrosion and cracking on pipe surfaces is intricate and difficult to monitor, consisting a complex process characterized by the presence of several conflicting elements [21]. Combining the Web and the Internet of Things, or IoT, with based on the cathodic inhibition (CP) systems is a novel method that can lead to corrosion prevention in pipes. Utilizing circuit boards with printed circuits (PCBs) for the measurement and regulation of current and voltage allows for the instantaneous surveillance of PC systems [22]. Figure 4 show s the corresponding supervision process using cathodic protection system.

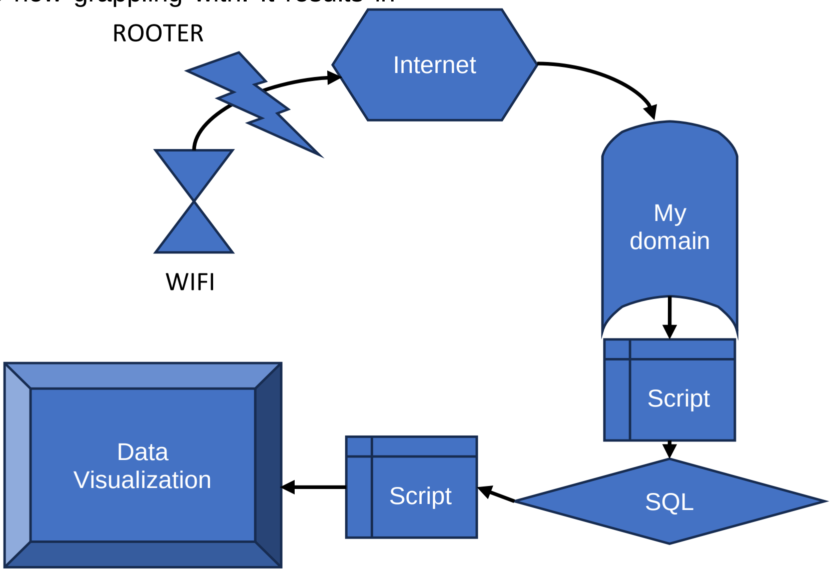

Figure 4. The supervision process in cathodic protection system [22]

The industrialization of the world has facilitated the emergence and advancement of numerous sophisticated technologies to tackle the intricate complex of evaluating the integrity of a wellbore. One of its most notable achievements was the integration of physics-based data science to enhance the accuracy and reliability of degradation observations. This article signifies the advancement in corrosion imaging utilizing electromagnetism and machine learning utilizing physical principles. The Learning Platform for Inspection of Metal Casing/Tube Cross-Sections (PIML) was thoroughly tested and verified using actual samples containing faults [23]. Luminescence was employed to observe the corrosion rate of aluminum alloy 2014 in NaCl and Ce $(NO_3)_3$. This technique, which is an upgarded type of electrochemical noise measurement, was combined with wavelet transform and artificial neural networks for analysis to determine the specific type of corrosion. The reliability of EES was confirmed through the monitoring of corrosion in 2014 aluminum alloys within the passivation process of pitting, and suppressive systems [24]. Assessing corroded regions within a system of engineering is often a crucial part of monitoring its health, even though it is inherently difficult to quantify and predict. Precise measurements can be achieved by considering the electrochemical nature of the corrosion process. Advancements in technology have enabled the development of devices capable of collecting data and performing complex analytical processes to assess the kind and rate of corrosion [25].

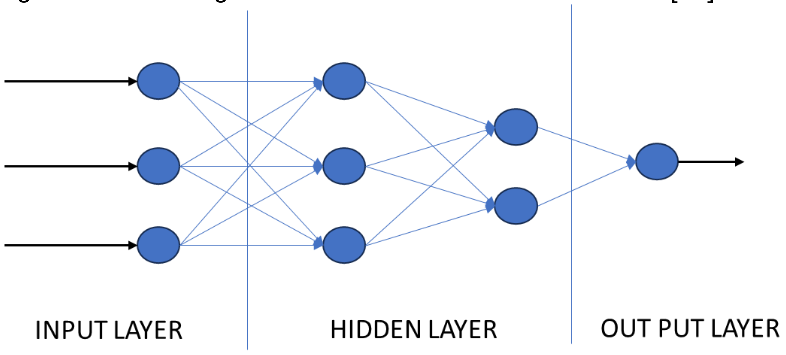

Figure 5. A feedforward neural network model with hidden layers [26]

Corrosion is an exceedingly intricate phenomenon in the fields of science and engineering. Several mathematical models have been developed over time to predict the damage caused by the process of corrosion. Artificial neural networks have increasingly been employed to simulate corrosion in recent years. Several factors that lead to corrosion provide significant challenges in terms of management. Neural networks that are artificial may be a favorable approach to consider due to their filtering capability, versatility, and ability to manage noisy, incomplete, or erroneous data [26]. Figure 5 shows the corresponding neural network model. The process of corrosion assessment and repair are crucial aspects of aero plane maintenance to ensure the preservation of structural integrity. After visual inspections, fuselage lap joints are typically subjected to time-consuming non-destructive procedures. The subjective aspect of visually assessing large areas is made worse by the varying likelihood of corrosion and the use of multiple layers in fuselage construction. A research presents a method that uses a network of deep neural networks to automatically identify corrosion in images of aero plane structures [27]. Aluminium alloy 7075 is a significant engineering material utilised in ship construction. However, the corrosion of Aluminum alloys is frequently observed in a wide range of conditions, particularly in marine settings. The current study focuses on the corrosion behaviour of Al alloy 7075 in the presence of sulfate-reducing bacteria (SRB). The aquatic ecosystem has not received adequate consideration. This article examines the corrosive effects of sulfate-reducing bacteria (SRB). An experiment was conducted to evaluate the corrosion resistance of 7075 aluminum alloy by immersing it in actual saltwater, along with the addition of a stress corrosion cracking (SCC) agent. To analyse the micro-structure and particles, an electron backscatter diffraction technique was employed to examine the symmetry of the cemented carbide Al alloy 7075 [28].

The aluminium alloy 7075-T6 is frequently employed in the field of mechanical engineering. Corrosion and wear can lead to failure for certain structure made of 7075, due to primary material defects. A study explores the synergistic impact of wear and corrosion on aluminium Alloy 7075-T6 [29]. Aluminium 7075 matrix composites are extensively utilised in the construction and aerospace sectors because of their exceptional hardness and resistance to wear and the ratio of strength to weight. Nevertheless, the limited widespread use of this material is due to its inherent drawbacks, including inadequate malleability and vulnerability to corrosion. Thus, an experiment aims to investigate and analyse the distribution of increased rates of reinforcement within the matrix influencing its degradation [30 - 33]. An in-depth analysis was conducted on corrosion management systems in oil and gas offshore infrastructures utilizing artificial neural networking and random forest techniques. The study concluded that these techniques are highly effective in identifying and mitigating corrosion, ultimately reducing costs associated with corrosion management [34,35]. The application of optical fiber-based sensors is used in corrosion monitoring systems for lengthy pipelines. The corresponding datasets are then input into artificial intelligence software in order to identify any anomalies that may be present in the massive amounts of data that have been logged. In a work that is very similar to this one, temperature readings that are related with electromechanical analysis techniques are utilized in order to monitor the health of structural features in industrial applications [36,37]. For the purpose of successfully monitoring the safety of structural elements in a variety of industries, techniques including machine learning are utilized. These techniques include defect identification, life time assessment, degradation rate, and others. In general, machine learning and deep learning techniques with supervised and unsupervised models are utilized in order to evaluate the state of structural characteristics and to reduce the amount of money that is spent on maintenance [38-42].

3. CONCLUSIONS

The thorough examination of the literature demonstrates that the construction sector effectively use artificial intelligence and machine learning applications to enhance the efficiency of manufacturing and construction operations. Similarly, numerous sectors employ artificial intelligence and machine learning to maintain large-scale engineering structures. The corrosion monitoring systems employed in the oil and gas industries utilise artificial intelligence and machine learning to efficiently monitor the condition of engineering infrastructure such as oil pipelines. Artificial intelligence and machine learning can be employed to monitor the upkeep of structures manufactured from aluminium alloys, as indicated by the analysis. Moreover machine learning techniques with supervised and unsupervised models can be highly effective in monitoring the health of structural features namely the fault detection, degradation rate and durability.

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IZVOD

ULOGA VEŠTAČKE INTELIGENCIJE (AI) I MAŠINSKOG UČENJA (ML) U PROCESIMA PRAĆENJA KOROZIJE

Kada je u pitanju održavanje inženjerskih konstrukcija u raznim industrijama, sistemi za praćenje korozije su izuzetno važna komponenta. Posebno, aplikacije kao što su rezervoari za skladištenje opasnih hemikalija i nosive konstrukcije velikih inženjerskih konstrukcija su u prvom planu u obraćanju pažnje na relevantnost. To je zbog činjenice da kvarovi koje dožive ove aplikacije mogu potencijalno dovesti do katastrofalnih posledica. Kao rezultat toga, savremene metode koriste primenu koncepata povezanih sa mašinskim učenjem i veštačkom inteligencijom u cilju efikasnog praćenja i identifikacije oštećenja uzrokovanih korozijom. Kao posledica ovoga, sistem za nadzor je u stanju da obezbedi kontrolu industrijskih objekata sa ažuriranjima iz minuta u minut. Dakle, katastrofa je u značajnoj meri sprečena, a postoji i značajna mogućnost smanjenja troškova vezanih za tehničke procedure koje zahtevaju održavanje. U okviru ovog rada, sprovedena je sveobuhvatna analiza primene veštačke inteligencije i tehnika mašinskog učenja koje se koriste u sistemima za praćenje korozije u širokom spektru industrija. Kroz ovu procenu, dostupna su rešenja i efikasne metode praćenja korozije koje su specifične za domene. Prema tome, svrha ovog rada je da se utvrdi odgovarajuća tehnika sistema praćenja za svaki poremećaj koji je povezan sa korozijom.

Ključne reči: *Veštačka inteligencija, mašinsko učenje, sistem za praćenje korozije, industrija nafte i gasa*

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