THE DESIGN AND FABRICATION OF A LOW-COST FIELD DEPLOYABLE CORROSION MONITORING SENSOR WITH WIRELESS SENSOR NETWORK

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DEPARTMENT OF METALLURGICAL AND MATERIALS ENGINEERING

FACULTY OF ENGINEERING

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A PROJECT WORK SUBMITTED TO THE DEPARTMENT OF MATERIALS AND METALLURGICAL ENGINEERING, UNIVERSITY OF BENIN, BENIN CITY

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF ENGINEERING (B.ENG) DEGREE IN MATERIALS AND METALLURGICAL ENGINEERING

APRIL, 2025

CERTIFICATION

This is to certify that the project work titled **'THE DESIGN AND FABRICATION OF A LOW-COST FIELD DEPLOYABLE CORROSION MONITORING SENSOR WITH WIRELESS SENSOR NETWORK'** carried out by:

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Of the Department of Materials and Metallurgical Engineering, Faculty of Engineering, University of Benin, in partial fulfilment of the requirement for the award of Bachelor of Engineering, (B.Eng.) in Materials and Metallurgical Engineering.

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DEDICATION

This project work is dedicated to God the fountain of wisdom and strength for his unending love and provision, good health and sustenance. Also, for taking us through all and bringing us to the prosperous completion of our undergraduate program, indeed God is too faithful to fall.

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ABSTRACT

Corrosive damage remains a critical issue across various industries, especially in remote oil and gas pipeline infrastructures.This study presents the design and implementation of an IoT-based wireless sensor network (WSN) integrated with machine learning Model (SVM) for corrosion monitoring and prediction. The system architecture involved deploying sensor nodes utilizing electromagnetic techniques for real-time corrosion data acquisition. These nodes communicated with an ESP32 microcontroller equipped with wireless transmission capabilities to relay data to the ThingSpeak cloud platform for storage and visualization. Subsequently, MATLAB was used to preprocess the acquired data, enabling the training and validation of a supervised machine learning model for corrosion classification and prediction.

With the help of the SVM model, corroded pipeline samples could be easily differentiated from a corrosion-free pipeline. 80% of the recorded data was used to train the algorithm, and the rest 20% was kept for testing the data without corrosion. The first graph displayed by the model shows that the resistance values from the corroded sample fluctuate only slightly over time Additionally, the chlorine level ranged between (1000–1500)ppm, showing emission of chlorine gas from the sample. There was a significant drop in resistance in the corrosion- free sample for the second graph, with values falling below 1000ohms and No chlorine data was indicated When the model was tested and validated, the model correctly classified 59 out of 60 test samples while one incorrectly indicating an accuracy of 98.33%.. When unseen samples were used, the model was still able to predict the presence of corrosion with almost the same amount of precision and gave results showing the state of the pipelines with a 50% chance of them being either corroded or not from a 40 sample prediction..

The results obtained affirm the effectiveness of both processes for corrosion monitoring in remote pipeline networks. The system's autonomous operation, real-time data handling, and intelligent decision-making capabilities highlight its potential as a cost-effective and efficient alternative to traditional, labor-intensive methods. Moreover, its predictive capabilities enable proactive maintenance scheduling and safer operational planning, significantly reducing the risk of pipeline failure. This research thus lays a strong foundation for scalable, field-deployable corrosion monitoring systems leveraging modern IoT and AI tools.

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background of Study

Industrialization is the backbone of any meaningful global development while material selection forms the basis or bedrock for industrial development and improvements (Ashby & Johnson, 2013). In the industries, there are key aspect of industrial processes among which is the transportation of materials (Roemer, 1979). Getting the right selection of materials for transporting a specific and the right kind of materials is one of the challenges that has bedeviled the industrial sector, which the engineers have been looking for ways to proffer solutions to this humongous challenge for several decades (Constable & Somerville, 2003). A lot of research has been done in getting materials that are corrosion resistant that is, having high resistance to chemical attacks (Mévrel, 1989). Nonetheless, this has not been eradicated as we still have lots of materials that are still highly corrosive. In the oil and gas sector for example, both the crude materials and refined products are mostly transported through pipes over long distance (Koch**,** 2017). This transportation comes with a lot of challenges among which is corrosion (Bender *et al.,* 2013). In as much as material science and metallurgical have played a significant role in getting materials that are corrosion resistant, we still have pockets of corrosion along these transport lines which over a period of time possess significant challenge and loses (Popoola *et al*., 2010), therefore the need to deploy means to monitoring the corrosion activities within the transport lines. (Pandey *et al*., 2023)The natural process of corrosion causes metals, especially steel and iron, to return to their most stable states. For instance, rust, which is chemically similar to the original iron ore, is often created when iron and steel react with oxygen and water, which are frequently found in natural settings.

Corrosion is the degradation or deterioration of materials, usually metals, due to chemical or electrochemical reactions with their environment (Harsimran *et al.*, 2021) the surrounding environment may vary by state (gas, liquid, or solid), composition, and temperature, all of which influence corrosion. In specific cases, factors such as fluid flow or mechanical stress also play roles. This research work focuses on aqueous corrosion through deterioration in high-temperature gaseous environments (Koch, 2017). Each year, hundreds of millions of naira are lost to corrosion, largely from steel and iron deterioration in industrial settings, though other metals are also affected. While industries employ numerous strategies to mitigate corrosion, eliminating it remains challenging, with high costs in designing and maintaining corrosion-resistant materials and ensuring a safe working environment. A particular problem with alloy steel and some other metals is that oxidation results in a non-adherent oxide layer, leading to "pitting" and, over time, structural weakening and material loss (Adesusi *et al*., 2023). Corrosion is primarily an electrochemical reaction where metal atoms at anodic sites lose electrons, forming ions that dissolve into the environment. These electrons then migrate to cathodic sites, where they interact with substances like oxygen to form oxides (Roberge, 2008). Corrosion takes several forms, each with unique risks. Uniform corrosion evenly affects metal surfaces, causing steady material degradation, while galvanic corrosion occurs when different metals are in contact, leading to accelerated corrosion of the more active metal. Pitting corrosion, a localized form, results in small, deep pits that can significantly weaken the metal structure over time (Melchers, 2018). Environmental conditions are critical to corrosion rates. For example, chloride ions in seawater can break down protective oxide films on metals, increasing corrosion rates in marine environments (Shifler, 2005). Additionally, pH levels influence corrosion; acidic environments speed up metal dissolution, while alkaline conditions can encourage oxide layer formation, offering limited protection on certain metals. Factors like high humidity and elevated temperatures further exacerbate corrosion by increasing reactivity and electrical conductivity, presenting additional challenges in corrosive environments. In oil refineries and petrochemical plants, effective corrosion management is essential for protecting assets, extending their lifecycle, and safeguarding the environment. Moving beyond regulatory compliance to comprehensive corrosion control strategies allows organizations to maximize benefits.

Experts recommend integrating corrosion management throughout organizational structures, defining roles clearly, and ensuring that teams understand the importance of these practices. Effective budgeting, construction practices, and operational procedures must be evaluated for their impact on corrosion, and resources allocated efficiently. Audit tools and cost-analysis methods are valuable in quantifying the effects of corrosion, making it possible to calculate resource needs, cost savings, and potential productivity gains while reducing environmental and safety risks (kane, 2007). Corrosion poses severe financial, environmental, and safety risks across industries, from marine infrastructure to oil and gas. High maintenance expenses, equipment downtime, and safety hazards underscore the need for effective monitoring and control, especially in transportation and energy. The National Association of Corrosion Engineers (NACE) estimated the global cost of corrosion at $2.5 trillion, or 3.4% of global GDP in 2013, emphasizing the need for effective monitoring and control (Koch *et al.,* 2016). Corrosion can compromise essential infrastructure like bridges and pipelines, as seen in the collapse of the Silver Bridge in 1967. Traditional corrosion monitoring methods, including electrochemical and manual inspections, are promising but often costly, labor-intensive, and lack real-time data collection (Agarwala *et al*.,. 2000).

To address these issues, researchers have explored a variety of corrosion detection and monitoring techniques. While established methods like electrical resistance method, corrosion coupon, linear penetration method, electrochemical impedance spectroscopy (EIS), radiographic inspection, and ultrasonic testing deliver precise measurements, they can be costly and require specialized equipment and expertise (Groysman, 2019). This highlights the need for cost-effective, easy-to-deploy alternatives capable of long-term, autonomous operation in demanding field conditions. Advances in wireless technology and sensor materials, such as nanomaterials, have led to the development of wireless sensor networks (WSNs), enabling affordable, scalable, and distributed monitoring solutions. WSNs consist of numerous sensor nodes, each with transmitters, power sources, and corrosion sensors, which collectively gather and transmit localized data for centralized analysis. These networks provide insights into corrosion trends, allowing for early detection and timely maintenance interventions. For example, a WSN along an oil and gas pipeline exposed to harsh environmental conditions can detect corrosion hotspots in real-time, offering a cost-effective alternative to manual inspections. The adaptability and scalability of WSNs make them suitable for broad infrastructure monitoring with minimal human involvement (Goyal & Bhalla, 2019; Fu *et al.,* 2014).

Although Wireless Sensor Networks (WSNs) hold significant promise for corrosion monitoring, implementing them in field environments poses unique challenges. Deploying sensors in harsh conditions requires robust materials and designs to ensure both resilience and measurement accuracy (Scully *et al.,* 2007). Moreover, because WSN nodes typically rely on battery power, efficient energy management is crucial to prolong system longevity in field applications. Recent studies have explored various power-saving strategies, including energy harvesting and low-power communication protocols like LoRa and Zigbee, which help optimize WSNs for corrosion monitoring (Kampman *et al.,* 2021). These protocols facilitate energy-efficient, long-range communication—vital for WSNs placed in remote or hard-to-access areas where maintenance or battery changes may be challenging. Ensuring data accuracy and reliability is another key requirement for WSN-based corrosion monitoring. Environmental factors such as temperature fluctuations, humidity, and pollutants can interfere with sensor performance, leading to data inconsistencies (Bashir & Khan, 2017). To address these issues, researchers employ advanced signal processing and data fusion methods. For instance, machine learning algorithms can enhance corrosion prediction by integrating historical data with real-time sensor inputs (Moya & Sanz, 2019). This intelligent data analysis enables WSNs not only to deliver real-time monitoring but also to provide predictive insights that are beneficial for planning maintenance and optimizing resource use.

Despite considerable advancements, deploying low-cost WSNs for corrosion monitoring in field settings is an evolving area, with room for further innovation. This study aims to address these challenges by developing a cost-effective, energy-efficient WSN system capable of detecting early corrosion in harsh environments. Leveraging recent advances in microelectromechanical systems (MEMS) and energy-saving communication protocols, this research seeks to deliver a practical, scalable alternative to traditional, expensive monitoring solutions. The system will undergo testing in a controlled field environment to evaluate its durability, performance, and data accuracy. Results from this research have the potential to guide future WSN applications in corrosion monitoring and similar industrial settings, ultimately contributing to safer and more cost-effective infrastructure management (Daousis *et al*., 2024).This study is motivated by the need to enhance field-based corrosion monitoring, where conventional techniques are often costly or impractical (popova & prosek, 2022). By developing a low-cost WSN specifically tailored for corrosion detection, this research aligns with industry demands for innovative, deployable solutions that provide accurate, real-time monitoring with minimal maintenance (Abduljawwad *et al*., 2023). This approach aims to equip industries dependent on effective corrosion management with a reliable tool, paving the way for safer, more sustainable operations.

1.2 Statement of the problem

The petrochemical industry together with oil refineries loses billions year over year to handle costs associated with maintenance and replacements brought on by corrosion. Extreme exposure through the environment damages pipelines that transport liquid hydrocarbons and gases which results in reduced structural strength as well as leakages. Mohammad A. Al Hatlani from Saudi Aramco who works as the General Manager of Pipelines presented at the Internal Corrosion Forum in Dammam Saudi Arabia during October 2019 that global corrosion expenses amount to $2.5 trillion. The solutions he presented include nonmetallic materials development together with effective corrosion management and new technological implementations and best practice deployment for inspection detection correction and prevention to lower these risks and related expenses. Manual monitoring of corrosion mechanisms frequently proves challenging for detection purposes thus increasing the possibility of pipe and vessel failure. Wi-Fi-enabled clamp-on sensors resolve this difficulty by sending continuous data streams to special applications that apply algorithms to generate early warnings before equipment breakdowns occur. Staff members in plants receive notification alerts that enable them to take preventive actions.

1.3 Aim and objectives

This study seeks to create an affordable wireless sensor network (WSN) for continuous, real-time corrosion monitoring in remote industrial settings, offering a more practical and cost-effective solution compared to conventional methods**.**

The following objectives of this study are as follows:

i. To design and develop a wireless sensor network (WSN) that can detect corrosion at essential points in infrastructure, tailored for use in remote and challenging environments.

ii. To assess the capability of affordable sensors to measure key corrosion indicators, such as corrosion rate, humidity, and temperature.

iii. To test the accuracy, performance, and resilience of the sensor network under environmental conditions.

iv. To assess the cost-effectiveness of the WSN, potentially through a cost-benefit analysis or by comparing WSN deployment costs with current corrosion management expenses.

1.4 Scope of study

This research encompasses the following areas:

1. WSN Design and Configuration
2. Sensor Calibration and Data Interpretation
3. Material selection (low carbon steel)
4. Specimen preparation
5. Exposure to environment
6. Performance Testing using WSN and various mediums
7. Economic and Practical Viability Assessment of WSN
8. Data Integration and Remote Accessibility
9. Field deployment

1.5 Significance of study

1. To detect the early sign of corrosion, helping prevent structural failures in critical infrastructure of the pipeline industries.
2. Early detection reduces maintenance cost by allowing timely repairs and minimizing extensive damage
3. Monitoring corrosion enhances safety by preventing accident that can arise from structural weaknesses
4. Sensors provide real time data, enabling informed decision-making regarding maintenance and resource allocation.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1. Corrosion

Corrosion is a natural process in which metals and alloys gradually return to their more stable forms through chemical reactions or interactions with their environment (Zehra *et al*., 2022). It can be triggered by both natural factors and human activities. Essentially, corrosion leads to the deterioration of metal properties when exposed to environmental elements, making it an unavoidable occurrence (Novák, 2007). It is widely acknowledged that corrosion poses environmental risks and negatively affects human well-being. Several factors contribute to corrosion, including moisture (such as atmospheric humidity), acidic or alkaline conditions, salts, liquid chemicals, corrosive polishes, and harmful gases, all of which can cause metal surfaces to corrode (Raja *et al.,* 2016). Additionally, ambient temperature influences corrosion, and certain bacterial species in biofilms on steel surfaces can accelerate the process. Metals and alloys are particularly prone to corrosion in acidic environments. Acids can attack metal surfaces, causing them to dissolve into their ions, leading to corrosion. This is a common issue in various industrial processes, where stable corrosion products form. (Harsimran *et al*., 2021) Acidic solutions are widely used in industrial applications such as acid cleaning, descaling, pickling, and removing mill scale from metal surfaces. In the oil and gas industry, corrosion is often caused by the impurities in crude oil, such as naphthenic acid and sulfur, which promote metal degradation (Groysman, 2017).

2.2. The chemistry of corrosion

Corrosion is a natural process that occurs when metals interact with their environment, leading to gradual deterioration. Steel, primarily composed of iron and carbon, undergoes corrosion through electrochemical reactions (Groysman, 2017). This process follows a galvanic mechanism, where metals degrade due to oxidation, often resulting in the formation of oxides. For example, iron rusts, silver tarnishes, and copper and brass develop a bluish-green patina upon exposure to air (Abdel-Karim & El-Shamy, 2022). Among corrosion-prone metals, iron is particularly significant commercially, with the United States spending over $100 billion annually on replacing corroded iron objects. As a result, extensive industrial research is dedicated to developing protective techniques for metal surfaces, including the study of both chemical and electrochemical corrosion processes. Additionally, efforts focus on understanding the chemical principles behind common corrosion prevention methods and treatments for corroded metal substrates (Ghali *et al.,* 2007).

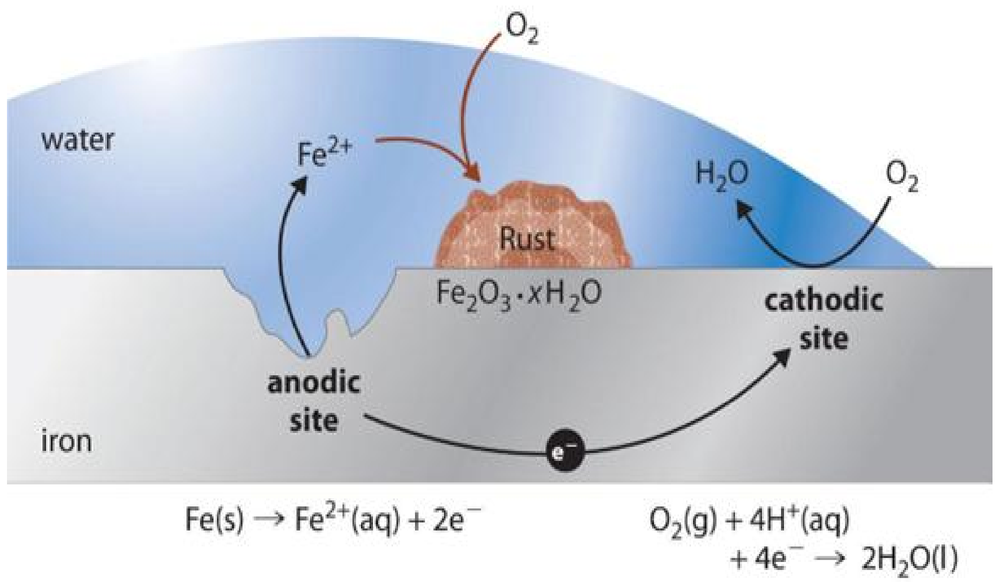


Figure 2.1 Aqueous corrosion of iron (Najem N. Al-Rubaiey, 2021)

2.2.1. Corrosion (Redox reaction).

Under normal conditions, oxidation naturally affects most metals, leading to their gradual deterioration, a process known as corrosion. However, gold and platinum are notable exceptions, as they do not oxidize spontaneously in Earth's oxygen-rich environment. Given this, it may seem surprising that some metals remain useful despite these conditions. However, certain metals resist corrosion due to kinetic factors. For example, aluminum, commonly used in soft-drink cans and aircraft, forms a protective metal oxide layer on its surface, acting as a barrier against further degradation. Additionally, aluminum cans have a thin plastic coating to prevent the oxide from reacting with acidic contents. Other metals, including chromium, magnesium, and nickel, also develop protective oxide films. Stainless steels, known for their corrosion resistance, derive this property from their high chromium and nickel content, which promotes the formation of durable oxide layers, enhancing longevity and functionality (Kelly, 2006).

As iron corrodes, it forms a reddish-brown hydrated metal oxide known as rust, chemically represented as $Fe_2O_3 \cdot xH_2O$. Unlike some other metals, the rust layer on iron is not protective; instead, it continuously flakes off, exposing fresh iron to further reactions with oxygen and water. This ongoing deterioration makes iron highly vulnerable to continued corrosion. Rust formation requires both oxygen and water, meaning it does not occur in environments where either is absent (Evans, 1967). For example, an iron nail submerged in deoxygenated water remains free of rust, even over time. Similarly, placing a nail in an organic solvent like kerosene or mineral oil—substances that lack water—prevents rusting, even if oxygen is present. These examples emphasize the critical role of oxygen and water in the rusting process and demonstrate conditions under which corrosion can be prevented (Islam, 2022).

In contrast to these metals, when iron corrodes, it forms a red-brown hydrated metal oxide (Fe2O3·xH2O), commonly known as rust, which does not provide a tight protective film. Instead, the rust continually flakes off to expose a fresh metal surface vulnerable to reaction with oxygen and water. Because both oxygen and water are required for rust to form, an iron nail immersed in deoxygenated water will not rust—even over a period of several weeks. Similarly, a nail immersed in an organic solvent such as kerosene or mineral oil will not rust because of the absence of water even if the solvent is saturated with oxygen (Evans, 1967)

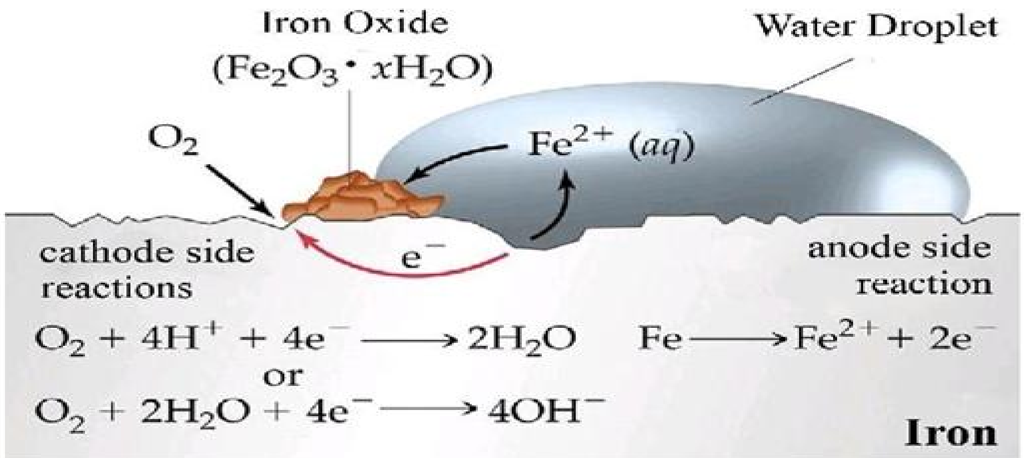


Figure 2.2 Corrosion of Iron (Buddha Bhushan Salunkhe, 2016)

In the process of corrosion, iron serves as the anode within a galvanic cell, undergoing oxidation to form Fe ions. Meanwhile, oxygen undergoes reduction at the cathode, leading to the production of water. The pertinent reactions can be summarized as follows:

At cathode:

$O_2(g) + 4\,H^+(aq) + 4\,e^- \rightarrow 2H_2O(l)$ . . . ($Equation$ 1)

With

$E_{SRP}{}^0$ =

1.23 V **at**

anode:

$(s) \rightarrow Fe^{2+} + 2\,e^-$ . . . ($Equation$ 2)

With $E_S{}^0{}_{RP}$

= -0.45 V

overall:

$2\,(s) + O_2(g) + 4\,H^+(aq) \rightarrow 2\,Fe^{2+}(aq) + 2\,H_2O(l)$ . . . ($Equation$ 3)

With $E_{cell}^0 \quad = 1.68\ V$

The Fe^{2+} ions produced in the initial reaction undergo further oxidation when exposed to atmospheric oxygen, leading to the formation of an insoluble hydrated oxide containing Fe^{3+}. This process is represented by the following equation:

$$4\ Fe^{2+}(aq) + O_2(g) + (2 + 4x)H_2O \rightarrow 2\ Fe_2O_3{\cdot}xH_2O + 4\ H^+(aq) \qquad \ldots (Equation\ 4)$$

The polarity and magnitude of E°cell in the corrosion reaction (Equation 3) indicate a strong driving force for iron oxidation by oxygen under standard conditions (1 M H^+). Even in neutral environments, this driving force remains significant (E = 1.25 V at pH 7.0). Typically, the dissolution of atmospheric CO_2 in water generates H^+ and HCO_3^-, lowering the pH enough to accelerate the corrosion process, a phenomenon further intensified by acid rain. To combat this, automotive manufacturers invest heavily in developing durable paints that form a protective barrier against oxygenated water, acids, and salts. However, even high-quality coatings are vulnerable to scratches or dents. Due to the electrochemical nature of corrosion, two scratches—regardless of their distance apart—can act as anode and cathode, leading to rapid structural degradation.

2.3. Causes Of Corrosion

Metals are susceptible to corrosion which reduces their lives. Here are some of the most common causes of corrosion.

The main cause of corrosion on most of the metals is its exposure to weather conditions. If you keep your metal objects outdoors in the open, they are going to corrode. Since they are exposed to environmental elements such as water, wind and moisture, they can oxidize quickly. Rain and exposure to too much sun can also expose metals to corrosion. Therefore, it is advised to keep your metals indoors or at least at places where they are safe from moisture and water. The drier you keep your metals, the more you will be able to extend their lives. (Bertocci, 1987)

Your metal objects will corrode faster if you live in coastal regions. Salty seawater, too much humidity and moisture in the air is serious destruction of metallic objects. If you keep your metals untreated or exposed to the elements, they are going to be highly susceptible to corrosion and hence a reduction in their lives. Similarly, very warm or very cold climates also have a similar effect on the corrosion of metals. (Hansson, 2011). Another common cause of corrosion is neglect. If you fail to take proper care of your metallic objects, from your vehicles to the tools and machinery, you will find them corroding fast before your eyes. Thus, it is very important to keep your metal objects clean and properly taken care of to ensure they do not corrode. Park your vehicles indoors, clean the tools as soon as you've used them to ensure they are not wet anymore. The more you can keep your metal objects dry, the more likely they will be free from the effects of corrosion. (North & MacLeod, 1987)

The following are explicit causes of corrosion

(i) Congested reinforcement in small concrete sections,

(ii) Excessive water-cement ratio,

(iii) Improper construction methods,

(iv) Inadequate design procedure,

(v) Incompetent supervising staff or contractor,

(vi) Initially rusted reinforcement before placing concrete,

(vii) Insufficient cover to steel from the exposed concrete surfaces,

(viii) Permeability of concrete which depends on various factors such as water- cement ratio, size of aggregate, curing, grading of aggregates, etc.,

(ix) Poor workmanship,

(x) Presence of moisture in concrete,

(xi) Presence of salts,

(xii) Type of atmospheric conditions surrounding the region of concrete,

2.4. Corrosion Cost To Society

Corrosion presents a major challenge to modern society, causing annual financial losses in the hundreds of billions of dollars (Berradja, 2019). Its impact is widespread, leading to several significant consequences:

1. Corrosion damages industrial machinery, increasing the risk of unexpected failures that could pose serious safety hazards.

2. It compromises key metallic components, such as boiler tubes in thermal power plants, resulting in operational disruptions and high maintenance costs (Kumar *et al.*, 2019).
3. The deterioration caused by corrosion reduces the overall value of products and leads to the waste of valuable resources.
4. Essential metal properties, including conductivity, ductility, and luster, are negatively affected by corrosion. Each year, approximately 20% of global iron production is lost to corrosion, further amplifying economic losses (Berradja, 2019).
5. Corrosion can also contaminate potable water sources, creating health risks and necessitating expensive purification measures.

Understanding the mechanisms of corrosion is imperative to mitigate its adverse effects effectively. By comprehensively addressing corrosion, industries can minimize financial losses and uphold safety standards (Berradja, 2019).

2.5. Role Of Oxygen In Corrosion

When metals are exposed to atmospheric oxygen, they undergo oxidation to produce oxides specific to each metal. Certain metals, such as lithium (Li), sodium (Na), and potassium (K), oxidize readily at lower temperatures, while others like silver (Ag), gold (Au), and platinum (Pt) require higher temperatures for oxidation. Upon exposure, the metal surface donates electrons to oxygen, leading to the formation of metal ions, while oxygen accepts electrons to form oxide ions.

$$\tfrac{1}{2}\, O_2 + H_2O + 2e^- \rightarrow 2OH^- (reduction)$$

or

$$\tfrac{1}{2}\, O_2 + 2e^- \rightarrow O^{2-} (reduction)$$

The presence of an oxide layer halts additional oxidation, which can manifest as either porous or non-porous. A porous layer permits ongoing oxidation through its gaps and fissures until the entire metal surface succumbs to oxidation, while a non-porous layer shields the metal from further oxidation. The "Pilling-Bedworth" Rule determines the layer's porosity: if the oxide's volume equals or exceeds the metal's volume, it is non-porous; otherwise, it is porous.

For instance, metals like aluminum form a non-porous oxide layer due to its greater volume, impeding further oxidation. Conversely, iron forms a porous oxide layer with a smaller volume, facilitating ongoing oxidation until complete corrosion. The rate of corrosion correlates with the concentration of oxygen in the presence of dissolved oxidizing agents (Lee *et al.,* 2008)

2.6. Factors Affecting Corrosion

The corrosion rate primarily relies on two key elements:

- ➔ Metal characteristics and
- ➔ Environmental conditions surrounding the corrosion process.

Additionally, corrosion is influenced by factors such as metal purity, surface film properties, corrosive product nature, ambient temperature, air humidity, and electrolyte pH levels.

2.6.1. Nature of The Metal

It additionally relies on:

I. Position in galvanic series
II. Purity of metal
III. Nature of surface film
IV. Nature of corrosive products

2.6.1.1 Position in galvanic series:

When two dissimilar metals are electrically connected in an electrolyte, the metal with a higher oxidation potential or a higher placement in the galvanic series undergoes corrosion, while the other metal remains protected. This occurs due to the movement of electrons from the metal with a lower oxidation potential to the one with a higher potential, leading to the former's corrosion. The rate of corrosion is further affected by the difference in their positions within the galvanic series, a larger difference results in a more rapid corrosion process due to the stronger driving force for electron flow. Consequently, a metal's susceptibility to corrosion is determined by its placement in the galvanic series, Understanding this concept helps predict and prevent corrosion in various environments and industrial applications.

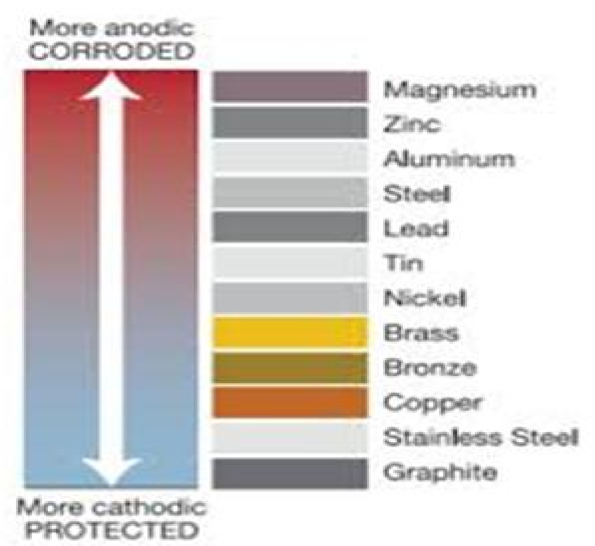


Figure 2.3 Corrosion susceptibility of metals (Elin Westin, 2023)

When considering a scenario where cast iron and copper are immersed in a specific electrolyte, the principle of galvanic corrosion comes into play. In this context, due to the dissimilarity in their electrode potentials, cast iron, being more reactive, becomes the anode and undergoes corrosion, while copper, with its lower reactivity, acts as the cathode and remains protected. This phenomenon occurs because electrons flow from the anode (cast iron) to the cathode (copper) through the electrolyte, leading to the oxidation of cast iron and the reduction of copper. Therefore, in the presence of the electrolyte, a galvanic couple is formed between the two metals, resulting in the sacrificial corrosion of cast iron to protect the more noble copper. This understanding of galvanic corrosion aids in predicting and managing corrosion-related issues in various industrial and consumer applications.

2.6.1.2 Purity of metal:

The corrosion rate typically rises with the introduction of impurities. This occurs because impurities create small electrochemical cells where the anodic portion undergoes corrosion. For instance, zinc with impurities such as iron (Fe) or lead (Pb) experiences accelerated corrosion.

2.6.1.3 Nature of surface film:

In an oxygen-rich environment, metals develop a fine layer of metal oxide on their surface. The impact of this layer is gauged by the "specific volume ratio," indicating the ratio of metal oxide volume to metal. A higher ratio corresponds to a lower oxidation rate. For instance, nickel, cobalt, and tungsten exhibit specific volume ratios of 1.6, 2.0, and 3.6, respectively. Notably, tungsten demonstrates the lowest oxidation rate, even under high temperatures.

2.6.1.4 Nature of corrosive product:

Corrosion accelerates when the resulting product dissolves easily in the corrosive environment or if the product is volatile, evaporating quickly upon formation, leaving the metal surface vulnerable to continued corrosion.

Consequently, this exacerbates the corrosion process by continually exposing the metal surface to further attack.

2.6.2. Nature of the Environment

It further depends on:

1. Temperature
2. Humidity of air
3. Effect of Ph

2.6.2.1 Temperature

The corrosion rate escalates as temperature increases, nearly doubling for every 100-degree rise, assuming other factors remain constant. This relationship is typically depicted by an exponential curve. However, temperature variations can also alter the impact of other factors, leading to a more complex relationship. Temperature elevation affects corrosion in two distinct manners (Coulon & Thauvin, 1979).

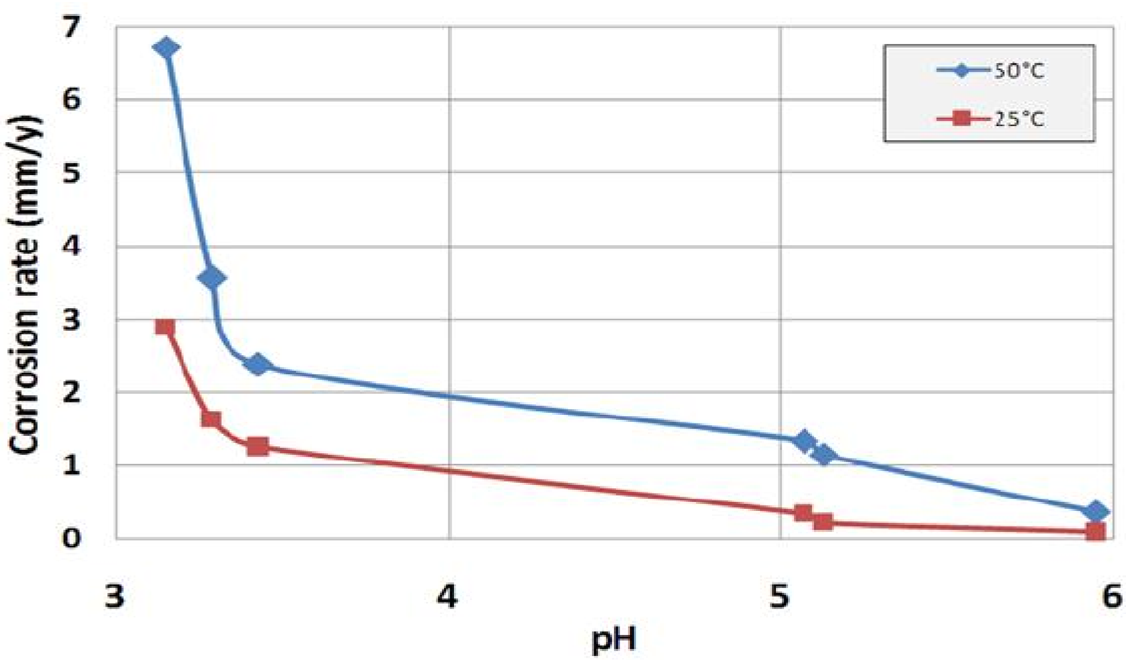
2.6.2.2 Humidity of air

Relative humidity significantly influences corrosion rates, particularly surpassing a critical threshold known as critical humidity. Beyond this point, corrosion accelerates sharply. The escalation in corrosion with humidity arises from the oxide film's propensity to absorb moisture, instigating additional electrochemical corrosion. Moreover, atmospheric moisture provides water to the electrolyte, facilitating the establishment of electrochemical cells, further exacerbating corrosion processes.

2.6.2.3 Effect of Ph

The primary determinant of corrosion rate is Ph, with lower Ph levels associated with higher corrosion rates.

Acidic solutions with Ph below 7 exhibit greater corrosiveness compared to neutral or alkaline environments. The initial diagram illustrating corrosion versus Ph, particularly for noble metals like gold and platinum, displays a linear relationship near the lower end of the Ph scale. This suggests that corrosion rates are minimally affected by Ph within this range. However, at very high Ph values, a slight increase in the corrosion rate is noticeable, although it holds little practical significance (Décarie & Geider, 2017).



Fi

gure 2.4 The Effect on pH on corrosion rate (prawoto, 2009)

The effects of pH and chloride concentrations on the corrosion behavior of duplex stainless steel were carried out in accordance with UNS S32205. The effect of pH has been determined by using different test solutions at different test temperatures. The duration of immersion tests was set in accordance with the ASTM G48 standard.

2.7.Types Of Corrosion

Metal corrosion manifests in various forms, as classified by Fontana and Greene (Fontana & Greene, 1967) into two distinct categories: both uniform corrosion and localized corrosion

1. Uniform or general attack corrosion
   I. Galvanic or two-metal corrosion
2. Localized corrosion
   I. Pitting corrosion
   II. Intergranular corrosion
   III. Selective leaching or parting
   IV. Erosion corrosion,
   V. Stress corrosion.

2.7.1. General corrosion

General corrosion, also known as uniform corrosion, is a form of corrosion that affects the entire surface of the metal, whereas other forms affect a specific spot or portion. It is the most common form of corrosion. This type of corrosion is commonly observed in pure metals which are metallurgical and compositionally uniform. Weathering steels, magnesium alloys, zinc alloys, and copper alloys are examples of materials that typically exhibit general corrosion. Passive materials, such as stainless steels, aluminum alloys, or nickel chromium alloys are generally subject to localized corrosion (klapper *et al.,* 2017). While general corrosion may not penetrate deeply into the metal, it can weaken structures over time, leading to potential failures (Lyon, 2012).

Despite its prevalence, general corrosion is often considered less severe compared to localized forms of corrosion, such as pitting corrosion or crevice corrosion. However, it remains a significant concern in various industries, including construction, transportation, and manufacturing, where metal structures are susceptible to degradation over time (Karlsdóttir, 2012).

Figure 2.5 The Schematic of General Corrosion of Carbon Steel in Aqueous Environment (pratask, 2009).

2.7.2 Localized corrosion

The occurrence of localized corrosion requires distinct anodic and cathodic regions which can be observed on the surface of a metal. The cause of localized corrosion depends on chemical differences in both materials themselves and surrounding environmental substances. Pitting acts as a localized corrosion form together with crevice corrosion and intergranular corrosion among other types of localized damage.

2.7.2.1 Galvanic Corrosion

The corrosive environment generates galvanic corrosion between two metals of different composition.

The electrochemical reaction of Galvanic corrosion causes one metal to corrode prioritized while electrically contacting another metal in electrolytic conditions (Goyal et al., 2018).The process occurs when two metals make contact close to each other within an electrolytic solution (Goyal et al., 2018). The contact of different metals alongside electrolytes will lead to galvanic corrosion. The process exposes the less noble metal to become an anodic element and thus corrodes at a higher rate while the more noble metal becomes a cathode to remain protected. This occurs because of direct metal contact in pipelines and boats. The cathode role of noble metal protects it from corrosion activity. The process strengthens under conditions that possess moisture or salt. A combination of strategies exists to stop galvanic corrosion from occurring. One approach involves using sacrificial Protecting the main metal structure occurs through sacrificial reactions involving corrosive anodes made from reactive metals. Protection of dissimilar metals is achievable by applying insulation methods or applying paint coatings.

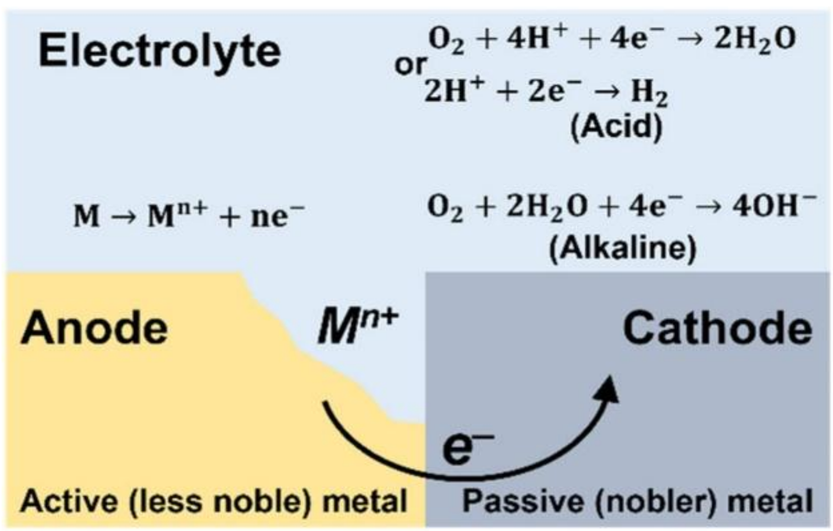


Figure 2.6 The Schematic-representation-of-the-galvanic-corrosion-process-with-the-electrochemical.(reynier, 2023)

2.7.2.2 Crevice corrosion

Localized corrosion, occurring within crevices and other shielded regions of metal surfaces subjected to aggressive environments, is another form of corrosion. Localized corrosion is an aggressive form of corrosion that targets specific areas of a metal surface in corrosive environments (Tait, 2018). It occurs when the protective passive film on the metal is breached, leading to accelerated corrosion at discrete sites. Common types include pitting corrosion, crevice corrosion, and stress corrosion cracking. Pitting corrosion manifests as small pits or craters on the metal surface, causing localized weakening. Crevice corrosion occurs in confined spaces such as gaps, joints, or under deposits, accelerating metal deterioration. Stress corrosion cracking is a result of the combined effects of tensile stress and a corrosive environment, leading to cracks and fractures *(*Karlsdóttir, 2012*)*.

Localized corrosion poses significant challenges in various industries, including marine, aerospace, and infrastructure. Preventive measures include proper material selection, design modifications to eliminate crevices, surface treatments, and corrosion-resistant coatings. Understanding the mechanisms of localized corrosion is crucial for implementing effective mitigation strategies and preserving the integrity of metal structures *(*Karlsdóttir, 2012).

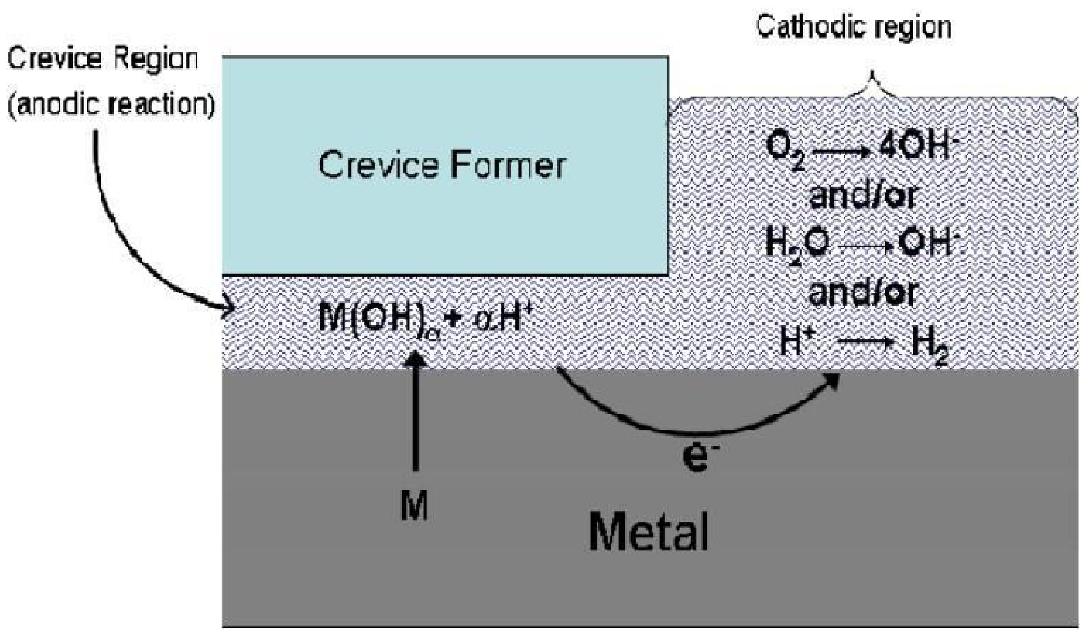


Figure 2.7 Schematic diagram of the crevice corrosion process *(Refait et al., 2020)*.

2.7.2.3 Pitting corrosion

The corrosion process of pitting results in damaged areas which appear as holes on metal surfaces. Small pits or holes form on metal surfaces due to localized corrosion which is specifically known as pitting corrosion (Goyal *et al.,* 2018). The appearance of electrochemical cells between an anodic metal area and cat hodic surroundings triggers accelerated corrosion.

The generated pits expand deep within the material structure thus weakening its operational capacity (Lyon, 2012).

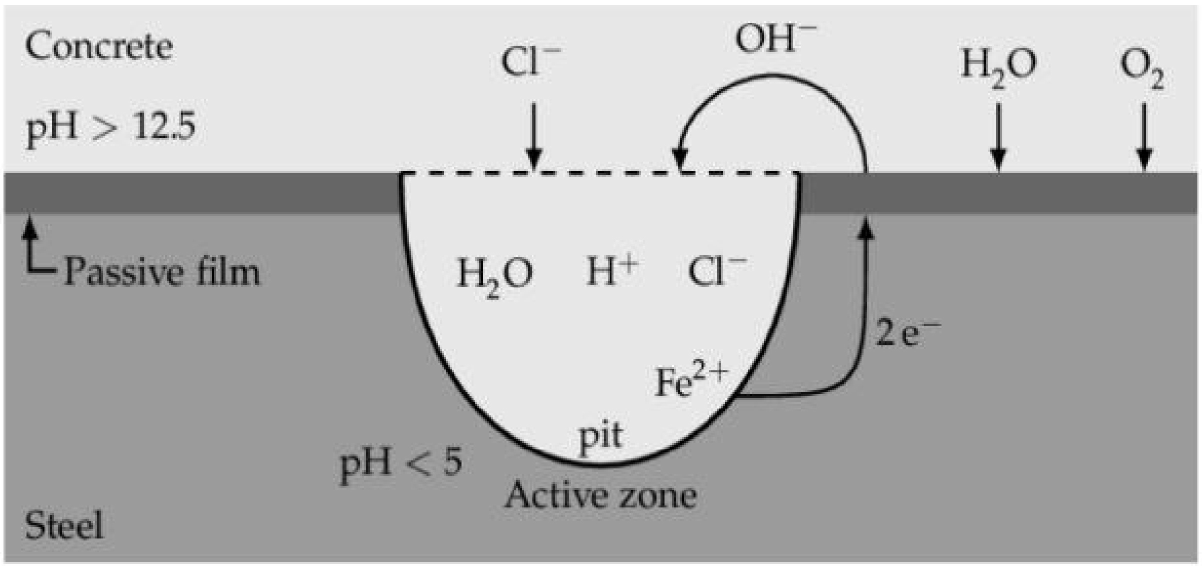


Figure 2.8 diagram of pitting corrosion (singh, 2008)

2.7.2.4 Intergranular corrosion

Within materials the boundaries that separate crystallites experience greater corrosion than the non-boundary areas. The main target of intergranular corrosion (IGC) stands at the interface points between metallic grains inside metal structures instead of surface attacks. Specific metals will undergo this type of corrosion when placed in harsh aggressive conditions that include heat exposure or contact with corrosive substances. The material structure becomes significantly compromised at grain boundaries because of IGC thus creating conditions for damage and failure. Grain boundaries initialize the attack mainly because they experience composition variations and impurity presence along with electrochemical potential differences between grains according to Karlsdóttir (2012). Metal protection against intergranular corrosion happens through two main methods: choosing specific corrosion-inhibited materials with suitable surface treatments such as passivation and alloying. (Karlsdóttir, 2012)

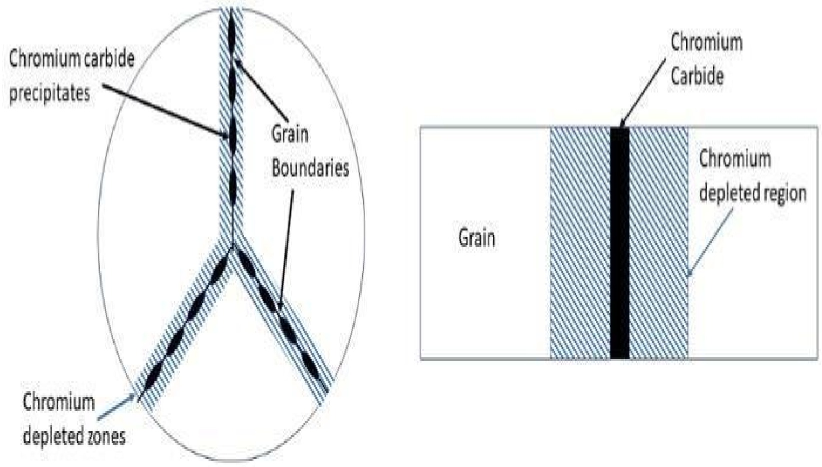


Figure 2.9 Schematic representation of grain boundaries in a sensitized austenitic stainless steel (Hackl, 2013).

2.7.2.5 Selective leaching

Selective leaching represents a method that extracts a particular element from solid alloys through corrosive processes which demonstrates its application in brass alloy zinc removal. The corrosion process of selective leaching operates through de-alloying by precisely extracting elements from alloys to create a defective residue. Alloys with different metallic components including brass experience this frequent (posts) chemical reaction that causes rapid corrosion of specific metals. Selective leaching creates a weakened material through its formation of porous structures which damage the mechanical properties. The selective leaching process affects brass alloys by extracting zinc from their composition which creates a remaining copper-enriched material. Multiple elements affect selective leaching because it depends on both the alloy materials and environmental conditions and electrochemical gradients. Different prevention strategies for corrosion prevention include employing corrosion-resistant alloys and controlling environmental conditions (Ahmad, 2006) alongside applying protective coatings to the material surface.

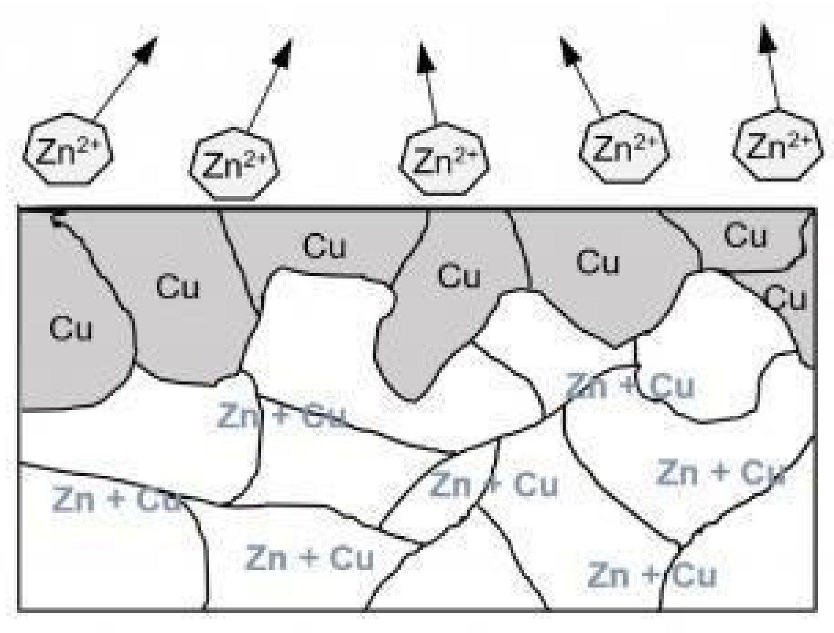


Figure 2.10 The Schematic diagram of Selective leaching (*Cammann K., 1977*)

2.7.2.6 Erosion corrosion

Selective leaching represents a method that extracts a particular element from solid alloys through corrosive processes which demonstrates its application in brass alloy zinc removal. The corrosion process of selective leaching operates through de-alloying by precisely extracting elements from alloys to create a defective residue. Alloys with different metallic components including brass experience this frequent (posts) chemical reaction that causes rapid corrosion of specific metals. Selective leaching creates a weakened material through its formation of porous structures which damage the mechanical properties. The selective leaching process affects brass alloys by extracting zinc from their composition which creates a remaining copper-enriched material. Multiple elements affect selective leaching because it depends on both the alloy materials and environmental conditions and electrochemical gradients. Different prevention strategies for corrosion prevention include employing corrosion-resistant alloys and controlling environmental conditions (Ahmad, 2006) alongside applying protective coatings to the materials surface.

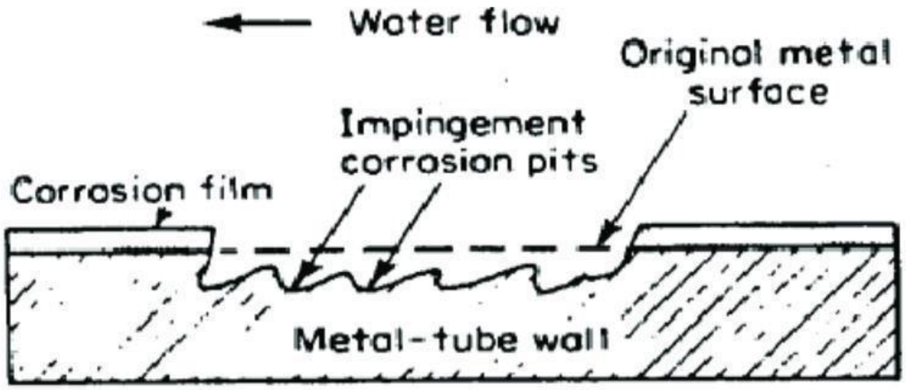


Figure 2.11The Mechanism of erosion-corrosion of metal (Larsen Delmar, 2020)

2.7.2.7 Stress corrosion

Stress corrosion cracking (SCC) is the cracking induced from the combined influence of tensile stress and a corrosive environment. The impact of SCC on a material usually falls between dry cracking and the fatigue threshold of that material. Stress corrosion cracking (SCC) is the cracking induced from the combined influence of tensile stress and a corrosive environment. The impact of SCC on a material usually falls between dry cracking and the fatigue threshold of that material. The required tensile stresses may be in the form of directly applied stresses or in the form of residual stresses, see an example of SCC of an aircraft component. The problem itself can be quite complex. The situation with buried pipelines is a good example of such complexity. (*Singh, 2018)*

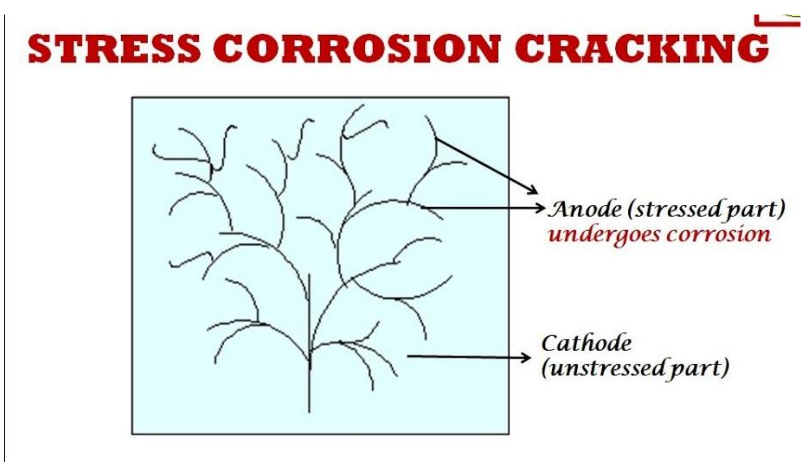


Figure 2.12 The Schematic diagram of stress corrosion cracking *(Singh, 2018)*

2.8. Corrosion Prevention

Noble metals typically exhibit resistance to corrosion; however, their elevated expense renders them impractical for general applications (Kumar et al., 2018). Consequently, alternative metals and alloys must be employed in the construction of various machinery to mitigate corrosion risks as represented in the figure below.

Figure 2.13 Corrosion prevention methods (Smith J., 2021)

2.8.1 Pre-treatment of Metals

Prior to implementing protective measures, it is essential to cleanse the metal surface thoroughly. Degreasing, a commonly utilized method for pretreatment, involves using volatile organic solvents such as trichloroethylene to dissolve oily and greasy surface films. Alternatively, acid pickling serves as another approach for scale removal compared to mechanical cleaning. Properly preparing the metal surface precedes the application of any coating; this may entail removing oils and grease through alkali solution washing (Jones & Foreman, 2015).

2.8.2. Proper Design and Selection of Right Material

The material's design should aim to minimize corrosion, following these key principles:

A. Proper Design
B. Selecting the Right Material

2.8.2.1 Proper Design

In corrosive environments, avoid contact between dissimilar metals. If contact is necessary, ensure the metal to act as the anode has the largest area, while the other metal has the smallest area possible. If dissimilar metals must be used together, they should be close in the electrochemical series. When direct dissimilar metal contact is unavoidable, insulating materials can be applied to prevent direct metal-to-metal electrical contact. Avoid sharp corners as they promote solid accumulation. Furthermore, refrain from painting or coating the metal, as any coating breakage would lead to rapid localized corrosion

2.8.2.2 Selecting the Right Material

Ideal materials for construction possess high tensile strength, exceptional corrosion resistance, and affordability. Material selection involves prior assessment based on past experiences and safety considerations, followed by laboratory testing under relevant conditions. Subsequently, laboratory results, including the effects of impurities, temperature, pressure, etc., are thoroughly analyzed (Islam, 2022).

2.8.3. Cathodic Protection

This technique is widely used to prevent corrosion, especially in pipelines, by applying an external electric current to the metal surface. To protect iron objects from rust, they are electrically connected to a more reactive metal, where iron serves as the cathode and the protective metal acts as the anode. Over time, the anode undergoes oxidation, gradually depleting as it loses electrons and transforms into ions. Rust prevention remains effective as long as the protective metal is present and the electrode potential stays below -0.62 V (S. Kumar et al., 2019).

Metals such as magnesium (Mg), zinc (Zn), and aluminum (Al), known as sacrificial anodes, are commonly used due to their higher oxidation potential compared to steel. This corrosion protection method is classified into two types:

- Sacrificial Anode Method: In this approach, the anode corrodes intentionally to protect the metal, hence the name. Zinc and magnesium are frequently chosen for galvanic anodes due to their superior oxidation potential relative to steel.
- Impressed Current Method: In this technique, the anode and the protected material are connected internally via an insulated wire. The current flows from the anode, through the electrolyte, and into the protected material. While this method resembles the galvanic system, its key distinction lies in the use of an external power source to drive the current, rather than relying solely on the oxidation potential difference between the anode and the protected metal.

2.8.4. Barrier Protection

The application of coatings on metal surfaces serves as a safeguard against corrosion. These coatings primarily act as a barrier, shielding the metal from its corrosive surroundings, hence termed as barrier protection (Qian & Fang, 2015). It stands out as one of the simplest anti-corrosion techniques, involving the placement of a suitable barrier between the metal and the atmosphere. This protective measure prevents corrosion by shielding the metal surface from the detrimental effects of air, water, and carbon dioxide. Various methods are employed to achieve barrier protection, including coating the metal with paints, oils, or grease, applying non-corroding metals, or treating the surface with specific chemicals.

Graphene, with its inert properties, unique structure, and electrical characteristics, is extensively utilized in barrier protection applications (Armijo, 1968). Its tightly bonded carbon atoms form a hexagonal structure, rendering it inert even under conditions that would trigger chemical reactions in other materials.

2.8.5. Electroplating

The main purpose of electroplating is to improve appearance, protection against corrosion, special surface properties, engineering or mechanical properties.

In the process of electroplating the anode is connected to the positive terminal, and the cathode (metal to be plated) is connected to the negative terminal. Both are immersed in a solution that contains an electrolyte and then connected to an external supply of direct current. When DC power is applied, the anode is oxidized—its metal atoms dissolve in the electrolyte solution. These dissolved metal ions are reduced at the cathode and form a coating. The current through the circuit is adjusted so that the rate at which the anode is dissolved equals the rate at which the cathode is plated

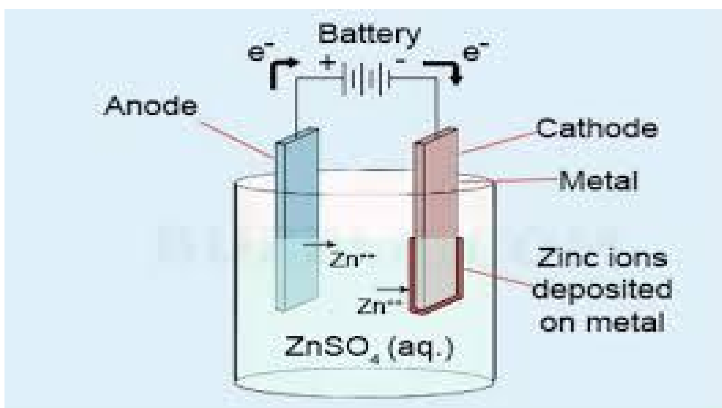


Figure 2.14 Electroplating Process (Singh., 2018)

2.9 Low Carbon Steel

Low-carbon steel (AISI 1010) which is also known as MILD STEEL is the predominant material used in industrial food processing equipment. The category of low carbon steel contains metal that features minimal carbon weight at levels between 0.05% and 0.30%. The oil and gas industry uses low carbon steel as pipe material because several essential factors make this choice possible. The needed weld ability of low carbon steel results from its minimal carbon content compared to higher carbon steels because it makes welding processes easier for both pipelines and various industrial components. The material shows excellent ductility alongside malleability therefore it maintains its integrity during pipe making processes and fitting operations. Good Toughness characterizes this steel because it demonstrates strength while avoiding fractures especially at sub-zero temperatures when compared to high carbon steel varieties (Adamczyk and Grajcar, 2007). A subset of low-temperature carbon steel grades known as LTCS keeps its desired properties unaltered when used in sub-zero temperatures reaching down to -50°C thus allowing the transport of liquefied gases. The material offers economic value by costing less than both high-strength alloys and stainless steels which makes it suitable for massive pipeline installations. DST has strength capabilities that match the demands of various oil and gas operations particularly when used to build lower to medium pressure pipelines... Such equipment is vulnerable to the corrosive environment produced by various production stages. Different processes, such as sulphonating and carbonation, are used in the processing of sugar in the sugar industry, creating a corrosive atmosphere.

The corrosion behavior of low carbon steel (AISI 1010) is strongly influenced by grain size variations, which in turn affect the microstructural mechanical properties of the material. The mechanical behavior and performance of metallic materials, including their corrosion resistance, is determined by grain size which is an important parameter for this phenomenon. The impact of low-carbon steel (AISI 1010) microstructure on corrosion behavior is discussed in this work. Heat treatment produces two different types of microstructures from the same material, which are then analyzed. Scanning Electron Microscopy (SEM) and Energy Dispersive Spectroscopy (EDS) have both been used to study characteristics including morphology and content. By supplying an appropriate corrosive medium, the corrosion performance of several microstructures of low-carbon steel (AISI 1010) was assessed, and corrosion rates were calculated using weight-loss and electrochemical techniques. (Sayer Obaid, 2024)

2.10 Corrosion Rate

When most metals encounter certain substances in the air or water, they undergo a chemical change which decreases the integrity of the metal. This process is called corrosion. Oxygen, sulfur, salt, and other materials can all lead to corrosion. At a certain point, corrosion can lead to dangerous conditions. Metal used in construction is all subject to corrosion. Because of this, it is important to monitor and manage corrosion to avoid structural collapse.

The rate of corrosion is the speed at which any given metal deteriorates in a specific environment. The rate, or speed, is dependent upon environmental conditions as well as the type, and condition, of the metal. Corrosion rates are normally calculated using μpy (microns per year). In other words, the corrosion rate is based on the number of microns (thousands of a millimeter) it penetrates each year. (Singh, 2015)

In order to calculate the rate of corrosion, the following information must be collected:

1. Weight loss (the decrease in metal weight during the reference time)
2. Density (density of the metal)
3. Area (total initial surface area of the metal piece)
4. Time (the length of the reference time)

Corrosion rates determine the lifespan of metal-based structures. This dictates the choice of metals used for different purposes, and in different environments. It also determines the maintenance requirements for structures: a metal structure in a wet and/or polluted environment may require more frequent maintenance than a similar structure in a drier or unpolluted environment.

2.10.1 How to measure corrosion rate

There are mainly 2 ways to measure the corrosion rate:

1. measuring the weight change of the metal after a specific time of exposure to the target environment
2. Using electrochemistry.

While the first option is accurate and believed to be the best type of corrosion test, it is a very lengthy process. Corrosion itself is a slow reaction and weight-based measurements might take weeks, months or even years before the experiments are finished.

Electrochemistry based methods, on the other hand, are able to measure corrosion accurately within a matter of hours or even minutes. This is because electrochemical methods can actively interact with the test sample to accelerate the corrosion process, enabling measurements of very low corrosion rates. (Gerard Macias, 2023)

2.10.2 Corrosion rate equation

The corrosion rate formula is quite straightforward:

$$\text{Corrosion rate (g/s)} = \frac{m}{t}$$

However, determining the amount of mass dissolved at any given time using traditional methods requires a very long time. Luckily, with electrochemistry we can estimate the mass using Faraday's Law of Electrolysis, which converts the corrosion rate equation as follows:

$$m = \frac{iM}{nF}$$

Where:

- it is the corrosion current, which can be obtained from the Tafel equation, the Butler-Volmer equation or the Stern-Geary equation,
- M is the atomic mass in g/mol
- n is the number of electrons of the corrosion reaction
- F is Faraday's constant 96485 C/mol (Gerard Macias, 2023)

This equation so far allows us to determine the corrosion rate in g/s from results obtained from electrochemical experiments. To transform it into penetration units, it must be divided by the material's density and the surface area exposed

Electrochemical corrosion rate formula for penetration unit

$$\text{Corrosion rate(cm/s)} = \frac{iM}{nF\rho A}$$

Where:

- ρ is the density of the material being corroded in g/cm^3
- A is the exposed area in cm^2(Gerard Macias, 2023)

To transform the resulting corrosion rate to mille-inch per year (mpy) or millimeter per year (mmpy) units, it just needs to be multiplied by 0.13 for mpy conversion and by 0.00327 for mmpy conversion.

2.11 Conventional Corrosion Monitoring Techniques

Examining material deterioration is the goal of corrosion monitoring through observation and assessment of metals and concrete and wooden materials decaying due to natural degradation processes that incorporate rusting and chemical processes and electrochemistry reactions (Agarwala *et al*., 2000). Special methods or instrumentation is utilized to evaluate structures and industrial facilities and buildings and bridges and other engineered systems. Deterioration results in multiple changes including material loss and changes to physical elements, chemical characteristics, electrical behavior, magnetic features, their mechanical condition and structural breakdown through the formation of cracks. Weight loss represents a universal sign of metal corrosion that manifests equally across the surface or within defined areas along grain boundaries and pits and crevices (Melchers, 2018).

The purpose of a corrosion monitoring device or technique is to detect damages from corrosion while providing assessment information and predictions that aid proactive maintenance planning (Groysman, 2019). Historically visual assessment served as the main approach to evaluate structural condition yet this process proved both time-consuming and expensive and produced unreliable results because of restricted access and failed to generate quantitative data. Corrosion management requires multiple technical activities which cover both protection method, prevention methods and exact measurement systems. Cathodic and anodic protection together with materials selection and chemical treatments require the precise evaluation of environmental corrosivity and metal loss rates for efficient corrosion control (Aljibori *et al*., 2024). Quantitative data obtained from corrosion measurement functions as the primary fundamental measurement tool for examining and enhancing corrosion mitigation initiatives. Weight loss monitoring remains one of the basic and easy-to-use techniques for corrosion assessment which continues to be employed by numerous research laboratories and industrial programs (Vasagar *et al*., 2024).

The broad range of corrosion measurement methods divides into two main categories which are non-destructive testing (NDT) and analytical chemistry with operational data analysis and electrochemistry and corrosion monitoring included. Ultrasonic testing and radiography represent NDT methods that allow non-invasive investigations of material integrity (Bray, 2002). The detection capabilities of NDT are affected by material accessibility and its type and the difficulty of detecting localized corrosion damage. Energy analysis combined with pH testing measures the corrosive agents within environmental systems (Roberge, 2018). Off-line analysis leads to delays while sample representativeness together with the inability to directly assume metal loss and time-lag represent the main limitations in this case. Machine data regarding operational flow rates together with operational temperatures provide key contextual information. These data have limited value because they need additional correlations with other investigation methods to determine actual corrosion rates. Electrochemical methods, such as potential and potentiodynamic measurements, delve into the electrochemical processes driving corrosion (Jones, 1996). The use of electrochemical methods typically requires set electrolytes while their corrosion data does not precisely match sustained corrosion patterns. Direct online measurements of metal loss and corrosion rate measurements can be achieved through corrosion monitoring which utilizes weight loss coupons and electrical resistance probes and linear polarization techniques (Revie & Uhlig, 2008). The process of corrosion monitoring faces constraints because weight loss coupons generate average corrosion rates yet electrical resistance probes show sensitivity to environmental changes.

On-line deployments of corrosion monitoring systems expose them to continuous process exposure while preventing offline laboratory testing. The ongoing process monitoring serves to interpret the evolving corrosive situations which enables prompt preventive measures. Both methods create direct measurements of metal reduction and corrosion speed measurements whereas alternative tactics supply secondary information about corrosive circumstances (Odeyemi and Alaba, 2025).

The need for effective corrosion monitoring emerges because it delivers more operational safety alongside better economic performance. The pace of corrosive processes determines the operational durability as well as safety levels of industrial equipment. The optimization of plant operations and reduction of life-cycle costs depends on accurate corrosion measurement followed by immediate solutions to high corrosion rates (Navarro *et al.,* 2019). Process monitoring systems provide organizations with diverse advantages that include detecting dangerous operational situations early and linking operational parameter fluctuations to corrosive conditions as well as diagnosing corrosion problems and measuring corrosion control measures and producing data for plant maintenance planning and asset assessment. Operators gain the ability to respond swiftly against corrosion risks by using corrosion monitoring systems that provide real-time data and insight to extend operational time of infrastructure while guaranteeing security for industrial assets.

2.12 Integration Of Sensor Networks And Machine Learning For Corrosion Monitoring

The harms of corrosion on metals can be seen everywhere in the transportation, energy, manufacturing and infrastructure sectors. As a result, this problem causes a lot of damage to buildings, leading to costly repairs and replacements. The dangers of corrosion are not limited to the budget; they can cause calamitous accidents and put people at risk. This means that corrosion also leads to environmental harm, so it's especially important to put in place proper ways of both detecting it and countering its threats (Agarwala, 2000). Methods that depend on manual checks and spot testing tend to have their own set of issues. Some of these methods require a lot of work, take a long time and are not always able to spot early or hidden corrosion in complex parts of a structure. Sometimes different people see things differently in visual inspections, so it's important to find better and more objective solutions.In response to these limitations, there has been a growing interest in leveraging advancements in technology to develop more efficient, accurate, and proactive systems for corrosion detection and monitoring (Akyildiz *et al.,*2002). The integration of sophisticated sensor networks with powerful machine learning algorithms represents a promising paradigm shift in this field. Sensor networks, comprising a multitude of interconnected sensing devices, can provide continuous, real-time data on various parameters indicative of corrosion. Machine learning algorithms can then be applied to analyze this vast amount of data, identify subtle patterns and anomalies that may signify corrosion initiation or progression, and even predict future corrosion behaviour (Ossai, 2019). This interdisciplinary approach holds the potential to overcome the shortcomings of traditional methods, enabling early detection, timely intervention, and ultimately enhancing the safety, reliability, and longevity of metallic infrastructure. This research paper aims to provide a comprehensive analysis of the current state of research on the integration of sensor networks with machine learning for corrosion detection. The scope of this research work will encompass a detailed examination of various sensing modalities, including electrochemical, optical, and environmental sensing, the critical role of wireless sensor networks in data acquisition and transmission, and the application of machine learning techniques for corrosion classification, prediction, and overall condition assessment.

The increasing adoption of sensor networks and machine learning for corrosion detection reflects a significant shift towards the broader digitalization and automation of structural health monitoring and predictive maintenance strategies (Plevris and Papazafeiropoulos, 2024). Traditional reliance on human-centric, scheduled inspections is gradually being augmented by technology-driven approaches that offer enhanced efficiency and responsiveness. The remarkable advancements in sensor technology, characterized by the miniaturization of devices, their decreasing cost, and improved sensitivity, coupled with the exponential growth in computational power and the development of increasingly sophisticated data analytics algorithms, have collectively made it feasible to implement continuous and intelligent monitoring systems for corrosion detection (Hussain, *et al.,* 2024). This fundamental shift is primarily driven by the critical need to achieve improved operational efficiency, minimize unexpected downtime in industrial processes, and significantly enhance the overall safety of critical infrastructure across diverse sectors. The synergistic combination of these technological advancements offers a pathway to move from reactive maintenance strategies, where interventions occur only after a failure is detected, to proactive and even predictive maintenance approaches, where potential issues can be identified and addressed before they escalate into significant problems.

The inherent interdisciplinary nature of this rapidly evolving field, which seamlessly blends the principles of materials science, electrical engineering, computer science, and data analytics, presents both remarkable opportunities for groundbreaking innovation and considerable challenges in terms of effectively integrating knowledge and fostering robust collaboration among experts from these distinct domains. Achieving truly effective corrosion detection and monitoring requires a deep and comprehensive understanding of the fundamental electrochemical and material science principles that govern the corrosion process (Odeyemi and

Alaba, 2025). It also necessitates the ability to design and implement appropriate and reliable sensor systems for accurate data acquisition, establish robust and secure wireless communication networks for efficient data transmission (Islam *et al.,* 2012), and finally, to apply advanced and nuanced machine learning techniques for insightful data interpretation, accurate classification, and reliable prediction of corrosion behaviour (Ossai, 2019).. This complex interplay of different technical domains underscores the critical importance of effective communication and close collaboration among specialists from these diverse fields to successfully bridge the inherent knowledge gaps and fully realize the potential of this integrated approach for enhancing the safety and longevity of our critical infrastructure.

2.12.1 Sensor Technologies for Corrosion Monitoring

1 Electrochemical Sensors: A diverse range of electrochemical sensors and techniques are employed for the purpose of corrosion monitoring, each offering unique capabilities in detecting and quantifying different aspects of the corrosion process (Komary *et al.,* 2023). Electrical resistance (ER) sensors are a common type, operating on the principle that as a metal corrodes, its cross-sectional area decreases, leading to a measurable increase in its electrical resistance. These sensors are widely used in industries such as construction, oil and gas, and nuclear waste management to monitor material loss due to corrosion. Ion-selective electrodes represent another category of electrochemical sensors, designed to selectively measure the concentration of specific ions in a solution (Solsky, 2002) For instance, sensors have been developed to detect the presence and concentration of chloride ions, which are known to be highly corrosive to many metals. Electrochemical Impedance Spectroscopy (EIS) is a more sophisticated electrochemical technique that involves applying a small alternating current to the metal surface and measuring the impedance response over a range of frequencies (Shan *et al.,* 2021). EIS can provide detailed information about the electrochemical reactions occurring at the metal-electrolyte interface, offering insights into the corrosion mechanisms and rates. Other electrochemical techniques like linear polarization resistance (LPR) and potentiodynamic polarization are also used to determine corrosion rates and assess the susceptibility of materials to corrosion (Papavinasam, 2021) These methods involve measuring the current response of the metal to an applied potential, allowing for the extraction of key corrosion parameters such as corrosion potential and corrosion current density. The variety of electrochemical sensors and techniques available enables the detection of different facets of the corrosion process, providing a more comprehensive understanding of corrosion initiation and progression. Electrical resistance sensors directly measure material loss, while ion-selective electrodes can identify the presence of corrosive species in the environment. Techniques like EIS offer detailed insights into the electrochemical reactions driving corrosion, and polarization methods allow for the quantification of corrosion rates (Kouřil *et al.,* 2013). The ongoing development of facile and cost-effective electrochemical sensors is crucial for the widespread adoption of sensor networks for corrosion monitoring. For sensor networks to be economically viable for large-scale infrastructure monitoring, the individual sensor nodes need to be inexpensive and easy to deploy. Research focused on developing simple and effective electrochemical sensors using readily available materials is essential for this goal.

2 Colour Sensors: RGB color sensors have emerged as a supplementary tool in the realm of corrosion monitoring, primarily utilized for detecting visual changes on the surface of metallic structures, such as the formation of rust, which is a common indicator of corrosion. (Singh *et al.,* 2023.) The principle behind their use lies in colorimetric analysis, where changes in the color of a material are quantified and correlated with its condition. It was demonstrated that colorimetric analysis using RGB sensors could aid in the early detection of rust formation by identifying subtle changes in surface color (Gao *et al.* 2014). While the present study reported limited differentiation using RGB sensors alone, the underlying principle of using optical information to detect surface changes remains valid. Several studies have explored the use of RGB imagery in conjunction with image processing techniques and machine learning algorithms for detecting and classifying corrosion on various structures, including steel bridges and vehicles. These approaches often involve analyzing the red, green, and blue color components of images to identify the characteristic reddish-brown hue associated with rust. While RGB sensors might have limitations in detecting subtle color changes associated with early corrosion, their low cost and ease of integration make them valuable for initial screening and as part of a multisensor approach. RGB sensors are readily available and inexpensive, making them suitable for deployment in large numbers within a sensor network. Although they might not be as sensitive as specialized electrochemical sensors for detecting the onset of corrosion, they can provide a visual indication of more advanced corrosion stages, especially when combined with image processing techniques. The success of colorimetric analysis for iron determination suggests that RGB sensors can be effective when the corrosion process leads to significant color changes, such as the formation of rust (iron oxide). Rust formation is a visually distinct process characterized by reddish-brown discoloration. RGB sensors are designed to capture color information, and their application in detecting iron content through colorimetric methods indicates their potential for identifying rust, a key indicator of steel corrosion. Combining RGB sensor data with other sensor modalities, such as electrochemical and environmental sensors, can lead to a more robust and accurate corrosion diagnostic system.

3 Environmental Sensors: Environmental sensors that measure parameters like temperature and humidity are indispensable for corrosion monitoring as they provide critical contextual information about the conditions under which corrosion is likely to occur and progress. Studies, have demonstrated a strong correlation between these environmental parameters and corrosion rates, particularly in aggressive environments like marine and industrial settings (Li *et al*. 2019). For instance, high humidity levels increase the time of wetness on metal surfaces, providing the electrolyte necessary for electrochemical corrosion. Temperature also plays a significant role, as higher temperatures generally accelerate the kinetics of chemical reactions, including those involved in corrosion. In marine environments, the combined effects of high humidity and salinity create highly corrosive conditions. Similarly, in industrial environments, the presence of pollutants like sulfur dioxide, coupled with varying temperature and humidity, can significantly impact corrosion rates. Monitoring these environmental parameters provides the necessary context for interpreting data from electrochemical and optical sensors, allowing for a more accurate assessment of corrosion risk and progression. The strong correlation between environmental parameters and corrosion rates underscores the necessity of integrating environmental monitoring into any comprehensive corrosion detection system. Corrosion is not solely a material property but is highly dependent on the surrounding environment. Changes in temperature and humidity directly affect the electrochemical reactions involved in corrosion and the availability of moisture, which acts as an electrolyte. Therefore, continuous monitoring of these parameters is essential for accurately assessing corrosion risks and predicting corrosion rates. The findings from Li et al. (2019) and related studies suggest that the specific relationships between temperature, humidity, and corrosion can vary significantly depending on the environment (marine vs. industrial) and the presence of other factors like pollutants (SO_2, chlorides). This highlights the need for environment-specific corrosion models.

2.12.2 Wireless Sensor Networks (WSNs) for Corrosion Monitoring

The deployment of Wireless Sensor Networks (WSNs) has been extensively explored as a promising approach for infrastructure monitoring, particularly in remote or hazardous locations where traditional wired systems are difficult or costly to implement. Foundational research has highlighted the potential of WSNs for various monitoring applications, including structural health monitoring (Akyildiz *et al.* 2002). WSNs offer several advantages, such as low installation costs due to the absence of extensive wiring, ease of deployment in hard-to-reach areas, and the ability to provide spatially dense measurements. These networks consist of numerous small, low-power sensor nodes that can collect data on various physical and chemical parameters and communicate wirelessly with a central data acquisition system. The applications of WSNs in infrastructure monitoring are diverse, ranging from monitoring the structural integrity of bridges and buildings to detecting leaks in pipelines and assessing the condition of concrete structures. This integration allows for the continuous and real-time monitoring of corrosion indicators, providing a significant advantage over traditional manual inspection methods. Manual inspections are often periodic, labor-intensive, and may not be capable of detecting early-stage corrosion or corrosion occurring in hidden locations (Nicola, 2012).

In contrast, a WSN-based corrosion monitoring system can provide continuous data streams, enabling early detection of corrosion initiation and progression, which can lead to timely maintenance interventions and prevent potentially catastrophic failures (Goyal & Bhalla, 2019). The ability of WSNs to operate autonomously and transmit data wirelessly makes them particularly suitable for monitoring large-scale infrastructure or assets located in remote or hazardous environments. The development of low-cost and deployable WSN solutions for corrosion monitoring has the potential to revolutionize structural health monitoring by enabling widespread and continuous assessment of infrastructure integrity (Fu *et al.,* 2014). Traditional monitoring methods often involve periodic inspections that can miss early signs of corrosion or damage in inaccessible areas. Low-cost WSNs equipped with corrosion sensors can be permanently deployed to provide continuous, real-time data, allowing for early detection and timely intervention, potentially preventing catastrophic failures and reducing maintenance costs. The integration of WSNs with corrosion sensors addresses the limitations of manual inspections, offering a more proactive and data-driven approach to infrastructure management, aligning with the principles of Industry 4.0 and smart infrastructure initiatives. WSNs can automate the process of data collection and transmission, reducing the need for manual inspections in hazardous or remote locations. The continuous data stream provided by WSNs allows for the application of advanced data analytics and machine learning techniques to detect anomalies and predict future corrosion behavior, leading to more informed decision-making in infrastructure maintenance and management (Lynch and Loh, 2006).

2.12.3 Machine Learning for Corrosion Classification

Support Vector Machines (SVMs) stand out for their outstanding performance on sensor data classification tasks., When dealing with small- to moderate-sized data containing many features, SVMs work well compared to other methods, a common challenge in corrosion detection due to the lack of a large number of suitably labeled examples. SVMs seek a boundary hyperplane that can divide the data points of each class in a high number of dimensions. Their way of dealing with complex relationships with kernel functions expands how appropriate they are for handling corrosion. Having seen the results of recent studies, it is now clear that WSNs joined with SVM classifiers is very powerful for watching over civil and oil/gas infrastructure. Accelerometers, acoustic probes or chemical probes battery-powered by WSNs are set up on different structures and pipelines, sending the obtained data to a main control point. Thanks to the measurements, SVMs can identify any signs of damage, leaks or corrosion. As an example, vibration information from bridges may be analyzed within the Network using FFT or wavelet methods and labeled by an SVM to indicate where damage is.

According to Kustiana et al study in 2024, data collected from an 8-node accelerometer network enabled the research on bridge vibration. From the FFT output, cluster-formed topology sent frequency and amplitude information to the base station for training the linear and RBF-kernel SVM models. The created classifier could recognize normal from damaged conditions with an average of 97% accuracy. Also, Liu et al designed a leak detector using WSN technology in 2019, with 4G uplinked sensors. A low-energy network protocol was activated using leaks and the following techniques were used to identify key characteristics: Empirical Mode Decomposition, Approximate Entropy and PCA. An SVM classifier with an RBF kernel was next trained on these features to spot leaks. When tested and simulated, the SVM proved it could reliably find leak events nearly all the time and was not easily affected by noise. To be precise, once their optimal model was fine-tuned, it was able to properly identify leaks or non-leaks 98% of the time.

Nikfar, Bitencourt and Mykoniatis presented, in their 2022 study, a two-step machine learning system for detecting faults and classifying them in low-voltage industrial motors using vibration data. In Phase 1, when we used the SVM to detect abnormalities, it showed very good performance on the three datasets, with two completing the tasks without error and the third having only minor errors. Because its performance was better than that of backpropagation neural network (98.75%) and random forest (96.25%), SVM was selected as the best option for phase two of the system. In Phase 2, we focused on identifying faults and the SVM algorithm produced accuracies of 95.23% and 90.48% on B-1 and B-2, respectively. To predict the steel reinforcement corrosion in a corrosion monitoring project, a wireless electromechanical impedance system was used together with ML. The main model used was a neural network, but similar studies have tried out SVMs for corrosion detection. Pipeline defect classification which included corrosion among the defect types, was carried out using SVMs and showed an outstanding accuracy. Many corrosion-monitoring reports as described in Su et al. 2018 suggest ways to design new sensors, yet current research is now blending WSNs and ML techniques, especially SVM, to handle corrosion monitoring automatically. In their research published in 2023, Ismail et al observed corrosion by using sensors on WSN nodes; afterwards, they made predictions about corrosion level by running these observations through Support Vector Machines. Outcomes from SVMs in this field are impressive, with accuracy often surpassing 90–

95% on tests in labs. Overall, combining different types of sensor information (e.g., electrochemical, colour, environmental), called sensor fusion and learning from data that has been labeled (as corroded or not) is considered the best approach to using machine learning for engineering diagnostics. Seeing how a classification model is performing is routine through confusion matrices and scatter plots.

The consistently high performance of SVMs in various predictive maintenance and anomaly detection tasks suggests their robustness and suitability for corrosion classification based on sensor data. SVMs are effective in creating clear decision boundaries in high-dimensional spaces, making them well-suited for distinguishing between corroded and non-corroded states based on multiple sensor readings. Their ability to handle non-linear relationships through the use of kernel functions further enhances their applicability to complex corrosion processes (Pani, 2022). The importance of data quality and the potential benefits of integrating different types of sensor data (sensor fusion) for improved accuracy indicate that a well-designed sensor network providing diverse and reliable data is crucial for the success of machine learning-based corrosion detection. The performance metrics for SVM in anomaly detection tasks, as summarized in the table below, further support its potential for corrosion classification:

CHAPTER THREE

3.0 MATERIALS AND METHODOLOGY

3.1 Materials

3.1.1 Fundamentals of Major Materials Used In the Design of This System

1. Microcontroller
2. Motor
3. Motor driver
4. Temperature and Humidity sensor
5. Color sensor

3.1.1.1 Microcontroller (ESP 32)

A microcontroller is a compact, self-sufficient computing device designed for executing specific functions or managing operations in embedded systems. It combines a processor (CPU), memory (RAM and ROM), and various peripherals (such as timers and I/O ports) into a single chip. Microcontrollers are widely used in devices like household appliances, automobiles, robotics, medical devices, and consumer electronics. Key features of microcontrollers include CPU, Memory, and Peripherals and so on.

Figure 3.1 a Microcontroller

Microcontrollers are typically programmed using low-level languages such as **C** or assembly, offering the advantage of efficiently managing real-time operations.

3.1.1.2 Motor and Motor Driver

In automated systems for detecting pipeline corrosion, motors and motor drivers are essential in enabling movement, positioning, and controlling inspection tools or sensors along the pipeline. These systems are critical in maintaining pipeline integrity, as pipelines are exposed to harsh conditions that can lead to corrosion. Motors provide the power necessary for robotic inspection devices or mobile platforms to move along pipelines. The types of motors used in these systems include DC motors, stepper motors, and servo motors, each selected based on the type of movement and accuracy required. Motor drivers are electronic components that control the motors by regulating their speed, direction, and torque. In pipeline corrosion detection systems, motor drivers work with the microcontroller or control unit to send commands to the motors based on input from corrosion-detecting sensors. Types of motor drivers include DC Motor Drivers, Stepper Motor Drivers, and Servo Motor Drivers. Motors and motor drivers are vital to the automation of pipeline corrosion detection, providing the mobility and control needed to inspect every section of the pipeline for damage. Their integration ensures reliable corrosion detection, enabling early identification of potential failures and reducing the need for expensive repairs or replacements.

Figure 3.2 a Motor driver

Figure 3.3 a Motor

3.1.1.3 Electrochemical Sensors

Electrochemical Sensors are devices that measure the concentration of specific chemical substances in a solution or gas by detecting changes in electrical properties, such as voltage, current, or resistance, caused by chemical reactions. These sensors are widely used in various fields, including environmental monitoring, industrial applications, medical diagnostics, and corrosion detection

Figure 3.4 An Electrochemical sensor

3.1.1.4 Temperature Sensor

Temperature sensors are devices used to measure the temperature of an object or environment. They are essential in various applications, ranging from industrial systems and consumer electronics to automotive and healthcare. Temperature sensors detect changes in temperature and convert them into electrical signals, which can then be read by a controller, display, or other devices. An example of the temperature sensor is the LM 35 sensor.

Figure 3.5 The lm 35 Temperature sensor

3.1.1.5 Humidity Sensor

Corrosion is a natural phenomenon that causes the deterioration of materials, mainly metals, due to their interaction with environmental factors such as moisture, oxygen, and pollutants. Moisture, particularly in high-humidity environments, is one of the key factors driving corrosion. Humidity sensors are essential for assessing and monitoring the environmental conditions that lead to corrosion. By tracking changes in humidity, these sensors can help predict and reduce the damage caused by corrosion across different industries.

Figure 3.6 Humidity sensor module

3.2 Methods

3.2.1 Block Diagram

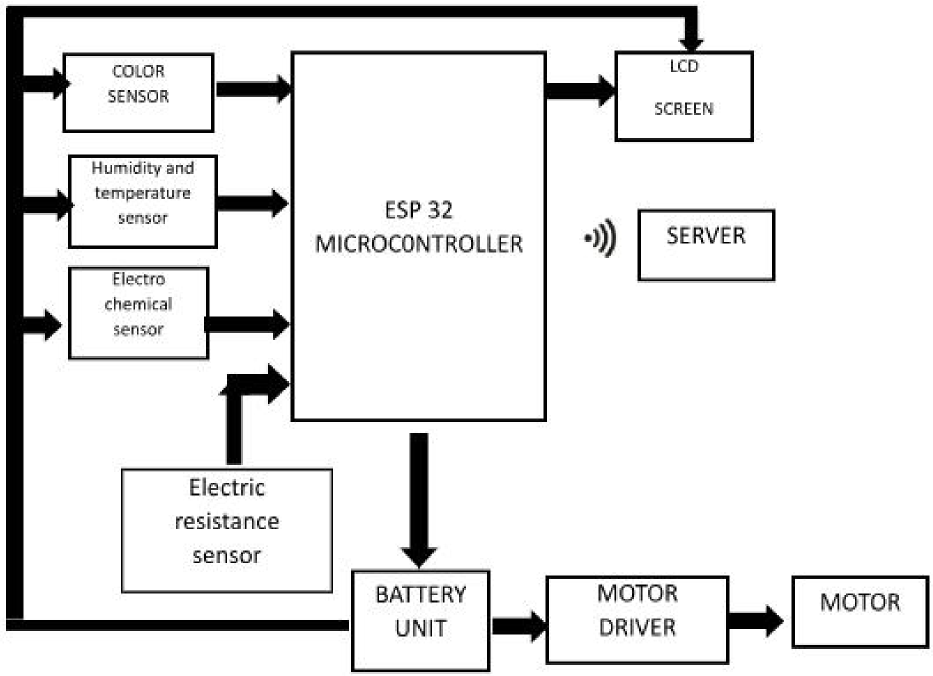


Figure 3.7 Block Diagram of the system

3.2.2 The Microcontroller Unit

3.2.2.1 ESP 32 Microcontroller

Referring to the block diagram in figure 3.7, this microcontroller was chosen because of its wide range of applications. This functionality is enabled by the presence of the Bluetooth and Wi-Fi modules. The Wi-Fi module ensures a wider physical connection while the Bluetooth module ensures mobile connection to a phone.

The operating condition of this microcontroller is convenient for the design of the project we want to achieve. The operating conditions for the ESP 32 Microcontroller are given in the table below.

Table I microcontroller unit

PARAMETER\SYMBOL	MINIMIUM	TYPICAL	MAXIMIUM	UNIT
Power supply voltage(VDD33)	3.0	3.3	3.6	V
Current delivered by external power supply (IVDD)	0.5	-	-	A
Operating ambient temperature (T)	-40	-	85	^{0}C

3.2.2.2. LCD Screen (LMO16L)

Referring to the block diagram in Figure 3.7 this unit consists of the 16 by 2 LCD screen. LCD stands for liquid crystal display. It serves as the channel which shows real time data generated by the system.

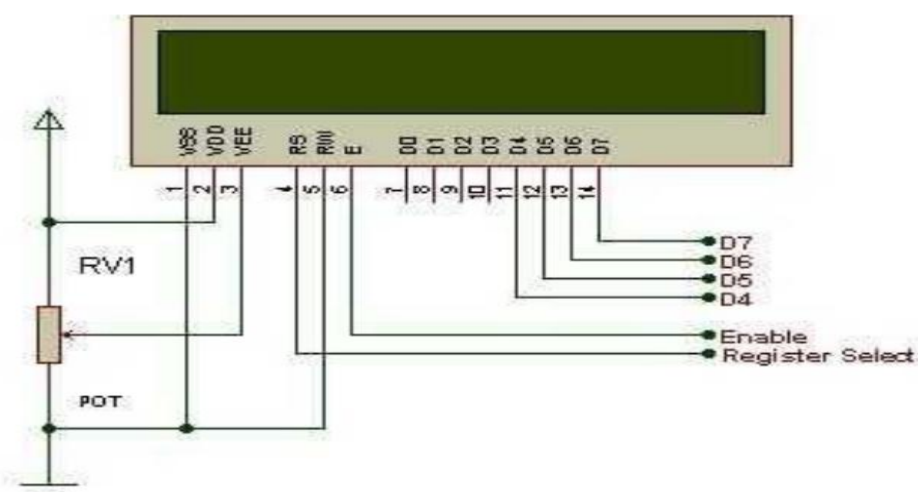


Figure 3.8 the lmo16lcd screen and its pin connections

3.2.3 Chemical Sensing Unit ($4CL_2$ -50)

Referring to the block diagram in Figure 3.7, this unit is responsible for detecting the presence of chlorine in our pipeline to determine its state. This unit consists of a chemical sensor capable of sensing chlorine gas. The presence of chlorine indicates that corrosion is taking place.

When pure and impure iron pipelines react with chlorine, the by-products indicate a presence or absence of corrosion. This makes chlorine detection a very reliable method of detecting corrosion in pipelines. The chemical equations for pure and impure iron pipeline are given below.

I) Pure iron reacts with chlorine gas to form iron (III) chloride, $FeCl_3$.

$Fe\ (s) + Cl_2\ (g) \rightarrow FeCl_3\ (s)$ ………………………………………. (3.1)

This reaction demonstrates how chlorine gas reacts with pure iron. The formation of iron chloride signifies a corrosion process, as iron is being converted to a less stable form, indicating potential degradation.

ii) Impure iron (such as steel, which contains carbon and other alloying elements) reacts similarly with chlorine gas, but the presence of other impurities can slightly modify the reaction. For example, carbon impurities might form carbon-containing compounds (like carbon monoxide), which could interfere with the corrosion process. Steel contains carbon, and it may react with chlorine in different ways depending on the conditions and the exact composition of the steel. The carbon present may result in the formation of iron chloride as well as other potential reactions.

The reaction can still be represented similarly to the pure iron reaction, though it may also involve additional side reactions related to the carbon content.

Equation:

$Fe\ (s) + Cl_2\ (g) \rightarrow FeCl_3\ (s)$ ……………………………………………… (3.2)

$C\ (s) + Cl_2\ (g) \rightarrow CCl_4\ (l)$ ………………………………………………… (3.3)

In this case, carbon reacts with chlorine to form carbon tetrachloride (CCl_4), which is not necessarily related to corrosion but can be a side product in the presence of chlorine.

The chosen electro chemical sensor is the 4cl$_2$-50 sensor. Its temperature range is from -20ºc to 50ºc and its pressure range is from 90 to 110kpa. Below is a graph showing its temperature dependence.

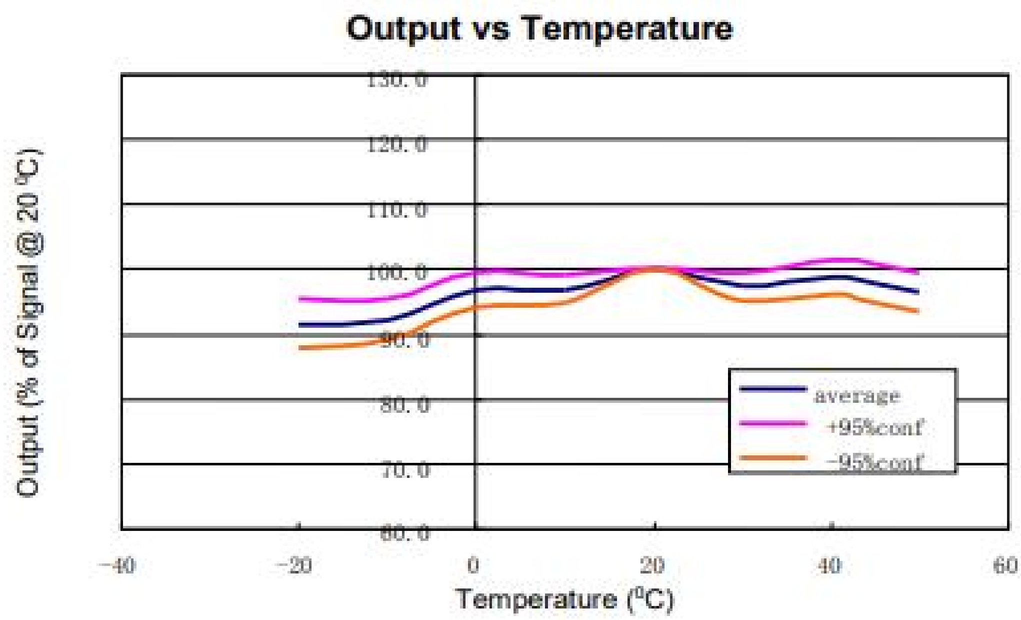


Figure 3.9 Temperature dependence of a 4Cl$_2$-50 sensor

3.2.4 Humidity And Temperature Sensing Unit (DHT 11)

Referring to the block diagram in Figure 3.7 this unit is made up of a single sensor capable of sensing both temperature and humidity. This sensor is called the DHT 11 sensor. It is commonly known as the digital relative humidity and temperature sensor. Some of its features include:

1. Good precision

2. Outstanding long-term stability.

3. Low power consumption.

4. Long transmission distance of up to 100 meters.

This sensor applies exclusive digital signal collection technique and humidity sensing technique ensuring its stability and reliability. Below is a table giving the technical specifications of the DH-11 sensor.

Table II humidity and temperature

Model	DHT 11
Power Supply	3.3 – 5.5V DC
Output signal	Digital signal via Ao song 1-wire bus
Sensing Element	Polymer humidity resistor
Operating Range	Humidity Temperature 0 ~ 50ºC
Accuracy	Humidity Temperature +-2ºC
Resolution or Sensitivity	Humidity P temperature 1ºC
Repeatability	Humidity Temperature +-1ºC
Humidity Hysteresis	+- 1%RH
Long term Stability	+- 1%RH/year
Interchangeability	Fully interchangeable

3.2.5. Thing speak Server

Referring to the block diagram in Figure 3.7, Thing Speak is a powerful, easy-to-use platform for building and managing IoT applications. By providing cloud-based storage, real-time data visualization, and integration with MATLAB for advanced analytics, Thing Speak simplifies the process of collecting, analyzing, and visualizing IoT data. Thing Speak is an IoT (Internet of Things) platform that allows you to collect, analyze, and visualize data generated by IoT devices (or "things") in real-time.

Corrosion detection typically involves monitoring environmental factors (like temperature, humidity, chemical concentration, etc.) that can influence or accelerate corrosion in materials, especially metals. ThingSpeak is essential in the setup of corrosion monitoring systems by collecting, storing, and analyzing data from corrosion sensors and environmental sensors in real-time. The IoT devices will send sensor readings to Thing Speak channels via the Thing Speak API. Corrosion probe could send data indicating whether the metal is degrading (corroding) or not, and environmental sensors could send temperature or humidity data to understand the conditions contributing to corrosion.

One of Things peak's unique features is its integration with MATLAB, a powerful tool for mathematical modeling, data analysis, and simulation. Thing Speak allows you to run MATLAB code directly on the server to analyze your IoT data. It also provides a cloud-based service, meaning it hosts your data on the cloud and allows you to access it from anywhere. This is crucial for IoT applications that require remote monitoring and control. MATLAB integration in Thing Speak allows you to run advanced analysis algorithms to detect patterns or predict future corrosion trends based on historical data. A model based on machine learning is created to predict corrosion based on the environmental conditions and historical corrosion data.

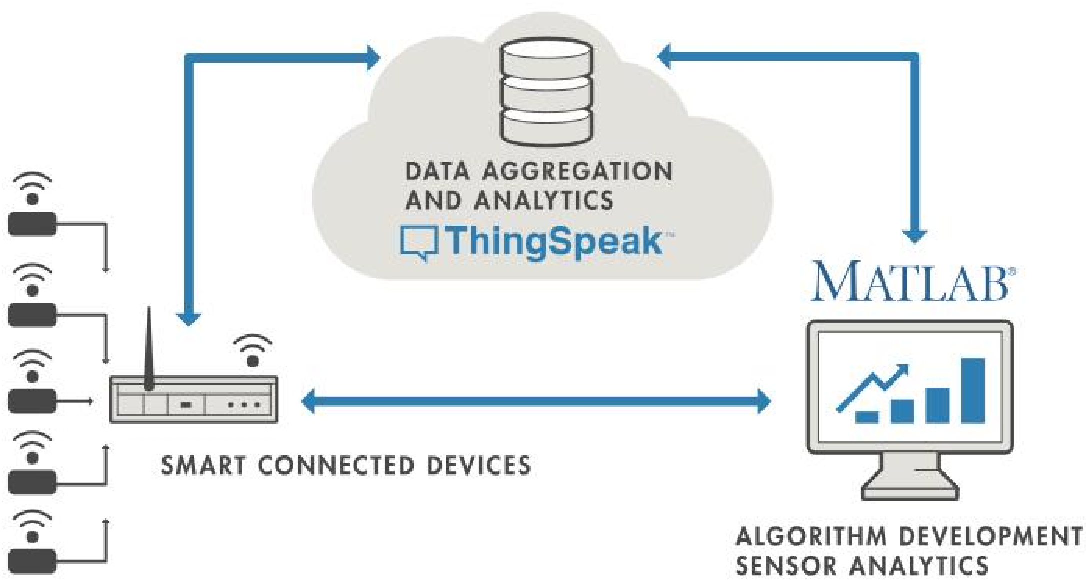


Figure 3.10 flow of data on things speak server

3.2.6. Colour Sensing Unit

Referring to the block diagram in Figure 3.7, An "O-255 color sensor" refers to a color sensor that outputs values within a range of 0 to 255, representing the intensity of red, green, and blue color components (RGB). The sensor provides readings for each color channel (red, green, blue) as a number between 0 and 255. A higher value indicates a greater intensity of that color. This type of sensor is essential in this project as a change in pipeline color may signify the presence of corrosion.

3.2.7 Motor and Motor Driver Unit

Referring to the block diagram in Figure 3.7, the motor driver provides the power required to drive the motor. The motor driver used here is the L293D motor driver. This motor driver is designed to drive inductive loads such as Dc motors and stepper motors. It provides a bilateral control in cases where two motors are involved, making it suitable for a variety of motor control applications. Its features include two H-bridges allowing it to control the direction of rotation and speed of two DC motors independently. It is designed to work with a wide range of motor voltages, typically up to 36v, making it suitable for various motor types. It can handle a continuous output current of up to 600mA per channel and a peak output current of up to 1.2Aper channel.

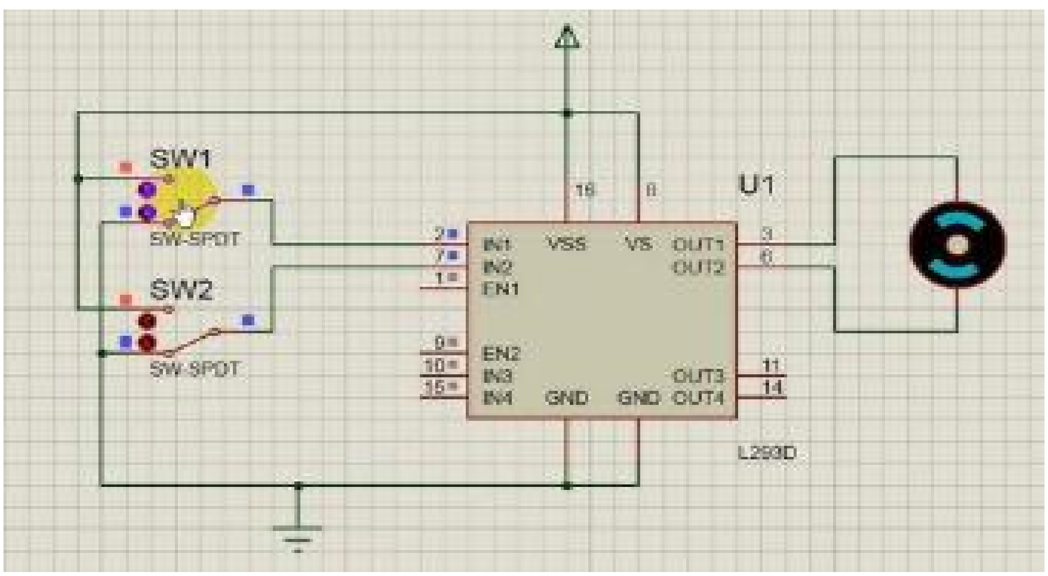


Figure 3.11 A Proteus simulation of the l293d motor driver.

3.2.7.1 Power Loss in the Motor Driver

When the L293D motor driver operates at full capacity, its typical voltage drop is around 2.5 volt.

Thus,

$P_{heat} = (V_{in} - V_{out}) \times I$

Where I represent the current,

V_{in} represents voltage in,

V_{out} represents voltage out and

P_{heat} represents the power lost in the motor driver due to heat

$= (36 - 2.5) \times 1.2$

$= 40.2W$

3.2.8 Support Vector Machine

SVM is a supervised learning model that aims to find the optimal hyper plane that best separates different classes of data points in a high-dimensional space. Think of it like drawing the best possible line (or plane, or hyper plane in higher dimensions) to divide your data into distinct groups. In WSNs, SVMs can be employed for correction detection by learning the patterns of "correct" or expected sensor readings. Deviations from these learned patterns, identified by the SVM as belonging to an "incorrect" class, can then flag potential errors or anomalies requiring correction. The SVM acts as a classifier, distinguishing between reliable and potentially faulty sensor data based on the features extracted from the readings.

3.2.9 Construction Process

The design of the corrosion detection system involved both hardware and software design. Software design involved programming the different sensors to function and respond accordingly. The physical stricture of the corrosion detection system is called the field track, and this was gotten by combining different materials together. Some of which include:

1. A box containing the soldered electronic components.

2. A metallic stand

3. A motor

4. Aluminum holder

5. A solar panel.

In assembling the components of the hardware, the following factors were considered.

1. Cost

2. Availability

3. Strength

4. Size

In constructing the corrosion system, the following steps were taken:

1. A Vero board was gotten.

2. Resistors and other electronic components were soldered following their correct electrical path on this board.

3. This circuit was tested for continuity to confirm if electronic components were soldered rightly.

4. This Vero board was then packaged in a box. This box also served as protection for the soldered components on the Vero board. The images below show the physical structure of the system.

Figure 3.12 construction process

3.2.10 Mounting and soldering of components

Soldering refers to the process of connecting electrical components together. In achieving the goals of this project, proper soldering was necessary to avoid bridging. The electronic components on the Vero board related to jumper wires before they were soldered.

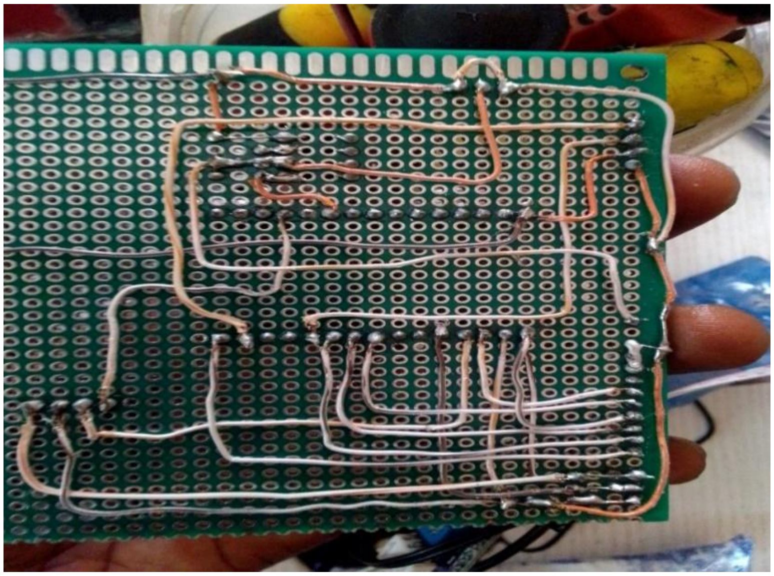


Figure 3.13 Soldering and mounting of components on the Vero board

after all the hardware connections have been made, A solar panel was attached and mounted on the track frame because the idea of the system was designed to be a standalone system not to get power from, external sources. That's why we have a 25 watt solar panel that is mounted on top of the device. So this 25 watt solar panel is going to power and charge the batteries and also power the system which is the final part involved in the assembly of the sensor machine

Figure 3.14 Field deployable wireless sensor network

3.2.11 Flowchart of the system

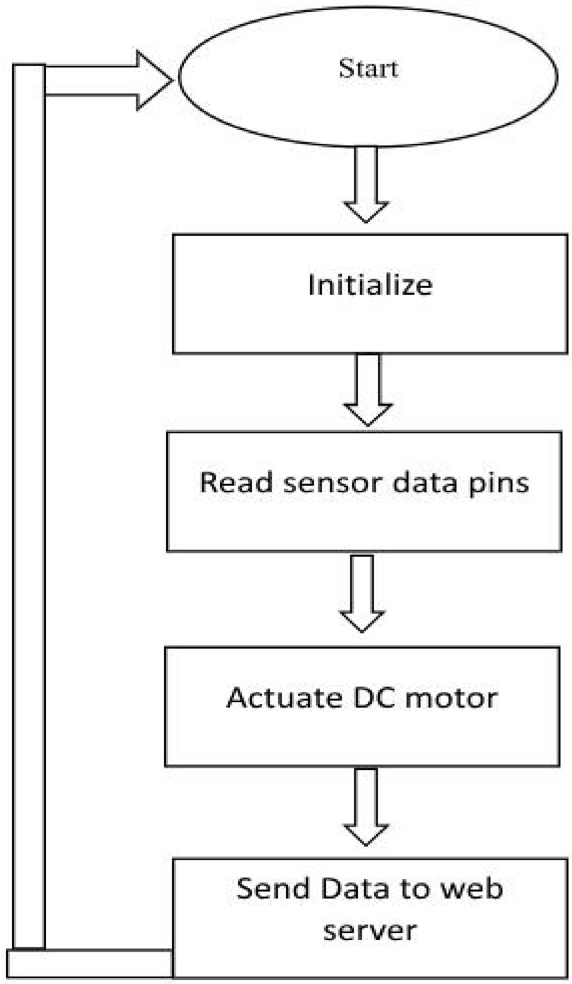


Figure 3.15 flow chart of the system

3.2.12 Working Principle of the System

The concept behind this system is the integration of wireless sensor matrices using some specific sensors for the sole purpose of detecting different factors that may signify corrosion in metal pipelines. The color sensor detects the surface color of the metal. The humidity sensor detects if the pipes are at high risk of corrosion. The resistance sensor checks the resistance across the surface of the metal. When the metal surface is exposed to chemical, it detects the presence of chlorine which can cause corrosion. Data from sensor analysis is then generated and extracted after metal samples for non-corroded metal and corroded metal have been tested and used to train a machine learning model. The model is going to draw an analysis based on data already generated and extracted. The first method is where we train it with a pipe that we are very certain that the low carbon steel pipe is none corroded and the integrity of the pipe has not been compromised in any way. Then it is in the second example when we use a low carbon steel pipe which is visually and clearly corroded. Therefore, with those two, systems fed into the model, the model is now capable of establishing the difference between the two. The model will clearly or be able to predict and give the percentage accuracy on that data for sure. This data will create a Support Vector Machine (SVM) model. The SVM model uses a linear regression method to align and draw map points across the data which can clearly be used to indicate when metals are corroded or are healthy. After creation of this model, a metal with an unknown corrosion feature is run through the system and data extracted. This data will be extracted and sent directly to the system. The model is then tasked to predict if the metal data that has been sent to it is healthy or corroded and if corroded, the percentage at which it has corroded.

3.2.13 Testing and Training process initiation

3.2.13.1 Acquisition of materials for data extraction

After design, the next phase of the operations was carried out which, due to the research of the most costless and available materials in engineering and pipeline applications as described by Adamczyk and Grajcar in 2007 are used for testing and training. The materials used are shown in the figure below

Figure 3.16 The corrosion free low Carbon Steel Pipe

Figure 3.17 The corroded low carbon steel pipe

3.2.13.2 Data extraction and Data verification

Data extraction has two phase i.e. one for non-corroded pipe and other for corroded pipe. The process requires that the specimen pipe is first placed on the designed machine and then the machine is turned on while the sensor has gone to and fro the specimen you keep on rotating the specimen till you have enough data entry. But while carrying out this process, there are few precautions you should note which are ensuring you handle the concentrated Hcl with care to avoid inhaling of the gas emitted, also ensuring you are well insulated from the chemical exposure. So when a total of 50 – 100 entries have been record, then the extraction process ends.

Data verification involves confirming that the data is been uploaded and received on the server the server discussed above. The sensor system was connected to the cloud-based IoT platform, ThingSpeak, which was used for real-time data logging and visualization. It contains a graph where you can visualize the data and verify that the data is been uploaded on the server just discussed and use in IoT and WSN based water quality monitoring system (Simitha & Raj., 2019). The data from the corrosion monitoring sensor can be accessed at

https://thingspeak.mathworks.com/channels/2486333."

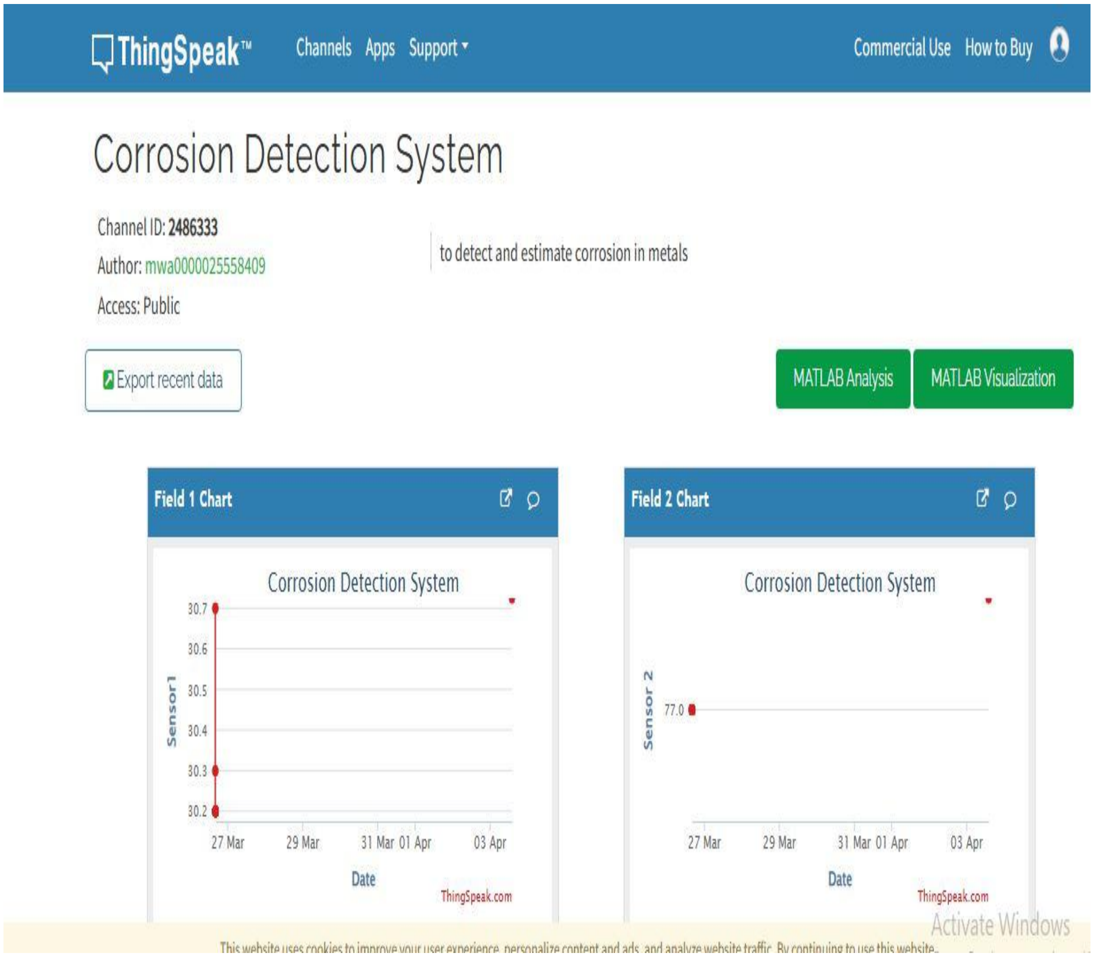


Figure 3.18 Thingspeak view

3.2.13.3 Data expotataion and training procedure

The first step we took was examining the data afterward, we exported it to Microsoft Excel and did our initial editing so that any faulty or inaccurate data is removed before testing or training, Then we load the data directly from excel to mat lab.

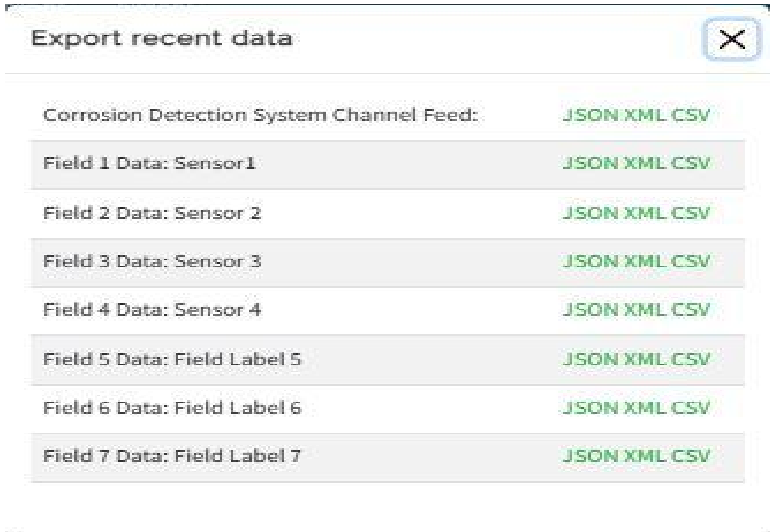


Figure 3.19 Exported data from thingspeak to excel

The data collected for the sensor network is for both corroded and non-corroded for the process of processing and visualization. The the next phase of the proess involves the Combination of all data tables and creating a label called Fault Status to differentiate faulty low carbon steel pipe data from healthy low carbon steel pipe,Visualizing new data table where status id with output 0 represent the non-corroded data while the other with output 1 represent the corroded data. Fault Status label is the target in predicting corrosion accurately from the pipe then the data is Splitted by mat lab into training and testing sets using SVM model discussed above then mat lab uses 80% for training and 20 % for testing. Train and Display the model

<u>SVM has the following classification and characteristics</u>

To support this project, an SVM model was created to identify corrosion conditions by using sensor data gathered in the field. 14 observations and 7 predictor factors were part of the dataset: temperature, humidity, resistance, chlorine concentration and the RGB color values.

Corrosion was indicated by the response variable as being present (1) or absent (0). A standard kernel was used with the SVM which was implemented using the Sequential Minimal Optimization (SMO) algorithm.

Reliability in the model was guaranteed by standardizing data using both the mean and standard deviation for all features. Support vectors and their corresponding Lagrange multipliers (Alpha) were used in the algorithm to help improve the desired classification boundary.

Based on the result obtained, we evaluated the Model by Predicting on the test data, Calculating performance metrics and providing a Plot for the confusion matrix

3.2.13.4 Machine learning model proceesing of New Data

With the following steps above, a new data can be extracted using apparatus designed above and the svm machine learning model can be used to predict the status. So this would require getting a sample pipe and undergoing the various extraction processes discussed in figure 4.2 and 4.3. then you follow the various steps here to test which are as follows

1. Load the trained SVM model,
2. Replace with your model file name and Extract the model from the loaded struct,
3. Load new data from an Excel file,
4. Ensure the file has columns: temperature, humidity, electrical resistance, chlorine concentration, and values of color intensity (red, green, and blue).
5. Replace with your Excel file name,
6. Display the first few rows to verify the data.

CHAPTER FOUR

4.0 RESULT AND DISCUSSION

4.1 Results

4.1.1 Data provided by WSN and exported to excel

Table III Low carbon steel corroded pipe

TEMPERATURE	HUMIDITY	RESISTANCE	CHLORINE	RED	GREEN	BLUE
30.8	78	4095	1273	185	238	205
30.8	78	4095	1200	182	236	203
30.8	78	4095	1215	179	233	202
30.8	78	4095	1246	177	232	201
30.8	77	4095	1229	175	229	198
30.8	77	4095	1264	172	226	196
30.8	77	4095	1302	171	224	194
30.8	77	4095	1180	171	224	193
30.8	77	4095	792	171	225	194
30.8	77	4095	1291	171	224	194
30.8	77	4095	1178	169	222	192
30.8	77	4095	1275	168	221	191
30.8	77	4095	1235	168	221	192
30.8	77	4095	1234	169	223	193
30.8	77	4095	1245	166	220	191
30.8	77	4095	1125	162	216	187
30.8	77	4095	1265	161	214	186
30.8	77	4095	1305	157	211	184
30.8	77	4095	1287	155	208	181
30.8	77	4095	1282	154	208	180
30.8	77	4095	1287	154	208	180
30.8	77	4095	1267	152	205	178
30.8	77	4095	1262	150	203	176
30.8	77	4095	1264	149	203	177

30.8	77	4095	1252	149	202	176
30.8	77	4095	1319	147	200	174
30.8	77	4095	1184	144	198	172
30.8	77	4095	1217	143	195	171
30.8	77	4095	1216	141	193	170
30.8	77	4095	1222	139	191	167
30.2	77	4095	1232	138	191	167
30.2	77	4095	1302	137	189	165
30.2	77	4095	1292	137	189	165
30.2	77	4095	1296	134	187	164
30.2	77	4095	1279	132	184	162
30.2	77	4095	1285	132	182	161
30.2	77	4095	1296	130	181	160
30.2	77	4095	1303	129	180	159
30.2	77	4095	1246	127	178	157
30.2	77	4095	1237	126	176	155
30.2	77	4095	1259	124	173	154
30.2	77	4095	1247	122	171	151
30.2	77	4095	1293	120	170	150
30.2	77	4095	1243	119	168	149
30.2	77	4095	1164	118	167	148
30.2	77	4095	1302	116	165	146
30.2	77	4095	1265	115	164	146
30.2	77	4095	1227	113	162	144
30.2	77	4095	1157	111	160	143
30.2	77	4095	1306	110	159	142
30.2	77	4095	1280	109	159	141
30.2	78	4095	1232	113	163	144
30.2	77	4095	1234	113	162	144
30.2	77	3232	1195	111	160	142
30.2	77	3390	1216	110	160	141
30.2	77	4095	1268	110	159	141

Table IV Low carbon steel corrosion free pipe

TEMPERATURE	HUMIDITY	RESISTOR	CHLORINE	RED	GREEN	BLUE
31.8	78	375	0	136	189	168
31.8	78	272	0	138	191	170
31.8	78	261	0	139	192	170
31.8	78	277	0	140	194	172
31.8	78	281	0	166	222	194
31.8	78	283	0	139	193	170
31.8	77	264	0	140	193	170
31.8	77	294	0	141	194	172
31.8	77	279	0	139	191	169
31.8	77	256	0	142	196	173
31.8	77	240	0	144	198	174
31.8	77	269	0	145	199	175
31.8	77	264	0	145	198	174
31.8	77	320	0	146	198	174
31.8	76	318	0	147	199	176
31.8	76	290	0	150	204	180
31.8	76	306	0	151	204	180
31.8	77	319	0	151	205	180
31.8	77	309	0	153	206	182
31.8	76	324	0	155	210	184
31.8	76	297	0	158	212	186
31.8	76	414	0	160	215	188
31.8	76	400	0	160	212	186
31.8	76	382	0	166	220	192
31.8	76	400	0	167	219	192
31.8	76	374	0	171	226	198
31.8	76	430	0	173	228	198
31.8	76	410	0	174	229	199
31.8	76	354	0	173	227	197
31.8	76	366	0	170	223	194

31.8	76	346	0	172	226	196
31.3	76	714	0	171	225	196
31.3	77	690	0	168	222	193
31.3	77	674	0	167	219	191
31.3	77	363	0	167	219	192
31.3	77	356	0	168	223	194
31.3	77	384	0	168	224	196
31.3	77	339	0	169	225	196
31.3	77	345	0	166	220	191
31.3	77	353	0	167	220	192
31.3	77	357	0	166	219	191
31.3	78	368	0	166	218	190
31.3	78	353	0	166	219	191
31.3	78	375	0	167	221	192
31.3	78	367	0	167	222	193
31.3	78	368	0	168	222	195
31.3	78	223	0	162	217	190
31.3	78	202	0	164	218	191
31.3	79	188	0	165	219	191
31.4	79	205	0	170	223	195
31.8	79	207	0	168	222	194
31.8	79	175	0	170	223	195
31.8	79	208	0	170	222	195
31.8	79	222	0	169	219	192
31.8	79	207	0	169	219	192
31.8	79	180	0	169	219	192
31.8	79	219	0	168	218	191
31.8	79	203	0	167	218	191
31.8	79	199	0	168	219	192
31.5	79	227	0	168	218	191
31.3	79	210	0	170	222	194

Display the first few rows of the table to understand its structure

Table V Loaded data of Low carbon steel corroded pipe

TEMPERATURE	HUMIDITY	RESISTANCE	CHLORINE	RED	GREEN	BLUE
30.8	78	4095	1273	185	238	205
30.8	78	4095	1200	182	236	203
30.8	78	4095	1215	179	233	202
30.8	78	4095	1246	177	232	201
30.8	77	4095	1229	175	229	198
30.8	77	4095	1264	172	226	196
30.8	77	4095	1302	171	224	194
30.8	77	4095	1180	171	224	193

Table VI Loaded data of low carbon steel corrosion-free pipe

TEMPERATURE	HUMIDITY	RESISTOR	CHLORINE	RED	GREEN	BLUE
31.8	78	375	0	136	189	168
31.8	78	272	0	138	191	170
31.8	78	261	0	139	192	170
31.8	78	277	0	140	194	172
31.8	78	281	0	166	222	194
31.8	78	283	0	139	193	170
31.8	77	264	0	140	193	170
31.8	77	294	0	141	194	172

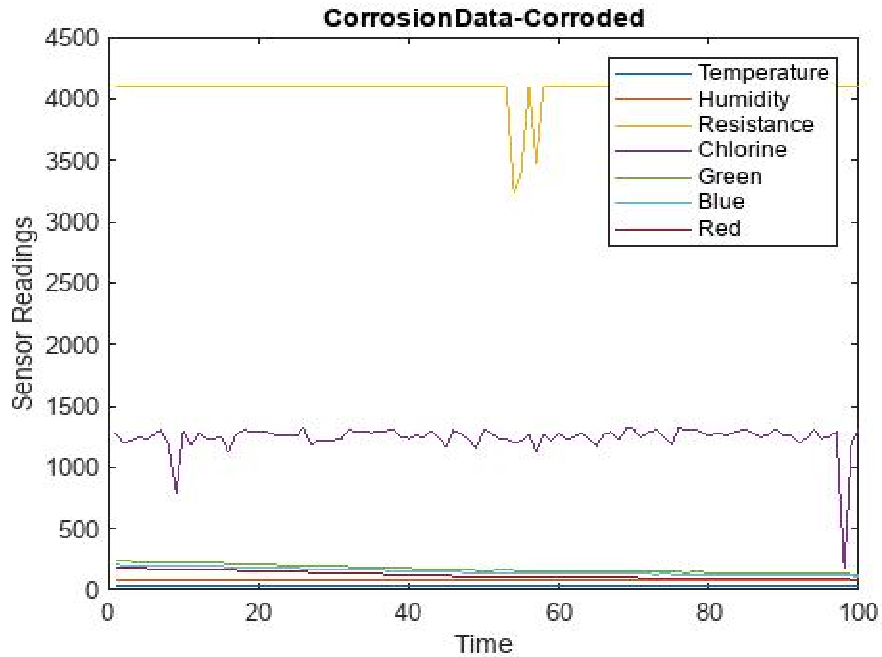


Figure 4.1 the graph of corroded low carbon steel pipe

The graph displayed above in figure 4.1 shows that the resistance values from the corroded sample fluctuate only slightly over time Additionally, the chlorine level ranged between (1000–1500) ppm, suggesting a significant emission of chlorine gas from the corroded steel pipe.

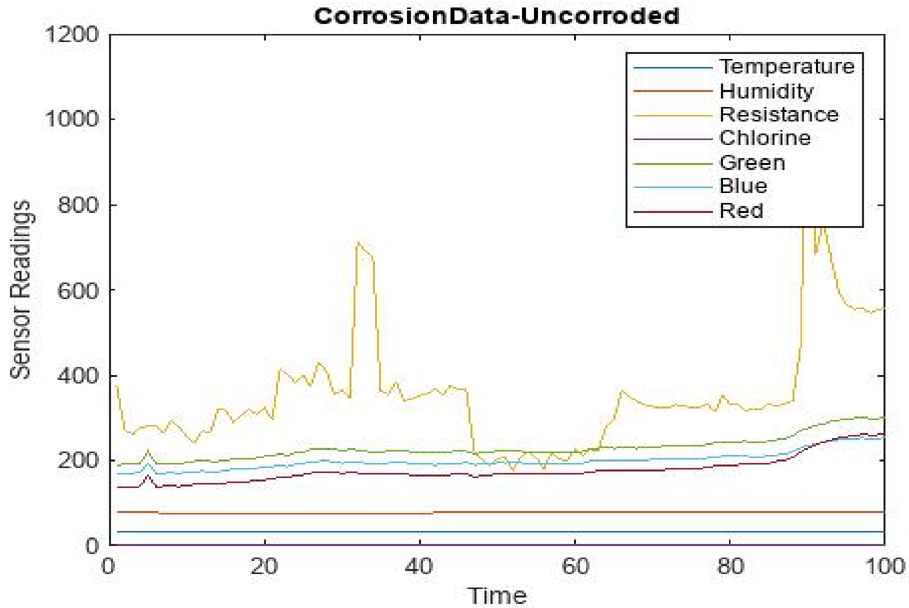


Figure 4.2 the graph of non-corroded low carbon steel pipe

The graph displayed in figure 4.2 shows a significant drop in resistance in the non-corroded data, with values falling below 1000 Ohms, unlike in Figure 4.1. No chlorine data is indicated in this case.

Table VII Low carbon steel pipe data training model

TEMPERATURE	HUMIDITY	RESISTANCE	CHLORINE	RED	GREEN	BLUE	STATUS ID
30.8	78	4095	1273	185	238	205	1
30.8	78	4095	1200	182	236	203	1
30.8	78	4095	1215	179	233	202	1
30.8	78	4095	1246	177	232	201	1
30.8	77	4095	1229	175	229	198	1
30.8	77	4095	1264	172	226	196	1
30.8	77	4095	1302	171	224	194	1
30.8	77	4095	1180	171	224	193	1
TEMPERATURE	**HUMIDITY**	**RESISTOR**	**CHLORINE**	**RED**	**GREEN**	**BLUE**	**STATUS ID**

31.8	78	375	0	136	189	168	0
31.8	78	272	0	138	191	170	0
31.8	78	261	0	139	192	170	0
31.8	78	277	0	140	194	172	0
31.8	78	281	0	166	222	194	0
31.8	78	283	0	139	193	170	0
31.8	77	264	0	140	193	170	0
31.8	77	294	0	141	194	172	0

Once the model was trained and validated, it managed to identify corroded and non-corroded samples with a classification accuracy of 98.33%. according to the process in 3.2.13.3. After the training was concluded, 20% that was extracted for testing was used and it gave accuracy of 98.33% and further analysis concerning this model is shown in the performance metrics as shown below.

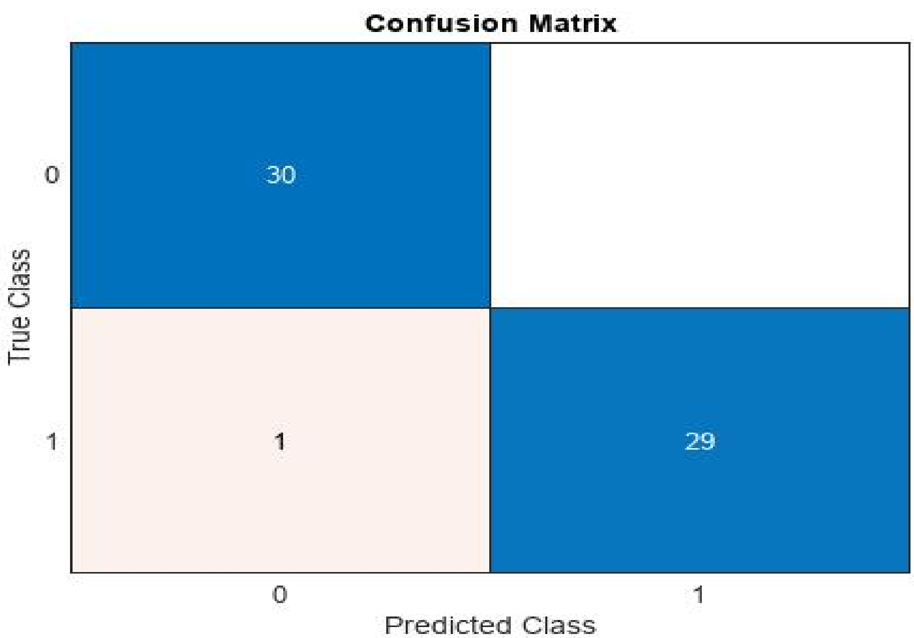


Figure 4.3 The performance metrics

This diagram displayed in figure 4.3 show that 30 of the predicted data was actually predicted correctly for corrosion-free low carbon steel pipe known as uncorroded on the graph below while 29 of the predicted data for corroded low carbon steel pipe were predicted correctly but 1 incorrectly.

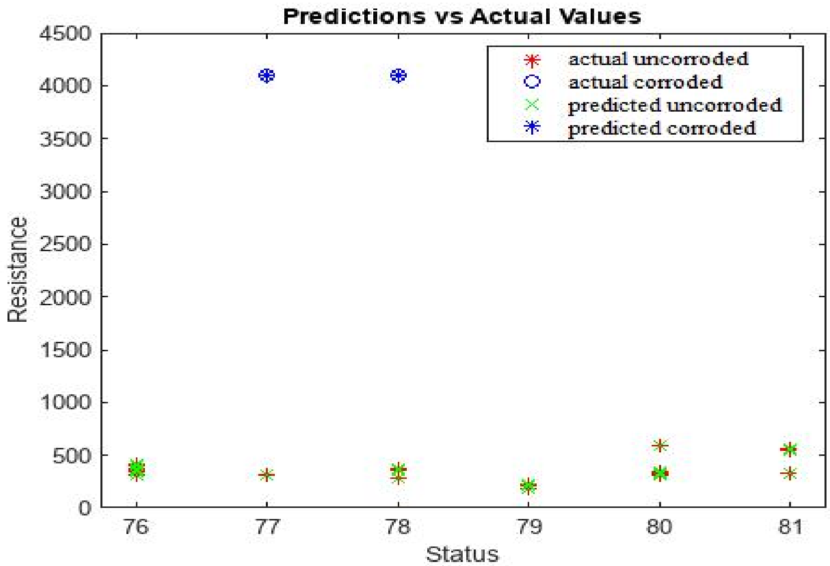


Figure 4.4 The scattered plot for resistance

This graph displayed in figure 4.4 shows correct prediction for resistance where both the actual values and predicted values were accurate and precise, matching on the graph above

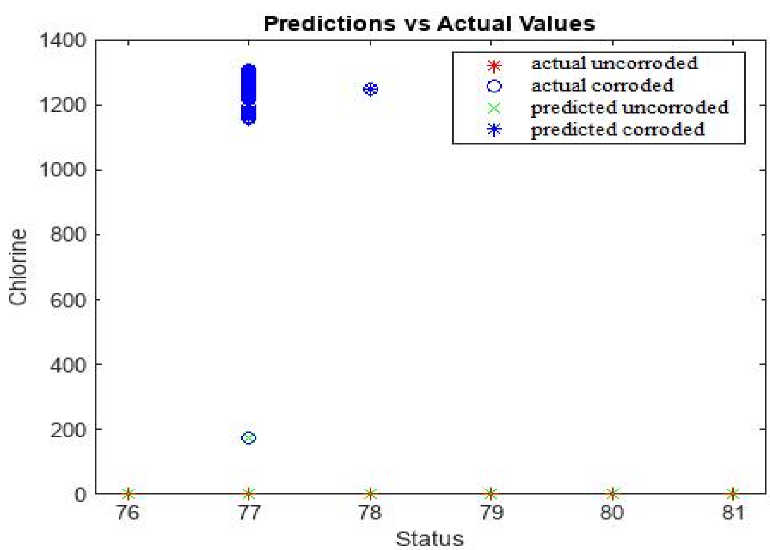


Figure 4.5 The scattered plot for chlorine

This graph displayed in figure 4.5 shows correct prediction for chlorine but one misclassification stating only incorrect value that was spotted on the graph which was actual corroded but predicted uncorroded

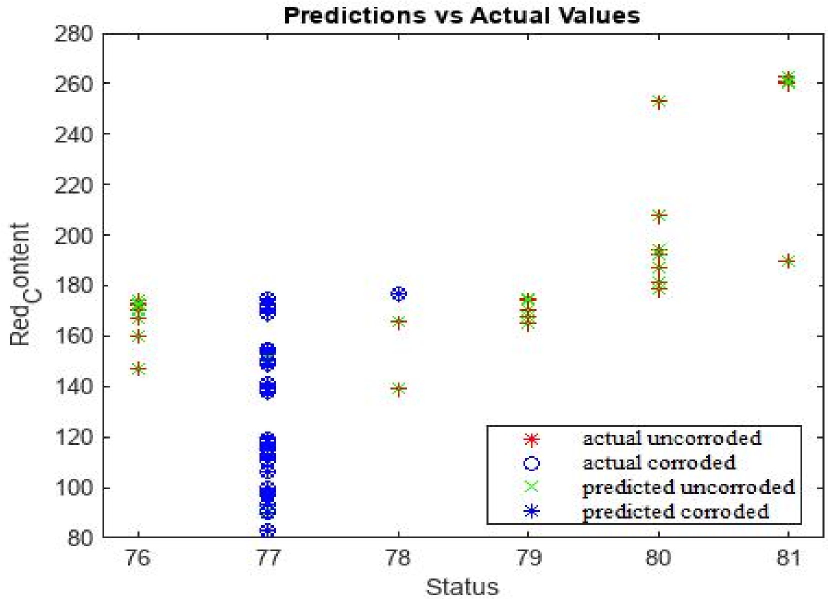


Figure 4.6 The scattered plot red colour

This graph displayed in figure 4.6 shows correct prediction for red colour where both the actual values and predicted values were accurate and precise, matching on the graph above

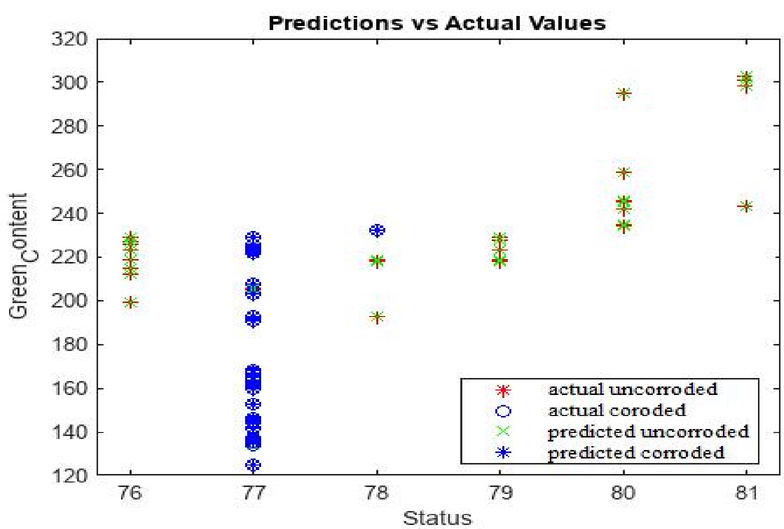


Figure 4.7 The scattered plot for green colour

This graph displayed in figure 4.7 correct prediction for green colour where both the actual values and predicted values were accurate and precise, matching on the graph above

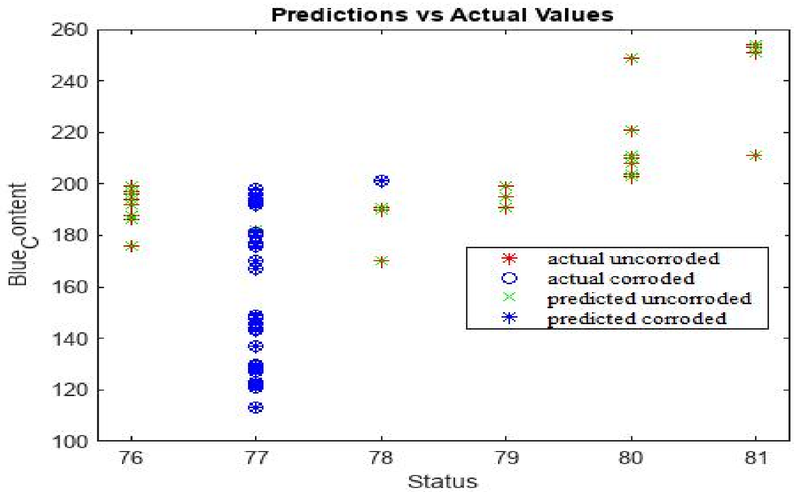


Figure 4.8 The scattered plot for blue

This graph displayed in figure 4.8 correct prediction for blue colour where both the actual values and predicted values were accurate and precise, matching on the graph above

The new data collected for the model is as follows:

Table VIII visualization of new data

TEMPERATURE	HUMIDITY	RESISTANCE	CHLORINE	RED	GREEN	BLUE
30.2	77	4095	1306	83	125	113
30.2	77	4095	1200	86	130	117
30.2	77	4095	1275	97	233	127
30.2	77	4095	1246	97	142	127
30.2	77	4095	1229	97	142	128
30.2	77	4095	1265	95	139	125
30.2	77	4095	1317	94	138	124
30.2	77	4095	1258	93	137	122

Following the formulation and training of a Support Vector Machine (SVM) classification model, the model was subsequently employed on an independent dataset to evaluate its effectiveness in predicting corrosion status based on sensor-derived inputs. The dataset comprised 40 distinct samples, each incorporating relevant environmental and material-related characteristics, including temperature, humidity, electrical resistance, chlorine concentration, and values of color intensity (red, green, and blue).

Before the prediction phase commenced, the dataset underwent a rigorous validation process to confirm that all necessary input parameters were present for each data entry. Subsequently, the model executed an analysis of each individual entry and anticipated whether the sample demonstrated signs of corrosion (designated as 1) or the absence thereof (designated as 0).

The findings derived from the model were as follows:

Samples 1 through 20 were categorized as corroded (status = 1).

Samples 21 through 40 were categorized as uncorroded (status = 0).

This result articulates a clear classification of the dataset into two distinct categories: corroded and uncorroded samples.

Table IX result of New data

Parameter	**Value**
Total number of predictions	40
Corroded predictions (1)	20 samples
Corrosion-free predictions (0)	20 samples
Percentage corroded	50.00%
Percentage corrosion-free	50.00%

4.2 Discussion

4.2.1 Interpretation of Sensor Data and Relationship Between Sensor Readings and Corrosion Process

The graph shows that the resistance values from the corroded sample fluctuate only slightly over time. The measured chlorine concentration during this period indicates that a large quantity of chlorine gas is emanating from the corroded steel pipe. At the same time, the graph for the non-corroded sample registers a lower resistance reading, going as low as 1000, and no trace of chlorine was detected.

The result provided above in between figure 4.1 and 4.2 highlight distinct changes in sensor readings that correlate with the presence or absence of corrosion. These changes are indicative of the electrochemical and physical transformations occurring during corrosion. Firstly the result indicates a significant difference in resistance between uncorroded and corroded samples.

Corroded samples exhibit a substantial high level in resistance compared to uncrowded ones. This observation aligns with the principle discussed in chapter 2 that Corrosion degrades the metal, reducing the cross-sectional area available for current flow. It forms non-conductive oxide that impede current. This leads to increased resistance.

The result also shows that chlorine levels are noticeably higher in the corroded state. This suggests that chlorine is involved in the corrosion process, potentially as a byproduct or a contributing factor in the electrochemical reactions. Where the electrochemical sensor was able to detect a high level of chlorine involving from the corroded sample because of the formation of iron oxide

The result shows colour sensor reading includes red, green, and blue light sensor data, which are affected by the color changes associated with corrosion. Though no significant different seen in figure 4.1 and 4.2 compared to the other sensor readings because of the appearances of both samples. Corrosion often leads to the formation of oxidation products (e.g., rust), which alter the surface color of materials as stated in chapter 2, figure 2.5 and also for the humidity and temperature sensor because the model has not yet been applied on a real field.

4.2.2 Evaluation of Model Performance:

The SVM model classified 59 out of 60 samples. So further analysis can be seen in the scattered plot below where we analyse each data extracted showing the prediction in each column. The scattered plot is used to show the predicted value over the actual value of each data column. These plots visually represent the SVM model's performance in classifying corrosion status (corroded or corrosion-free) based on different sensor parameters. Data Points means Represent samples. Markers**:** Show actual (ground truth) and predicted corrosion status (corroded/uncorroded).Axes means X-axis is sample status; Y-axis is sensor reading. Interpretation means Overlapping predicted and actual markers indicate correct classifications; non-overlapping markers indicate misclassifications; yielding an overall accuracy of 98.33%. This can be evidenced on the result above in figure 4.3. The high accuracy of 98.33% reported in this work and study is consistent with findings from other research studies and works which have highlighted the efficacy of SVMs in predictive maintenance especially Kustiana *et al* study in 2024, the SVM model created could recognize normal from damaged conditions with an average of 97% accuracy. Also corresponding with Liu *et al* work in 2019, with 4G uplinked sensors. it was able to properly identify leaks or non-leaks 98% of the time. Also inlign with previous work carried out by Nikfar, Bitencourt and Mykoniatis in 2022, they carried out a two-step machine learning system for detecting faults and classifying them in low-voltage industrial motors using vibration data. In Phase 1, when they used the SVM to detect abnormalities, it showed very good performance on the three datasets, with two completing the tasks without error and the third having only minor errors. Because its performance was better than that of backpropagation neural network (98.75%) and random forest (96.25%), SVM was selected as the best option for phase two of the system. In Phase 2, they focused on identifying faults and the SVM algorithm produced accuracies of 95.23% and 90.48% on B-1 and B-2, respectively.Also following Ismail *et al* in 2023, they observed corrosion by using sensors on WSN nodes; afterwards, they made predictions about corrosion level by running these observations through Support Vector Machines. Outcomes from SVMs in this field are impressive, with accuracy often surpassing 90–95% on tests in labs. This high performance demonstrates the SVM's ability to capture and leverage the patterns in the sensor data (temperature, humidity, and resistance, chlorine, and RGB colour values) to distinguish between corroded and corrosion-free samples. SVMs are well-suited for problems involving multiple input features. In the current case, the model performed a combination of environmental and visual sensor data well. The ability of SVM to function in high dimensional spaces probably assisted in the outstanding marking of the non-linearly separable corrosion patterns in the initial feature space. The dataset's cleanliness and balance further enhanced the model's learning process. The model misclassified one corroded sample as uncrowded (false negative) clearly shown in the confusion matrix seen in figure 4.6. This kind of error is especially problematic in the context of corrosion detection, as missing detection of corrosion, therefore, can result in the lack of detection of structural damage or failure. Possible causes of such error are Sensor noise or an ambiguous corrosion state in that sample Feature values of the misclassified samples may overlap strongly with that of uncorroded ones, leading to confusion In practical applications such as monitoring of pipes or infrastructure, a false negative would allow corrosion to progress unnoticed thereby threatening safety. The Support Vector Machine (SVM) model's ability to correctly classify all newly introduced samples as we see above with 40 samples where 50% were both corroded and non-corroded sample reinforces its generalizability.The model proficiently and uniformly categorized each of the 40 samples concerning their corrosion status. Given that the prediction results exhibited an equivalent quantity of corroded and corrosion-free samples, it is evident that the model exhibits no bias towards either classification. In practical applications, the consequences of erroneously detecting corrosion when it is absent, or conversely, failing to detect existing corrosion, can be profoundly detrimental. Moreover, the findings substantiate that this model can facilitate rapid decision-making in location When the early detection of corrosion is paramount, particularly in the contexts of infrastructure, pipelines, or marine apparatus, such a system enables enhancements in maintenance scheduling, reductions in inspection expenditures, and the prevention of structural failures.

4.2.3 Implications for Corrosion Monitoring

From the results of this Studies, there is the real feasibility of the use of an inexpensive wireless sensor system for the monitoring of corrosion both in the fixed and mobile situations. For permanent deployment- industrial facilities, oil refineries or storage tanks, among others, but this system can provide 24-hour monitoring on an automatic mode without having to check on them as humans do according to what was discussed in chapter about WSN in 2.11. It quietly and efficiently gathers key data such as temperature, humidity, electrical resistance, chlorine levels, and even color changes (via red, green, and blue values). Because it's wireless setting it up is easy and there is no need to spend huge money on cabling and systems that are costly. This system also works out well in the moving or shift situations like the inspection of pipelines, remote installations or even the offshore platforms. It can be readily deployed; it's light and affordable; hence it can be applied where it would be too bulky or too expensive to use classic variants or where any sensor can simply be challenging to install. It has a wireless capability, hence it can send data back in real time; thus it is suitable for field inspection where portable kits or even drones are used.

This system becomes all the more powerful because of its use of machine learning. The support vector machine (SVM) model we developed was able to correctly identify corrosion with 98.33% accuracy. It would mean that it will be used in the identification of the problems before they turn into serious failures. Saving time and money, and also reducing the likelihood of accidents or pollution. It is a benefit that is very clear compared to the traditional techniques for monitoring corrosion. Through the years this has been done using traditional methods that most of the times involved scheduled manual inspection that tended to overlook early signs of corrosion. Our system, on the contrary, monitors and it notifies the users if something changes. Manual inspections are often expensive and time-consuming. This system is also cheap to maintain it is also low cost and further does not require the constant human intervention. It also collects richer data more often to allow it to make smart, informed decisions. In particular, the system is capable of covering such areas that might be dangerous or difficult to get for people.

Through overall, this solution takes an intelligent way of controlling corrosion. It moves away from the old visual approach and instead supports a proactive maintenance strategy. Whether it's watching over a fixed structure day after day or quickly checking out a remote site, this system provides timely, accurate information to help make better maintenance decisions.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATION

5.1 Conclusion

From the results obtained, the following conclusions were made:

Through detailed sensor analysis and data interpretation, it was observed that electrical resistance and chlorine concentration serve as reliable indicators of corrosion. Corroded samples consistently exhibited higher resistance values and elevated chlorine levels, aligning with known electrochemical corrosion processes. Although color, temperature, and humidity sensors provided supporting data, their influence was less significant in controlled environments but still valuable when applied in field conditions.

The Support Vector Machine (SVM) model developed for classification achieved an outstanding accuracy of 98.33%, successfully distinguishing between corroded and uncorroded samples across both training and new datasets. The model's performance was consistent with findings from previous research and was further validated through confusion matrices and scatter plots, which illustrated a near-perfect classification outcome, with only one instance of misclassification. Importantly, the model displayed no classification bias, correctly predicting an equal number of corroded and corrosion-free samples in the test dataset, underscoring its generalizability and robustness.

From a practical standpoint, this system demonstrates the feasibility and effectiveness of using inexpensive, wireless technologies for continuous corrosion monitoring**.** Its autonomous operation, real-time data transmission**,** and integration of intelligent analytics position it as a valuable alternative to traditional corrosion monitoring methods, which are often manual, costly, and less timely. Moreover, the system's adaptability to both fixed and mobile deployments—including industrial sites, offshore platforms, and remote pipelines—makes it a scalable and versatile solution.the project represents a significant advancement toward smarter, safer, and more sustainable infrastructure maintenance. It transitions corrosion management from reactive to **proactive**, empowering stakeholders with timely insights that can prevent structural failures, reduce maintenance costs, and enhance operational safety. This work lays the foundation for future enhancements in low-cost sensor design, edge-computing integration, and real-time decision-making frameworks, further solidifying its relevance in industrial and environmental monitoring applications.

5.2 Recommendations

Having conducted some research and carried-out the development of a field deployable corrosion monitoring and detection using wireless sensor network composed of four major sensors which are the resistor sensor probe, humidity and temprature sensor, electrochemical sensor, and the colour sensor for data collection. Also making use matlab for data comparison between pipes and machine learning model for training and testing. The following recommendations should be considered:

1. In order to fully realise the potential of the model, it should be incorporated in a small, on-site device, which will be capable of monitoring corrosion in real-time. Through wireless sensor network, engineers and technician can be updated in a timely manner once corrosion is about to begin.

2. The better the model gets based on the number of data that it has seen. Gathering other samples in diverse weather scenarios and from diverse materials will help the system gain knowledge of detecting corrosion in a variety of conditions especially for the effectiveness of the humidity and temperature sensor.

3. Some extra tweaking—like creating new combinations of existing data (for example, comparing humidity to resistance)—can help the model perform better. It's also important to regularly calibrate the sensors so the data stays reliable over time.

4. Although the SVM model works fine, it is a good idea to compare it to other machine learning techniques such as Random Forests or Neural Networks. This may cause even better accuracy or faster predictions.

5. A short and straightforward interface would do to make the system convenient to the grass-roots munitions users. Automatic alerts through SMS or email whenever corrosion is detected would aid to ensure prompt action taken.

6. To verify the efficiency of the system in a not lab environment, it should be tested in the field, and for a long period of time. By comparing the model's prediction with manual inspections, one will be able to prove its reliability in actual conditions.

7. Applications of other sensor network such as acoustic emission sensor,pressure sensor and galvanic sensor in predicting corrosion attack.

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APPENDIX

```
#include <Wire.h>

#include <LiquidCrystal_I2C.h>

#include <WiFi.h>

#include <ThingSpeak.h>

#include "DHT.h"

// LCD setup

LiquidCrystal_I2C lcd(0x27, 16, 2);

// WiFi credentials

const char* ssid = "MTN_4G_47C5D0";

const char* password = "5436F8BD";

// ThingSpeak API

unsigned long myChannelNumber = 2486333;

const char* myWriteAPIKey = "89OFYNKDUWBVTPCR";

// Sensor pins

#define DHTPIN 4

#define DHTTYPE DHT11

#define RESISTIVE_SENSOR_PIN 34

#define CHLORINE_SENSOR_PIN 35  // LM358 output connected here

#define COLOR_SENSOR_S1 15

#define COLOR_SENSOR_S0 5

#define COLOR_SENSOR_S2 19

#define COLOR_SENSOR_S3 23

#define COLOR_SENSOR_OUT 18

#define MOTOR_ENA 14

#define MOTOR_IN1 27
```

```
#define MOTOR_IN2 26
#define leftendstop 17
#define rightendstop 16
DHT dht(DHTPIN, DHTTYPE);
WiFiClient client;
float lastTemperature = -1;
float lastHumidity = -1;
int lastResistiveValue = -1;
int lastChlorineValue = -1;
int lastRedValue = -1;
int lastGreenValue = -1;
int lastBlueValue = -1;
int Diright, Dirleft;
void setup() {
  Serial.begin(115200);
  lcd.init();  // Initialize LCD
  lcd.backlight();
  lcd.setCursor(0, 0);
  lcd.print("APPARATUS FOR");
  lcd.setCursor(3, 1);
  lcd.print("CORROSION");
  delay(2000);
  lcd.clear();
  lcd.setCursor(3, 0);
  lcd.print("DETECTION");
  lcd.setCursor(1, 1);
  lcd.print("IN METAL PIPES");
  delay(3000);
  lcd.clear();
```

```
  lcd.setCursor(0, 0);
  lcd.print("PLS Connect WiFi");
  pinMode(MOTOR_ENA, OUTPUT);
  pinMode(MOTOR_IN1, OUTPUT);
  pinMode(MOTOR_IN2, OUTPUT);
  WiFi.begin(ssid, password);
  pinMode(leftendstop, INPUT);
  pinMode(rightendstop, INPUT);
  while (WiFi.status() != WL_CONNECTED) {
    delay(1000);
    Serial.println("Connecting...") }
  lcd.clear();
  lcd.print("WiFi Connected");
  delay(2000);
  dht.begin();
  ThingSpeak.begin(client);
  // Set color sensor pins
  pinMode(COLOR_SENSOR_S2, OUTPUT);
  pinMode(COLOR_SENSOR_S3, OUTPUT);
  pinMode(COLOR_SENSOR_OUT, INPUT);
  digitalWrite(MOTOR_IN1, HIGH);
  digitalWrite(MOTOR_IN2, LOW);}
void loop() {
  float temperature = dht.readTemperature();
  float humidity = dht.readHumidity();
  int resistiveValue = analogRead(RESISTIVE_SENSOR_PIN);
  int chlorineValue = analogRead(CHLORINE_SENSOR_PIN);
  int redValue = readColor(LOW, LOW);
  int greenValue = readColor(HIGH, HIGH);
```

```
int blueValue = readColor(LOW, HIGH);
// Update the LCD only when values changelcd.clear();
    lcd.clear();
    lcd.setCursor(0, 0);
    lcd.print("Temp: "); lcd.print(temperature);
    lastTemperature = temperature;
lcd.setCursor(0, 1);
    lcd.print("Humd: "); lcd.print(humidity);
    lastHumidity = humidity;
delay(2000);
    lcd.clear();
    lcd.setCursor(0, 0);
    lcd.print("Res: "); lcd.print(resistiveValue);
    lastResistiveValue = resistiveValue;
    lcd.setCursor(0, 1);
    lcd.print("Chlr: "); lcd.print(chlorineValue);
    lastChlorineValue = chlorineValue;
delay(2000);
   lcd.clear();
    lcd.setCursor(0, 0);
    lcd.print("R:"); lcd.print(redValue);
    lcd.print(" G:"); lcd.print(greenValue);
    lcd.setCursor(0, 1);
    lcd.print("B:"); lcd.print(blueValue);
    lastRedValue = redValue;
    lastGreenValue = greenValue;
    lastBlueValue = blueValue;
 // Send data to ThingSpeak if connected
if (WiFi.status() == WL_CONNECTED) {
```

```
    ThingSpeak.setField(1, temperature);
    ThingSpeak.setField(2, humidity);
    ThingSpeak.setField(3, resistiveValue);
    ThingSpeak.setField(4, chlorineValue);
    ThingSpeak.setField(5, redValue);
    ThingSpeak.setField(6, greenValue);
    ThingSpeak.setField(7, blueValue);
    int response = ThingSpeak.writeFields(myChannelNumber, myWriteAPIKey);
    if (response == 200) {
      Serial.println("Data sent to ThingSpeak"); } else {
      Serial.println("Failed to send data to ThingSpeak. Retrying...");
      delay(5000);  // Retry after 5 seconds    }}
  delay(18000);  // Send data every minute
  digitalWrite(MOTOR_ENA, HIGH);
  Dirleft = digitalRead(leftendstop);
  if(Dirleft == HIGH)  {
  digitalWrite(MOTOR_IN1, HIGH);
  digitalWrite(MOTOR_IN2, LOW);   }
    Diright = digitalRead(rightendstop);
  if(Diright == HIGH) {
  digitalWrite(MOTOR_IN1, LOW);
  digitalWrite(MOTOR_IN2, HIGH);  }
  delay(2000);  // Send data every minute
  digitalWrite(MOTOR_ENA, LOW); }
int readColor(int s2State, int s3State) {
  digitalWrite(COLOR_SENSOR_S2, s2State);
  digitalWrite(COLOR_SENSOR_S3, s3State);
  delay(10);
  return pulseIn(COLOR_SENSOR_OUT, LOW); ,}
```