Developing intelligent and interactive HVAC pipe network system

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Developing Intelligent and Interactive HVAC Pipe Network System

by

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Finally, I like to remember those who we have lost during this difficult time.

Abstract

There is abundant evidence that greenhouse gas (GHG) emissions and global warming have resulted in unpredictable and extreme weather patterns. According to the literature, buildings consume approximately 40% of the world's energy due to increased demand for heating and cooling systems. Academics, researchers, stakeholders, and policymakers have turned their attention to energy-efficient buildings in an effort to reduce energy consumption and GHG emissions. As a result, in order to mitigate this effect, the UK government has set an ambitious target of reducing CO2 emissions by at least 80% from 1990 to 2050. Whereas the Climate Change Act, as amended in 2019, commits the UK to achieving "net zero" emissions by 2050.

Temperatures below 2°C are the global targets required to reduce GHG emissions, which is critical and necessitates the development of a performance monitoring model of the heating, ventilation, and air conditioning (HVAC) pipe network system. Research on HVAC pipe networks and their performance prediction is still limited, particularly in predicting the future effect of corrosion in steel HVAC pipe performance using experimental and field data to develop a model. There has been very little research into the use of transparent HVAC design and maintenance systems to predict the effect of corrosion in pipe. Corrosion is a major factor that affects pipe performance, and predicting it is difficult due to the interlink system of steel pipe.

This study looks into the factors that influence pipe performance in high energy demand buildings in terms of corrosion in pipe network systems. The study also examines how temperature, pressure, galvanic current, and corrosion rate affect energy consumption in HVAC pipe networks. This research was carried out in two stages. The first phase was accomplished through laboratory experiment classification of collected data in order to identify the most influential individual rigs that designed and built the study elements that influence the corrosion rate in steel HVAC pipe network.

The second phase concentrated on developing a Machine Learning model with the help of BIM model data to develop an ANN model to predict corrosion level and, as a result, the process of linking to VR visualisation. Through laboratory experiments, this AI approach is based on the artificial neural network (ANN) feed forward neural network model. To ensure optimal HVAC systems, a black box model based on ANN was developed to predict the performance of the off pipe network and determine early prevention. Simultaneously, validation analysis was carried out to provide evidence for the model's validity in ANN using 30% laboratory data.

The research results in a validated toolkit for predicting HVAC pipe performance in terms of an ANN model that predicts corrosion rate in steel pipe while maintaining pipe performance. The study found that an ANN validated model had 98 percent accuracy of Performance Predicting Model (PPM) data, resulting in an efficient HVAC system development that allows for a predictive model. By developing a visualisation platform using the Validation Performance Model (VPM) with VR linked to BIM, this study has created novel knowledge in pipe performance.

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Nomenclature

Abbreviations

Abbreviation	Meaning
ARMA	autoregressive moving average
HVAC	Heating, Ventilation and Air Conditioning
FDD	Fault Detection and Diagnosis
GHGs	Greenhouse Gases
AI	Artificial Intelligence
VR	Virtual Reality
MAS	Multi-agent system
PID	Proportional-integral-derivative
ANN	Artificial Neural Network
LSTM	Long Short Term Memory
RNN	Recurrent Neural Network
SNN	Spiking Neural Network
kNN	k-Nearest Neighbours
ARX	Autoregressive Exogenous
HMM	Hidden Markov models
MPC	Model predictive controller
GRU	Gated Recurrent Unit
DL	Deep Learning
ML	Machine Learning
GAN	Generative Adversarial Network
ACO	Ant Colony Optimization

GA	Genetic Algorithm
SVM	Support Vector Machines
PSO	Particle Swarm Optimization
BIM	Building Information Modeling
CPVC	chlorinated polyvinyl chloride
KBS	Knowledge based system
SNN	Spiking Neural Network
MAS	Multi-agent system
FLC	Fuzzy logic controller
AHU	Air Handling Unit
POEM	Power-Efficient Occupancy-Based Energy Management
DRL	Deep reinforcement learning
LPR	Linear polarization resistance
EN	Electrochemical noise
EIS	Electrochemical impedance spectroscopy
UT	Ultrasonic testing
FOTS	Fiber optic temperature sensor
ARIMA	Autoregressive Integrated moving average

List of Publications

Publication 1:

Predicting Corrosion rate in Chilled HVAC Pipe Network: Coupon vs Linear Polarisation Resistance method

Durrani, F., Wesley, R., Srikandarajah, V., Eftekhari, M., & Munn, S. (2020). Predicting corrosion rate in chilled HVAC pipe network: Coupon vs linear polarisation resistance method. Engineering Failure Analysis, 109, 104261.

Chapter 1 Introduction

This chapter focused on the existing knowledge developing an efficient HVAC system for low carbon emission levels contribute to global warming mitigation.

1.1. Background

Global greenhouse gas (GHG) emissions have risen dramatically in recent decades. Energy resources are depleting as the world's population grows and energy consumption rises. The depletion of fossil fuels and the rise in GHG emissions have sparked interest in energy-efficient solutions to reduce reliance on oil and gas fuel technologies (Vatougiou et al., 2018).

Buildings account for approximately 30% of the global CO_2 emissions and 40% of energy used by Heating, Ventilation and Air Conditioning (HVAC) systems for humidification and dehumidification. Buildings, for example, account for approximately 40% of global energy consumption and approximately 36% of GHG emissions in the European Union (M. W. Ahmad et al., 2016). Similarly, 39% of the UK's total energy consumption is used in buildings, while they account for 41.7% of the country's total energy consumption in the United States. This is the case in several advanced countries, including China and India; Figure 1.1 for the countries with the highest GHG emissions.

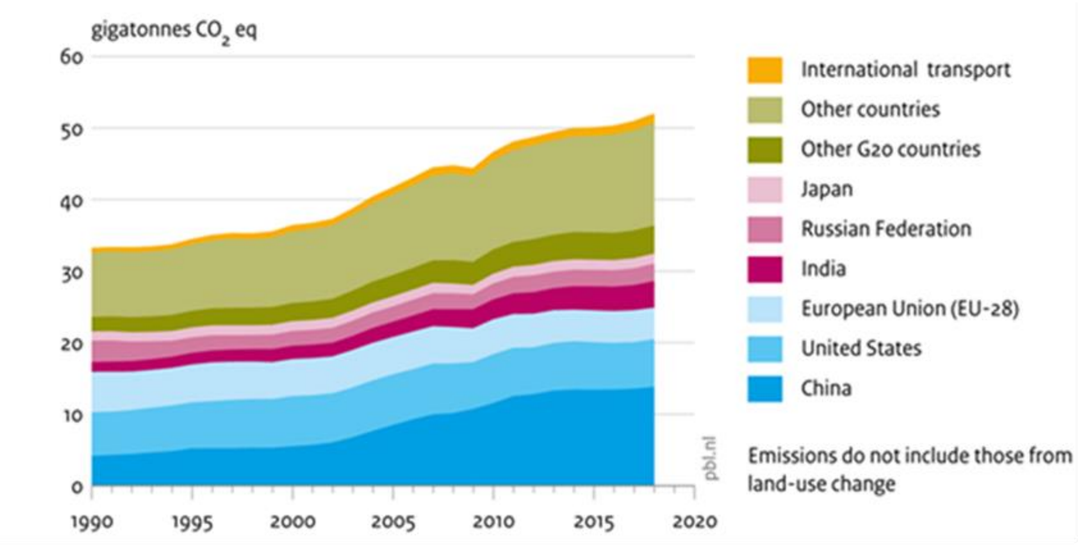

Figure 1.1 Global CO_2 emission (Adapted from EC-JRC/PBL, 2016)

HVAC are components linked together to regulate buildings' inner temperature of buildings, which is highest energy usage for heating systems such as hot water, air conditioners, thermostats, heat pumps, boilers, chillers and package systems and cooling systems suitable safe, comfortable, and better air quality in buildings (Cheng & Lee, 2019). Due to these underlying issues of GHG emission, the EU aims to reduce GHG emissions by 2030 compared to 1990 levels by increasing renewable energy use (Caird et al., 2008). Similarly, the UK government has implemented stricter regulations to reduce energy consumption, such laws include DECC 2018 and Energy Savings trust (2012), which require mandating that the building industry to reduce energy expenditure through improved HVAC system designs and maintenance and to phase out gas boilers by 2023.

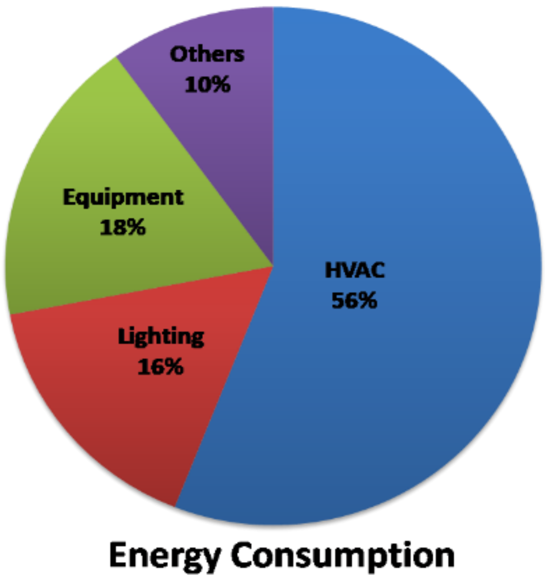

Figure 1.2 Energy Consumption in Buildings, IOTomation, 2018

However, the proposed regulations can only be implemented by improving HVAC system efficiency in order to address energy problems in buildings that use air handling delivery methods, equipment, air ducts, pipes, and fan coils (Seyam, 2018). It is critical to reduce GHG effects in order to meet the global target of lowering temperature below 2 degrees Celsius, making it feasible to develop an HVAC energy efficiency system that can save energy. It is also critical to understand how buildings use energy and to develop strategies or systems to reduce building energy consumption. Despite the fact that many new buildings are designed with low carbon emissions in mind (Al-Waked et al., 2017), green buildings alone are insufficient to reduce GHGs. As a result, buildings and building services must be designed, built, monitored and maintained using formulated methods for carbon-neutral processes efficiency as illustrated in Figure 1.2, HVAC energy usage in UK.

1.2. The gap in the knowledge

Developing an efficient HVAC system with low carbons emission levels provides an opportunity for building owners, developers, designers, and contractors to reduce GHG emissions in buildings and thus help to mitigate global warming (Al-Waked et al., 2017). However, much research has used.

However, much research has used laboratory experimental data and field data to develop a model using higher-level knowledge of modern technology to visualise and predict future HVAC pipe performance. Even though new buildings are designed with a low carbon footprint, it is vital to have transparent HVAC design and maintenance systems that enable energy consumption reduction. Even if new buildings are designed to have a low carbon footprint, transparent HVAC design and maintenance systems that enable energy consumption reduction are critical.

According to Energy Information Administration (EIA) projections energy consumption will rise by nearly 50% by 2050, while energy consumption in buildings will rise by 65% (FUJII, 2019). Each year, approximately 30,000 heat pumps are installed (heat network for hot water pumps, warm air pipe dwellings). The UK government anticipates that this figure will rise to 600,000 per year by 2028 in order to achieve at least 300 percent greater heat pump efficiency than conventional gas systems using renewable energy.

Despite growing concern about energy-inefficient buildings, the HVAC pipe network remains the standard system used in buildings. This has necessitated the creation of a new evolutionary HVAC pipe network that employs new technology to measure, monitor, and control building systems. In particular, the advancement of modern monitoring senses sensors and the Internet of Things (IoT) has resulted in new ways of thinking and making decisions about how buildings should be designed. This is important, especially because Building Management Systems (BMS) integrates modern technologies and innovation at the design and construction stage. Building energy management systems (BEMS) predicted, for example, predicted that computerized smart buildings could quadruple in the near future (Bloom & Van

Reenen, 2009). With the possibility of use, this analysis has become a motivation for this study.

1.3. Motivation of the study

The need to develop efficient performing HVAC pipe using modern technology in Artificial intelligence (AI) Machine-learning such as Machine-learning (ML) Artificial intelligence (AI) has become a motivation for this study because developing HVAC efficient pipe using critical sensors data is critical to energy-efficient buildings. Use of AI in HVAC AI systems dates back to two decades but one of the issues identified is inefficient, making it unsatisfactory to many. AI has significantly improved people's lives in a variety of ways. AI uses mathematical models and mechanics to solve problems that humans are incapable of solving. As a result, it has assisted individuals, scientists and researchers in a variety of applications to new innovations. Using an AI model to monitor and assess energy consumption in the pipe process ensures energy optimisation, according to Cheng and Lee. Between 1976 and 2014, the energy saved by using application scheduled control technique was approximately14.07%, compared to 46.9% saved by using AI HVAC smart sensors system in buildings. When compared to traditional energy management systems (EMS) control systems, AI was found to save up to 14.02% energy (Lazrak et al., 2015; Lee & Cheng, 2016).

As a result, to determining, analysing, and measuring energy consumption using AI advance technology has become critical, as it could enable the development of new algorithms and methods that could improve energy efficiency. The large amount of data available could also aid in model development and variables evaluation and measurement of energy efficiency. The use of AI would enable the creation of an allow one to create a sophisticated and smart system that would be used to monitor HVAC pipes and conserve the energy for use when needed. The system built would allow one to monitor the pipes' health and detect how long it will take to corrode off, allowing workers to replace it before it completely corroded off, saving time and money in the process.

The Building Information Model (BIM) will be used to visualize and simulate the environment in order to test the viability and performance of ANN model's in order to achieve the study objectives. BIM is the future of digital construction, but no framework is used to connect BIM to the predictive validation model and VR for visualization. According to (Johansson et al., 2014), BIM improves model accuracy in order to reduce energy consumption.

1.4. Justification of the research

The need to develop a method for identifying smart pipe systems where the performance of pipe data has been imbedded to improve the performance and reliability of HVAC pipe networks has become critical, because the ability to regulate and monitor the potency at the design stage would help the effectiveness of the HVAC pipe network performance. Previous research has focused, but it is critical to investigate a larger HVAC pipe network in order to develop a validated predictive model. Conventional methods such as pressure Drop, continuity equation, Moody Diagram and CIBSE pipe sizing table, are still widely used in the HVAC pipe system design. With the increase in data from the BEMS and IoT eras, a new design approach and validation that improves the performance gap between designs to build is required to reduce energy loss through inefficient buildings and pipework. Additionally, aid in better energy conservation and utilization.

As a result, an AI model must be developed to monitor the ability to send alerts when pipe performance drops in order to maintain the pipe system’s effectiveness over time. This is significant because it will aid in determining which methods are best for regulating, conserving, and monitoring the energy of buildings. This study is because using AI to measure various tools and methods would allow to discover a finding that would help users, designers, or decisions makers make better decision about HVAC systems. This research employs MATLAB software to create the AI algorithm used to monitor the HVAC system's along with train and evaluate the design model performance. This validated model would then be configured within a virtual environment VR simulation to determine how the model would perform under different conditions without the use of real-world components, thereby lowering design and management costs.

1.5. Research questions

For this study, the following research questions have been established:

1. What are the major factors influencing the corrosion of steel pipes?

2. What are the connections between galvanic current, temperature and pressure in the steel pipes?
3. is it possible for a model or process of creating a model to include the embedded intelligent performance?

1.6. Research aims and objectives

The overarching goal of this research is to develop an Artificial Neural Network model that improves HVAC pipe network system performance and efficiency. This would aid in understanding what solutions can be developed which can allow monitoring of the performance of the designed and installed steel pipes. It will aid in ensuring that the HVAC designers and maintenance teams could spend less time on maintaining and more time on conserving the energy, as using a poor steel pipe network system will result in energy and resource waste. In the worst-case scenario, replacing the entire HVAC pipe network and cleaning up the source of the damage caused by pipe leaks and bursts. Additionally, this research focus on the feasibility of implementing a virtual reality platform to visualise BIM components.

1.7. Research objectives

Based on this the following objectives are defined for this study have been established.

1. To construct a smart system for the HVAC pipes using an Artificial Neural Network for energy efficiency
2. Using experimental and field data, evaluate the neural network model created for the development of Black Box model in MATLAB to analyse the corrosion of steel pipes.
3. To evaluate and research the performance and applicability of building information modelling (BIM) in virtual reality (VR) environments.
4. To shed light on how a neural network model can improve HVAC performance.

1.8. Research overview and structure

Figure 1.1 depicts the structure of this thesis, which is divided into six chapters. Following the introduction chapter 2 examines existing literature on BIM, pipe network technology, software development and data exchange. The chapter also reviews factors that could affect network pipe performance, with an emphasis on current and future technology. This is important because it will provide insight into the benefits and drawbacks in current HVAC model. It would also help in providing a clear overview of the AI tools and methods used in HVAC system development to efficiently manage energy resources. The chapter also goes over how to monitor the health of the HVAC pipes.

The third chapter of the methodology describes how the research was carried out. The third chapter went over the evaluation process for monitoring the HVAC pipes on top of the laboratory experiments. It also discusses how the collected data was used to train the model and develop the ANN model for assessing the performance of steel pipes, which was then validated. This chapter described how the BIM will be integrated with a VR environment to create a virtual environment to test the model performance under various controlled settings.

The fourth chapter of the analysis illustrates and elaborates on the results and study findings achieved through various tests, along with detailing how the BIM data was translated in VR and to create a simulation to test the model. The analysis results will be illustrated with graphs and figures to demonstrated the model's performance and the model's capabilities, and how it performs under different conditions.

Chapter 5 introduces the new ANN model and discusses the limitations of the measures based on the observations from chapter four. In addition, Chapter 5 discusses how the mode limitation was addressed using various methods and technologies to improve the design efficiency. The chapter will also go over the model's advantages and disadvantages.

The final chapter 6 discusses the thesis findings, how the study contributes to knowledge and discusses the study's policy impactions. Before the thesis completed, the chapter will present the study's limitations and set a future research agenda. The thesis structure is depicted in Figure 1.3.

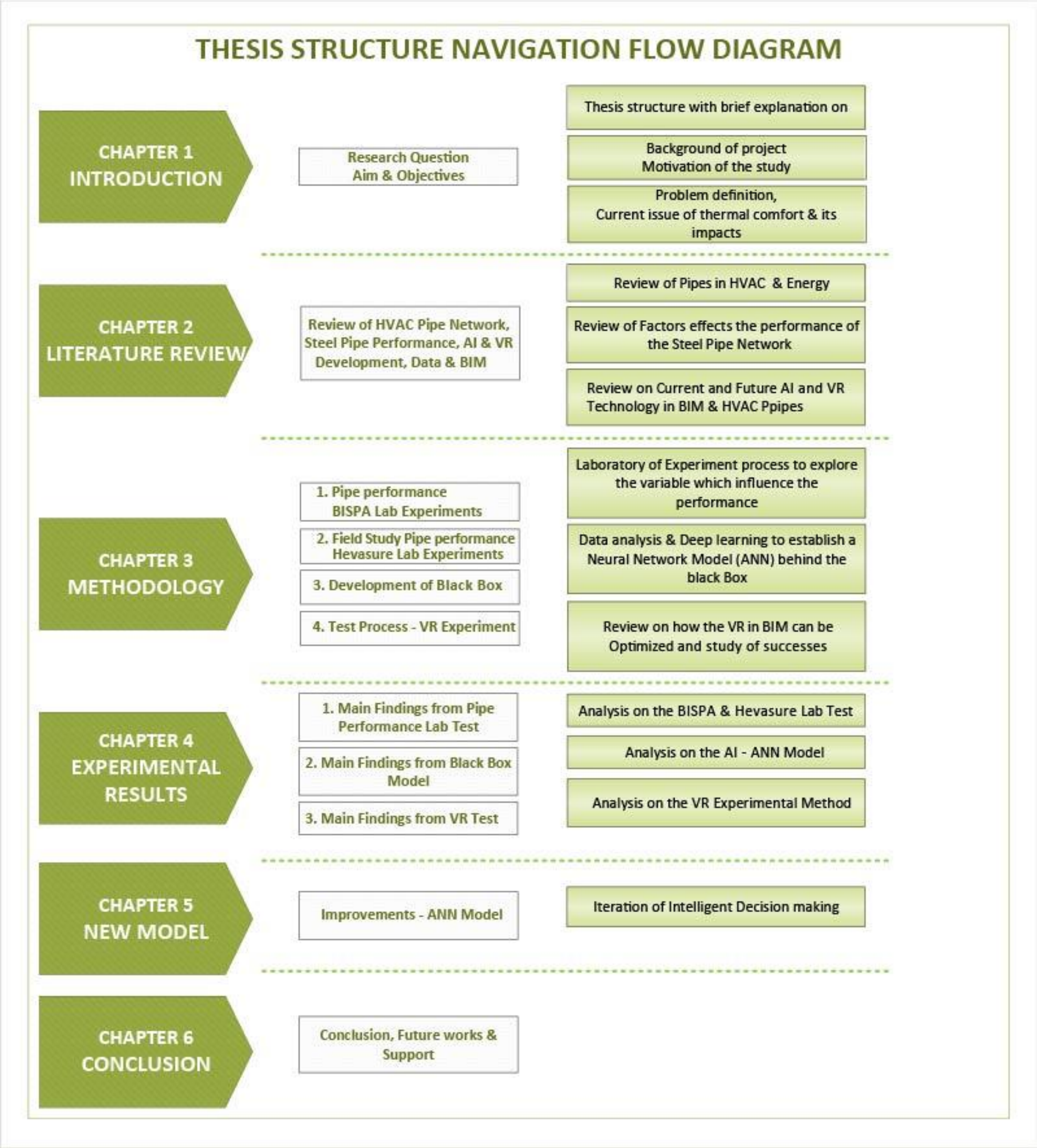

Figure 1.3 Thesis structure flow diagram

Chapter 2 Literature Review

2.1. Introduction

In this chapter the current research on pipe design flaws, maintenance issues, and a lack of awareness about waste energy and resources is reviewed and presented in this chapter. These chapter highlights that corrosion limits the output of steel pipes, which affects all other parameters such as temperature, strain, and flow, resulting in energy waste in the HVAC industry. This chapter examines current knowledge in pipe efficiency and, as a result, corrosion and the problems associated with it, focusing on key factors such as pH, temperature, dissolved oxygen. The use of artificial intelligence (AI) in predicting HVAC performance is discussed and the most recent methods of improving system maintenance presented.

2.2. An overview

In the construction industry, Pipes and piping systems have a wide range of applications. An HVAC piping system's service conditions include a variety of fluids at varying temperatures and pressures. When designing the HVAC piping system, temperature, pressure, and fluid conditions must be taken into account in the full life cycle analysis of components. Water is used as a heat transfer medium because of its high thermal capacity and low viscosity, plus it lower cost. The hydronic HVAC system is widely regarded as the most dominant system for climatizing large-scale commercial facilities (2019, August 22).

The most cost-effective materials for hydronic HVAC piping systems are mild carbon steel and, on occasion, stainless steel. Water has been proposed as an ideal heat transfer medium for a variety of HVAC applications in the literature. Though there are numerous advantages to using water as a heat transfer medium, there are also risks involved (Harvey, 2020). In nature, water is an electrolyte, which promotes corrosion in metallic pipes and components.

To determine and create a model that can aid in the formation of a smart monitoring model that can aid in the monitoring and health of the HVAC pipe system, first need to have a detailed understanding of how the HVAC pipe system performs, what algorithm it works on, what it was created using Artificial Intelligence. It would also be used to and how and what effect it would have on its performance if it was created using Artificial Intelligence. It would also be used to investigate how factors such as temperature, pressure, and pipe corrosion can affect how HVAC systems regulate and perform by investigating the properties of the water within. Understanding water performance in HVAC systems can have a negative impact on the system's energy efficiency and longevity. According to some sources, an additional 30% of energy will be consumed due to decreased efficiency as a result of poor water quality, poor maintenance, and component oversizing (US Department for Energy, N.D). By investigating the properties of the water proper information can be collected about how factors such as temperature, pressure, and pipe corrosion can affect how HVAC systems regulate and perform. Understanding water performance in HVAC systems can have a negative impact on the energy efficiency and longevity of the system. According to some sources estimate that an additional 30% of energy will be consumed due to decreased efficiency as a result of poor water quality, poor maintenance, and component oversizing (US Department for Energy, N.D).

2.3. Statement of the problem

Corrosion is a major issue in piping systems that use water as a heat transfer medium, which is why, researchers have focused on the corrosion analysis of hot water heating pipes in a closed system in recent years. According to an exploratory research study, approximately 70% of the cases reported in the last decade involve HVAC systems corroding experiencing various types of corrosion in hydraulic environments, resulting in significant structural and financial loss (Opel et al., 2018).

As a result, the problem statement refers to corrosion in the heating HVAC piping system, with water acting as the heat transfer medium. The purpose of this chapter is to conduct a literature review on the various types of corrosion in hot water HVAC piping systems, and then to present methods for detecting, preventing, and controlling corrosion.

2.4. The history of HVAC pipes

After the introduction of piped water systems, heating buildings with steam or hot water became common. However, the need to separate the use of HVAC pipes became necessary because it would ensure that one can adjust the performance could be adjusted as needed. By the late 1880s, it had become a general rule in HVAC design that separate pipe network systems were required, and designs that were being adopted across multiple countries were created (McDowall, 2007).

Heating and cooling in buildings and industry are the largest energy consumers. It accounts for half of total EU energy consumption (Commission, 2020). Building conditioning relies heavily on water systems. Cold or hot water is provided for space and process cooling or heating. The general heating of water is accomplished through the use of hot water as a heat source.

District heating is ranked 27th among the 100 solutions to global warming by Project Drawdown, so the number of district networks, which are large-scale hydronic circuits, will continue to grow (Hawken, 2017). The overall performance of hydronic systems is harmed by corrosion. The thermal performance of hydronic systems suffers as a result of dirt and scaling. Foreign particles increased the flow resistance. Energy consumption rises in order to achieve the required heat transfer and flow. The performance of hydronic heating system degrades over time. Hydronic systems must be operated and maintained continuously and optimally to ensure good thermal and energy performance. While some corrosion research has been conducted, no effort has been made to investigate the impact of corrosion on the quality of pipe system performance or the prediction of corrosion development in buildings.

2.5. Importance of Corrosion

So far, the benefits of maintaining and preventing corrosion in closed systems have been regarded as minor in the building sector, and as a result, this area has received little research has been conducted in this area, resulting in its under-appreciation (Opel et al., 2018). Furthermore, the effects of corrosion and reliability issues caused by clogging issues were rarely observed during the service life of the system (Opel et al., 2018; Standard, 2005). However, there has been a recent surge of interest in closed-loop systems. Clogging and corrosion had developed within two years of system commissioning.

According to (Brown et al., 2013), pipelines fail even before the building is completed. According to (BSRIA, 2013), there is a distinction between modern pipework and older pipework, which has a higher failure rate during the first three years of service.

Opel et al., (2018) discuss a research study on corrosion issues and how many participants had significant financial damage as a result of corrosion in their systems, in which 79 percent of the participants reported corrosion damage and 76 percent reported a high or very high risk of that issue in their hydraulic systems. As a result of this study, Opel et al., (2018) conclude that corrosion issues have increased and are highly problematic for hydronic systems.

According to (Brown et al., 2013), recent corrosion problems are caused in part by changes in pipe materials and system designs, over and above a general lack of awareness of the risks of corrosion. Hydronic systems are becoming more complex and efficient, with intricate valves resulting in smaller part tolerances. As a result, particulate matter is a greater threat to modern systems. When smaller gaps in the control valves and finer particulates in the water are mentioned, this valve opens. As a result, it appears that water quality issues are inextricably linked in modern systems. (Opel et al., 2018; Wiegand et al., 2017).

2.6. Steel pipe corrosion

The preceding section discussed corrosion in general, and this section focuses on corrosion in steel pipes specifically. To ensure that the HVAC system can regulate the building's temperature, it must be ensuring that the steel pipes are in good condition and free of flaws. This necessitates that the performance be efficient and that it not degrades as a result of the varying temperature and pressure applied to it. This is critical because corroded pipes can increase energy consumption along with disrupt how the system regulates the building's internal temperature.

Pipelines are considered critical infrastructure because they are known to play an important role in ensuring people's long-term facility. The majority of these types of pipes are manufactured and used by metal manufacturers (Hou et al., 2016). Because of their long use and exposure to varying temperatures and/or pressures, the pipes aged, resulting in an increasing failure rate (Hou et al., 2016).

This could lead to large explosions in pipes, a reduction in quality of life, economic loss, and an increase in pollution and casualties within the building.

Metals with thermodynamic stability, such as gold and platinum, can exist in their natural state. Every other metal, on the other hand, is susceptible to corrosion due to its thermodynamic instability. This is because the refining process used to extract the metal from the ore extracts the ore's latent energy as the ore is processed to its corresponding metal. The ore changes into a metal as a result of this energy transfer. Taking the energy, on the other hand, causes the metal to transition to a more natural, thermodynamically stable “ore” state. Corrosion is the transition of a metal from a high energy state to a low energy state. In general, corrosion causes the metal to form a porous metal oxide film, whereas other metals form a film that buckles and flakes off. In both of these cases, the metal oxidises and loses its metallic properties, resulting in metal loss.

Corrosion is defined as the loss of metallic properties and behaviour as metal ages. It is also defined as the degradation of a metal as a result of a chemical or electrochemical reaction. This research can be traced back to the essays and research of Boyle and Michael Faraday. Both made significant contributions to corrosion research, which served as the foundation for Faraday's first and second laws (Burstein, 2013). These are thought to be the basis for determining metal corrosion rates. Following Faraday's contributions, many electrochemists have contributed to expanding and researching the factors that cause metals to corrode, plus how the electrochemical behaviour of metals changes. Corrosion, according to the study, occurs primarily as a result of the interaction between the materials, in this case metal, and the environment in which it is present. The environment can be either dry or wet depending on the conditions, temperature, and humidity. Dry corrosion is common when a material is exposed to high temperature systems, such as those found in nuclear and fossil fuel generation systems, aerospace and gas turbines, and heat treatment plants, among other places. Meanwhile, wet corrosion happens when a material goes through an electrochemical process that results in aqueous corrosion (Ukpai, 2014). This is most common at low temperatures, where corrosion can occur quickly in an aqueous environment. It's a type of electrochemical process. The electrochemical spices are then dissolved in the electrolyte, assisting with aqueous corrosion. (Faes et al., 2019) for example, has written extensively about what causes aqueous corrosion and how it affects metals.

Corrosion of pipe and equipment, biofilm and scale formation, and suspended debris in water all have an impact on the thermal energy of hydronic systems, resulting in system failure in the worst-case scenario (BSRIA, 2013; Wiegand et al., 2017). Though there is no way to completely eliminate these problems, the key is to keep them to a minimum. Controlling the factors that contribute to hydraulic system expansion helps to maximise their performance potential. Maintaining low corrosion rates is critical for good water system performance, and keeping the hydronic system operational is required for a longer system life. Both are intertwined, and the latter may be the only options (BSRIA, 2013).

2.7. Corrosion prevention is the mission.

Water-side issues in a hydronic system, such as corrosion, scale formation, biological growth, and suspended solids, are complex issues influenced by a variety of factors ranging from pipe and component materials to water chemistry and quality (Hegberg & Tone, 2015).

Metals and plastics are examples of materials used in closed systems. Corrosion can be classified as a result of a variety of environmental factors that affect different materials. BSRIA guide BG 50/2013 (2013) This guide, based on research on corrosion materials found in open water, can be used in a variety of situations, including those that occur in closed systems.

Pipes, valves, heat exchangers, and other hydraulic system components deteriorate due to their corrosive nature. Radiators, boilers, chillers, valves, and pipe sections will need to be replaced if inadequate maintenance is not performed, and boilers and chafing coils (condensers) are prone to damage and costly downtime.

Two systems demonstrated how poor water quality contributes to the failure of hydronic systems. His paper described a system that served multiple office locations in a business park and included both chillers and boilers. Several system components began to fail one year after installation. After five years of operation, all of the boilers needed to be replaced. The system continued to fail because the problem was not properly diagnosed. Before the corrosion in the entire system was discovered, many valves and even the entire chiller had to be replaced. As part of the repair work, the entire network, multiple evaporators, and a couple of control valves had to be replaced. Furthermore, the system was thoroughly cleaned to ensure that no contaminants remained. Almost the entire system had to be replaced due to poor water quality and an incorrect diagnosis.

Corrosion incidents have been reported to some plumbing companies, resulting in blocked pipework and radiators, boilers and condenser coils failing. Air ingress and poor water quality were proven to be the primary causes of corrosion in every set of circumstances. So we've read about several cases where the financial burden on the system and personal data recovery was more than £1 million due to corrosion, lost time, and legal fees (S. Munn, 2016).

Corrosion in hydronic systems has not only an economic cost, but also an energy cost. Corrosion and the formation of scale or biofilm reduce heat exchanger heat transfer efficiency and the performance of boilers, chillers, control valves, and pumps, resulting in poor system performance (ICOM, 2017; S. Munn, 2016). Furthermore, the energy consumption of the pumps increases as a result of the restricted flow caused by a reduction in the flow area of the pipes and valves.

Despite the efforts of organisations such as CIBSE and BSRIA, there is widespread misunderstanding of corrosion in HVAC systems and the methods for controlling it, according to (S. Munn, 2016). While the most important method of corrosion control is selecting an appropriate corrosion resistive material, reducing the presence of essential corrosion reactants in the transport medium through the use of corrosion inhibitors is required to regulate the corrosiveness of the environment (Cicek, 2017). According to research and many industry experts, a lack of or improper water treatment can be costly to correct (ICOM, 2017; Opel et al., 2018). As a result, it is critical to maintain water quality in order to control corrosion and maintain the performance of the hydronic system.

2.8. Types of corrosion and their causes in a pipe network

Because HVAC systems are typically closed loop systems, it is critical that all system components function properly in order to achieve a higher output. Corrosion is the most serious threat to the HVAC system because corrosion requires three elements, all of which are normally present in the HVAC system: cathode, anode, and electrolyte. Corrosion in HVAC systems can occur due to a variety of factors such as component materials, environmental conditions, and service conditions, and can include pitting, electrochemical, bimetallic, or galvanic corrosion, among others (Valdez & Schorr, 2010). Almost every metal corrodes, some as scaling and other rusting, whereas polymers do not corrode but instead degrade when exposed to UV light. The section that follows contains a detailed discussion of the most common type of corrosion found in HVAC steel pipes in hot water environments, plus the factors that speed up the corrosion rate (McNeill & Edwards, 2001).

A variety of factors influence corrosion rates, including galvanic potential difference between pipe surfaces, dissolved oxygen, carbon dioxide, total dissolved solids, chlorides, sulphates, bacteria, pH of water, flow velocity, and temperature (BSRIA, 2013).

Corrosion can occur as a result of differences in the redox potentials of the pipe metals (galvanic corrosion) or as a result of microbial activity (microbiological induced corrosion). A chemical's redox potential is a measure of its ability to gain or lose electrons through ionisation. Galvanic corrosion occurs when metals with different electrolytes come into contact with each other; it typically involves more metal dissolution and, as a result, should result in more metal loss on the metal, as the surface with the least amount of noble metal is connected to the surface.

The most important chemical factors influencing galvanic corrosion are pH and concentrations of dissolved oxygen, carbon dioxide, and dissolved solids (BSRIA, 2013).

When bacteria in biofilms are exposed to low water velocity or slow flow, they grow and spread as microbiological induced corrosion (MIC), and water quality suffers as a result. Movement restrictions, stalled flows, and stagnation in specific areas are all significant issues for any fluid-processing system because the possibility of microbiological contamination is increased in systems with a high total bacteria concentration.

BSRIA is an abbreviation for the British Standards (2012) Plastic pipes are resistant to galvanic corrosion, but they are prone to biofilm formation and scaling (BSRIA, 2013).

Black or brown circulating water, valve and heat exchanger blockages, complaints of ineffective heat from radiators due to the formation of cold spots, and an increase in the level of suspended solids of insoluble iron compounds are all signs of corrosion in hydronic systems (BSRIA, 2013; Wiegand et al., 2017).

Corrosion increases pipe roughness, or the k/D ratio (the ratio of the pipe's mean height of roughness to its diameter), resulting in a slight increase in pumping power. Furthermore, corrosion-induced roughness will promote the growth of hard scaling and accelerate the rate of fouling deposition.

2.9. Corrosion in the HVAC piping system for hot water

Corrosion monitoring is an important performance indicator parameter for thermal installations in the construction industry. Internal corrosion can occur in almost any component of a building system that uses water as a heat transfer medium. Corrosion can be localised or uniform, and almost every metal is susceptible to corrosion due to defects, crystal orientation, and grain boundaries that become incorporated into the material during manufacturing and processing. The main causes of corrosion in hot water HVAC piping are when metal is exposed to air, water, or comes into contact with another metal. Corrosion and its by-products can reduce pipe efficiency, leading to increased operating and maintenance costs also sudden catastrophic failure (Andrianov & Spitsov, 2017). Water leakage from HVAC piping systems due to corrosion is common in tall buildings, and in some cases, repair necessitates the shutdown of all facilities. Figure 2.1 depicts a water leak in a tall building's HVAC piping system.

Figure 2.1 Water leakage in the buildings hot water system

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2.10. Corrosion mechanism in hot water pipe

To predict mild steel corrosion in a hot water system, first understand the electrochemical process that causes it (Figure 2.2). The corrosion process in steel is a coupled process of two electrochemical reactions, as shown in the equation below:

1. anodic metal oxidation equation 2.1

$$Fe_{(s)} \rightleftharpoons Fe^{2+} + 2e^{-} \qquad (2.1)$$

2. cathodic oxygen reaction equation 2.2 (Chukhin et al., 2018).

$$O_2 + 2H_2O \rightleftharpoons 4e^{-} + 4OH^{-} \qquad (2.2)$$

Initially, steel corrosion produces soluble Fe^{2+} in water, which reacts with hydroxide ions to produce a mixture of hydrous iron oxide known as rust. Normally, the inner surface of a steel pipe has a heterogeneous hot water environment composed of various types of iron scaling.

The Fe^{+2} ions in the anodic region of the corroding steel are oxidised by dissolved oxygen, resulting in Fe $(OH)_3$ as a result of the following chemical reaction. (Chukhin et al., 2018) used the following equation 2.3 in his work.

$$2Fe^{2+} + 2H_2O + 1220 \rightleftharpoons 4W + 2Fe(OH)_3 \qquad (2.3)$$

On the surface of the steel pipe, this $2Fe(OH)_3$ has a gel-like structure that is yellowish or brownish in colour. OH^- ions, on the other hand, are formed as a result of the reaction at the cathodic side, resulting in $CaCO_3$ deposition as a result of the neutralisation process, as shown in equations 2.4 and 2.5 below.

$$OH^- + HCO_3^- \rightleftharpoons CO_2^{-3} + H_2O \quad (2.4)$$

$$CO_2^{-3} + Ca^{2+} \rightleftharpoons CaCO_3 \quad (2.5)$$

The corrosion process in hot water steel piping systems is quite complex and does not only cover one type of corrosion because optimum parameters are difficult to maintain in such conditions, but lower pH also accelerates corrosion rate while high pH causes scaling. The various factors that accelerate corrosion in the HVAC hot water piping system in the tall building are important to highlight here because engineers can minimise the rate of corrosion in the hot water pipes by carefully controlling these dependent factors, which may result in an increase in the life span of water pipes in hot water environments (Opel et al., 2018).

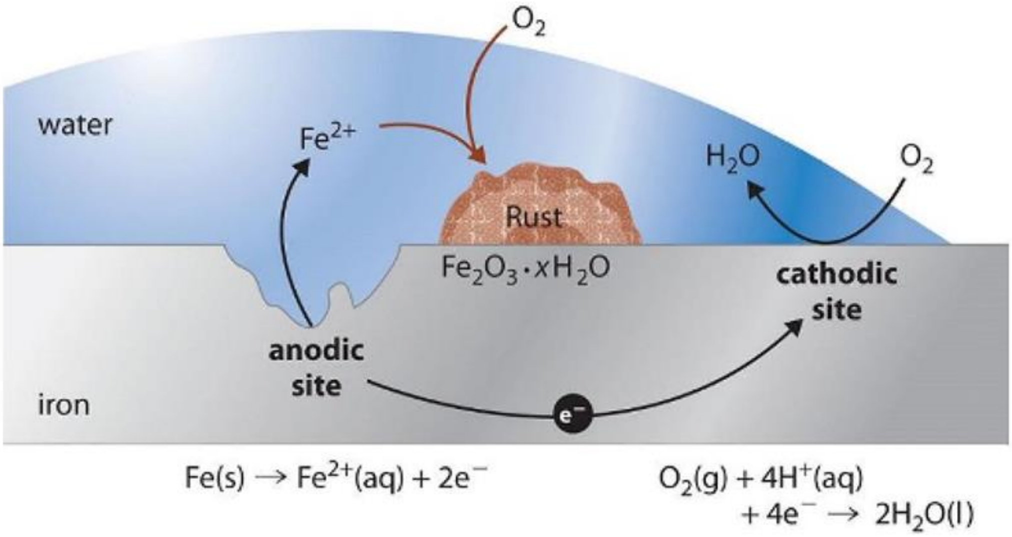

Figure 2.2 The corrosion mechanism of mild steel pipe in contact with hot water, adapted from (Salunkhe & Rane, 2016)

2.11. Action of galvanic current

The majority of corrosion is caused by galvanic action at a negatively charged pole on the metal surface (Stanford III, 2011). Anodes and cathodes form in metals as a result of impurities added to them, stress that forms on them, differences in the composition of the metal, or the amount of scratches on the surface. Because of the metal's positive and negative poles, there can be an electric potential between the positive and negative terminals, and current flows from anode to cathode using the surrounding environment as an electrolyte (Stanford III, 2011).

The anodes in steel pipes react by giving off two free electrons in order to become positively charged. This reacts with two OH radicals to form ferrous hydroxide. When it reacts with water, it forms ferric hydroxide, which is iron oxide or rust that is then dehydrated. Corrosion is frequently caused by impurities in metal, their environment, or the metal's properties. These factors may cause a reduction in metal quality or fouling of the metal's surface. Corrosion is primarily caused by scratches, stress applied to them, or the environment. When metals have different electrical potentials in nature, the corrosion level rises and the corrosion rate accelerates (Stanford III, 2011).

Steel pipe has traditionally been the preferred HVAC product for tall towers. Steels such as galvanised steel and stainless steel are used to reduce corrosion effects and keep the pipes from corroding. Galvanized steel is made by coating mild carbon with metals such as zinc, lead, and aluminium, which serve as corrosion inhibitors for pipes. Steel is galvanised by first coating it in a caustic pool and then pickling it in a mild sulfuric acid solution. Steel was then fluxed with a solution of zinc ammonium chloride. Early galvanization methods involved the addition of a balanced layer of zinc ammonium chloride to the molten Zn. The large steel chamber was then introduced and placed inside zinc, which is then passed through the flux layer while the remainder is the molten bath. This bath is then cleaned with flux before the sheet is removed. Following that, it was placed to lower the temperature and allow it to be handled properly. The water is usually treated with sodium dichromate to further protect the steel.

However, since the 1980s, a new method of galvanising steel, known as the dry kettle method, has been developed. The steel sheets are fluxed by dipping them in zinc ammonium chloride using continuous rolls and then drying them in the dry kettle method. This sheet is then zinc-coated by being dipped in molten zinc. Following heating, the steel is removed and immersed in water. The advantages of this method in terms of providing a high-quality finished product and utilising a better cleaning route, the quality of the resulting galvanising remains a significant argument in favour of using it. As a result, most cooling tower HVAC designers and manufacturers advise that galvanised structures be coated with a polymer finish.

Steel has less structural strength than galvanised steel, but it compensates by being corrosion resistant when exposed to wet environments, such as those found inside an HVAC system. One of the primary advantages of stainless steel is its ability to retain structure while not corroding. Stainless steel is made by combining steel alloys such as carbon with nickel, molybdenum, chromium, and/or nitrogen. Steel's corrosion resistance is due to a fine layer of chromium oxide on the surface of the steel, which prevents corrosion. If this fails over time, the Cr layer is exposed, exposing the steel, and an oxide layer forms on top of the exposed chromium layer.

2.12. Water purification

Corrosion is regarded as a critical issue in the pipe system that must be addressed. Quality water treatment should be applied on a regular basis to control corrosion, biofouling, and sedimentation to keep the hydronic system in good condition throughout its use life. (BSRIA, 2013) water treatment programme in hydronic systems aims to keep the system clean, efficient, and to extend the system's life by controlling corrosion and fouling (BSRIA, 2013).

HVAC systems, in general, contain corrosion inhibitors and even biocides. HVAC system designs are entirely composed of molybdates, particularly if the system is intended for chilled water systems. It does, however, allow the entry of molybdates or nitrites in order to raise the temperature of the water during the winter season. Finally, the temperature of the water rises above 140°F (60°C).

It can be seen that the process that leads to the cause of a pipe's improper operation has not been clearly defined for any type of pipe (Makar & Kleiner, 2000). The causes of failure in metallic and restressed concrete pipes, on the other hand, are known to the members who are involved. Corrosion can be attributed to both the metallic pipes and the PCCP failure. The way the pipe corrodes, however, varies depending on the pipe (Makar & Kleiner, 2000). Corrosion pitting is a phenomenon that causes steel and cast grey iron pipes to flop due to ductile iron. A corrosion pit can be seen emerging from the pipe walls and growing from either side of the pipe in this case. This procedure is repeated until the pipe has been completely penetrated or water begins to leak from it. In this case, the pipe is rendered unusable and becomes unstable and brittle as a result. Steel can behave similarly to grey cast iron in some cases, causing metal pipes to crack wide open. It is widely assumed that these failures are frequently associated with graphitization corrosion, in which material in the pipe is leaked by the region that closely resembles the corrosion and leaves the flake matrix.

Pipes are treated with inhibitors to protect metals that corrode more easily than steel, such as copper. Steel is relatively corrosion resistant at basic pH levels. This scale is used to determine a substance's acidity or basicity. If the pH is less than 7, it is considered acidic, and if it is greater than 7, it is considered basic, making the pH of 7 neutrals. A pH of 8 to 10.5 is commonly used for steel pipe systems. Steel, on the other hand, can corrode if the pH is lowered or if it is attacked chemically. To combat the possibility of corrosion, many corrosion protection systems are made up of materials with a high pH. Aluminium-based systems, on the other hand, are prone to corrosion because they are incompatible with high pH levels. As a result, it is protected from corrosion by a combination of steel pipes and aluminium exchangers. This is because it requires a very narrow range in the HVAC system, typically ranging from 8 to 8.5.

HVAC systems are important because they regulate the temperature of the building, which aids ventilation, indoor air quality, and other factors while consuming the majority of its energy. As a result, appropriate precautions and measures must be implemented to ensure that the system conditions do not corrode the steel pipes. The precautions taken will prevent metal pipes from corroding as the weather and pressure change (Arriba-Rodriguez et al., 2018). Because this is an important consideration when designing such infrastructure, care must be taken to ensure that structural resistance is taken into account when designing the network so that it can withstand varying temperature and pressure fairly well (Arriba-Rodriguez et al., 2018). This is because the corrosion of steel pipes varies depending on their environment (Arriba-Rodriguez et al., 2018; Mak, 2002). To determine how steel behaves when subjected to changes, it is frequently thought necessary to properly identify and process the environment so that appropriate measures can be taken to reduce the likelihood of corrosion. The primary focus would be on predicting the pipe's behaviour based on changes in temperature and pressure, as well as how much energy is consumed. This could lead to an increase in galvanic corrosion, which is the most common cause of metal corrosion, such as steel (Mak, 2002).

When two metals come into contact with each other, steel corrodes. To avoid galvanic corrosion, these metals should be made to insulate from one another if possible. However, if the metals come into indirect contact with each other, such as when they are enclosed in a steel enclosure by copper bonding conductors, an oxide-inhibiting plate should be added to reduce the likelihood of corrosion. This has the advantage of keeping moisture away from the metals, reducing the possibility of galvanic corrosion of the metal or steel pipes. Because corrosion alters the structure of metal pipes, it can affect their performance. The process by which metal reverts from a high-level form to a low-level form, causing the metal to lose its lustre and metallic properties, making it weak and easily broken (Mak, 2002).

This is especially true for steel, as it is well known that steel corrodes or rusts quickly in moist environments, and the rate of corrosion increases as it is exposed to salt water. This is because saltwater is a fairly good conductor of electricity. The Fe_2O_3 ions form a layer on top, but with the addition of minerals such as oxygen, sulphur, and carbon dioxide, side by changing temperatures, this layer transforms into a layer of rust on the surface caused by Fe_3O_4.

Typically, the layer formed flakes off the surface of steel, exposing the fresh metal to corrosion. This type of process is typically repeated until the entire surface of the steel has been corroded or until the aforementioned minerals have been removed or consumed. Steel, on the other hand, is commonly used for housing enclosure systems; however, care must be taken to ensure that the steel pipes do not corrode when exposed to varying temperatures and pressures from the environment. This must be addressed in order to control and measure corrosion through processes such as galvanising, alloying, and painting. Steel pipes can be galvanised with zinc or copper; after which they can be plated. Its anodes serve as a sacrificial anode, protecting the steel from corrosion for a longer period of time. Meanwhile, the use of alloys like chromium allows for the formation of a tightly adhering surface oxide layer, which prevents corrosion. The combination of steel and chromium produces stainless steel, which is naturally anti-corrosive. Meanwhile, the use of paint increases the likelihood that materials such as carbon dioxide, sulphur dioxide, oxygen, and water will not corrode the pipes, ensuring their continued use.

Inadequate water treatment and the need for continuous monitoring are issues. Air conditioning components that are insufficient and water that is of poor quality reduce system performance by 15 to 30 percent. Reduced system life expectancy is only appropriate when combined with improvements to other systems that may increase energy use; this is the only way to ensure conservation. A number of studies, the most notable of which are the BSRIA BG 29, BSRIA BG 50, and the German directive VDI-2035, have been written to respond to this issue from the standpoint of water quality. In this case, the role of water in regulating energy consumption and the overall cost of system lifecycle is more important.

Water is clean in its natural state, but finding pure water that is free of impurities is extremely rare. Impurities include dissolved gases, gaseous contaminants, particulate matter, and minerals. This has the potential to improve overall system performance of individual impurities.

According to (BSRIA, 2013), some heating and cooling systems lack a water treatment system but continue to operate. The inverse is also true: a few water treatment systems have suffered from corrosion.

(Opel et al., 2018) discovered in their field study that the worst cases occurred with chemicals used to prevent corrosion in the cases where the systems were discovered. According to (Wiegand et al., 2017), inadequate water treatment can promote microbiological growth and cause further harm to the system. (ICOM, 2017) claims that causes economic harm.

Corrosion had no effect on the water chemistry or bacterial concentrations tested in accordance with the BSRIA (2013) guidelines.

During a study, Guardian Water Treatment Services discovered oxide deposits in an office building's water system. The building's radiators had been causing issues on a regular basis. However, the water chemistry and bacterial levels were consistent during sampling. Guardian Water Treatment discovered that the system's air lock mechanism was frequently misadjusting, resulting in oxygen ingress into the water. (Opel et al., 2018) propose continuous water quality monitoring to ensure proper water treatment and to reveal hidden actions in heating and cooling systems. As a result, it can be demonstrated that continuous hydronic water treatment programmes are required.

2.13. Corrosion factors in a hot water HVAC piping system

The impact of various parameters on the corrosion rate of the carbon steel hot water piping system must be investigated in order to control the corrosion rate in the HVAC piping system. Though many factors contribute to corrosion but this study will be focused on concentrate on pH, temperature, water flow rate, pressure, and dissolved oxygen.

2.14. The influence of pH on corrosion rate

The corrosion rate and pH have an inverse relationship, with lower pH in untreated water increasing the corrosion rate. The main cause of this phenomenon is that low pH can dissolve various types of oxide, exposing the material surface to corrosion (Rodbumrung et al., 2016). The standard assumption is that as the pH of the circulating water rises, so will the water's corrosivity. It should be noted, however, that this reduction in corrosivity comes at a cost, as scaling tendencies of calcium phosphate and calcium sulphate will increase, which is another major issue. As a result, optimal conditions are critical for HVAC system efficiency.

The effect of pH on steel corrosion is depicted in Figure 2.3, as the rate of corrosion can be simply expressed in terms of dissolve oxygen in the pH range of 5 to 9. Near the pH of 4.5, acidic corrosion begins to suppress the influence of oxygen content. Because of the deposition of an insoluble ferric hydroxide layer on the surface of steel at high pH values of 9.5, the corrosion rate decreases.

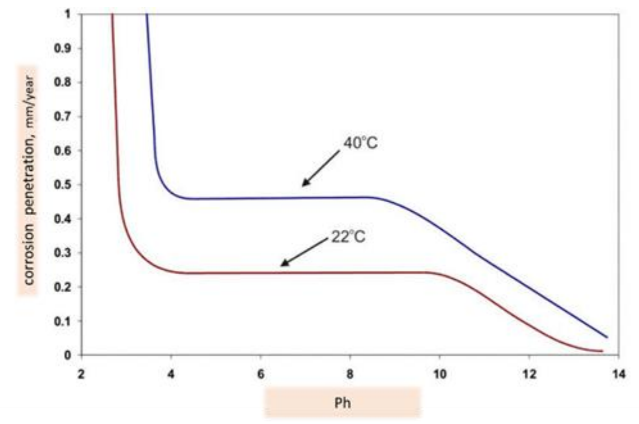

Figure 2.3 The consequence of water pH on the rate of corrosion for hot water steel pipe (Water Constituents, 2020)

2.15. Corrosion and dissolved oxygen

The dissolved oxygen content is by far the most important factor in the acceleration of corrosion in closed loop heating and cooling systems, as it is the primary chemical reaction that speeds up anodic dissolution, which leads to corrosion (BSRIA, 2013; Munn, September 2016).

Several researchers have identified oxygen as the root cause of corrosion in closed-loop systems. Oxygen-induced corrosion occurs both during system operation and when the system is not in use.

There is a relationship between the rate of dissolved oxygen and active metals in neutral solutions, according to (BSRIA, 2013). The formation of electrochemical cells at the surface with varying oxygen concentrations demonstrates the role of oxygen in accelerating corrosion rates.

According to BS EN 14868 (2005), reducing the amount of dissolved oxygen in the system reduces the rate of corrosion to the point where damage from corrosion build-up is usually avoided.

There is evidence that simply decreasing dissolved oxygen levels can significantly slow corrosion. Reducing the amount of dissolved oxygen from 9 mg/L to 2 mg/L, according to (Jung et al., 2009), can reduce the rate of corrosion by up to 91 percent depending on the pipe type. As a result, it is critical to limit the amount of oxygen entering the system.

To reduce the amount of oxygen entering the system, systems must be properly designed and maintained from the beginning. However, properly designed systems will limit and prevent ingress while the water is being filled, allowing metal corrosion to occur when it reacts with oxygen. However, because the system's demands are lower, no harm will be done to the system. It is important to note that larger and more complex systems become more difficult to keep airtight in the presence of diffusion.

2.16. Dissolved oxygen is a critical mechanism in the formation of corrosion.

Understanding the anodic and cathodic reactions is critical for understanding the influence of oxygen on closed loop heating and cooling systems. The anode is where the oxidation reaction occurs. Furthermore, metal ion loss occurs at the anode due to hydration, dissolution, and complex formation (Z. Ahmad, 2006).

A cathodic reaction is a reductive reaction that occurs at the cathodic end of a process. The cathode is where electrons are ejected and chemical reduction occurs in a conventional closed loop heating and cooling device.

Dissolved oxygen is reduced to hydroxide ions in aqueous environments. Corrosion is typically seen all over the metal surface and is not limited to a single fixed point. Pitting corrosion, on the other hand, can occur only in one place within a metal. Metal ions erode from the pipe into the solution at the anodic end of steel pipes in an amount equal to the cathodic portion of the pipe. In equation 2.6, the following reaction occurs at the anodic end.

$$Fe_{(s)} \rightleftharpoons Fe^{2+} + 2e^{-} \qquad (2.6)$$

There is no polarisation when the anode is powered by an external current, indicating that the reaction is occurring quickly. The rate of iron corrosion is then controlled further by the rate of the cathodic reaction, which appears to be much slower due to cathodic regulation. The chemical reaction equation in equation 2.7 can be used to describe the cathodic reaction.

$$2H^{+} \rightarrow H_2 - e^{-} \qquad (2.7)$$

The reaction occurs at a much faster rate in acidic aqueous conditions and at a much slower rate in alkaline and neutral conditions. Because mains water has a pH range of 6.5–8.5 (Dirisu et al., 2016), it can be deduced that by keeping the iron potential as low as possible, the rate of iron corrosion can be slowed as much as possible. The rate of hydrogen growth at a given pH is determined by the amount of hydrogen overvoltage contamination embedded in the metal. For example, in the case of pure grade iron, the metal surface will contain areas for Hydrogen growth. Thus, corrosion will occur in a higher purity iron even in acidic conditions, but the rate of corrosion will be significantly lower than in a less pure iron (Jones, 1997). However, the cathodic reaction can still be accelerated in equation 2.8 due to depolarisation (an increase in dissolved oxygen concentration).

$$2H^{+} + \frac{1}{2}O_2 \rightarrow H_2O - 2e^{-} \qquad (2.8)$$

The dissolved oxygen reacts with the hydrogen on the iron surface in an instantaneous reaction. When the anodic reaction equation is added to the above equation, the reaction shown in equation 2.9 occurs at the surface of the steel pipe.

$$Fe + H_2O + \frac{1}{2}O_2 \rightarrow Fe(OH)_2 \qquad (2.9)$$

The resulting product is Ferrous Hydroxide, which is white in its pure form but darkens to a darker green colour as it oxidises in the air. Because it reacts with dissolved oxygen in water, ferrous hydroxide has a pH of 9.5, making it an alkali surface (Revie, 2008). Because the outer surface is now Ferrous Hydroxide, it reacts with the aerated water in the system to form Hydrous Ferric Oxide, as shown in equation 2.10 below.

$$Fe(OH)_2 + \frac{1}{2}H_2O + \frac{1}{4}O_2 \rightarrow Fe(OH)_3 \qquad (2.10)$$

In its dehydrated state, hydrous ferric oxide has a reddish-brown appearance and rusts as Fe_2O_3. Rust is formed when Fe (III) oxidises further. Hematite is a more stable type of Fe_2O_3 due to its lower negative free energy of formation. Magnetite, on the other hand, is a lower oxidation state of Fe (II) and Fe (III) as Fe_3O_4. Both types can be found on an iron surface exposed to aerated water, but their existence is determined by the amount of dissolved oxygen in the water. Between the ferrous hydroxide and the hydrous ferric oxide, the magnetic Fe_3O_4 appears to form a blackish sheet. As a result, rust residues on metal surfaces are typically composed of three layers of varying degrees of oxidation iron oxides.

2.17. The Influence of oxygen on the rate of corrosion

Because oxygen is the primary source of corrosion in water containing metallic components, its role in the corrosion of HVAC hot water pipe systems is critical and must be understood (Wiegand et al., 2017). The oxygen in the water is approximately 30% by weight, and it degrades the carbon steel through the electrochemical corrosion process, which is discussed in section 5.1. Internal oxidation causes electrochemical corrosion, which results in thinning of the protective surface, pitting, grove, and rusting of carbon steel pipe, and failure of the overall assembly if not detected in time (Harvey, 2020). Figure 2.4 depicts how corrosion penetration increases with increasing water temperature and oxygen content.

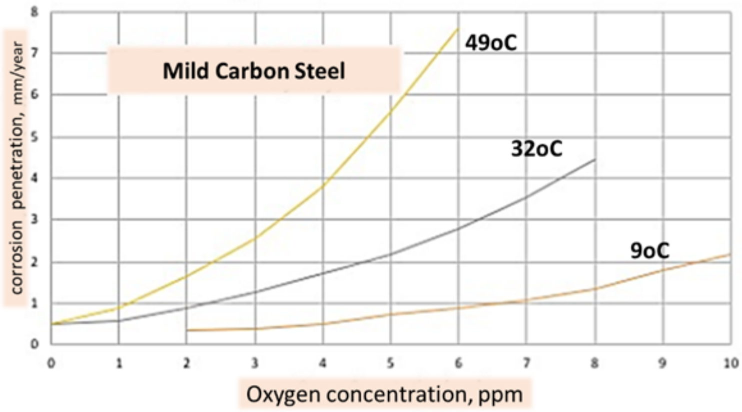

Figure 2.4 Corrosion rate of mild carbon as oxygen content in water increases, adapted from (Water Constituents, 2020)

Figure 2.4 shows how important it is to avoid continuous fresh water supply in the hot water HVAC pipe made of carbon steel to avoid severe corrosion, such as the heating system or a system similar to it that works at high temperatures. During the electrochemical corrosion process, oxygen acts as a cathodic depolarizer, removing hydrogen from the cathode side and energising it. During the electrochemical corrosion process, oxygen acts as a cathodic depolarizer, removing hydrogen from the cathode side and allowing the corrosion to proceed at a rapid pace (Wiegand et al., 2017). As a result, high oxygen content must be avoided in HVAC steel pipe networks to control corrosion, particularly in the heating closed system, because high oxygen content combined with high temperature causes severe corrosion of carbon steel pipe.

2.18. Temperature and corrosion capability

Temperature, according to Johnston et al., has a significant impact on the behaviour of dissolved oxygen in water (2017). (Revie, 2008) discovered that raising the temperature of the water by 30°C appears to double the corrosion rate at a known amount of dissolved oxygen. Figure 2.5 clearly demonstrates this by demonstrating that, when exposed to the same amount of dissolved oxygen, an increase in corrosion is proportional to an increase in water temperature. Furthermore, as the amount of dissolved oxygen in the water increases with temperature, the rate of corrosion accelerates dramatically, as illustrated in figure 2.5. According to (Jones, 1997), corrosion is a reduction reaction of oxygen reduction reaction, and this reaction is dependent on the rate of oxygen diffusion to the surface of the pipe, and since diffusion is a thermally ignited method, it is directly proportional to the rate of corrosion.

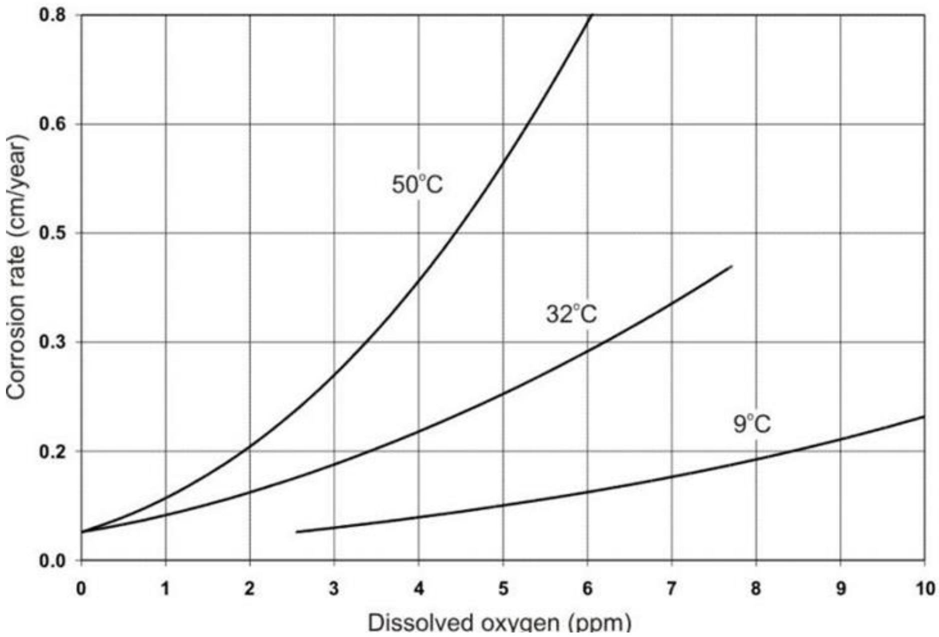

Figure 2.5 The influence of oxygen concentration on low-carbon steel corrosion in tap water at different temperatures. http://corrosion-doctors.org/

2.19. The Influence of temperature and pressure on the rate of corrosion

Because electrochemical reactions occur faster at higher temperatures, the rate of corrosion increases with temperature. Because the kinetics of the oxygen-electronic reaction are fast at the steel pipe's surface, the formation of hydroxide ions at the cathode increases as the water heats up (Rodbumrung et al., 2016). The general rule is that every 18°F increase in temperature doubles the rate of corrosion. Because the HVAC pipe network is a closed system, the corrosion rate increases at high temperatures, as illustrated in Figure 2.6. Deionized oxygen must be removed from the heating system in such cases.

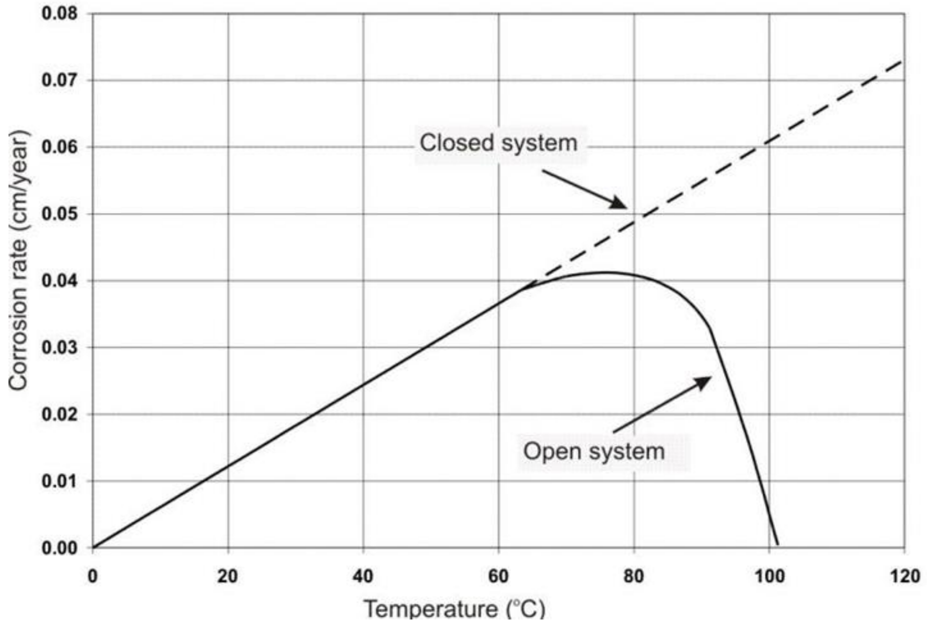

Figure 2.6 Mild carbon corrosion rate vs. temperature, adapted from (Water Constituents, 2020)

It is important to note that the oxygen content decreases as pressure and temperature rise, but high pressure and high temperature are the conditions that cause the corrosion rate to accelerate at the evaluated pressure and temperature. As a result, if water has a high oxygen content and is at a high temperature and pressure, the situation is extremely dangerous. Because our system requires a high temperature, proper control of pH and dissolved oxygen in the hot water is critical. As a result, the increase in corrosion at high temperatures and pressures is caused by the kinetic of corrosion rate.

Figure 2.6 shows how, as temperatures rise above 70 degrees Celsius, the rate of corrosion varies depending on the type of system. Water will exit the solution as it warms up in an open vessel system with air allowed to escape. According to the graph, the rate of oxygen-induced corrosion decreases significantly as the oxygen concentration falls below 3 mg/l; at 100°C, the steel corrodes no more than it did in aerated water at 25°C. In this case, the effect of rising temperatures is overshadowed by rising temperature-induced oxygen insolubility in water. In a closed system, however, oxygen is confined and pressurised within the system and cannot escape, increasing the rate of corrosion before the oxygen is consumed. As the water is heated, the dissolved air in it is released, resulting in the formation of air bubbles inside the closed loop system and pipe network. Because the air bubble slows the flow of heat through the pipework, more energy from the boiler is required to compensate for heat loss. Air bubbles, according to (Qin et al., 2017), can cause additional system issues such as noise, cavitation corrosion, restricted flow, reduced heat production, and premature failure of plants and equipment such as heat exchangers and pumps. It is critical to remember that air bubbles are not always caused by oxygen; they can also be caused by other dissolved gases that have degassed as a result of a temperature increase, such as nitrogen, hydrogen, and carbon dioxide (Qin et al., 2017).

2.20. Corrosion monitoring in the HVAC system

HVAC system monitoring in tall buildings is critical and can provide numerous benefits. Long-term benefits of HVAC system monitoring include sustaining capital stock through defect reduction, also reducing downtime and maintenance costs in the event of a sudden failure (Preventing Corrosion in HVAC Systems, 2018). Monitoring can help predict the hidden processing taking place in the HVAC system in the short term, which has the long-term benefit of avoiding system failure.

Corrosion coupons are the most widely used and reliable methods of detecting corrosion in HVAC hot water steel piping systems, where the electrochemical corrosion process is continuous and the end product is rust (Hevasure, 2021). Coupons are small thin bars of various metals that are inserted inside the hot water piping system via the external coupon rack, which is linked to the main layout of the piping network, as shown in Figure 2.7.

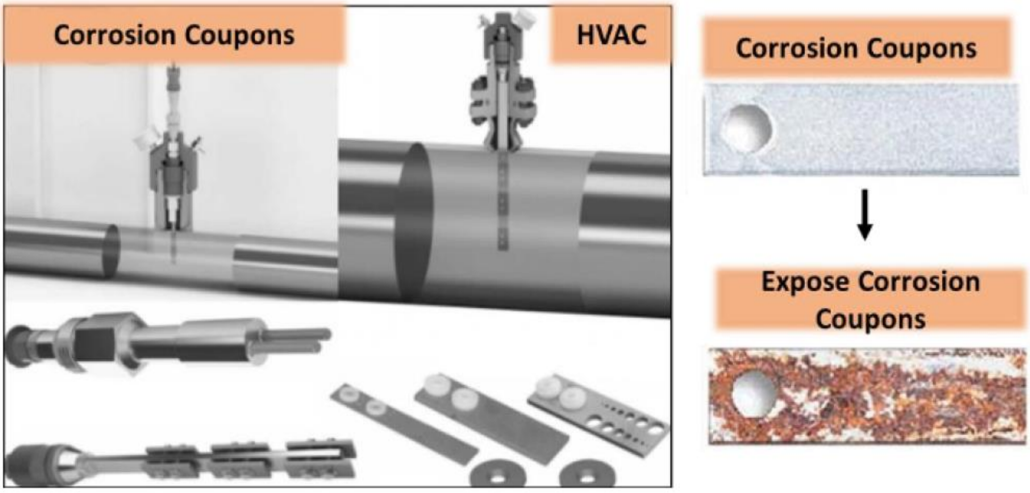

Figure 2.7 Corrosion coupons and probes for monitoring corrosion in an HVAC piping system, adapted from: What are corrosion coupons, probes, and holders? (2020.)

The corrosion coupon functions by being pre-weighted before being inserted into the piping network. For a period of 1-6 months, it is installed inside the pipe. These coupons are removed and analysed by corrosion consultants after being exposed in a hot water environment (Cox, 2014). Corrosion rate is normally measured in mass loss in millimetres per year over the time of coupon exposure in service, allowing the corrosion condition of pipe to be predicted. The most advanced type of corrosion monitoring is the use of sensors and probes with coupons that automatically analyse and predict corrosion as part of an online application that alerts when the corrosion threshold value inside the HVAC hot water piping system is exceeded.

Some commercially available applications, such as the monitoring and prediction of corrosion in HVAC systems using electrochemical noise and linear polarisation curves, have been reported in the literature (Ameh et al., 2017). Corrosion Inspection Honeywell's Smart CET transmitter equipment is an example of a smart corrosion monitoring system. It is a reliable transistor system that provides corrosion consultants with an accurate measurement of the corrosion within the HVAC system (Liu et al., 2007). The information provided by these systems aids in predicting the corrosion condition within the system and optimising the processing parameters to control the corrosion rate, such as water pH, temperature, and oxygen content, among other things.

2.21. Corrosion control and prevention in HVAC hot water steel pipe

Corrosion prevention consists of three major steps. The first step is to determine the type of corrosion that is likely to occur in a given system. Because the system under consideration in the literature is a hot water HVAC system, the presence of water as an electrolyte raises the possibility of electrochemical corrosion. The dependent factor of electrochemical corrosion is already discussed in Section 4.0.

The second step in corrosion prevention is the analysis of component materials, such as pipe material and the quality of water used as a heating source in an HVAC pipe network. Corrosion can be effectively prevented by carefully controlling the quality of the materials used in the HVAC system and the quality of the water flowing through it (Smith et al., 2003). In the literature, various materials that resist oxidation under hot water treatment have been reported. The use of these materials can also help to prevent corrosion in the HVAC system (Wiegand et al., 2017). Various treatments capable of slowing corrosion in steel hot water pipes have also been reported. Some of them are detailed below:

1. Creating an electron-transfer barrier by coating an oxidant-resistant layer inside a steel pipe.
2. Insertion of a corrosion-resistant cement lining or glass glaze into the walls of hot water pipes.
3. To prevent steel pipe corrosion, use a sacrificial element lining inside the pipe.
4. The most common and cost-effective method of preventing or controlling corrosion rates inside hot water steel pipes is water treatment. Water treatment, according to corrosion consultants, should be used to optimise the corrosion dependent factor that accelerates the corrosion rate.

Two common water treatment methods are used to prevent corrosion accelerating factors. The process of softening water before it enters a steep pipe, also known as the ion exchange method, is known as softening. Polystyrene (PS) resin is the most commonly used material for this purpose because it removes unwanted dissolve solids that cause scaling and corrosion in steel pipes.

Dissolved oxygen and low pH of water, as previously stated, accelerate corrosion in hot water steel pipe. Thus, dissolved oxygen and CO_2 can be removed from water before entering the system via daeration, but this is not the ultimate solution because both can enter the system later during service via various means, so chemical treatment is considered necessary in this case.

2.22. Inhibitors of corrosion

Corrosion inhibitors are the most effective and cost-effective way to control corrosion in HVAC hot water steel pipe, as they can extend the life of HVAC hot water steel pipe by years. Corrosion inhibitors come in a variety of classes and types, but the cathodic corrosion inhibitor is the most common type in the water environment for metallic materials. As shown in Figure2.8, the ions of the metallic inorganic inhibitor react with the hydroxyl (OH^-) to form protective oxide, which when deposited on the cathodic side of the steel pipe protects it from rusting due to corrosion.

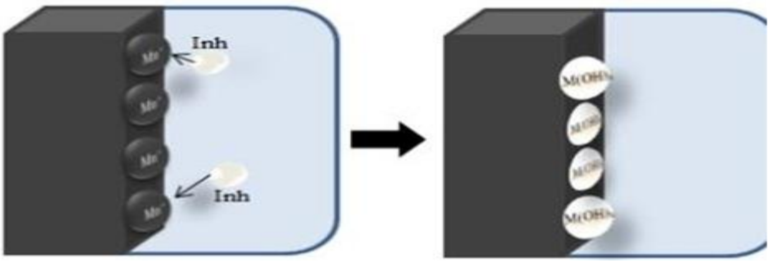

Figure 2.8 Cathodic inhibition mechanism in a water steel pipe. A.F. (Dariva & Galio, 2014)

System cleaning and pre-treatment are critical steps in the inhibition process. The corrosion consultant recommends that the inhibitor be added at the recommended level to maintain protection. The important point to emphasise here is that, in addition to the corrosion inhibiting ion, the pH of the water must be kept at an optimal level because, at very low pH, the inhibitor's efficiency becomes ineffective.

A very high pH is also not recommended because it may cause scaling on the walls and surface of the pipe.

2.23. Machine learning (AI) in corrosion prediction.

In all buildings, the integrity of the HVAC system and the proper operation of hot water pipes are major challenges. Because of its strength and low cost, mild steel, the material under discussion in this literature review, is widely used for hot water steel pipe. Corrosion in steel pipes causes severe damage to a building's steel pipe network and raises building maintenance costs due to a reduction in the life span of the HVAC pipe network. The Future of Machine Learning on Corrosion. (2020).

Various manual methods for detecting corrosion in the HVAC pipe network system have been reported in the literature, but all of them have limitations, such as high cost and inability to detect corrosion in areas that are impossible to reach manually. The use of machine learning tools to predict HVAC system corrosion is a significant academic and practical breakthrough. In his published work, Hoang, 2019, proposed an image processing-based technique for detecting corrosion in a pipe network. He used the concept of support machine learning in his work to create a boundary line capable of distinguishing between corroded and intact pipe surfaces. As a result, his research shows that the machine learning concept can be effectively used as a source of building maintenance agent for pipe network corrosion status surveys.

Ossai develop a machine learning method for detecting corrosion in a pipe network (Ossai, 2019). The authors used various machine learning models such as Particle Swarm Optimization, Feed-Forward Artificial Neural Network (FFANN), Principal Component Analysis, and others to investigate the corrosion of the steel pipe in the proposed research work. According to a review of the literature, using machine learning is the quickest and most effective way of predicting corrosion because the entire machine learning procedure is based on data obtained from various historical events.

2.24. The use of artificial intelligence in the HVAC system

This section will define and demonstrate how artificial intelligence (AI) tools have been developed to improve the HVAC system's performance and usability. Artificial intelligence is being used extensively across all industries to extract insights from complex and highly unpredictable data. Machine learning serge has recently gained popularity in the HVAC and construction industries. Organizations such as ASHRAE and CIBSE are utilising artificial intelligence to advance knowledge about non-linear relationships for cost and energy savings. Despite the abundance of AI tools for HVAC systems that have been developed over the last two decades, their performance has been generally unsatisfactory. AI has primarily been used to save and consume energy, assess the precision of how much heating and cooling is generally required, and predict controls. Since 1976, the result of HVAC systems achieved through the use of schedule controlling techniques has been approximately 14.07%. The maximum amount of energy saved from using this was approximately 46.9 percent when smart sensors were included. These would allow the HVAC system to detect its surroundings and adjust the temperature based on the data collected by the sensors.

They like to go over previous methods that researchers have used to improve how the HVAC system performs in the building, and methods that can monitor the performance of the steel pipes, before doing so. The need for real-time HVAC systems to provide an energy-efficient solution has piqued the interest of researchers, who are investigating the feasibility of developing an occupancy-based system. Inside multi-zone spaces, proactive and reactive zone heating and cooling activation contributes to energy savings as a significant improvement in the thermal comfort of the building's occupants (Terziyska et al., 2006). Several studies have yielded valuable results in terms of safe energy that can provide the occupants with the desired comfort. Several types of sensors, such as CO_2 sensors, motion and heat detectors, and others, are used to detect building occupancy and determine how many people are inside the building. Meanwhile, a series of combinational systems are used to predict how much energy the occupants will require. These systems analyse how much energy should be allocated to each individual or occupant using mathematical models such as Markov chains and real-world data.

(M. H. Lee et al., 2013) proposed an automatic control system for a thermostat that predicts the endpoint using an occupancy prediction system, allowing the thermostat to adjust itself (Terziyska et al., 2006). The data collected from cell phone towers is used to forecast the mobility of the occupants. Meanwhile, a model trained on the patterns discovered in their arrival time and route was used to predict their arrival time.

Meanwhile, their arrival time was predicted using a model trained on the patterns found in their arrival time and route based on cell tower data (Dobbs & Hencey, 2014). Finally, the prediction of the location of the destinations is discovered to be relatively close, and a “Order-Markov” predictor is used to accurately predict these factors (S. Lee et al., 2013).

In their research, (Erickson et al., 2013) created a system to control HVAC systems. This is accomplished by utilising occupancy-based data from POEM Systems. In order to detect occupant transitions, the researchers built a two-part wireless network. The occupancy estimation system (OPTNet) is the first component, and it is made up of 22 camera nodes plus passive infrared (PIR) sensors that detect participant movement (Terziyska et al., 2006). It was discovered that combining the data from these systems with the output of the occupancy transition model inside a particle filter resulted in more accurate estimates of current occupancy. The HVAC system's control schedule generally takes over the pre-heated areas of the target temperature based on the current occupancy in each room and the predicted result from the transition model (Terziyska et al., 2006).

(Kamthe et al., 2009) collected data through wireless networking. The data collected from it was then used to create occupancy models, which were then used to control and regulate the HVAC heating and cooling (Kamthe et al., 2009). This model is composed of two types of Markov Chain models: single MC and/or blended MC, and the results of these two models are compared to determine which one is best (Kamthe et al., 2009). The main discovery was the best efficiency of BMC, so it was incorporated as the tenancy of method, which is a controlled temperature strategy.

(Balaji et al., 2013) developed the SENTINEL integrated system, which is defined as HVAC systems serving as a control that uses occupant data. As can be seen, the system uses the building's Wi-Fi networks of the smartphones of each client to triangulate their location and collect data in order to detect and predict it (Balaji et al., 2013). This mechanism is based on AP communication with the user's smartphone, so if the resident's call ends while he is within its range, he will be notified. If a title holder is detected approaching the space or is within the area where the individual's office is located, or when the network detects that the occupants are in the same area or room, the HVAC system is triggered (Balaji et al., 2013).

(Dong & Lam, 2014) proposed an existing temperature regulating system in their research, with the goal of minimising energy consumption while ensuring an ideal environment for the occupants. The behaviour of occupancy expectation and weather forecasting, as introduced in the building model, can be used to determine HVAC system control. This technique makes use of Gaussian Mixture Models (GMM), which are used to categorise specific features and produce the best results based on residents. The chosen data is then sent to a Hidden Markov Model, which is used to estimate the number of system occupants. In order to evaluate the required time for occupants in the mentioned space, a semi-Markov model was established based on a pattern composed of data collected by sensors such as CO_2 production, acoustics, and motion detection, and changes in the environment's lighting (Terziyska et al., 2006).

(Dobbs & Hencey, 2014) propose a predictive control model that is used to save energy by the HVAC while also ensuring that the environment is ideal for the occupiers. This model is based on a two-state Markov chain in which the model and working conditions are important in determining how much energy the occupants require (Terziyska et al., 2006).

(Brooksa et al.) proposed a feedback control algorithm for variable air volume (VAV) HVAC systems. This is accomplished by dividing the room into zones, which is repeated for each room. The proposed algorithm, MOBua (Measured Occupancy-Based Setback for Under Actuated Zones), makes use of occupancy data collected in real time via a WSN. The algorithm used could be used in traditional systems without the knowledge of the building's occupants, and it is thought to be scalable to buildings of any size.

There are approximately 18 AI tools specifically designed for the HVAC system. A neural network, which includes an artificial neural network (ANN), a recurrent neural network (RNN), a spiking neural network (SNN), and a wavelet ANN, has been used by many people. The former is based on how the human brain works and how it learns new information (Kalogirou, 2006; Mihalakakou et al., 2002; I.-H. Yang et al., 2003; Yao & Steemers, 2005). A set of neurons typically has three layers: an input layer, an output layer, and a hidden layer (Kalogirou, 2006). Most of the time, the controller is not required to identify the control model (Kalogirou, 2001). The mass coefficients could be controlled before or after the training process to keep the costs of making it work as low as possible (Yao & Steemers, 2005). It can be used to simulate how the brain works and functions, giving insight into a complicated system (Kalogirou, 2001). This can be advantageous because it enables the development of a model capable of handling multiple tasks at the same time. The disadvantage is that such a model would take a long time to train and would require a large set of data to train the model (G.-C. Liao & Tsao, 2006; Z. Yang & Becerik-Gerber, 2014).

A fuzzy or model-based predictive control, also known as an MPC, is an HVAC system tool (Huang et al., 2009; Shengwei Wang & Jin, 2000). MPC is commonly used to provide feedback from the results of the prediction made on the system itself if any adjustments to the system's parameters are required (Huang et al., 2009; Lazrak et al., 2015; Serale et al., 2018; Terziyska et al., 2006; Shuaixing Wang et al., 2019). The feedback system is thought to be different from what has previously been seen due to the way the sensors are designed. In their study to detect the indoor temperature of a room, developed an autoregressive neural networking with non-linear and an external structure in auto regressive (Yun et al., 2012). Along with improved control performance, the system signal for the non-linear system can be discontinuous (Yun et al., 2012). It is thought to be distinct from continuous signals used in linear systems like a PID controller, which are generated using the Laplace transform and linear transfer functions. ANNs are similar to how humans gain insight into the information they receive (Serale et al., 2018).

A distributed AI system is the next most commonly used tool in HVAC systems, and it is primarily used to develop systems that can have multiple agents working on the system at the same time (Kim et al., 2012; Klein et al., 2012; Lee & Tsai, 2020; Nguyen & Aiello, 2013; Qolomany et al., 2019). It not only improves an HVAC system's overall process by using an MPC or an ANN, but it also employs sensors, actuators, and sensors that are designed to communicate and interact with one another. By utilising MAS, it allows the system to be more intelligent (Klein et al., 2012).

SVMs, which work similarly to how humans' reason and are generally used to control the IF-ELSE conditions, are another tool used for fuzzy control systems. The use of ambiguous logic grades and/or rules generally results in slow time response, which can be a problem if a real-time based system is required (Kolokotsa, 2003; Kummert et al., 2001; Terziyska et al., 2006) .

When using fuzzy logic grades and rules, the response time is generally slow, which can be a problem if a real-time system is required (Kolokotsa, 2003; Kummert et al., 2001; Terziyska et al., 2006). As a result, using SVM or R in conjunction with fuzzy control systems for data classification would allow one to discover the hard margins that exist in various types of data that are used to find the best methods, modelling, and regression (Kummert et al., 2001). These are commonly used for large-scale data analysis, but they are not commonly used in HVAC system applications. Furthermore, distributed AI tools such as model-based controls or the application of DL (Dalamagkidis et al., 2007; Qela & Mouftah, 2011; Wei et al., 2019) SVM and R tools, can be used to collect and analyse distributed data. Using a MAS tool, the outcomes are then communicated and interacted with (Qela & Mouftah, 2011).

The main benefit of using these is that it allows one to use a logic controller within an HVAC system application while monitoring the HVAC system's performance. Furthermore, it can help to improve predictive strategies and high observational capabilities, which can help to improve the way the HVAC system can bring to the system itself (Qela & Mouftah, 2011). It does not solve problems involving non-linear time variable systems in general, but these can be implemented in time independent systems (Wei et al., 2019). Deep learning is a broad area of artificial intelligence that has gotten a lot of attention in recent years. Deep learning has the primary advantage of determining a control strategy that can be configured to work according to the system's predefined conditions (Qela & Mouftah, 2011). Deep learning is primarily based on data representations, which are obtained by identifying patterns in data. Unlike previous methods, which required the use of a task-specific algorithm, which limited how the model could perform, this method does not require the use of a task-specific algorithm. The use of a deep learning algorithm ensures that the model can be made more dynamic based on the rules it generates based on the patterns it observes (Cheng & Lee, 2019).

Knowledge-based systems are analogous to DL tools. In contrast, the DL tool is used to control the system. Knowledge-based systems provide the best conditions control strategy for various HVAC systems via the expert system (Clark & Mehta, 1997; Panchal & Knudsen, 1998). These are mostly used for problem solving and to help the models with their human learning, actions, and decision making (Cheng & Lee, 2019; Clark & Mehta, 1997). Case-based reasoning is also used to help with this, but there aren't many articles on the subject (Monfet et al., 2014). It can determine the best conditions for energy savings and, if necessary, use model-based control (Cheng & Lee, 2019; Monfet et al., 2014). However, these tools are generally time consuming and costly to train, plus how long it will take to train it (Cheng & Lee, 2019).

Other tools, as a result of recent technological advancements, have been used in addition to these. PSO, AFSA (which is primarily used for optimising the HVAC system's control strategy), hidden Markov models (which are used for modelling data in order to create logic rules), kNN (which is primarily used for determining the nearest data attribute that matches the input it receives), and ARX (which is primarily used for regression tasks and implements an external input and a feedback loop) are among them (Cheng & Lee, 2019). Other tools were used in addition to these to create a better model that could be used to better predict and monitor the performance of the HVAC system. Data collection and analysis tools, such as the radial basis function, can be used to identify patterns in the data that can be used to make predictions and determine what actions should be taken.

As previously stated, most commercial and residential buildings use a combination of ANN and fuzzy tools to monitor and assess the performance of HVAC tools. These two have around 34.5 percent and 24.2 percent adoption rates, respectively. The ANN tool learns and adapts to the data that is fed to it. This ensures that it can perform as accurately and efficiently as any human would (Cheng & Lee, 2019).

The use of ANN and fuzzy logic tools is generally found to be useful in commercial buildings because the occupants work on a set schedule, necessitating the use of these models in a commercial building. ANN is unsuitable for residential buildings, however, because different users have different needs that a single algorithm cannot predict and adjust the HVAC system for. To combat this, an ANN tool combined with DL, reinforcement learning, or DFL can allow the system to make the necessary adjustments to the HVAC system based on the needs of each occupant without the need for a professional energy manager once trained and capable of identifying the patterns found in it (Cheng & Lee, 2019).

CBR and KBS tools, and fuzzy logic tools, are used in commercial buildings. These systems can use model-based control to predict various conditions such as weather, energy consumption, and occupancy, optimise and increase HVAC systems to ensure thermal comfortability. Distributed AI, on the other hand, is intended to complement ANN + fuzzy tools in residential buildings. Sensors are outfitted with distributed AI tools to conserve and save energy while also ensuring thermal comfort in the environment by sensing occupancy, temperature, and CO_2 levels. This is then used to interact with a MAS tool, resulting in the discovery of optimal conditions that can improve the system's overall performance (Cheng & Lee, 2019).

Finally, predictive control is a recently developed tool that is applied to composite buildings. It is used to improve the control act by making the system predict based on the previous data that it is trained on and the data that it receives after being trained. These systems are a cross between residential and commercial construction (Cheng & Lee, 2019). As a result, the people who live there are generally regarded as the type of building that is regarded as a modern and effective residential construction method. It is built in accordance with international standards to ensure that it is both sustainable and environmentally friendly. This is supported by the continuous and changing developments in steel processing, building materials, and the wide range of architectural solutions made possible by steel.

This assessment will use a deep learning-based approach to monitor the system's pipes and ensure that they do not corrode due to changes in water pressure and heat in the environment. This is done to ensure that it can be monitored efficiently and used to predict when the pipe will corrode based on the temperature and water pressure applied to the pipe. As a result, the model must be built to meet the specifications that have established in this study. In the following chapters, a detailed overview of how the model is created and what steps and measures are taken to ensure that the model performs optimally and predicts the condition of the pipes under different temperatures and pressures that will be applied to it due to seasonal changes and user needs will be provided.

2.25. Artificial intelligence in HVAC pipe network

Corrosion is a natural process that destroys metals by reacting chemically or electrochemically with their surroundings. The corrosion process is influenced by diffusion, pH value, temperature, pressure, and galvanic current (Seal, 2017). Steel pipes are the most commonly used for substance transportation (Natural gas, oil, water, etc.). There are currently several methods for estimating the corrosion rate in steel pipes. Because of the complexities of this phenomenon, most models fail to estimate the corrosion rate accurately. Machine learning is rapidly evolving and is being used to solve a wide range of complex real-world problems. Several attempts to apply Machine Learning methods to corrosion prediction have recently been made. (G De Masi et al., 2017) proposes a novel naval approach to identifying the most important factors influencing the corrosion process. Mutual Information Theory (MI) and the Shannon Entropy method underpin this scheme. Based on their estimated entropies, the MI factor of two variables measures their interdependence. After calculating the entropy of each factor, the factors with the highest entropy are fed into an ANN to predict the internal corrosion section. Elevation, liquid velocity, pressure, and gas flow are identified as critical variables in the corrosion process by the technique. Another machine learning technique is used to predict corrosion in (G De Masi et al., 2017). The solution for this specific regression problem included a feed-forward neural network (FNN). The feed-forward network is used to figure out the relationship between two independent variables. The scheme employed three distinct types of inputs (pipeline characteristics, Fluid dynamic multiphase variables, Deterministic models). All of these variables were used as input parameters, and the corrosion rate was the system's output (CR). The FNN model's performance was estimated using four statistical methods: correlation coefficient (R), root mean square percentage error (RMSPE), mean absolute percentage error (MAPE), and SI (scatter index). The scheme also discusses how fluid dynamic factors (flow regime, gas pressure, flow, liquid velocity, and gas velocity) affect corrosion prediction. The author of (K. Liao et al., 2012) predicts corrosion rate using another ANN with backward propagation (BP) and genetic algorithm (GA). The machine learning model suggests The ANN algorithm is a non-linear model, and its primary application is to map complex relationships between input and output variables. Because input and output parameters are crucial for ANN, the author claims to have compiled a list of the most critical and important input parameters for the ANN learning process. System design parameters include pipeline length, pipeline material, and geographical distribution. The pipeline mapping data includes inlet and outlet pressure, inlet and outlet temperature, flow, and flow rate. The fluid composition includes the presence of CO_2, O_2, and H_2S, and liquid composition. The proposed model had a margin of error of less than 0.01 mm/a. As a result, the GA and BP model was chosen as the most effective method for estimating wet gas gathering pipeline corrosion rates in Sichuan Province (China). describes how the researcher predicted the corrosion rate of steel pipes in seawater using an ANN with backward propagation. The sea environment, temperature, salt content, oxygen content, and pH value were used as input parameters for ANN training. The evolution parameters were MSE, MSRE, and volume of fluid (VOF). The findings also explain the relationship between the input and output variables. Corrosion rate, for example, decreased as temperature and pH value increased, but increased as oxygen level increased.

In that order, content and salt content. (Canonaco et al., 2020) used machine learning (ML) to determine the best input variables for predicting corrosion rates in oil and gas pipelines. The author explained that for corrosion prediction, there are two types of data: geometrical data and fluid-dynamical data, and that the relationship between these variables must be integrated. Both types of data are important when predicting corrosion rates. Furthermore, no guidelines exist for integrating these two major data sources. This is significant because proper theme integration results in a reliable analysis of the parameters involved in the corrosion process. For data modelling of corrosion rate, the proposed scheme in (Nesic et al., 2001) used the probabilistic neural network (PNN), also known as a feed-forward network. The PNN adjusts its weights for better training by propagating backward errors through the network layers during training. The Gaussian distribution was used to calculate the uncertainties and the impact of input variables on output variables. This experiment made use of the dataset from (Sinha & Pandey, 2002; Sun et al., 2010). Input factors include temperature, pipe flow, velocity, pH value, pressure, and ferrous ion concentration. The experimental results show that the proposed feed-forward neural network predicts corrosion in the oil and gas industry. To estimate the likelihood of pipeline failure due to corrosion, the proposed simulation-based probabilistic neural network model was used. To compare the results, three different neural networks were used (standard backward propagation neural network, general regression neural network, and radial basis function networks). In terms of learning speed and success rate, the comparison results show that PNN outperforms other neural networks.

Because of the nature of the problem and the factors involved, corrosion prediction is a very sensitive and complex problem, according to the study. According to the study, pipeline lifespan and corrosion rate can only be evaluated if the best factors and prediction tools are used. Temperature, pressure, pH value, and flow rate are the most important factors, as described above in the literature review, and are commonly used in experiments to detect and predict corrosion rate (G De Masi et al., 2017; Giulia De Masi et al., 2014; K. Liao et al., 2012; Seal, 2017). Furthermore, when comparing different models for this specific task, machine learning algorithms outperform them (Giulia De Masi et al., 2014; K. Liao et al., 2012; Shirazi & Mohammadi, 2017). While (Nesic et al., 2001) demonstrated that the PNN has a higher prediction rate with less training time and data than the other Neural Network algorithms such as backward propagation neural network, general regression neural network, radial basis function networks, and probabilistic neural network (PNN). In order to achieve accurate results, best possible factors and model have been chosen for this experiment. As a result, best possible factors are variables temperature, pressure, pH value, flow rate, and PNN machine learning model for this study.

2.26. The impact of BIM on HVAC steel pipes

To better understand the influence of BIM on HVAC steel pipes, it is thought necessary to have a clear understanding of what BIM is and how it has been useful in the construction of HVAC steel pipes. BIM is designed to allow stakeholders, typically employees or project managers, to create, manage, exchange, and share building information. In the construction industry, these processes are constantly evolving in order to make them more appealing to stakeholders in order to better simulate and visualise how the building project will look before construction begins. It is also defined as the gathering of information about a building and storing it in a virtual model that can be reused for a variety of purposes. BIM, in general, focuses on almost all of the factors required in construction, with its scheme forming a whole database that includes a geometric model information that defines the material being used and the properties that it contains. It interferes with every stage of building development, from the early stages to the later stages when the building's final design is approved (Sampaio, 2017). It also includes phases such as the planning process, building usage, and the various structure phases of the study.

BIM allows for the preservation of information generated throughout a building's life cycle, which can then be used to improve the building. The level of consistency discovered between design data and quality data, the construction process and control quality (Sampaio, 2017). The use of BIM in quality management is based on their ability to provide multidimensional data, which includes time sequences and data design (Sampaio, 2017). The general idea behind implementing BIM is that it is used as a database in parallel with the specific project and during the utility phase to store, add, or collect any type of relevant information that can help in the construction of the building, such as maintenance, building economy, and climate control, among other things.

The architecture, engineering, and construction industries have used BIM to address performance and productivity issues that have plagued these industries. It was discovered that, when compared to traditional working methods, BIM assisted them in achieving better coordination, integration, and coordination while improving the flow of information and the processes associated with it. With these benefits discovered, the majority of businesses in these industries have begun to use BIM in their projects and have made efforts to avoid reverting to traditional methods. This is because using BIM increased their productivity while decreasing the likelihood of having to rework existing work to improve it.

This is because it can be seen that using BIM increased their productivity and decreased the likelihood of reworking existing work to improve it, which also extended to the management of waste caused by demolishing buildings. Despite evidence of its potential benefits, BIM adoption varies by industry. In their research, (Harty et al., 2015; Kouide & Paterson, 2007) discovered that, despite the availability of cutting-edge software tools, significant technological constraints exist that can stymie widespread adoption in small and medium-sized businesses (SMEs).

Using BIM at the beginning of a project allows engineers and designers to make better decisions sooner in the process. The graphics of buildings, the systems within them, are typically generated by data, which can be changed to meet the needs of the project as the requirements become clearer over time. The majority of this software connects smart objects so that changes made to one object are automatically applied to others linked to it.

The information is the most important component of BIM, and it is similar to what is found in a spreadsheet. The data for the building is described in a spreadsheet, which begins with a room. To help sort the data and explain it better, columns and sub-columns are added to the spreadsheet. This spreadsheet can be used to add more materials to the building or to upgrade the existing materials.

BIM, on the other hand, has its own set of drawbacks that may have an impact on the construction process. The main issue with BIM is that it requires more work to establish the initial framework because BIM software is generally more complex than CAD software and requires a large amount of project information. This must be entered, which can be challenging for a novice designer. Some claim that in order to make better use of the software and create virtual building designs, they must adopt a new way of thinking. Designers who are used to using more traditional 2D or 3D CAD software may find the transition to BIM tools difficult. Designers who are more up to date with current technology will be able to adapt to the change more effectively than those who are satisfied with their current knowledge. It takes a lot of precise information to calculate the building's thermal composition properties. Any calculation error, incorrect data, or data omission would result in an incorrect thermal analysis of the building. In general, software tools include a model checking capability that gives the end user feedback on the quality of the model's information. However, in their current state, these functions are deemed untrustworthy. They will be able to be as efficient as possible in the future in order to make model checking more reliable and usable with smaller data sets.

This allows one to obtain a digital representation of the building or structure that may appear once the building is completed (Razali et al., 2019). This model could be used during the design phase and during the construction stage for building operation and maintenance. This not only helps engineers, builders, and architects identify potential problems that may arise as a result of the model an artificial environment, but it can also ensure that everything remains intact (Razali et al., 2019).

Furthermore, the advantage of BIM allowing later changes to the building design may impact construction and design costs as the client decides to make these changes. Because BIM tools are parametric in nature, changes can be easily propagated through other related models and analytical tools. When using non-parametric tools, this can lead to confusion and unintended consequences. It may also cause issues with coordination among the parties involved, which may have an impact on how the project is formed in the future. This could have an effect on the development of the building later in its life cycle.

Currently, the use of BIM to develop and design HVAC systems is in its early stages, making determining how good it can be in general unreliable. In addition, the lack of standards makes it difficult for new designers to assist in the design and construction of HVAC systems. This creates a steep learning curve for the people, which may influence how they design the pipes. As a result, it is not used by the vast majority of designers. However, the advantages it offers ensure that it can improve pipe design and that its application can provide an accurate simulation of how the pipes perform and act under various conditions (Azhar, 2011).

As can be seen, BIM offers numerous advantages to construction workers, such as assisting them in managing their workflow and providing. This provides a significant benefit by visualising the buildings in 3D mode (Azhar, 2011). Unlike previous 2D methods, 3D renderings are easy to understand and allow for the creation of buildings with minimal additional effort. Furthermore, it can be seen that drawing various building systems using a BIM can make it easier to build if they can learn it. Drawings for various building systems can be generated based on previously created designs or a designer sketch. Other stakeholders can use this to review the project, how it will be built, and what will be used, which can be used to estimate the cost of the entire construction process, rather than just the designers to build the buildings and their systems. For example, fire departments and other officials could use the model to evaluate building projects in order to determine how they can save people in the event of an emergency. The BIM software includes cost estimation features. This could then be added to the original cost in order to compare and contrast how changing one component affects the overall cost of the building. Furthermore, it can be used in construction sequencing to organise the various building components. It can also be used to detect any type of conflict, interference, or collision that may occur in the system. This is because building information models are typically created in 3D space to scale. This information will be useful in ensuring that the building remains safe and that they are notified if anything threatens them. This could be used to improve the construction management of the building (Azhar, 2011).

The primary benefit of a building information model is that it provides an exact geometrical illustration of the parts of a construction. According to the CRC report's findings (Construction Innovation 2007). Faster processes are one of the benefits. The statistics can be easily shared and reused, resulting in a more efficient construction process. Furthermore, it is capable of producing the most comfortable design. Furthermore, it can be used to control the total cost, which could be used to ensure that performance is more predictable and the cost of life cycles is better understood, potentially leading to higher production quality: The documentation output is adaptable and takes advantage of automation. As a result, there could be an increase in better production and goods manufacturing. Accurate visualisation improves understanding of the proposals, which can lead to better customer service and help stakeholders understand how the construction process will unfold. Finally, creating and managing the entire building life cycle would be relatively simple (Azhar, 2011).

The Centre for Integrated Facilities Engineering at Stanford University reported some BIM paybacks based on data statistics from 32 major projects (cited in CRC Construction Innovation 2007).

¶ Change that is unplanned can be reduced by up to 40%.

¶ When compared to traditional estimates, the actual estimated cost for accuracy is 3%.

¶ An 80% reduction in the amount of time required to generate

¶ By clashing, 10% of the contract value could be saved.

¶ The time required for the project can be reduced by 7%

These points can provide a detailed overview of how beneficial BIM can be to a company and how it can be used to cut costs.

2.27. Summary

Building conditioning relies heavily on water systems. The overall performance of hydronic systems is harmed by corrosion. Poor water quality, poor maintenance, and component oversizing will increase energy consumption by 30%. Steel pipe corrosion can lead to an increase in energy consumption and a disruption in how the system regulates internal temperature. Low corrosion rates are required for optimal water system performance. Corrosion has both a financial and an energy cost to the building's energy bill. If radiators, boilers, chillers, valves, and pipe sections are not marked, they must be replaced. In the building services industry, AI is designed to work in conjunction with ANN to improve human comfort in buildings. Sensors are equipped with artificial intelligence tools to conserve and save energy while ensuring thermal comfort. This is then used to interact with ANN models, resulting in the discovery of optimal conditions that can improve the system's overall performance. Corrosion caused by hot water When metal is exposed to air, water, or comes into contact with another metal, it forms HVAC piping. The majority of corrosion is caused by galvanic action at a negatively charged pole on a metal surface. Corrosion is a natural process that destroys metals by reacting chemically or electrochemically with their surroundings. The proposed model had a margin of error of less than 0.01 mm/a. To model corrosion rate data, the proposed scheme used a probabilistic neural network (PNN), a type of feedforward neural network. In terms of learning speed and success rate, PNN outperforms other neural networks. BIM is designed to enable stakeholders to create, manage, exchange, and share building information. Buildings can be quickly created using 3D renderings because they are simple to use. Drawings for various building systems can be created from pre-existing designs or from a designer sketch.

The application of artificial intelligence to predict steel pipe corrosion in HVAC building services networks is the most significant gap in the literature. There is a gap in the study of the optimal accurate corrosion rate prediction using an ANN model due to the numerous divisions and subdivisions of ANN models. This literature review and discussion of related research and studies narrowed it down to the selection of meaning full ANN model division, but this can only be validated by running the model and observing the accuracy output. I was able to develop and compare a basic ANN model to an optimised ANN model as a result of the literature review. A large data set is the foundation of any model. This review of the literature identifies the most important parameters influencing corrosion in steel pipes, but there is a gap due to a lack of or inability to develop a relevant data set for developing an ANN model.

Chapter 3 Research Methodology

3.1. Introduction

This chapter goes into great detail about laboratory methodology, field studies, neural network development, and BIM to VR. On BISPA training, various tests will be performed to determine the rate of corrosion of steel pipes based on temperature and pressure. Experiments in the Hevasure Lab will be carried out to monitor and determine the rate of corrosion of steel pipes, with the focus is on galvanic current. For this case, an ANN model will be used because it allows better analyse and predict the rate of corrosion of steel pipes. This will also help to understand the relationships between the variables discovered, such as the galvanic current produced and the oxygen dissolved in the water.

3.2. Methodology

The purpose of this chapter is to explain the research’s methodology and design of the research. This is useful in gaining an understanding of how this can predict or forecast pipe corrosion, which will help in ensuring that the pipe's longevity. The data collected from laboratory experiments could lead to the development of the Neural Network – model, which will predict and monitor the performance of the pipe by analysing the health and the rate of the corrosion of the steel pipe. This section describes the methodology used to building the black-box model.

This chapter is divided into three sections: BISPA rig experiments, Hevasure laboratory experiments, and Black box modelling. This section also discusses the methodology of the overall framework of linking BIM to intelligent visualization, and discusses the methodology of feasibility of BIM to VR study.

The first step is to design and build rigs to conduct experiments and collect data. Data collection describes how the laboratory experiments will be set up, for the considerations and criteria that will be used to ensure accurate results and repeatability. The parameter settings could be adjusted based on the results of laboratory tests. It would provide us with a good understanding of how the performance of the steel pipe could vary depending on factors such as temperature, pressure, dissolved oxygen and corrosion. It can also be used to ensure that the results are as clear and concise as possible. Furthermore, the laboratory experiment setup could be tweaked to allow for more data collection based on the conditions set and to determine the causes of corrosion.

This chapter will describe how the ANN model will be created, the algorithms that will be used to create it, and the parameters will be used. It describes how the VR environment will be built using BIM and Unity3D and viewed using devices such as the HTC Vive to run simulations to evaluate the ANN model's performance. The diagram below depicts how the experiments will be carried out.

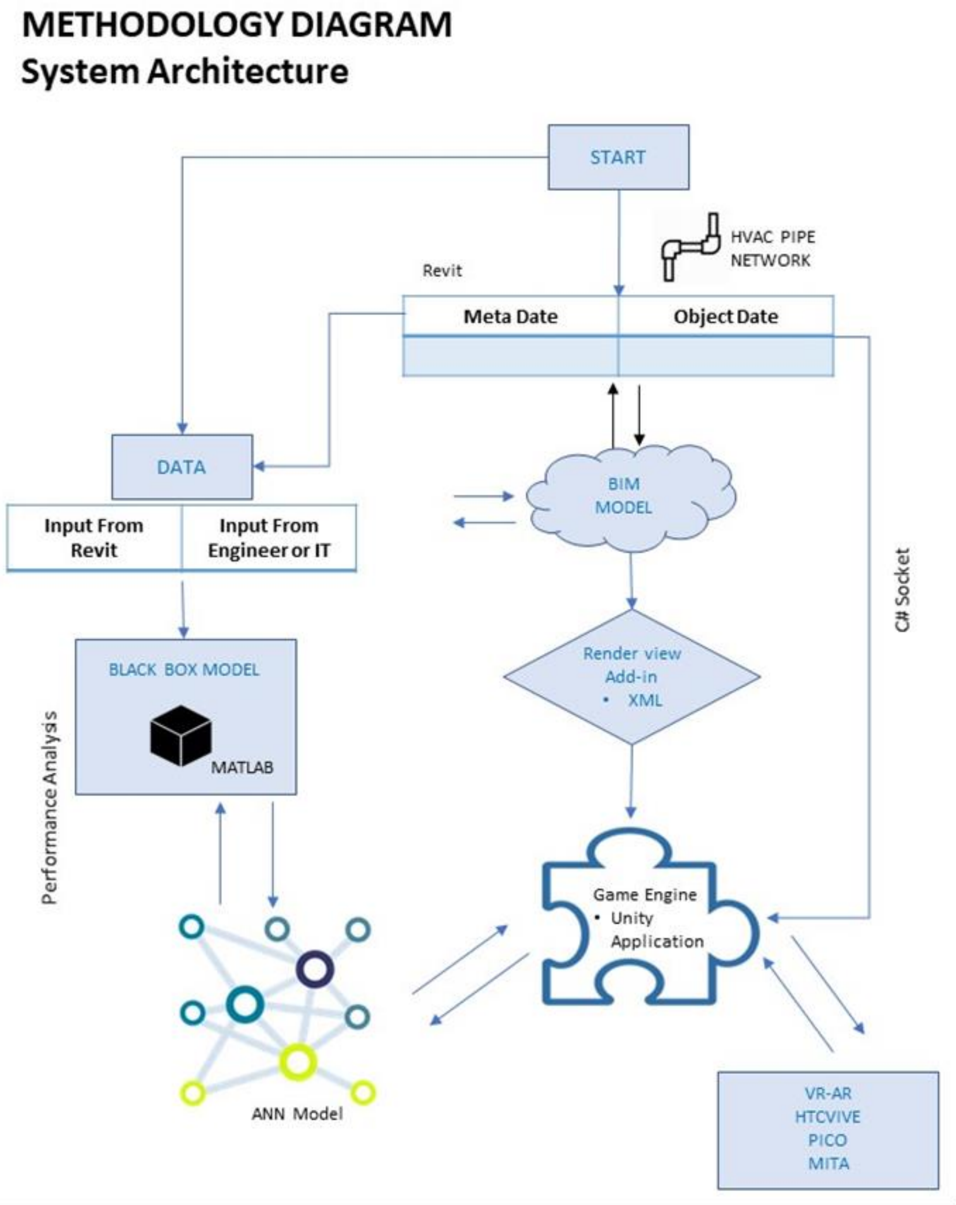

Figure 3.1 Methodology diagram pf the system architecture

The methodology diagram demonstrates how the experimental data will be processed by the Black Box model in conjunction with BIM data / Design Data, where the Neural network model will be deployed and trained. The model output is used to provide predictive corrosion information on whether the pipe is performing properly or not, and this information is then passed through VR for visual representation.

This model communicates with the simulation in the Unity VR game engine, allowing to display it inside a VR environment. The environment and simulations are created by sending the necessary parameters and values in XML format to the game engine, which can be translated and understood by the Unity VR platform.

The environment is then viewed through a VR headset, such as an HTC VIVE or an Oculus Rift, which are commonly used to look at the VR environment or games. The BIM will be used to provide not only the metadata that is used to build the components in a way that they can work as user would in real life, but also data that can be used to ensure that they have the right measurements for it, which can add to the realism of the environment along with the testing process.

Figure 3.2 depicts a simplified version of this exact process, in which instead of using BIM and Revit with a Unity VR game engine to build 3D models of the environment, CAD packages are used to do the same thing in order to render these in Unity VR. These are routed through Revit add-ons, which then converts them into the necessary metadata for displayed in the VR environment.

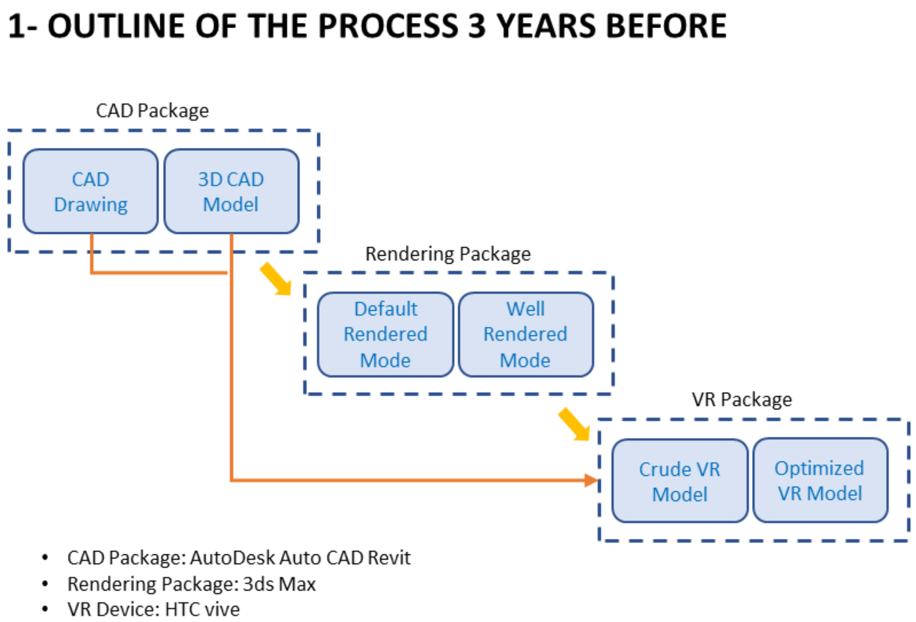

Figure 3.2 The outline of the process

3.3. BISPA lab experiments

These set of laboratory experiments are carried out to determine the difference of measurable parameters, such as temperature, pressure and the corrosion rate it would have on the pipe structure. The goal of these laboratory experiments is to understand and analyse how the differences in temperature and pressure can affect the performance of the pipe structure. It could be useful in learning how it could be used to monitor the health of the pipe structure. For the HVAC system to function properly, the pipes that connect to it must be able to withstand the temperature and pressure that it is subjected to. This is considered necessary because it would allow it to monitor better and assess the health and condition of the pipes to ensure that the pipes are not corroded. It will be useful to determine the factors and conditions that can cause steel pipes to corrode in a more detailed analysis that will evaluate each of the major aspects of it.

The tests for this will be conducted on BISPA training rigs to determine the rate of corrosion of steel pipes based on temperature and pressure. There are three rigs, each used for different purpose. The first rig is used to evaluate the effect of changing pressure on the pipe, the second for temperature, and the third for measuring the rate of corrosion based on the previous two factors.

Figure 3.3 BISPA Heat loss experimental Rig

Figure 3.4 BISPA Pressure loss experimental Rig

Figure 3.5 BISPA Corrosion Experimental Rig

Each BISPA Rig was meticulously designed and outfitted with sensors to monitor various parameters according to the parameters that affect the pipe's performance. Because the basic construction is the same, this chapter only explains the methodology for building the corrosion rig. This includes the measuring range, accuracy, response time, power supply, for the material, and dimensions. This section contains the commissioning, which is a detailed description of the system from initial setup to final operation.

These experiments will also look at the corrosion of the steel pipes based on the temperature and pressure as these are the two most important factors in determining the rate of corrosion on steel pipes.

Because corrosion unavoidable due to a variety of circumstances and factors, predicting, and identifying the condition of steel pipes is difficult. To ensure optimal HVAC pipe performance, it is essential to understand the factors that can cause HVAC steel pipes to corrode under normal operating conditions. As a result, this laboratory setup is intended to mimic the pipe network of a real-world building's pipe network

The diagram below illustrates and summarises how the experiments will be carried out, about how the data will be filtered to create the dataset for the ANN model.

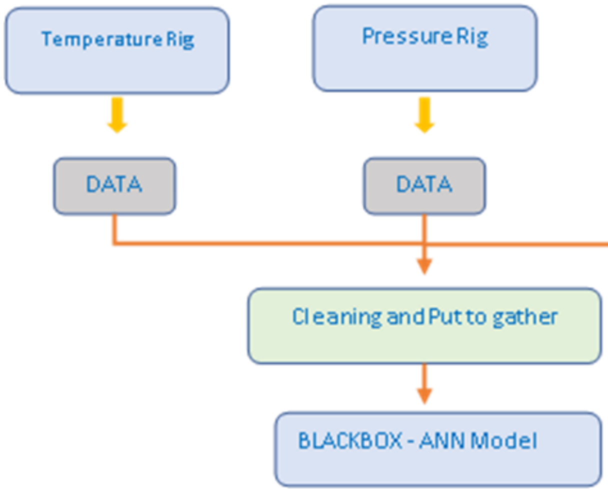

Figure 3.6 The process of how the BISPA laboratory will be conducted

This diagram shows the three rigs that will be used to carry out the BISPA laboratory experiment. This will be done using pressure, temperature and corrosion rigs will be used for this. Each will be used to detect a specific feature of the steel pipe. For example, the temperature rig measures and monitors the temperature that is applied and observed on the steel pipe, about how it leads to corrosion, whereas the corrosion rig is primarily used to detect the rate of corrosion and the accompanying galvanic current that is produced. The pressure rig is made up of pressure sensors that measure the applied pressure. The data is collected by using sensors, which are then analysed to validate the corrosion rate of steel pipes. Electrochemical sensors, electromagnetic sensors, corrosion coupons, electrical resistance probes, magnetic flux leakage sensors and ultrasonic testing sensors are examples of conventional corrosion sensors. Each sensor in the rig has a distinct advantage, and disadvantage in terms of simplicity, ease of operation and versatility. For instance, pressure coupon sensors are limited by the average corrosion rate, have limited sensing coverage and do not provide real-time data updates. In the meantime, electrical resistance probes are used to monitor corrosion in real-time using electrical resistance. These sensors function by combining elements such as

LPR (linear polarisation resistance), EN (electrochemical noise), galvanic current measurement, and EIS (electrochemical impedance spectroscopy).

As demonstrated by the research presented by (Papavinasam et al., 2010)one important feature of electrochemical sensors is their ability to directly capture the rate of corrosion directly compared to other sensors. The drawback of this is that the electrical voltage and current passed through the rig may accelerate corrosion. Transducers are commonly used in Ultrasonic testing sensors to generate high-frequency pulses and signals. As a result, m it is one of the most widely used non-destructive methods for measuring and monitoring pipe corrosion (Chapuis & Sjerve, 2017; Rodríguez-Olivares et al., 2018). According to Rodriquez-Olivares et al. (2018) the signals found in the form of a wave bounced back the internal and external walls of a pipe. This is then received by the transducers, how use it to record the thickness and also the information and irregularities that are found in it. The main drawback is that it has low sensitivity to small corrosions, making it unsuitable for detecting small corrosions in pipes as well as being affected by casing scales, which can reduce accuracy.

Temperature sensors, such as FOTS (fibre optic temperature sensor), are used to detect signal channel propagation by compensating for temperature variations. This results in the detection of the thickness of the pipe walls. In addition, infrared thermography imaging is a non-destructive method of monitoring piping corrosion. This approach employs the detection of differences in thermal radiation where the change in the thickness of the pipes due to corrosion causes discontinuities in solid materials, resulting in an increase in the temperature fluctuation of the pipes.

The pipe used in the rigs is made of carbon steel that falls into the ASI 1010-1045 range, and its density is calculated to be around 7.85 g/cm3. Because it contains 10% carbon, this type of steel is softer than other types of steel.

3.4. Hevasure lab experiments

The purpose of this experiment is to monitor and determine the rate of corrosion of steel pipes. It is usually done to accurately assess the corrosion rate of the pipe. This is accomplished by utilizing oxygen levels and pipe temperature, as each would be beneficial in providing an insight into the factors that could be used to accurately estimate the corrosion rate. This is primarily used in industries to generate data and gain an insight into the rate of the corrosion of the pipe in a controlled environment or under different conditions, such as different oxygen levels and pressures that it can be subjected to. This will be done to ensure that it must have enough data to provide a clear analysis of how the oxygen levels in the pipes affect the corrosion rate.

Because HVAC pipe is primarily made of water, dissolved oxygen in the water is an unavoidable factor, which then undergoes an anodic reaction with the steel pipes, resulting, in a corrosive and porous surface on the steel pipes (Eyu et al., 2016). As a result, a clear understanding of what can and cannot cause corrosion of steel pipes due to dissolved oxygen should be developed. HEVASURE laboratory experiments are used in this case to determine the corrosion rate of the steel pipes based on the increase of the oxygen levels. A temperature controller is also used to monitor how the steel pipes change as the temperature changes. The pressure in the water that is applied to the steel pipes will be controlled using similar processes.

To carry out this experiment, Hevasure training rigs will be used to understand the rate of corrosion of the steel pipes; however, the time around the data collected from this would be with respect to the dissolved oxygen levels of each of the pipes and the temperature associated with it. The Hevasure rig will include of a Hevasure corrosion monitoring rig that will be used to assess the rate of corrosion based on multiple factors in addition to traditional corrosion monitoring methods that will be used to collect data in the past. Based on the dissolved oxygen found, data from it will be collected to better understand the corrosion rate of the pipes.

The figure below depicts the process for this, about how it will be used in the ANN model.

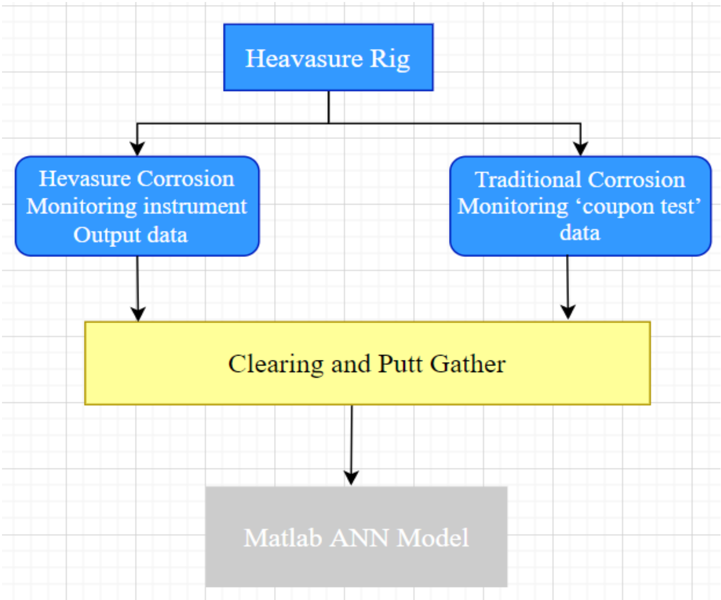

Figure 3.7 Diagram illustrating the Hevasure lab experiments

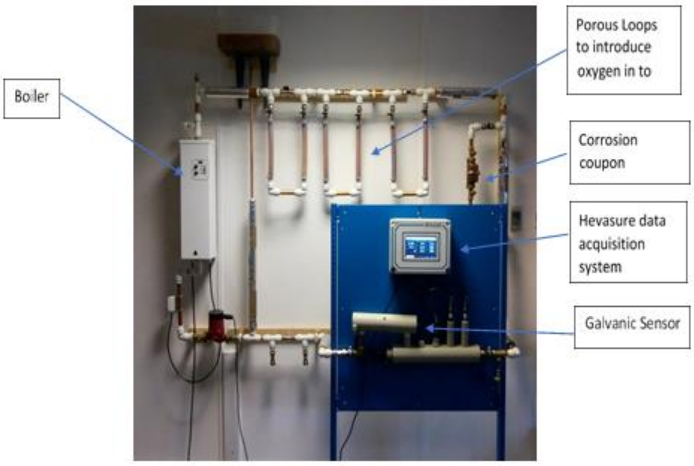

Figure 3.8 Hevasure Corrosion Experimental Rig

Experimentation will be carried out by repeating the same experiment with a gap of fifteen minutes between each test, this time interval will provide a clean optimal reading. This is done to evaluate the pipe's health and condition following experimentation. The data will be used to assess and understand how the rate of corrosion changes over time, and the rate of the dissolved oxygen, in relation to the temperature of the environment and the pressure applied to it.

Two closed-circuit water systems use thin-walled steel, i.e. ASI 1010, to provide heating and cooling water for the rig itself. This type of steel is commonly used in buildings because it is lightweight, simple to install, and inexpensive, while also being sturdy and effective in transferring heat and cold water from the HVAC system, provided that dissolved oxygen (DO) is kept out of the system. Hevasure was hired to monitor both the rigs during the critical commissioning phase. During this phase, Hevasure's monitoring technology is used to identify any aeration issues that, if left unchecked, could lead to corrosion damage. By assessing these ahead of time, it is possible to avoid any type of corrosion or corrosion-related problems, which can increase the likelihood of major repairs or pipe breakdown.

Because dissolved oxygen will only corrode the pipes if it were dissolved in water and then undergoes an anodic reaction with the steel pipes, forming a corrosive and porous surface on the steel pipes. As a result, a clear understanding of what can and cannot cause corrosion of steel pipes due to dissolved oxygen in the water that is subjected to it should be developed (Eyu et al., 2016; Shuaixing Wang et al., 2015). This laboratory setup is used to calculate the corrosion rate of the steel pipes based on the oxygen level to monitor the steel pipes' response to temperature changes, a controller is used to control the temperature and pressure while they are subjected to it. These controllers are intended to assist the rig in obtaining accurate measurements.

3.5. Black box model

This chapter deals with explaining and outlining the processes and the steps involved in developing the smart HVAC pipe system through the use of an ANN model. It describes the decisions made to develop the system about how the testing process will be performed. It outlines how the Black Box model for the Smart HVAC system was created, to how the data collection process was carried out in order to train and evaluate the model's performance. This chapter delves into the outcomes obtained when laboratory experiments data was applied to Black Box model. This would be used to review the experiment process the considerations that were made while carrying out the experiments. It would also help in demonstrating how the Field Test Model was developed and analysed in relation to literature findings.

It can be seen that the black-box model concept can be used to fit the transfer function model to the input and output of the real model data to yield coefficient polynomials that can be factored to provide resonance frequencies and damping coefficient characterisation without having a generalised understanding of how the model works. Individuals are given an overview of the model in black-box models, but they do not have a detailed understanding of how the model works. This can be useful in ensuring sure that the people can adapt and test it based on how capable it is remaining unsure of how it works on the inside. In general, the mathematical models that are present in the model are not revealed to the user because the primary goal of using black-box models is to abstract the complexities and present the user with the important parts of it. This makes it easier for people to use because it allows them to construct them without prior knowledge of the model or the internals of the system.

In this case, the black box model allows user to determine and examine the condition of the pipes based on the temperature, and pressure and the galvanic current found to see if the steel pipe is corroding. As a result, using a black box model ensures that it can predict the condition quickly as possible while being as accurate as possible based on the provided data. In general, the use of neural network model should be able to accurately predict the health of the pipes based on the variables present around them.

A neural network model will be used because it allows to analyse and predict the rate of corrosion of steel pipes more effectively. This was formed with the intention of assisting in the understanding and prediction of future values in a time series. This is a generalised form of a neural network model, and it functions similarly to one in that both are used to either understand data or predict future values from it. neural network models are only used when he data is discovered to be non-stationary, and the initial differencing step can be repeated one or more times to eliminate any non-stationarity (Box et al., 2015).

Because of its high accuracy, a neural network model will be used as the black box model for this, allowing for the development of a profound ANN model.

This is a subset of a linear regression model that is used to observe past observations of the target variables and predict future values based on this (Zhang, 2003). One of the key aspects of a neural network model is that they are not considered exogenous variables in their basic form because the forecasts are created solely with the past values (Zhang, 2003).

Developing ANN model allows to create a tool that can calculate accurate output and can be used to ensure that it should accurately predict the corrosion rate of the pipes without having to spend most of the time training the model. Since black-box models have already been trained and tested to ensure that the model is capable to execute the task of predicting the performance of pipe. it would also depend on a number of factors such as quality of the data, the parameters used, and so on In this case, by being able to predict future values based on past values, this research can concentrate on developing the ANN model, which will use it as part of its model to perform as intended. According to Zhang (2003), a combination of ARIMA and ANN was able to significantly improve forecasting accuracy. Its accuracy is said to be far greater than what was observed when each of the components was used separately (Khandelwal et al., 2015; Zhang, 2003).

3.5.1. Data cleaning

This section describes how the data cleaning step was carried out, will provide a clear overview of how the research will be handled and what steps and measures were taken. It explains what variables were considered for this, how the data was filtered and cleared to ensure that got the right type of data to train the ANN. This included learning about the considerations being made and the data analysis tool that will be used to collect and form a dataset that will aid in better monitoring the performance of the HVAC system.

Understanding these will ensure that when work on the dataset is finished, this research will be able to merge and add those data that are useful. It also includes the strategies and methods that were used to work on the data in order to remove any noise that was present. In this case, noise consists of inconsistent or missing data in the dataset, either due to the equipment left out the values of those or due to it was not being recorded by the equipment. As result, dealing with noise necessitates the use of strategies and methods.

To process the data, the appropriate analysis method must be chosen in order to obtain the appropriate amount and type of data for research purposes. To do this, a series of steps must be taken in order to clean up the data and use the relevant variable or data. The data analysis will entail cleaning and filtering out the appropriate types of data and variables that would be used to train the model and then assess the performance of the steel pipes over time. As previously stated, the data used in this would include both experiment and field study, which would be initially divided 80% for training and 20% for evaluating and assessing how the model performs under different temperature and oxygen levels, and the rate of corrosion. This ensures that the developed model will be able to better analyse the health of the steel pipes in the HVAC system and determine the rate at which corrosion will occur. This is crucial because factors such as a faulty pipe caused by waste or corrosion could potentially waste the resources and time of the building maintainers.

In addition, this will aid in understanding the relationships between the variables discovered, such as the galvanic current produced and the oxygen dissolved in the water. This is significant because it has been discovered that the amount of dissolved oxygen present in the water is directly proportional to the galvanic current produced when metal such as steel is exposed to that water. A similar result was observed in research where the relationship between the corrosion rate of the metal. It was discovered that as the concentration of NaCl increased, so did the rate of conductivity within the solution, resulting in significant metal loss and the galvanisation process. It can expose the softer side of the metal that is usually proven to corrosion, which can lead to it become damaged or clogged as the corrosion increases.

To ensure that the data is relevant and free of flaws, care must be taken to ensure that the data is clearly assessed and free of errors. This is because the fact that any type of error or missing value reduces the model's accuracy and can cause the model to fail to perform as intended. Because this study selected data-driven approach to monitor the energy consumption of the HVAC system, it is critical that the datasets used are error-free, as this can affect how the model is trained.

In this case, the two data sets from the Hevasure and the BISPA laboratory experiments must be combined to create a comprehensive dataset on which the ANN model will be trained. Data collected using sensors around the rigs, which transmit data every fifteen minutes and yield high-resolution data, will be considered in this regard. Because the temperature rise is a slow process, a large sampling would be required if the data collection process is considered to be dynamic in nature. One of the key advantages of using this data is that it results in smaller chunks of data that can be processed significantly faster as compared to other methods that may have their overhead. It may lengthen the time required to analyse the data. The important variables that are considered based on domain knowledge are the oxygen levels, the water temperature, the pressure exerted on the pipe, the galvanic current, the conductivity, and the flow counter and dissolved oxygen rate that is found in it. To derive the value, it is considered necessary to use the appropriate tools that can aid in better understanding the data. For this, firstly the statistical measures will be done i.e. the mean and standard deviation to understand the patterns in the data, the average values found in it. The figure below summarizes how this will be done to build the dataset for the ANN model.

In the laboratories, a series of tests and measurements will be performed in a controlled environment. The tests will involve immersing the pipes in water at a controlled temperature at a steady rate to see how the pipes change when exposed to different temperatures It will also entail determining the corrosion rate by monitoring the oxygen levels around the pipe as water is introduced to understand the effect of changing oxygen levels on the rate of corrosion. These readings will be used to calculate and determine the observed heat and pressure losses. In addition, the data will be compared and contrasted to see if there is any correlation between the corrosion of the pipes. Consequently, the temperature and pressure to which they are subjected, also their effect on corrosion are affected

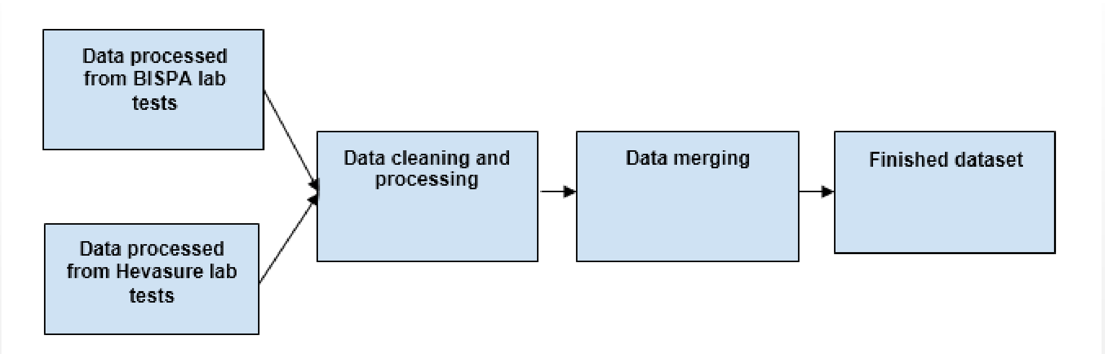

Figure 3.9 The process detailing the data merging of two laboratory experiments

The first step when working with the data collected will be to process and clean it. This is necessary so that it can reduce the noise in it, standardise any type of data found in it, and deal with any missing data that is present in it. This will ensure that the resulting data is easier to work with, and that there will be no issues when later it merge with the two datasets into a single one.

When analysing and working with the data, the next step will be to combine the information gathered from the two laboratory experiments, namely the BISPA and Hevasure tests. Instead of using both datasets separately, the Data cleaning process will be working on creating a dataset for ANN model. Combining the data from those two sources will result in a single data source. It is then used to build the model in addition to investigate any patterns discovered in variables of interest. This is required so that all of the necessary variables can be used to monitor the conditions of the steel pipes. For example, from BISPA laboratory tests, can collect data that can help out by using temperature, pressure, and the rate of corrosion, but this study cannot determine the corrosion rate using the dissolved oxygen found in the water itself, which can be a factor that causes galvanic corrosion in steel pipes. The data for this can primarily be found using Hevasure laboratory tests, which can merge with the results of BISPA laboratory test and use the rate of corrosion through dissolved oxygen with the data found in BISPA laboratory test to better understand this while also being able to add more variables that can be used better to predict the corrosion rate of the steel pipes.

after the data has been merged, it is used to recognise and identify any patterns that are associated with and discovered in it. As previously stated, will use the dataset's means and standard deviation to identify any patterns. Detecting and regulating outliers will be used to understand how to clean the data, which can be useful later in creating the ANN model. After the data has been merged, the final and completed dataset will be formed, which will be used to monitor the rate of corrosion and the health of the steel pipes. The rate of corrosion is set as the output value that must be found, while the rest of the variables are set as input values of the ANN model that will be used to pass in the model so that it can make a prediction on what the rate of corrosion and the likelihood of it getting corroded relative to temperature, pressure, pH and galvanic current.

The results of the data analysis done will be presented in the form of tables (for determining the mean and standard deviation) graphs and figures (for when training the model,). Using these, this study can gain a clear understanding of not only what type of data dealing with, but also how to understand and interpret the information that receive from it. It will also be useful in future work when the analyse the relationships that present within the variables themselves.

3.5.2. ANN model

This section of the chapter is used to explain in detail how the model for the Validated Performance Model (VPM) would be developed, the considerations that were made when developing it. Testing the model with different iterations would allow VPM to demonstrate a detailed understanding of what type of ANN will provide the most reliable results. The ANN model method would be useful in monitoring and predicting the performance of HVAC pipes in a novel way. This is due to the fact that galvanic current, oxygen level, and temperature all have an effect on corrosion rate.

For this study, selected to develop a model using an RNN algorithm such as Long Short-Term Memory (LSTM). RNN is defined as a type of ANN in which the connections between the nodes form a directed graph with a temporal sequence. This is made up of a series of neural networks that share a state that is shared across all networks. It distinguishes RNN from feed forward neural networks in that the latter can use internal state or memory to process variables or data that are larger in size or in a long format. Some of these are used in handwriting recognition, speech recognition, time-series forecasting, and other areas.

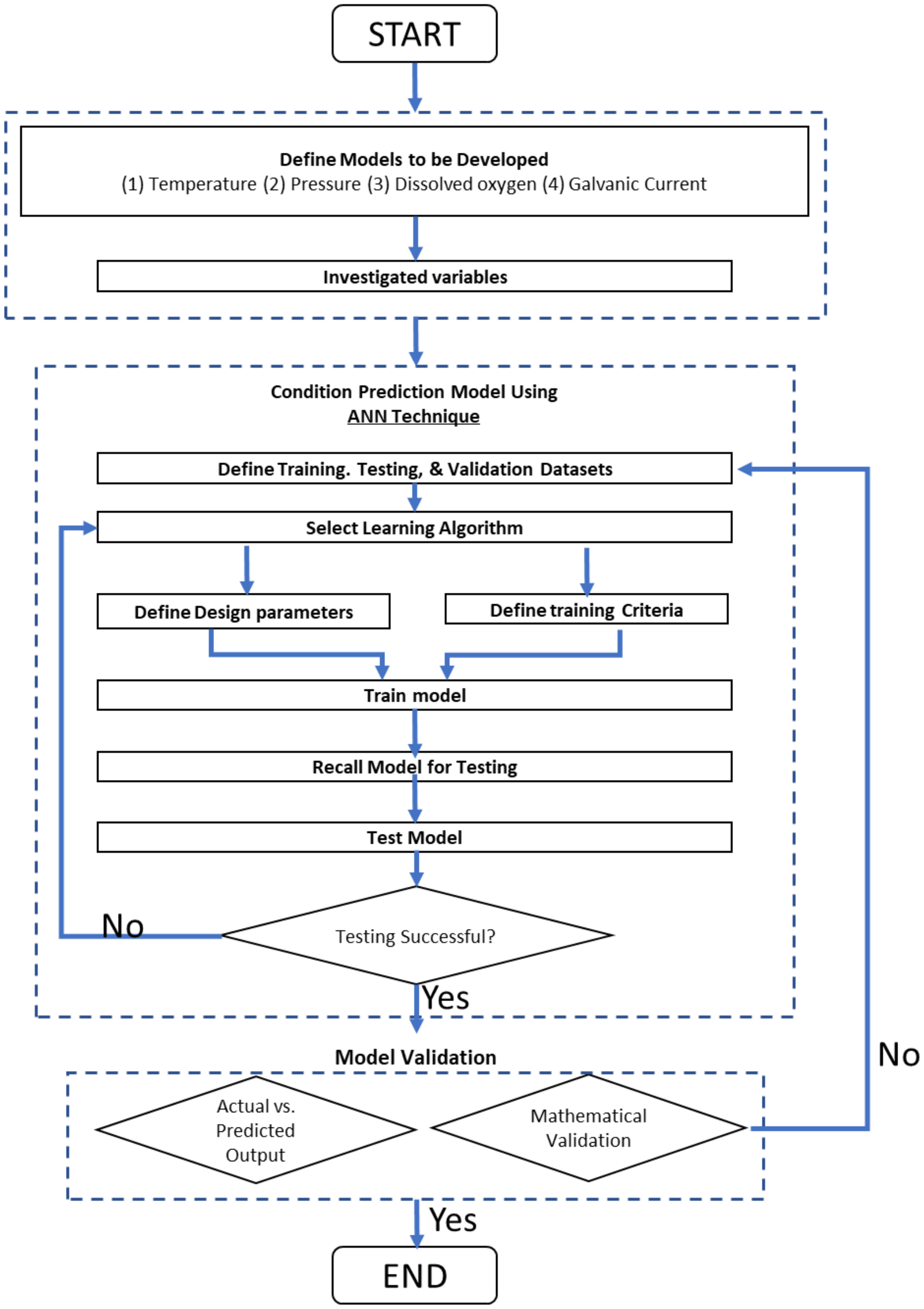

Figure 3.10 Neural Network Model Development Framework

Figure 3.11 depicts how the ANN model for research will be constructed, how the black box model will be integrated into it. To begin, there is a need to expose the training data to the black box model so that it can make assumptions and rules based on this dataset. After that, the obtained data will be sent to the LSTM layer of the ANN model, which is computed from the neural network model. The LSTM layer is the first layer because it allows us to make an accurate prediction based on the previous values that have been passed. The processed value is then sent to the dense layer, which is an output layer and will compute the expected rate of corrosion. The dense layer is simply a regular layer of neurons within the ANN model that receives input from the previous layer and displays the output. Once the predicted output is confirmed, it is compared to validation data, which comprises 80% of the data set for training and 20% for validation

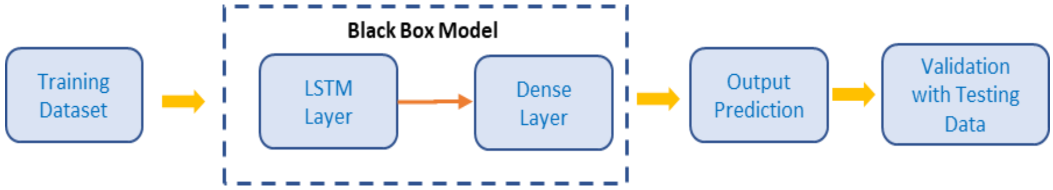

Figure 3.11 General overview of how the ANN model will work

The problem with a standard RNN is that it suffers from the vanishing gradient problem, which means that when training it to work with back-propagation, the gradients formed by it can vanish, meaning that their values turn to zero, or explode, meaning that the data turns into infinity. As a result, the neural network model may be unable to learn from the training data provided, and it may also become more unstable. This is due to the computational problem involved, as it employs finite precision numbering. As a result, the small gradient values will lead to it, preventing the weights from changing their value, potentially affecting model training. In the worst-case scenario, this can prevent the neural network from training at all. Meanwhile, exploding gradients can make the neural network's learning process unstable, causing it to be unable to process large chunks of data at the same time. The latter can be a problem for us because it can result in the model not being created, which can result in US unintentionally creating an inconsistent and poorly trained model that will not be able to assist in solving problem.

To combat this, LSTM could be used, which could solve the vanishing gradient problem because the LSTM units would allow the gradient to flow unchanged. This can make it resistant to vanishing or exploding gradient problems, which can improve the training process and allow the model to learn more efficiently.

One of the most common LSTM architectures is comprised of a cell and three regulators. The latter is commonly referred to as a gate, and it is primarily used to control the flow of information within the LSTM. This is made up of an input gate, an output gate, and a forget gate. Some of the variations include more than one of the previously mentioned gates, for this additional gate used for specific functions. GRUs, for example, do not include an output gate.

For this case, the use of a LSTM would allow for a better analysis and prediction of the condition of the pipe itself, for determining whether it is corroded or not based on the previous historical data on which it is trained. It would aid in ensuring that the pipe's health and structure are preserved while monitoring how it performs under various temperatures and pressures. Furthermore, LSTM models can perform fairly well while predicting well from historical data.

The model would be trained using data from laboratory experiments collected during the BISPA Lab experiment, field study data collected from a real HVAC system. This is done so that the model can be trained to predict better and to monitor the conditions of the pipe itself so that its performance is not impacted when it is subjected to varying levels of temperature and pressure, or any corrosion implications.

Furthermore, the data will be divided so that training data can be used to train the model and test data can be used to validate the model's performance. Because this study used LSTM models to develop a model, data validation was performed to ensure that it could train the two networks and, most importantly, improve the accuracy of the generator that is present. The training data will comprise eighty percent of the dataset, with the remainder used to validate and test the model's performance. To evaluate the model's performance and ensure that it does not over fit, a portion of the dataset will be used to validate the training process. This will be used to see how the model performs after completing one cycle of training with unseen data. The figure below depicts the overall description of an ANN model, which will be used to describe how an ANN model looks for the most part.

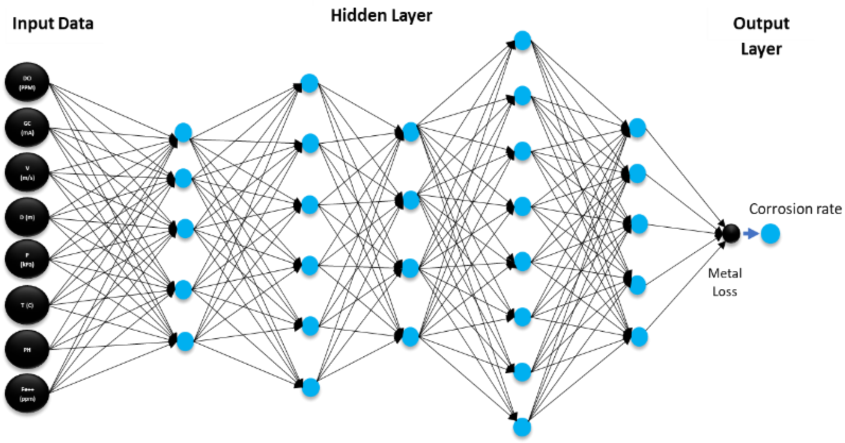

Figure 3.12 ANN Model Layout

3.6. VR experiment

This chapter would outline the development of the VR process and how it would be built, as it would be used to simulate how the model would perform under various simulations that would be create in them. It will include the creation of VR simulations that will be used to evaluate the model's performance. It will describe how the BIM was integrated into the VR in order for it to model the environment itself. Furthermore, it would be able to assist the individual in interacting with the environment in order to determine how the HVAC system interacts and performs when different temperatures and pressures are applied to it.

Virtual reality has provided people in the business and construction sectors with an efficient and effective way to communicate with stakeholders, allowing them to better understand the message that the individuals are provided while interacting with the simulations that it is based on (Sampaio, 2018). It allows one to freely navigate through various 3D scenes and environments that act as a way to simulate the environment while communicating and explaining the ideas related to the building's construction, which could allow one to convey their message to all of the bodies involved, regardless of their background or professional expertise. The use of this technology was previously restricted due to technological limitations, meanwhile a lack of 3D data that could be used in the building design process (Sampaio, 2018). With advancements in this area, it has become much easier to create a VR environment while not requiring a large amount of computational resources.

In addition, advances in BIM allow for accurate 3D data on the building, which can then be used to design an accurate representation of the building. Building simulations are now significantly faster than before, thanks to the recent introduction of Building Information. The use of BIM allows an organisation to extract the necessary 3D data from the architect's design environment rather than sketching it, developing it from scratch, or using the like, which can be time-consuming. This could lead to the use of real-time visualisations, which are becoming more popular and widely available in practise (Sampaio, 2018).

To improve the technology, the use of immersive display technologies allows one to immerse the user in the environment itself, which may aid in better exploring the environment (Cipresso et al., 2018). Real-time visualisation has been useful in general, but combining stereoscopes, a large screen, and a wider field of view provides a much better overall experience. It can provide a better experience because it can increase the level of realism, provide ease of navigation, a sense of scale, and overall suitability for design and decision-making tasks. This can provide a better experience for users while also allowing them to interact with their virtual surroundings, which is possible with virtual reality (Cipresso et al., 2018).

Because of the immense potential it possesses and how it can be used in a variety of fields, virtual reality (VR) has evolved into one of the most advanced technologies in today's day. As a result, it has piqued the interest of many researchers who have worked in various fields, including construction, to learn how VR can be used to solve complex problems (Cipresso et al., 2018). It is an umbrella term that refers to the user's real-time presentation of a computer-generated environment. It can provide a virtual environment that functions in the same way as the real-world environment. This essentially leads to VR becoming a more complex form of human-computer interaction in which the user directly interacts with and is a part of the environment, as opposed to traditional methods in which they can see objects on a 2D plane on their computers. It can be divided into two types: non-immersive applications, such as 2D screen presentations where the only way to interact with the environment is through the keyboard, mouse, or touch screen, and immersive applications, which are significantly more complex and require computers to communicate with devices such as HMDs, VR controllers, and body-tracking sensors (Cipresso et al., 2018).

R can be used to facilitate better communication among stakeholders in the building sector, which is based on increased design visualisation, and contribute to a better understanding of the project. When team members want to analyse problems and discuss alternative solutions, they need to be familiar with the various types of data that can be associated with the set of parameters that identify each parametric object, which is the foundation of the BIM modelling process. Interacting with the BIM model to visualise element geometry and consult parametric data is a step forward in the development of a collaborative project.

The acceptance of VR in the construction industry has grown in recent years as a result of the benefits it offers and how it can aid in better communication with stakeholders. It allows users to immerse themselves in a virtual world that is similar to the real world, and it is built with BIM data that can change based on changes made to the data or by users exploring the virtual environment (Sampaio, 2018). This ensures that the individual exploring the environment is provided with an immersive environment and that they are provided with a real-like environment where the building is being constructed and how changes in the environment would affect it. Management professionals in the construction and architecture industries recognise that VR applications make it easier for stakeholders to visualise the design early in the development stage, reduce material costs, and aim to reduce the number of workers needed for the projects. A VR tour, for example, can be created using BIM to provide an idea of how the building would function from various perspectives. This includes facility management, maintenance perspectives, the project team's perspective, and a review of how it will be built. Each of these points of view can help with decision-making, which can lead to a better design process (Sampaio, 2018).

The 3D model for this will be created using BIM and a game engine to render the pipes and environment for the VR model. This is critical because it will allow for a better design and development of the 3D model. A 2D array is created using the Unity3D game engine and used to design the pipes and environment. Each array location is then matched by a plane (Unity3D primitive 3D object) that contains the corresponding texture. The visual masks are uploaded to 2D planes and placed in front of the avatar's main camera to blur the scene and represent the patient's VF impairment. In the 3D virtual environment, the avatar represents the maintenance worker who is in charge of the pipes. The camera attached to the avatar's head serves as his eyes, and its view is used to represent the environment. The camera view is displayed in the Unity 3D game view window. As a result, the user can experience the environment or any details contained within it.

The data will be passed from BIM to the Unity3D engine using Revit, which allows the data to be easily passed to the Unity3D engine. The advantage of using Revit over other tools is that it can provide a diverse set of tools and methods. This will then be viewed with an HTC Vive headset, one of the leading VR devices. With Revit's recent advancements, this can be used not only to visualise the data but also to build the pipes, but it can also be used to ensure that the pipes in the virtual environment mimic or behave exactly like their real counterparts. To use VR, a high-end computer with a cutting-edge graphics card is required. As a result, providing a smooth user experience does not result in users becoming nauseated as a result of framerates or low-quality environments.

The collected data or results are then passed from the VR environment to an Excel spreadsheet, allowing a perform a series of analyses and results that will help to make a formulated analysis on how the model performed and whether it was able to detect the corrosion in the pipes or not. The ANN model will be passed through the environment using the Unity APIs, allowing to introduce an ANN model into the environment. This will allow to run a series of tests to determine whether the created model meets the requirements and is capable of monitoring and accurately predicting the corrosion rate of steel pipes.

The experiments will consist of manipulating BIM to VR studies, which will be applied to the pipes in the VR environment, in order to examine and test how the ANN model performs when certain variables are changed. The reason for this change is to discovered during the data collection process that temperature and pressure play a significant role in the corrosion of steel pipes, and the galvanic current that accumulates from it. In addition to these, the VR environment will be designed in such a way that it can provide a consistent amount of data in a short period of time, allowing to constantly monitor how the ANN model performed to identify any flaws in it.

The environment for this will consist of installing the HVAC system inside a basement of a building created using Unity3D assets. Existing assets are used to create the environment so that it does not spend the majority of its time setting up the environment. can spend the remaining time configuring the ANN model that will be tested in the environment, to configuring Revit to pass the BIM data on the environment to passed through it. Using that data, it will configure the VR environment in such a way that it will allow for a close examination of the performance of the BIM model in a setting that closely resembles the real world, to a close examination of its accuracy.

The goal of this study is to analyse and quantify the feasibility of the method of data transfer from Revit to VR, thereby determining the viability of incorporating VR into the AEC industry. A site visit was used for VR Company Bloc Interactive to assess existing industry transfer practises and validate the results of the literature review. For a detailed analysis of the site visit, see Appendix A. Using all of the provided data, and previous experiments on the subject of VR and construction, an experiment to quantify the value of VR was established. This included subjecting volunteers from BISPA Lab Loughborough University to a series of tests comparing Revit and VR in terms of appeal and dependability in the use of the kid's tool VR GUI. This article will also go over the equipment and transfer method used to carry out this experiment.

For this analysis, Revit and VR models of pipe rigs with deliberate tasks were created to test their intuitiveness and clarity in relation to the use of the PPM Tool kit to classify pipe output. Tutorials, a survey, and experiments were held after the models.

The latter reported the views of the participants' perspectives on the consistency of the transfer process between Revit and VR. This resulted in five assessments for each participant to ensure a diverse range of answers for review. By comparing the time and score from the assignment, and the experiences of participants, the potential value of VR for daily use in the AEC industry was defined.

A test in a series of four experiments evaluating student success had an additional impact on the nature of the proposed experiment. Students were graded out of one per assignment based on the accuracy of the data obtained. The latter defined the significance of BIM and AR. Time was calculated for each mission to determine the mean, median, range, minimum, and maximum period. As participants became more familiar with the software, time converged, with slower times indicating a longer familiarisation process. This study influenced the use of multiple tests and the method of analysis while attempting to achieve gender balance and an appropriate sample for preliminary analysis.

Experiment Design Decisions: The design of this experiment was based on the expansion of previous VR testing to ensure its viability and avoid previous test limitations.

The experiment's basic format was derived from trials consisting of a public survey conducted in Barcelona, in which participants used a virtual environment to shape a public space. This entailed instructing participant on how to use the system, allowing them to modify the virtual environment, and then asking them to complete a questionnaire (Monica V. Sanchez-Sepulveda 2019).

A second significant experiment examined the efficacy of VR in improving visitor perception and behaviour by relying on people's recall of theme park attractions. This experiment provided a detailed statistical analysis using a Stepwise regression, allowing the participant knowledge to be evaluated based on a subset of variables. A sensitivity test was performed to assess user familiarity with VR and personal intuitiveness. However, there were some significant limitations:

¶ The experiment was carried out using the participants' memories.

¶ The participant's answers may have been influenced by combining memories of the actual rollercoaster ride with the VR experience.

¶ By considering the entire theme park, the researchers were able to obtain only generalised findings, rather than focusing on a single roller coaster to allow for greater comparison of participant responses (Wei et al., 2019).

The key points raised by this experiment were thus the need to incorporate sensitivity tests for software familiarity and efficient documentation of a participant's experience without the influence of externalities.

The Experiment: The experiment required participants to complete the five short phases listed below:

Task 1:

The participants were required to complete a Revit tutorial to ensure that they had the necessary skills to easily manipulate a TATA Steel pipe rig. The level of assimilation was assessed by requiring participants to locate data from a pipe and set up a camera view, adjusting the level of detail and visual style. Timing this process without putting pressure on the participant demonstrated how easily the Revit programme could maintain data and a participant's intuitiveness.

Task 2:

A Revit model with a series of toolbox tasks was created. Participants in Revit were asked to find as much information as they could until they felt confident that they had found everything possible. When the individual spoke up, the time it took to find each piece of information was recorded. In addition, the total time was recorded.

Task 3:

As an introduction to VR, participants were asked to complete a VR tutorial built into the Steam VR framework. Participants were then asked to complete an archery mini game from the game "The Lab". This game assessed a player's ability to retain information from the tutorial.

Task 4:

After being imported from BIM to VR, participants were asked to look around a model that had not been changed and to identify any problems in the model that they felt reduced their immersion within the scene.

Task 5:

Participants were asked to explore a PPM toolkit interface uploaded VR model and define the level of user experience as best they could, until they were satisfied. When the individual spoke, the time it took to locate each user interface point was recorded. It also recorded the total amount of time.

Participants were also asked to complete a survey that had sections before each test, after each test (referred to as Test 1, Test 2, and so on), and after the experiment. This survey was conducted using Microsoft Forms for ease of use and replicability. See the Appendix for the Survey.

Equipment Setup: The experiment took place at the Sir Frank Gibb Laboratories at Loughborough University in the United Kingdom, and was led by PhD student Vijay Srikandarajah, as shown in Figure 3.13-3.15.

Figure 3.13 Sir Frank Gibb Laboratories at Loughborough University

Figure 3.14 VR section in the Sir Frank Gibb Laboratory

Figure 3.15 VR participant

3.6.1. Practical test

This section is intended to visually represent the study design and model under consideration. This is for demonstration purposes, demonstrating the viability of the HVAC pipe network VR visualisation model. The model's accuracy will be useful in determining the condition of the steel pipes and whether they are on the verge of corroding. It will also be used to gain a thorough understanding of how the model works and its limitations. It will also provide a comprehensive overview of the environments created to test the ANN model. The environments that are created differ from one another based on predetermined variables and criteria.

As stated, testing is defined as the process by which errors can be detect in software or any product that is being manufactured. This will allow us to ensure that the product being manufactured has been thoroughly tested and is free of flaws. If it does, these flaws can be fixed as well, allowing the product to function properly. Furthermore, it can be used to determine how effective it is and understand the limitations that it presents, about how the results of it can be translated and used as a future reference to improve the product or expand its capabilities.

In this case, physical tests will be performed to determine how well the BIM model on VR detects changes in HVAC pipes based on the intelligent information embedded in the system. The user experience of a virtual environment has been investigated so that it can be tested in a simulation consisting of a virtual world based on real-life artefacts, where it will be tested under various conditions and aspects to determine its feasibility and performance. Furthermore, it will provide a general idea of how the model would behave in a real-world scenario, about how it will be able to assess and identify the condition and health of the pipes to ensure that they are not corroding.

3.7. Summary

This chapter describes the overall framework for connecting BIM to intelligent visualisation. It describes how the VR environment will be constructed using BIM and Unity 3D and viewed on devices to evaluate the model's performance. The research facility Experiments are carried out in order to monitor and calculate the corrosion rate of steel pipes. The data collected could lead to the development of an ANN model that will predict and monitor the pipe's performance and provide predictive data. The BIM model communicates with the simulation of the Unity VR game engine, allowing to display it in a VR environment. This chapter describes the data collection process and how to build a smart HVAC pipe system using an ANN model. Using the black box model, this can determine and inspect the condition of the pipes. As the concentration of NaCl in the solution increased, so did the rate of conductivity within the solution. As a result, a significant amount of metal was lost, which resulted in the galvanisation process.

Chapter 4 Results from Laboratory Tests

4.1. Introduction

The data generated by the laboratory experiments described in the preceding chapters will help us better predict the point at which corrosion may occur. This will help to better understand the factors that may contribute to corrosion. A BISPA LAB experiment on the corrosion rate of Tata steel tubes treated with various methods will be discussed. While the situation is comparable in both tests in two test rounds, the tubes' and water's commitment, which includes the corrosion declaration and the pH value of the water. The information gathered from it could be used to train a neural network model to predict when the corroding will occur and then notify the people. The former could be done to replace pipes before they corrode or to regulate the temperature of the pipe itself.

4.2. Outcome: BISPA laboratory experiment:

A BISPA LAB Experiment on the corrosion rate of Tata steel tubes with various treatment methods was carried out. Temperature effects on corrosion rate are also investigated. Corrosion rates are faster at higher temperatures and lower pH, and pH varies. In a long-term process, the corrosion rate and PH value are addressed at various temperatures, including 10°C, 15°C, 20°C, and 25°C. The corrosion efficiency over time is measured and observed in a short period of time.

The goal of this experimental research is to determine what factors contribute to elevated corrosion rates in hot-finished steel tubes, to collect data for an AI study. The findings and interpretation are based on corrosion rate analysis in various conditions for pH, temperature, and flow rate. The data collected during the experiment in the same steel conduit, BISPA corrosion rigs, and process temperature is used. Examine the reasons for the disparity in corrosion rates.

The results will include four analytical objects based on the technique portion. These were: Is the corrosion rate of steel at different temperatures comparable to previous testing, the degree of corrosion rates and pH importance, and the uncertainty over corrosion rates.

The section of the results will explain the different corrosion rates under different conditions, to compare the corrosion rates at various temperatures in the analysis section. A follow-up study compares the corrosion rate in the second round of the experiment under the same conditions to the data from the first experiment.

In the final stage, the equation is examined to verify the result at the stage of the corrosion rate in various activity statements. Following that, the uncertainty is assessed, including the rate of corrosion at various temperatures after a long period of activity at various set-point temperatures after the corrosion rig. Finally, the clean data set was obtained by observing the data output while training an ANN Model.

4.3. Experimental DATA Collation and Data comprehension

4.3.1. 1st set of experiment

The first set of experiments took place between 04/08/2017 and 30/08/2017. The data is recorded without washing the probe, and the results are shown in Figure 2 in Appendix. In this figure, the temperature was 12 degrees Celsius, and the corrosion rate was 7.7 milligrams per year. The corrosion rate also shows an increasing pattern as the temperature rises, peaking at 32°C at 22 mil/year. The figure also shows that at certain temperatures, the corrosion rate is constant, and that as the temperature rises, the corrosion rate tends to increase.

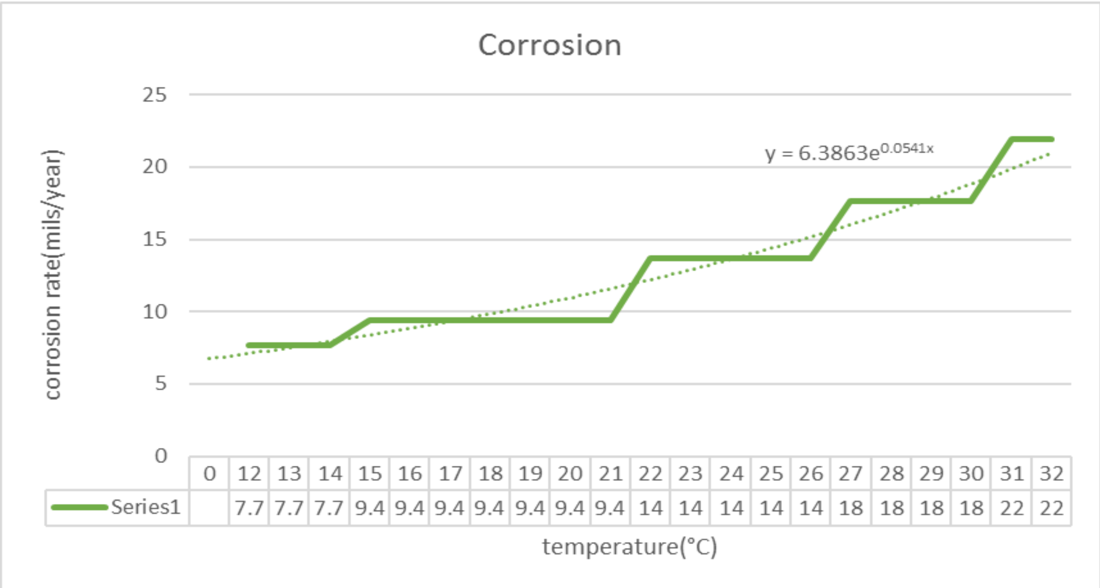

Figure 4.1 Corrosion and water temperature relationship

When the pH value (Figure 4.1) and temperature (Figure 4.2) are compared, they show an opposite pattern, with the temperature being 12 degrees at the start of the cycle and the pH valve being 8.4. As the temperature rises, the pH valve weakens and eventually stops at 8°C at 32°C. The corrosion rate in (Figure 4.1) increases faster than the pH value decreases (Figure 4.2). Whereas the relationship between pH value and corrosion rate in (Figure 4.3) is not as steep as in (Figure 4.1).

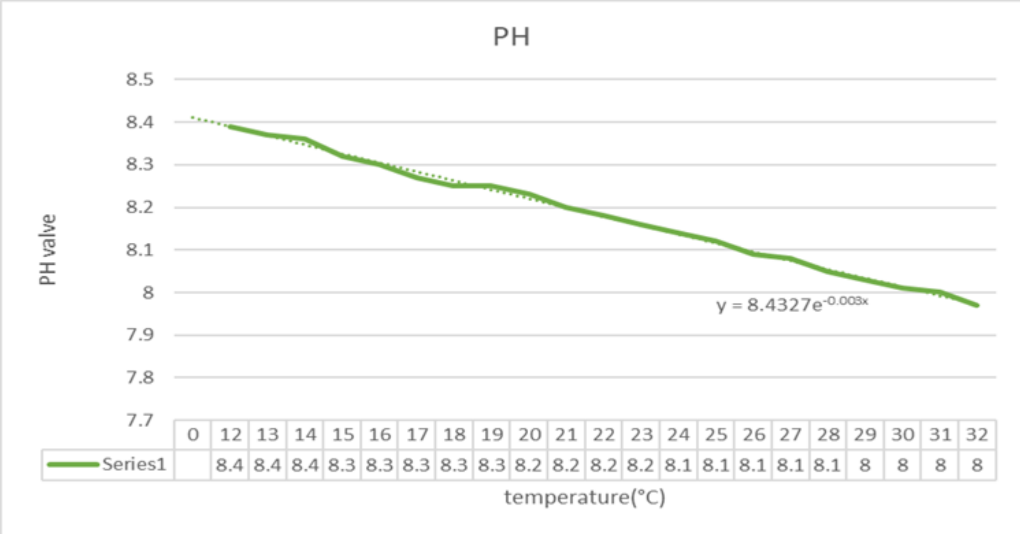

Figure 4.2 pH and water temperature relationship

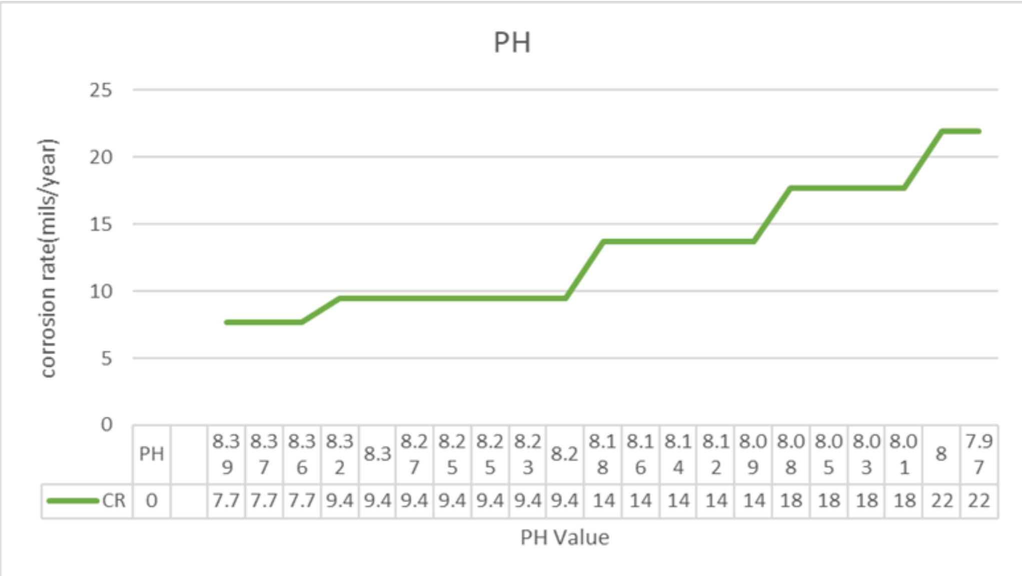

Figure 4.3 Corrosion rate and pH value relationship.
(The probe before cleaning)

4.3.2. The probe after cleaning

The results of the rerun test. The data was retrieved with a probe and cleaned as needed, as shown in the figure (Figure 4.4). The temperature was 8 °C at the start of the period, and the corrosion rate was 5 mil/year, as shown in the graph. When the temperature rises, the corrosion rate rises as well, but the increase stops at 18 million at 32°C. The (Figure 4.4) shows that corrosion rates typically increase slowly at the start of a period, but significantly when the temperature exceeds 20°C.

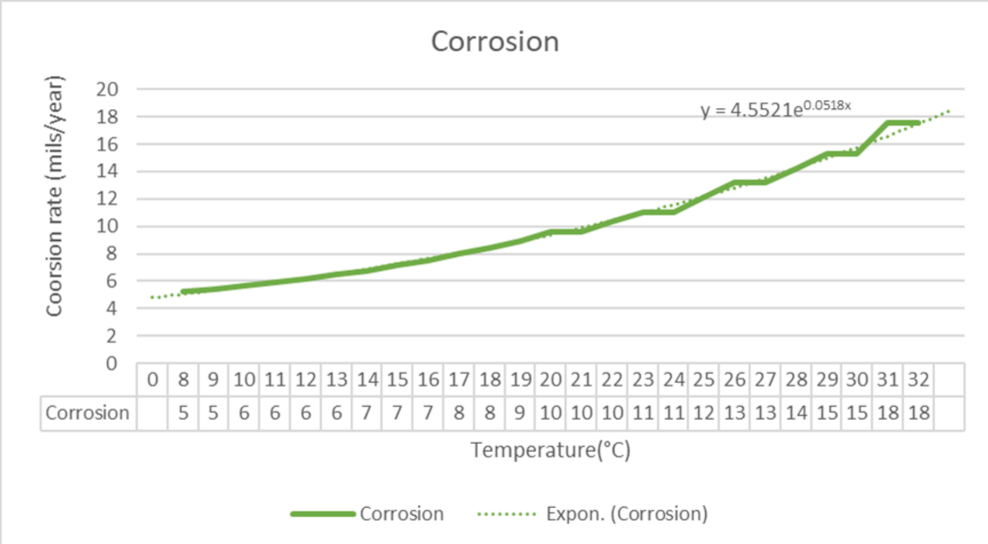

Figure 4.4 Corrosion rate and the water temperature relationship.

Figure 4.5 shows that the pH of the water increases as the temperature rises, reaching 10.3 at the start of the period. When the temperature rises, the pH valve decreases for a short time before returning to 9.6 at 32°C. The corrosion rate increases faster in the previous figure than the pH value decreases in the current figure.

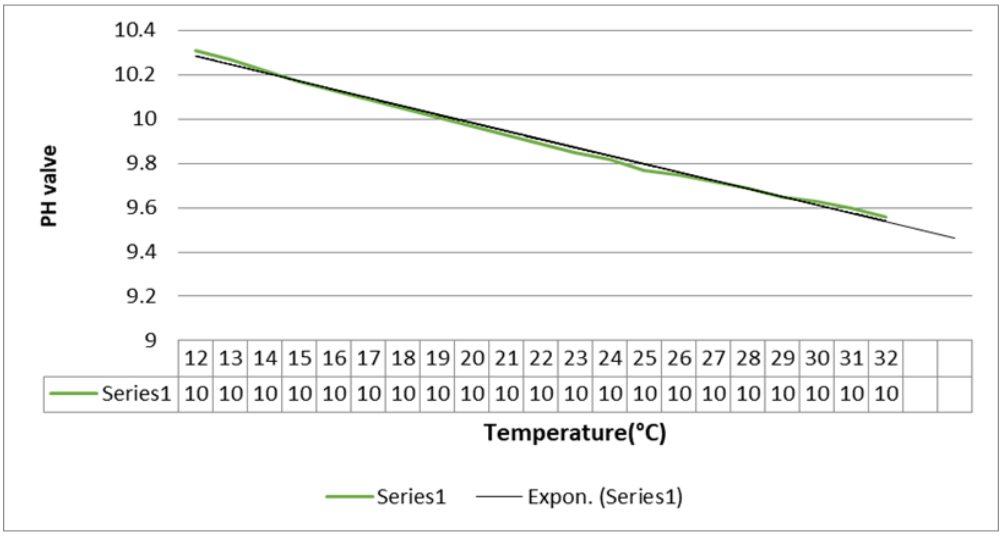

Figure 4.5 The pH value and the water temperature relationship.
(The probe after cleaning)

Looking at (Figure 4.5), the pH value of the water increases as the temperature rises, reaching 10.3 at the start of the period. When the temperature rises, the pH valve decreases for a short time before returning to 9.6 at 32°C. The corrosion rate in the previous figure is increasing faster than the pH value in the current figure (Figure 4.6)

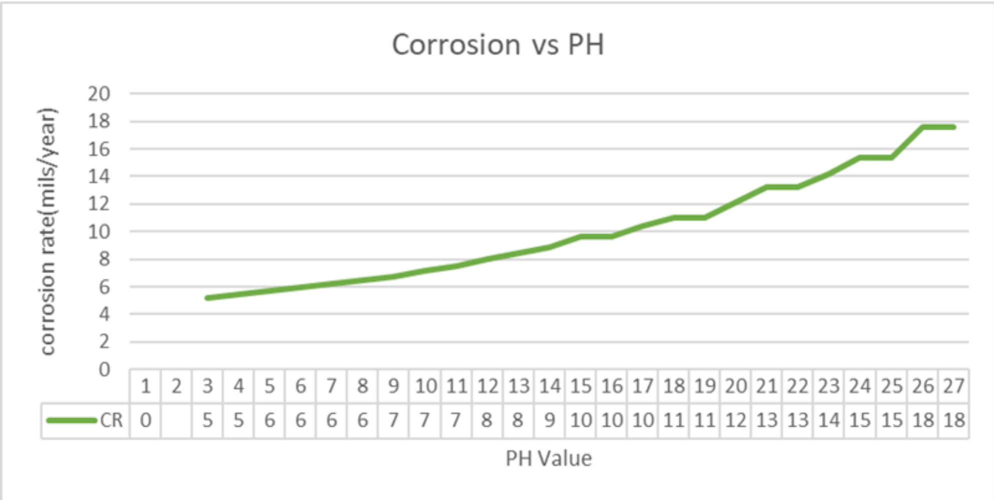

Figure 4.6 The relationship between the corrosion rate and pH value.
(The probe after cleaning)

4.3.3. The probe after cleaning in two months later

This was the probe's condition two months later, on June 17, when it was cleaned, and the data was recorded on June 17 and displayed in the (Figure 4.7).

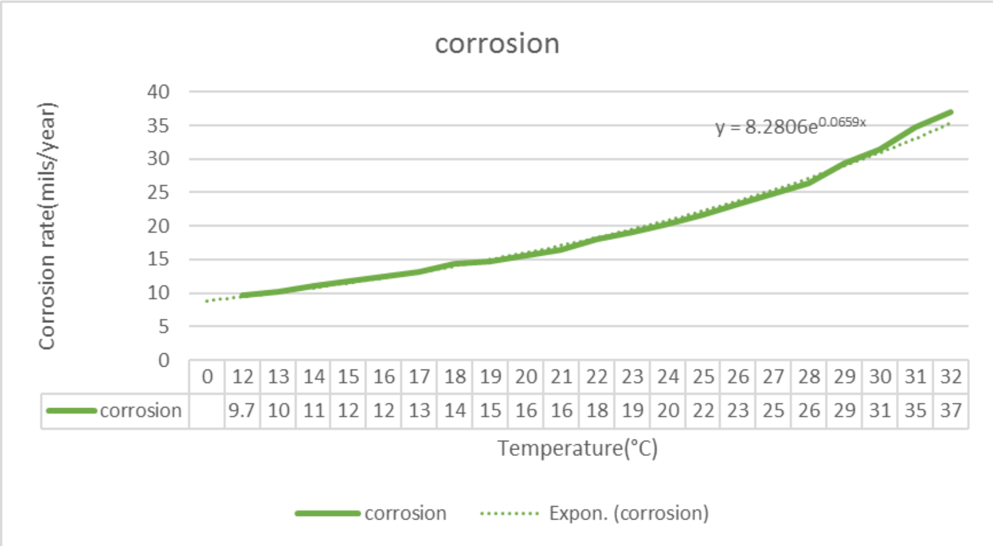

Figure 4.7 The corrosion rate and the water temperature relationship.

During the first year, the temperature in the figure is 12°C, and the corrosion rate is 9.7 mil/year. The corrosion rate increases as the temperature rises, and when the temperature reaches 32°C, the corrosion rate stops at 37 million years. The graph shows that corrosion rates typically increase slowly at the start of a period, but significantly when the temperature exceeds 20°C.

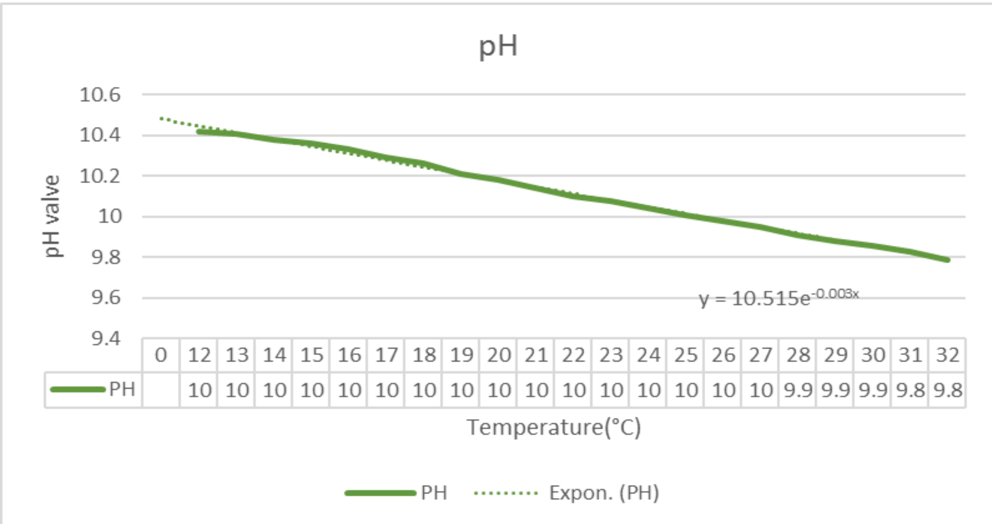

Figure 4.8 The pH value and the water temperature relationship.

The (Figure 4.8) compares pH levels and the temperature at the start of the period, which is 12°C, with the pH level at 10.4. When the temperature rises, pH levels decrease until they reach pH 9.8 at 32°C. In comparison to the decrease in pH value in (Figure 4.8), the corrosion rate in increased faster than the decrease in pH value in (Figure 4.8).

4.3.4. The system with inhibitor

The data was collected on June 20, 2018, with a set point temperature of 10 degrees Celsius. The data was collected with the probe after it had been cleaned and washed with cold water. After introducing the inhibitor into the pipe rig system, the corrosion rate was reduced to less than a millimetre per year, and the pH was set to 7. Throughout the second day, the corrosion rate suddenly increased to 99 (maximise corrosion monitor value) and the pH value increased to 7.5. (Maximize value of pH monitor). After a short period of time, the pH value continues to rise while the corrosion rate decreases.

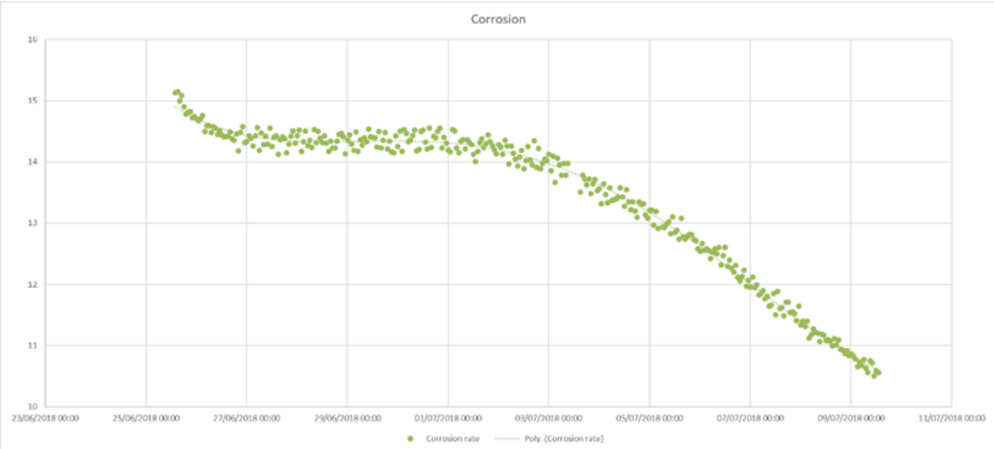

Figure 4.9 The corrosion rate performance in the set-point temperature 10℃.

The samples are measured at 10 degrees Celsius in (Figure 4.9). As shown in (Figure 4.9), the corrosion rate of the system decreased from 15.0 mils/year to 14.5 mils/year between June 23rd and June 27th, 2018. From June 27th to July 3rd, 2018, the system's corrosion rate remained relatively stable at 14.5 mils/year. Corrosion has slowed over time and is now faster than it was previously. The corrosion rate of the system is relatively stable at 5.5 mils per year.

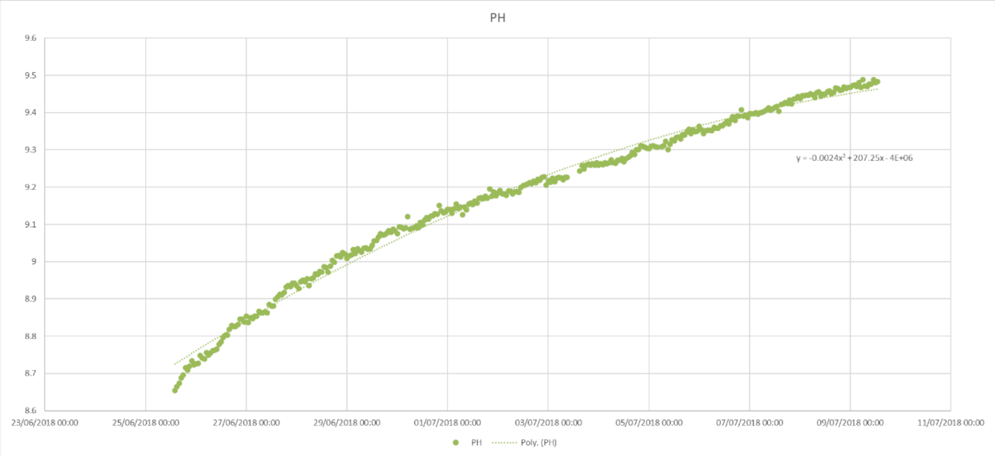

Figure 4.10 The pH value performance in the set-point temperature 10℃.

When the pH value and temperature are compared in (Figures 4.9 and 4.10), a negative trend emerges that begins at pH 8.6 at the start of the test. The pH level in the experiment gradually increased, but the rate of increase slowed as the experiment progressed. In contrast to the decrease in pH in figure 4.9, the increase in corrosion rate in figure 4.10 is faster than that in figure 4.9. (Figure 4.10). The pH of the system remains stable at 9.7.

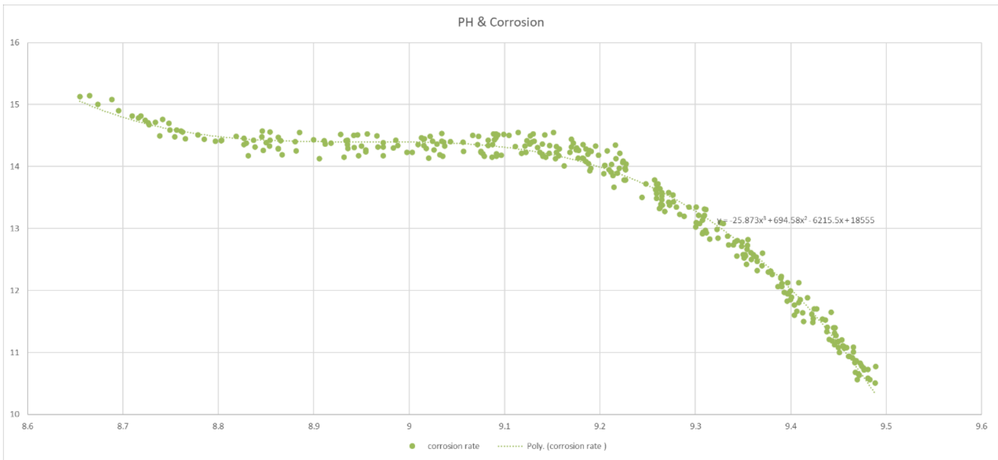

Figure 4.11 The relationship between the corrosion rate and pH value in the set-point temperature 10℃.

When comparing (Figures 4.9 and 4.11), the relationship between pH value and corrosion rate is similar to the relationship between temperature and corrosion rate, but it is flatter than the relationship between temperature and corrosion rate. Both the system's concentration and corrosion rate remain constant at 5.5 mils/month and 9.7, respectively.

The data was collected on 27/07/2018 and analysed using the probe with cleaning, a set-point temperature of 10°C, and a running time of more than one month. The data are shown in the (Figure 4.12).

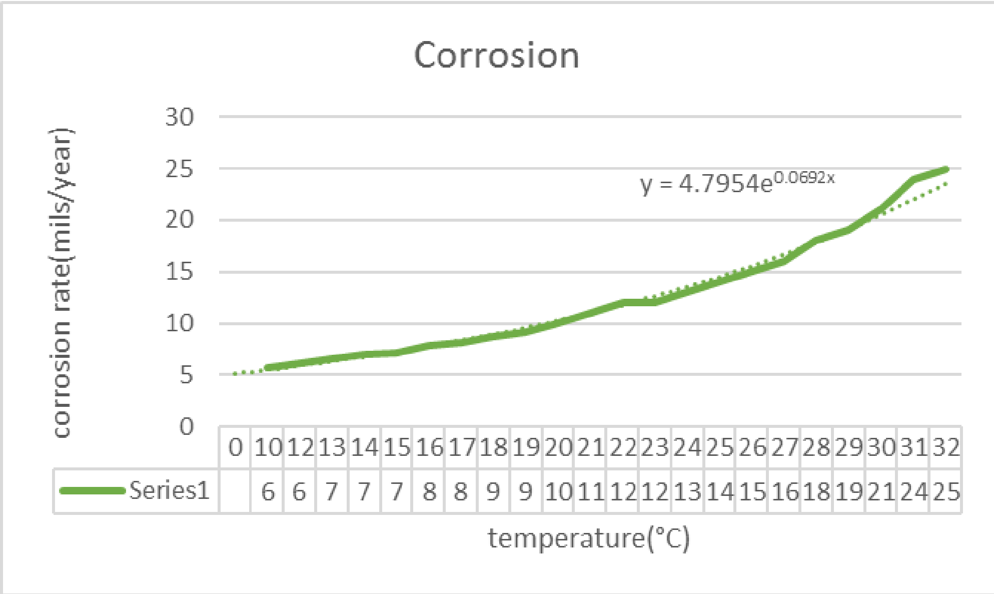

Figure 4.12 The relationship between the corrosion rate and the water temperature.

In the beginning of the period, the temperature is 10°C, and the corrosion rate is 5.5 microns per year. When the temperature rises, the corrosion rate rises as well until it reaches a certain threshold, but it does not stop there. The graph shows that as the temperature rises, so does the rate of corrosion when the temperature exceeds 20°C.

Until the beginning of the period, the corrosion rate and temperature are the same; however, after the period, the temperature is 10 °C and the pH valve is 9.6. The pH valve shows a decreasing trend at 32°C and tends to stop at 9. In comparison to (Figure 4.12), the rate of corrosion increased faster than the pH value in the (Figure 4.13).

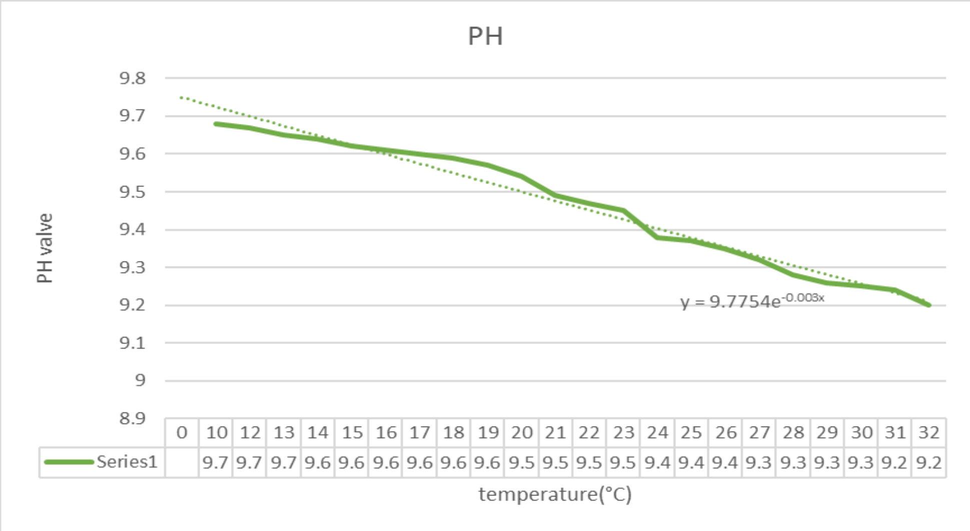

Figure 4.13 The relationship between the pH value and the water temperature. (After operation temperature: 10℃.)

The relationship between pH value and corrosion rate in (Figure 4.14) is flatter than the relationship between temperature and corrosion rate, but it is similar to the relationship between temperature and corrosion rate in (Figure 4.14).

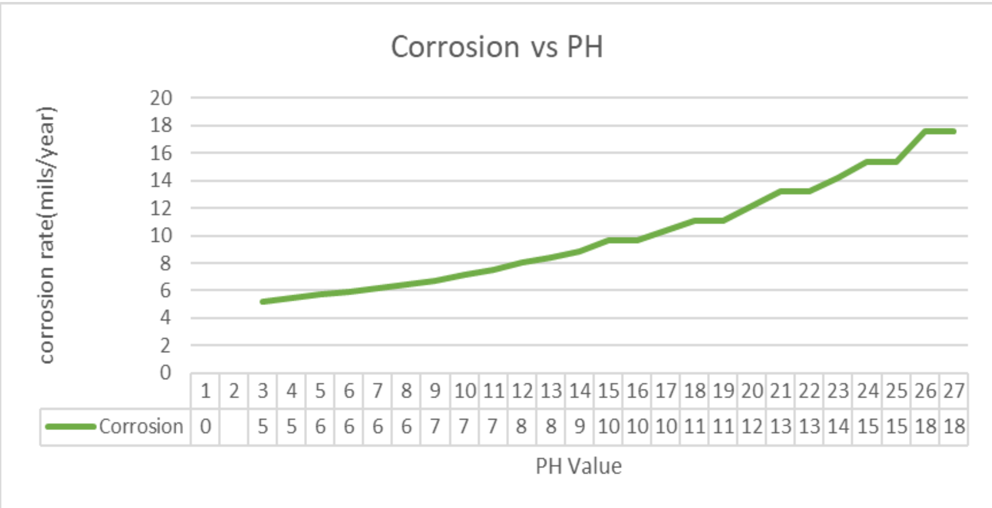

Figure 4.14 The corrosion rate and the pH value relationship. (After operation temperature: 10℃.)

4.4. Analysis

It is widely accepted that the corrosion effect caused by increasing oxygen and oxidisation allows for an increase in corrosion, as evidenced by the literature review. The corrosion rate increases as the temperature rises and the pH falls. The figure below depicts the output of the same type of result. Because the various phases all have some variation, each test result has a different variation in certain aspects.

Corrosion rate in different temperature in four stages

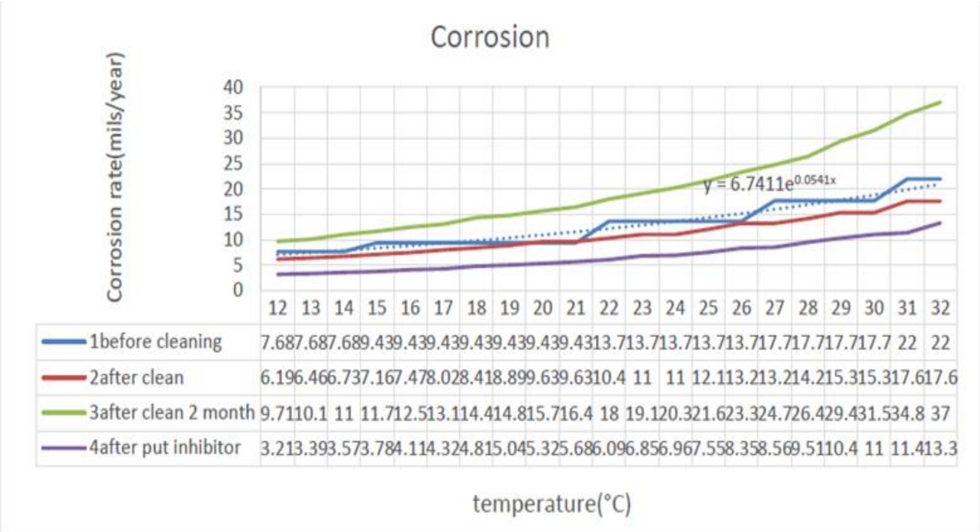

Figure 4.15 The corrosion rate in four stages and temperature

¶ The corrosion rate is plotted prior to cleaning the probe. The initial temperature of the stream was 12°C, and at this rate, corrosion is 7.7 mil/year. The corrosion rate increases with increasing temperature, peaking at 22 mils/year at 32°C. The corrosion rate steadily increases at the start of the first heating cycle. When the temperature reaches 18°C, the corrosion rate suddenly increases.

¶ After the probe has been cleaned, the corrosion rate for line two is calculated. According to the graph, the temperature is 12 degrees Celsius, and the corrosion rate is 6.2 micromoles per year. The corrosion rate increases with increasing temperature, peaking at 18 mil/year at 32°C. The corrosion rate climbs to a high level at the start of the cycle, but then abruptly increases when the temperature rises above 16°C. Line 2 is lower than line 1, indicating that the corrosion rate is lower after cleaning the probe. The probe's accuracy, however, decreases at low temperatures, such as 16°C. After washing, the corrosion rate of the probe increased.

¶ The data on the third line show the corrosion rate after two months of cleanings. The temperature is 12°C at the start of time, and the corrosion rate is 9.7 mil/year. As the temperature rises, so does the corrosion rate, which reaches a halt at 32°C. Line 1 shows that the corrosion rate rises to a high level at the start of the cycle, but then drops sharply when the temperature rises above 16°C. Line 3 is higher than lines 1 and 2, indicating that the corrosion rate of the system will increase if the system is in regular service for an extended period of time or requires frequent cleaning. The data show that, in the same setting and under the same conditions, line 3 is 3 mil/year higher than the previous lines. The impact was greater after the temperature rose. After adjusting for time, the difference between lines 3 and 1 and 2 is 10 mils/year. It shows that corrosion occurs throughout the lifetime of a steel pipe network.

¶ The linear three-hour data show the corrosion rate after the inhibitor was applied two months later. The temperature is shown by the linear two starting at 12°C, and the corrosion rate is calculated to be 3.0 mil/year. As the temperature rises, the corrosion rate rises and peaks at 32°C before levelling off. The linear line shows that the corrosion rate increases slowly at first, but then suddenly increases when the temperature exceeds 20°C. When compared to linear one, two, and three, linear four has the lowest value, indicating that it is useful for lowering the corrosion rate.

It is clear from the corrosion rate in four stages shown above. The best operation statement with the lowest corrosion rate is stage four, which is the system after cleaning the probe and putting the inhibitor in for more than two months.

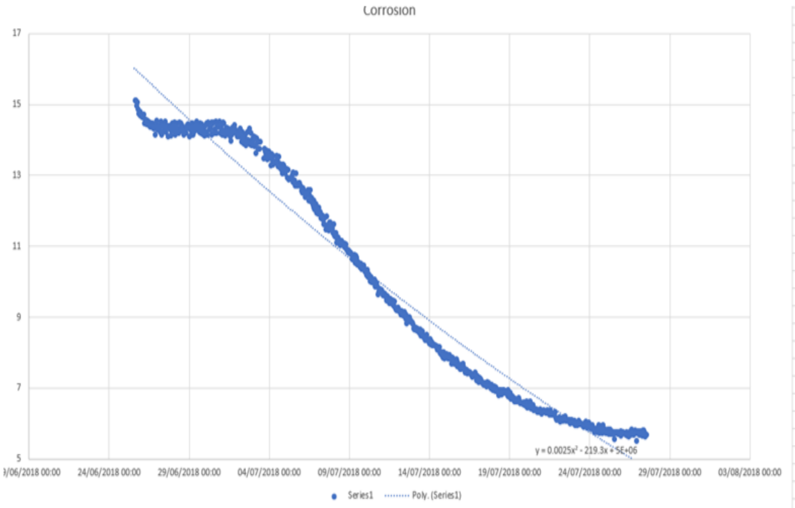

Figure 4.16 The corrosion rate performance in the set-point temperature 10 ℃. (The system within inhibitor)

presented above were collected during the first year of monitoring. The rate of corrosion varied from 16 to 4 MPY at the start of the three-week period. After three weeks of completing the MPY data flow, the corrosion rate of 2 MPY reaches 4. (MPY). There is a difference between the data from the first round of testing and the corrosion rate in the second round of testing. The corrosion rate drops dramatically on the first day of the first few weeks, but not as dramatically as in the past. This year, it will be reduced by one mil per year. 15 million to 14 million per year Following that, the linear trend increased to 14 mils/year. Following that, the corrosion rate has steadily decreased. The thickness reduction can be accelerated over two years, reducing the rate of reduction from 14 mils/year to 11 mils/year. In the following stage, the trend is the same as the date from four weeks ago, but the performance of the accelerated velocity is different, which continues to decrease from the test carried out flowing four weeks, which decreases around 4 mils/year from 11 mils/year to 7 mils/year. Throughout the last time period, the corrosion rate has remained stable at 5.5 mils/year. When the data from two test rounds are compared, it is observed that under the same conditions, the corrosion rate of the first test product is 5 mils/year and the second test product is 4 mils/year, but the data revealed an increase in corrosion.

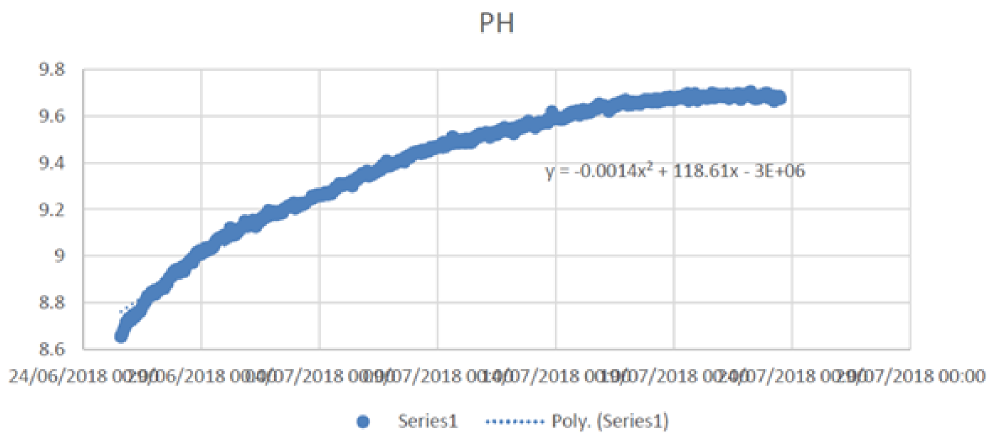

Figure 4.17 The pH value of corrosion experiment with the same conditions as last year in this year

The corrosion rate shifts from 7.5 to 9.0 over the course of three weeks for the pH value. Following that, the MPY data for corrosion rates was 8.5 Mils/year from the first round of testing.

In comparison to the previous experiment, the date result is an improvement from the second round of testing. During this time, the pH rises from 8.6 to 9.6 and then remains stable at 9.6. The accelerated speed rapidly decreased during the first measurement period. The most noticeable difference is the difference between the images. There appears to be no change in the pH level after measuring it for the first three days. However, during this test experiment period, the pH valve rises after being exposed to the inhibitor, reaching 9.6 after one month.

As can be seen from the comparison results, although the conditions are similar in both experiments in two rounds, the statement of tubes and water, which includes corrosion statement and pH value of the water, are different, causing the corrosion rate in the second round of test to be higher than the corrosion rate in the first round of test.

4.5. Results and analysis in summary

The first set of experiments, the probe after purification, the probe after purification for two months, and the device with the inhibitor are the results and data obtained. The results of this laboratory experiment are mentioned. The increasing influence of corrosion by oxygen and oxidizers is widely known to increase the corrosion seen in the review: as temperature rises and pH value falls, the rate of corrosion increases.

The portion of the corrosion rate at various temperatures in four stages depends on the process section in above, which are from 7.7 mil/year at 12°C to 22 mil/year at 32°C, from 6.2 mil/year at 12°C to 18 mil/year at 32°C, and from 9.7 mil/year at 12°C to 37 mil/year at 32°C, respectively, and analysing the cause, which is pH, oxygen, and oxidizers indicated in above.

The control experiment in this corrosion rate test revealed a rate of 5.5 mils/year after a month of continuous service; this rate remained constant at 5.5 mils/year. The first test run's experiment data is approximately 3 mils/year. When two results are compared, it is discovered that the second operation of the corrosion rig and no corrosion rate in this test is 2 mils/year higher than the initial test data.

The study concluded that, while the situation is comparable in both tests in two test rounds, the commitment of the tubes and the water, which includes the corrosion declaration and the pH value of the water, is different, resulting in a higher corrosion rate in the second year of corrosion rig service than in the first year.

In the fourth level's section of the corrosion rate of different operation statement, a point out in the beginning period of putting into the inhibitor and after turning off and turning on the pump, it may increase the corrosion rate and require a long-time operation to back and get a stable corrosion rate again. After one month, the sample showed consistent corrosion rates when inhibited and immediately after when the pump was turned off and then back on.

The uncertainty is examined, which includes the corrosion rate in different temperatures after the corrosion rig has been active for a long time in different set-point temperatures. The study's findings are presented in such a way that they allow for rapid control of the rate of corrosion. It means that the device must operate over time in accordance with a set-point at the same temperature/humidity.

The resulting inferences are the result of the analysis of the results. The cooling system's operation method is as follows: flow rate and temperature must be constant, and the system must be able to maintain the set point value for an extended period of time.

4.6. Data findings and outcomes

This chapter section will detail and analyse the results of the experiments that were carried out in order to provide insight into what these results inform us and how they can be useful in the future proceedings. It will also be used to assess how the model performs after being trained on the data collected in previous chapters.

This will outline the precision with which it can detect the health and condition of the pipes based on the values sent to it. Along with that, it will provide insight into whether the model created for this was efficient enough to not only train on the data being used, but can also aid in understanding whether the model created for this is suitable for this application or not. Finally, it will describe how this model is used in the VR environment that created in this study is prior to conducting the experiments. It will be used to gain insight into how the model will perform under various conditions similar to those encountered by the building in the real world. The results of this will be able to help determine how efficient the model is and what its inherent limitations are.

As previously stated, the dataset that is selected for this research by combining and processing the results of two laboratory experiments in order to gain insight into the type of data and any patterns for correlations that are discovered in it. The results of these tests will be used in subsequent sections to consider the key variables that will aid in determining the rate of corrosion of steel pipes.

The mean and standard deviation are the first two methods of the dataset. This will assist in gaining an understanding of the average values found in the dataset and the deviation found in it. These are used to help understand how close or far the values are to being as close to the real-world environment as possible. The mean and standard deviation from the dataset are shown in Table 4.1.

Table 4.1 Mean and Standard Deviation of the dataset

Data	Mean	Standard Deviation
Conductivity [uS]	169.004	10.140
Corrected GC	3.300	1.506
Corrosion rate (steel) [mpy]	0.202	0.486
DO [PPM]	0.201	0.498
Flow Counter [Litres]	30621.479	8949.605
Galvanic Current [mA]	3.698	1.239
Metal Loss (steel) [mm]	0.003	21.301
Pressure [kPa]	22.542	33.994
Temperature [degC]	45.783	10.253

The mean and standard deviation of the laboratory datasets, which was combined to form the core data, are represented in this table. The results of this demonstrate two important points.

1st point: which parameter has a large variation, and which one has a small variation, both of which have an impact on the rate of corrosion and ultimately the rate of performance.

Point 2: The range of outcomes that can be expected from the Black box model, given that the results were not far off from the real-world performance of the pipe in question.

4.6.1. Laboratory experiments results

This section will be used to highlight and illustrate the findings from the laboratory experiments that were carried out. It consists of BISPA laboratory tests and Hevasure laboratory tests, which are performed to analyse and determine the factors that can contribute to the corrosion of steel pipes. This will be useful in later stages of this research because understanding the main factors that can impact the health of steel pipes may lead to the development of an ANN model capable of efficiently predicting the condition of the pipe when subjected to changing values of those variables. It will also aid in the analysis of any relationships and patterns discovered when the value of one change as a result of the other, which can be used to analyse the significant factors that can contribute to the corrosion of steel pipes.

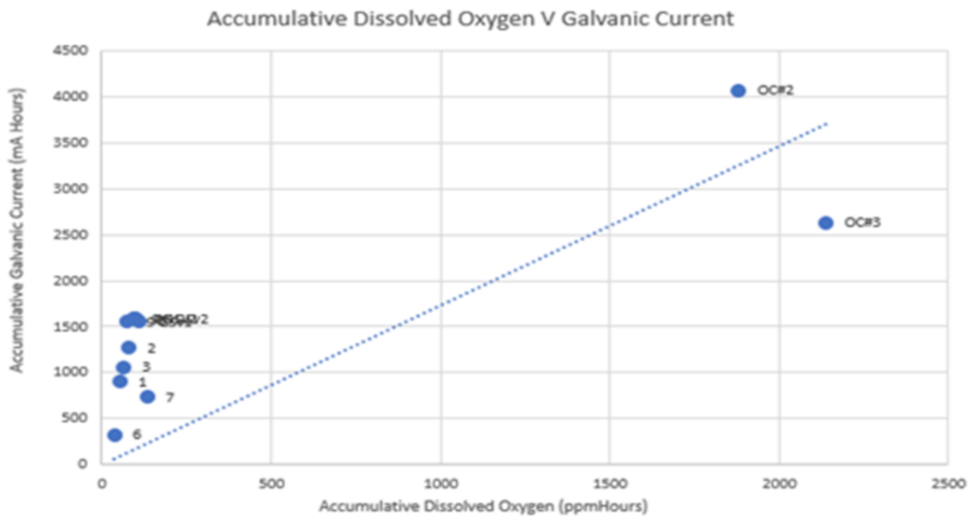

Figure 4.18 The relation between Accumulative Dissolved Oxygen and the galvanic current

The data generated by the laboratory experiments described in the preceding chapters will allow us to better predict the point at which corrosion may occur, and the factors that may lead to corrosion. This would be ideal for this research because it would aid the model in understanding the factors that could cause corrosion criteria that could cause it. The data collected from it could be used to train the agent to predict when corrosion will occur and alert people to it, or to try to regulate the temperature or pressure that is passed through it to increase the longevity of the steel pipes. The former could be done to either replace the pipes before they corrode or to regulate the temperature of the pipe itself. Doing so will allow us to determine the rate at which corrosion could occur based on increasing and decreasing oxygen levels, about how it can be used to ensure that the health of the steel pipes can be monitored and assessed, allowing us to get the most out of the steel pipes.

According to the findings, there is a positive relationship between dissolved oxygen and the galvanic current produced as a result of it. This can be seen in tests

1-3, where a positive correlation was discovered between galvanic current and dissolved oxygen. In the case of test 4, the relationship discovered was negative in nature, indicating that as the dissolved oxygen rate increases, the galvanic current may decrease over time.

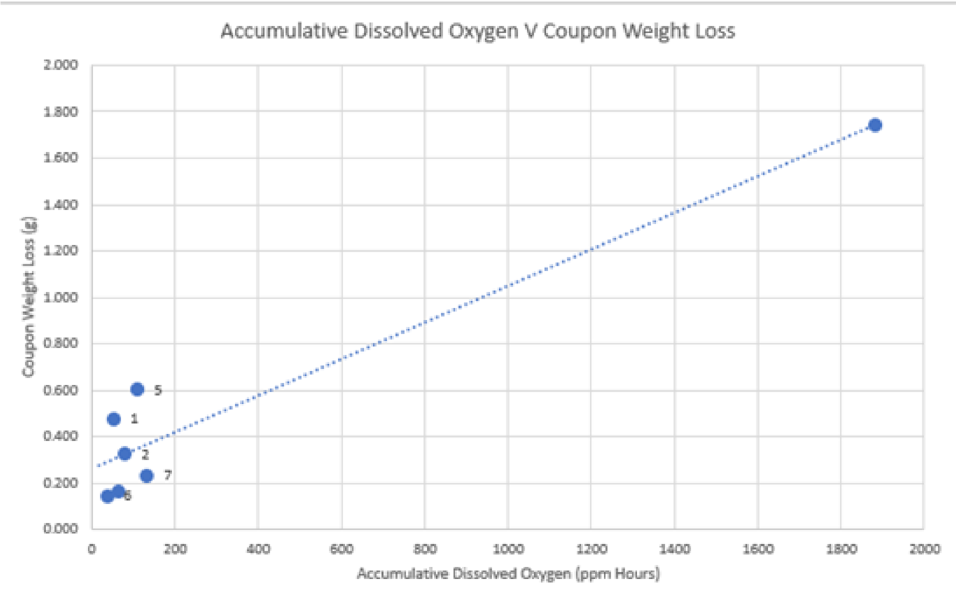

Figure 4.19 Accumulative Dissolved Oxygen Coupon vs the Coupon Weight Loss

Figure 4.19, which contains a correlation, yields a similar result to Figure 4.18. The difference between the two results is that the correlation found in this is lower than that found in Figure 4.19, indicating that the results Weight Loss found from the increase in dissolved oxygen would not have a significant impact on the steel pipes. The variation in the DO in the loops 1, 2, and 3 were considered open for the different durations of the test that were conducted, resulting in this result in test one. In the subsequent tests, primarily tests 2, 3, and 4, some correlation was found between the increase in coupon weight loss as the DO increased over time, along with the experimental error that was present.

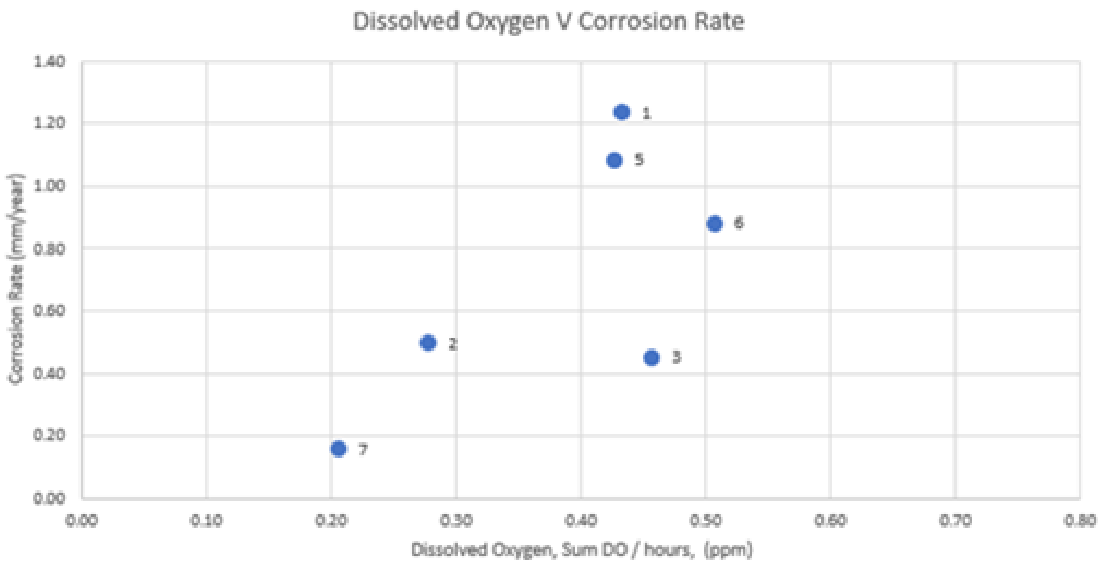

Figure 4.20 Dissolved Oxygen Rate vs. the rate of corrosion

According to the results shown in Figure 4.20, there is a limited correlation between the rate of dissolved oxygen and the rate of corrosion, indicating that the relationship that exists between the two variables influences the other but only for a limited time or until a value is reached. There may be issues when plotting the corrosion rate against the dissolved oxygen rate because the corrosion rate is measured in mm/year and the dissolved oxygen rate is measured in ppm/hours. To convert the dissolved oxygen from ppm/hours to ppm/years, divide the value by 8760, which will make it plot with the corrosion rate.

The experiments in this case would primarily focus on determining the rate of corrosion through the emission of galvanic current. ASI 1050 steel used for this, which has 10% carbon in it, as previously mentioned. The laboratory experiments would be carried out in series and under various conditions and settings to analyse the rate of corrosion based on galvanic corrosion of steel pipes. It will also aid in understanding how the corrosion rate changes over time and how different temperatures affect it. Understanding it also aids in determining how much corrosion should be allowed to occur in the pipes before they must be replaced.

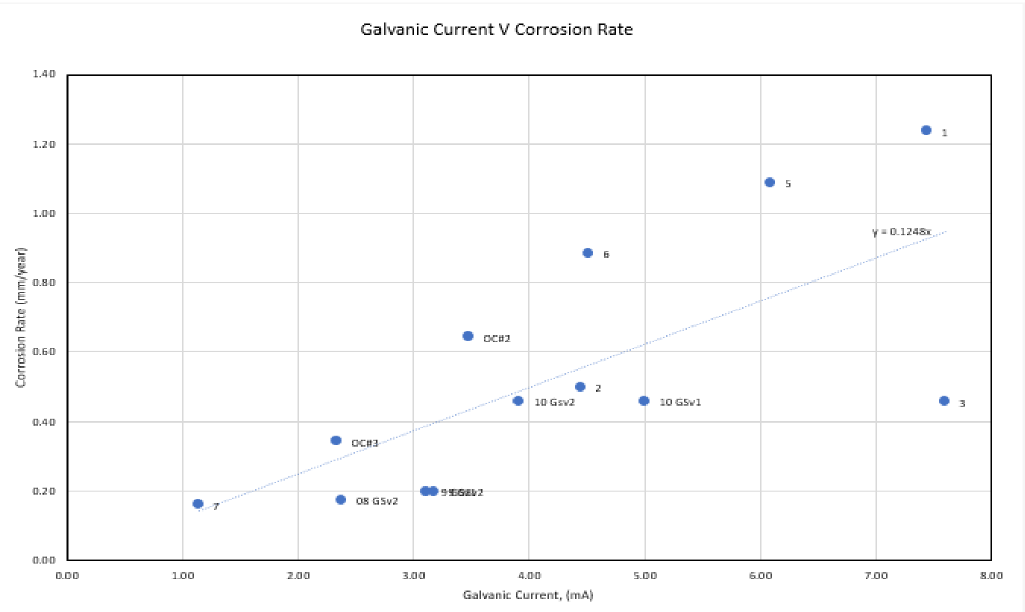

Figure 4.21 Graph showing the galvanic current corrosion rate against the galvanic current produced

According to the graph in Figure 4.21, the corrosion rate has a significant correlation with the galvanic current produced in the system, indicating that as the galvanic current produced increases, so does the rate at which corrosion occurs. The corrosion caused by it has a low value, indicating that the corrosion caused by it is significantly weaker than that found under other conditions. This could be attributed to the fact that the iron surface corrodes faster because it readily oxidises with the available oxygen on the surface. When exposed to oxygen or sulphur, iron readily reacts and begins to oxidise. Because pure iron oxidises quickly, it is frequently difficult to find.

Figure 4.22 shows a similar result: as the galvanic current increases, the material loses its properties. This is to be expected because the galvanization process in steel pipes takes the free electrons present on the metal's outer surface and then reacts with the electrolytes nearby, causing the metal to lose its metallic properties. As a result, it loses its structure, which causes it to break as the galvanic current increases.

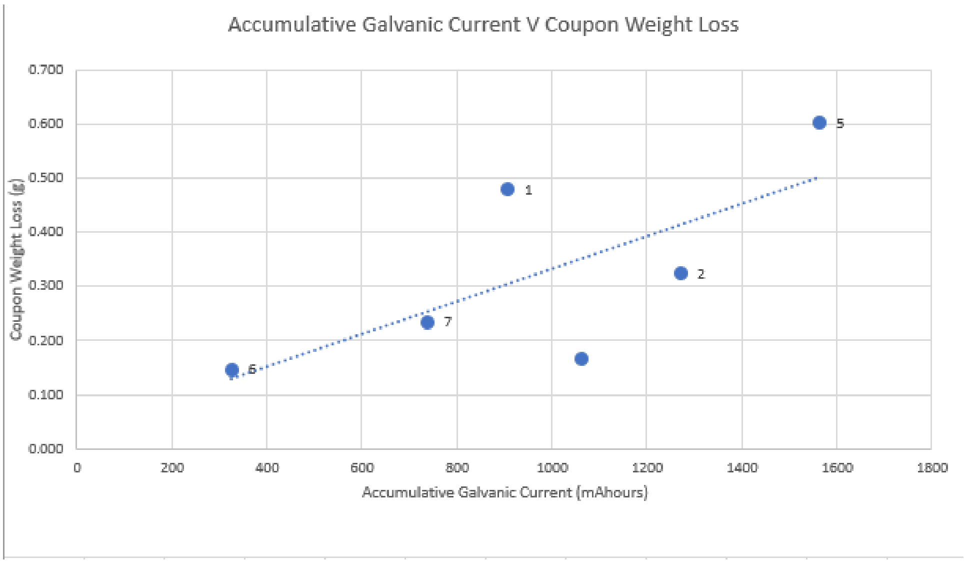

Figure 4.23 Galvanic Current vs. the Coupon Weight Loss

As shown in Figure 4.23, the galvanic current causes the metal to lose weight as well. As the galvanic current increases, so does the coupon weight loss. The correlation between them is considered to be extremely strong, indicating that when one value changes, the other value changes significantly.

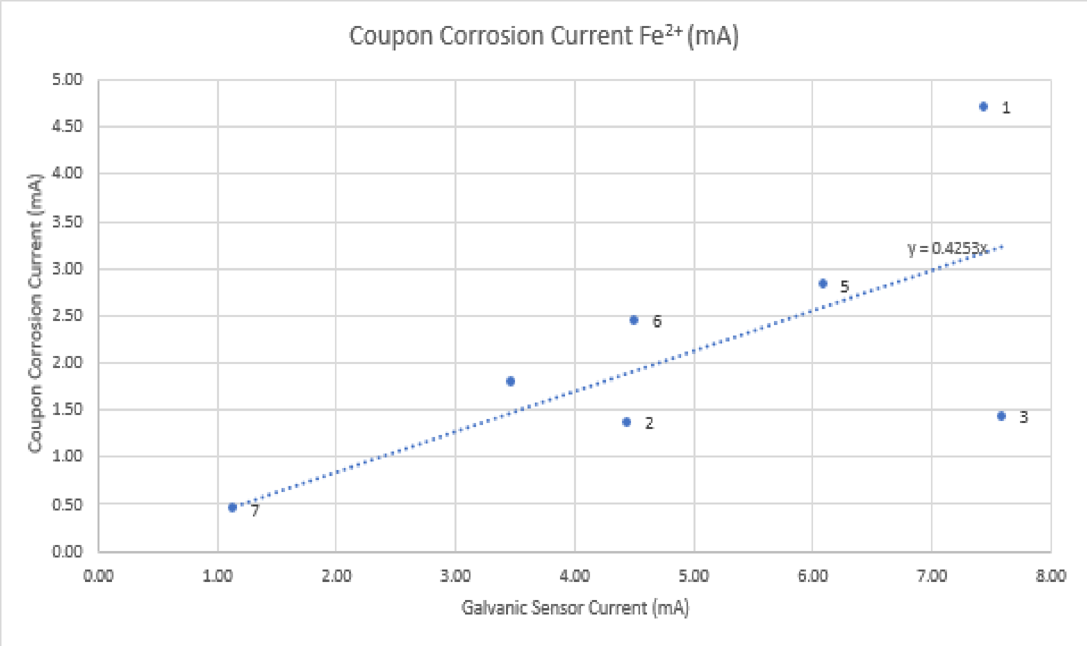

Figure 4.24 Coupon Corrosion Rate of a Ferrous ions (Fe^{2+})

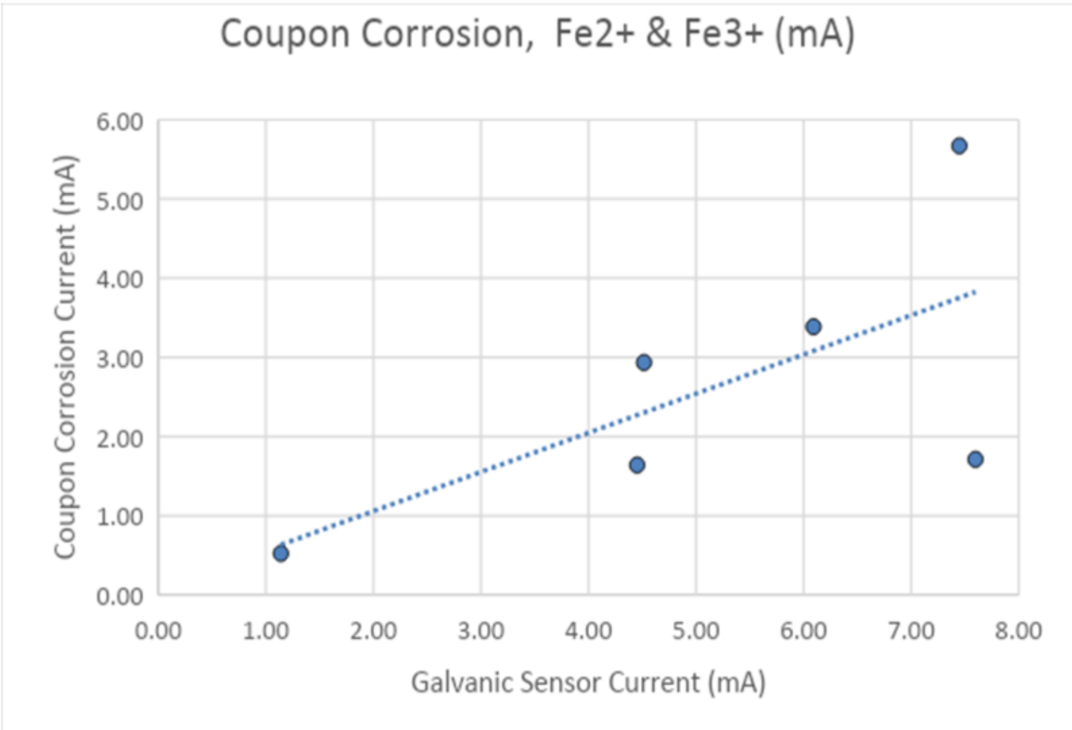

Figure 4.25 Coupon Corrosion Rate of both Ferrous (Fe^{2+}) and Ferric (Fe^{3+}) ions

The experiments performed on different ferrous and ferric surfaces reveal a significant difference in these and how galvanic corrosion may impact these. This will help us understand how iron-based surfaces corrode over time. Because steel is an alloy of iron and other metals, it contains some iron, which aids in understanding how ferrous and ferric ions react during galvanization. Figures 4.24 to 4.26 show the results of these tests. Figure 4.24 shows that the ferrous ions have a strong correlation with the galvanic current produced by galvanization. This is because ferrous ions lose electrons more quickly than ferrous ions that lose electrons more slowly.

Meanwhile, when both ferrous and ferric metals are combined, the results are similar to what was discovered in the previous assessment, where the correlation was discovered to be similar to what is shown in Figure 4.25. This could be attributed to the fact that ferrous materials are more affected by galvanic current than ferric ions, which require more energy. Furthermore, it is not easily affected by galvanic current because it has a weak correlation with it, as shown in Figure 4.26.

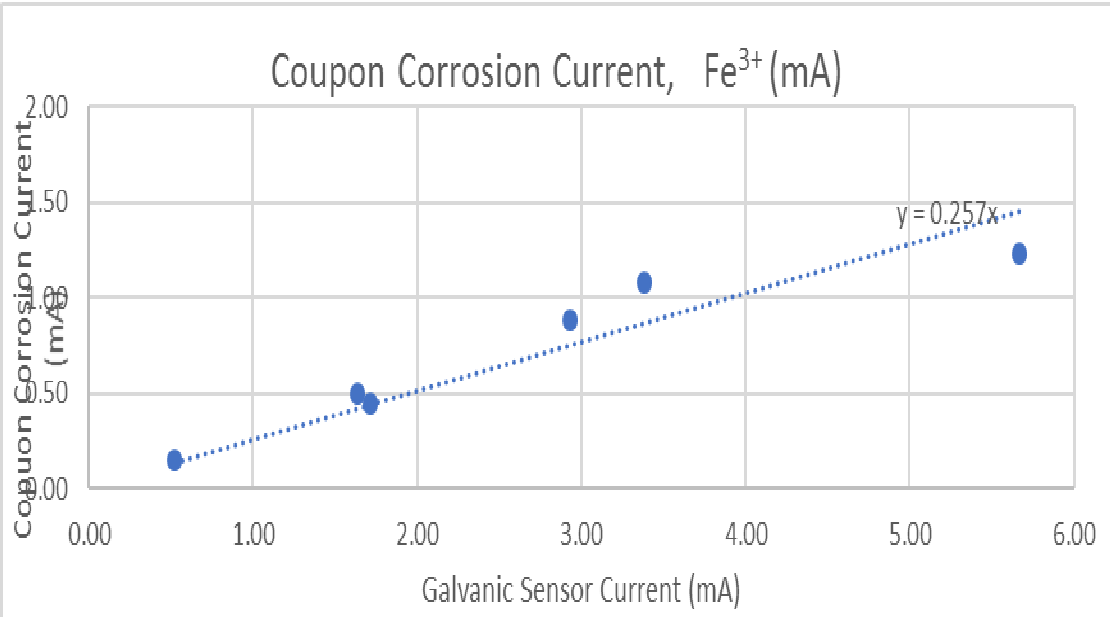

Figure 4.26 Coupon Corrosion Current of Ferric (Fe^{3+}) ions

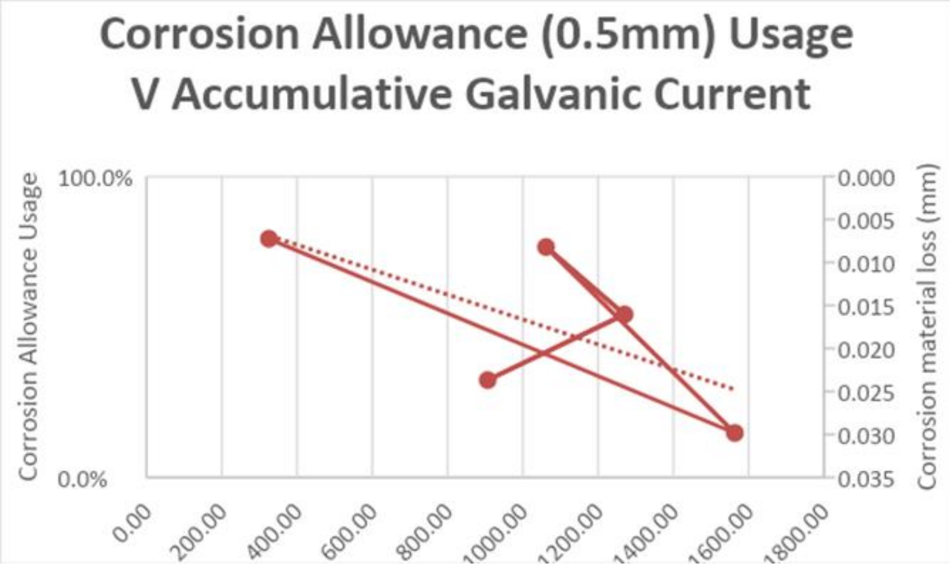

Figure 4.27 Corrosion Allowance usage vs. the Galvanic Current

When evaluating the relationship shown in Figure 4.27 between the Corrosion Allowance and the Galvanic current the material is subjected to, the results show a significant correlation and that the value found is significantly lower than the corrosion allowance of steel pipes, which is 3mm. Under a 100% corrosion allowance, the resulting value is around 0.03mm, which is one-tenth of the average allowed corrosion rate of steel. This indicates that the corrosion allowance would peak at that when 100 percent usage is applied, indicating that this is the point at which peak corrosion would occur and the galvanic current would peak.

The data is used to generate the following table, which includes the average temperature discovered through the series of tests, the average dissolved oxygen measured, the average galvanic current produced by the tests, the cumulative galvanic current, and the dissolved oxygen in the water. This also includes the sum of the dissolved oxygen collected per hour in each test, and the galvanic current produced each hour in the tests performed.

Table 4.2 Sample of data that is collected through the experiments

Avg Temp (^oC)	Average Dissolved Oxygen (ppm)	Average Galvanic Current (mA)	Cumulative Dissolved Oxygen (ppm hours)	Cumulative Galvanic Current (mA Hours)	Coupon Weight Loss (g)	Coupon Corrosion Rate (mm/year)	Coupon mm Reduction	Sum Dissolved Oxygen/hours (ppm)	Sum Galvanic Current/hours (mA)
60.96	0.43	7.44	52.66	906.61	0.479	1.24	0.024	0.43	7.45
59.45	0.27	4.44	79.13	1270.24	0.325	0.496	0.016	0.28	4.45
56.25	0.48	7.72	63.82	1061.72	0.166	0.454	0.008	0.46	7.60
60.72	0.43	6.60	109.52	1563.36	0.603	1.085	0.030	0.43	6.09
61.47	0.52	4.46	36.50	325.25	0.147	0.882	0.007	0.51	4.52
57.00	0.21	1.16	132.96	736.72	0.235	0.157	0.012	0.21	1.14
59.39	1.26	4.13	1882.21	4075.56	1.74	0.641	0.086	1.61	3.48
48.85	1.54	2.70	2138.87	2637.66		0.34	0.044		2.34
43.95	0.15	2.39	99.73	1585.76	0.266	0.172	0.013	0.15	2.38
43.89	0.15	3.15	76.12	1554.49	0.228	0.196	0.011	0.15	3.12
43.89	0.19	3.18	91.82	1585.78	0.228	0.196	0.011	0.18	3.18
56.8	0.29	5.24	88.94	1779.06	0.373	0.455	0.018	0.25	5.01
56.8	0.41	3.65	105.3	1393.6	0.373	0.455	0.018	0.30	3.92

Using this data, it will be able to gain a clear understanding of how it can use this to generate a model, what parameters should be focused on, and what can be done to further improve it in the future. The focus of the model should be done on the Galvanic Current, Dissolved Oxygen, Temperature which could be used to determine what the corrosion rate would be which can be useful in building the model and what variables should be considered in order to accurately determine the health and condition of the pipes based on the average values that were found.

4.7. Analysis on the ANN model

This section will be used to illustrate the results of training and developing an ANN model that will be used in the HVAC system to provide insight into the model's performance about how it will be used in the future. This will be used to highlight the performance and the precision with which it can predict the condition of steel pipes. Furthermore, it will be used to determine any errors discovered during the training and testing phases of the ANN model's development. This metric will be determined by analysing the ANN model's loss metric, which will aid in determining how accurate the model was during training.

A learning curve graph depicts how quickly a model's performance improves over time. In the early stages of ANN modelling, learning curves are used to assess how well an algorithm performs on a dataset after it has been trained. The model can be tested on training data and held out data after each update during training, and plots of the estimated performance can be created to show learning curves.

This section will also detail any steps and measures taken to improve the model's accuracy and training process. The reason for this is to document the changes so that it can examine what changes and measures were necessary to achieve the desired state. Because selected data generated from two laboratory experiments, the data for this is large, so it is necessary to investigate measures and methods for training the ANN on a large dataset. Finally, it will be used to examine and identify the parameters and measures to ensure that it does not overfit or lose accuracy during the training stages. Overfitting can be a problem that reduces model accuracy because the model is unsure how to generalise the patterns when they move from training data to unseen data. This is common because the model becomes accustomed to the training data and, as a result, generalises their assumptions based on it. As a result, caution must be exercised to ensure that this does not occur in order for the model to be highly accurate. Finally, it will go over the results of the testing process, which will allow us to evaluate the model's performance based on the data that is provided to it. This data will be a part of the dataset that is not used during the model's training stage, as it will be used to validate and assess the model's accuracy when it is introduced to data that it has not seen before or was not trained on.

In the first set of training, the model was trained through 100 epochs in order to efficiently train it. Furthermore, it will reduce the batch size to 24 in order to reduce the time required to train the model. The dataset will need to be divided into two parts, one for training and the other for validation or testing. For this iteration and subsequent ones, 60% of the data is used to train the model and the remaining data to validate and test the model. Finally, this model will begin with a standard ANN model to determine whether the model will over fit or not in the current context.

Based on previous evaluation, the model had an accuracy of 99.8 percent, indicating that the model is fairly accurate in detecting the corrosion rate of steel pipes. However, upon closer inspection, the model in its current state is discovered to be over fit, indicating that the model was not properly trained and may result in false positives. This is also evident in Figure 4.28, where the validation graph during training reveals that the model is significantly over fit. This is accomplished by observing that the model's accuracy is close to 100 percent during the training stages and an average of 80 percent during the testing stages. Meanwhile, the loss in figure 4.29 shows that the loss discovered during the testing stages was significantly higher than the loss discovered during the training stages, indicating that the model was over fit during the training stages.

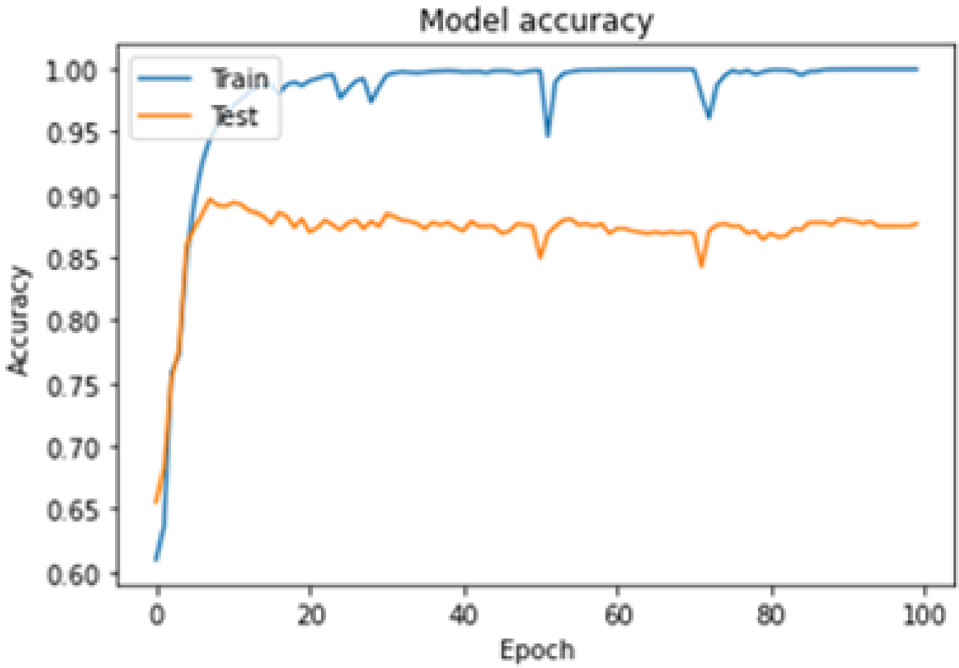

Figure 4.28 Model accuracy in its initial stage

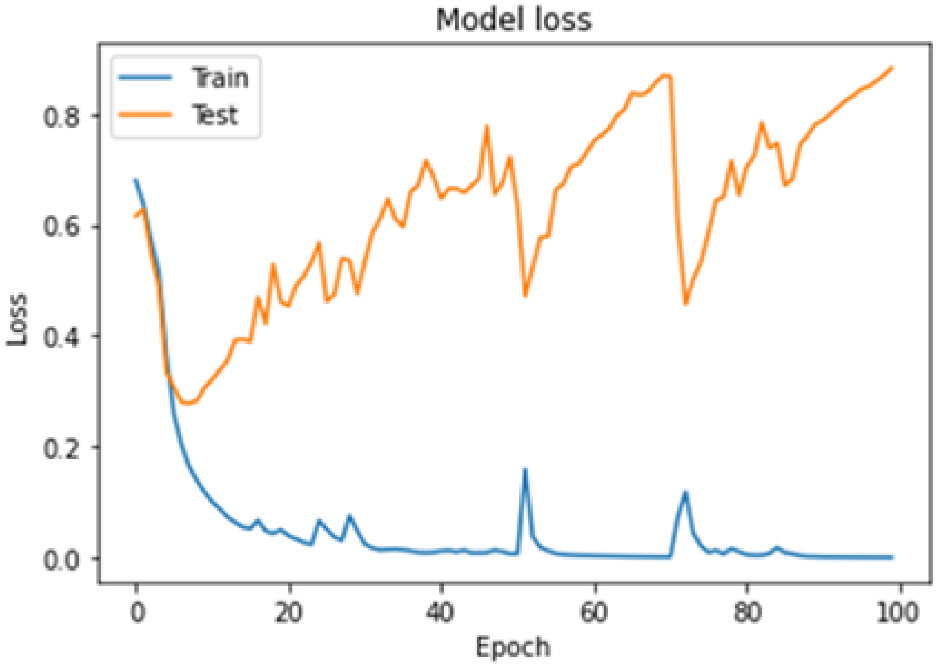

Figure 4.29 Calculated loss for initial model

The model will be refined in the following stage to reduce the likelihood of model overfitting. This will introduce dropout layers into it to reduce the likelihood of it overfitting. The dropout rate for these will be kept at 50% so that in each turn, the training of around 50% of the neurons can be stopped, which can help improve the training of the remaining 50%.

According to the evaluation, this model has an accuracy of around 98 percent, which is similar to what was discovered in the previous model. The accuracy of the test model is found to be around 85 percent by the end of it, indicating that the model is an improvement over the previous one. However, the model is still over fit because this model is only a 6% improvement over the previous one, indicating that it will need to evaluate a different measure to further reduce the likelihood of its overfitting.

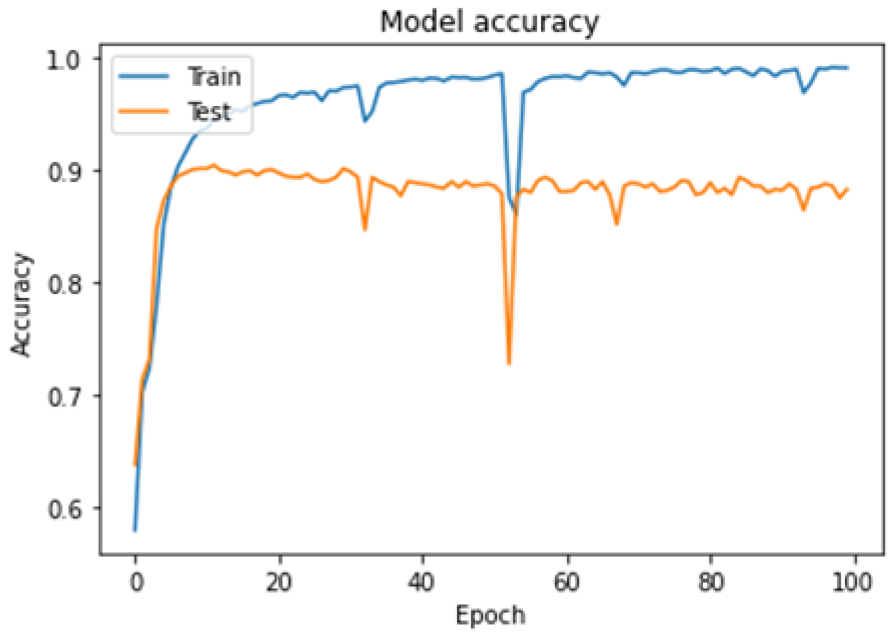

Figure 4.30 Accuracy of the new model that is made

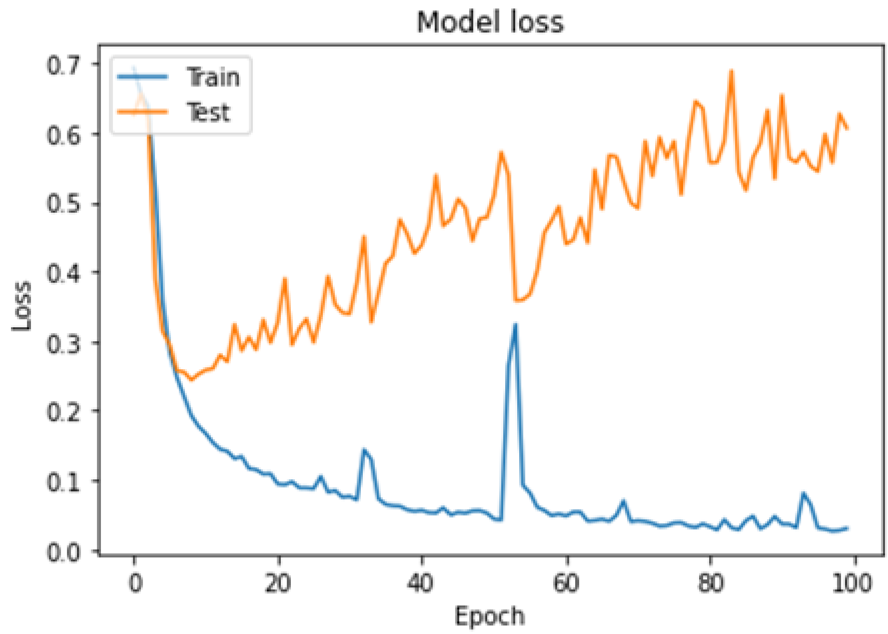

Figure 4.31 Calculated Loss of the new model

The accuracy of this new model is illustrated in Figure 4.30, which shows that the training and testing accuracy of the model has around 14% difference between them, indicating that the model might have over fitted. The loss that is calculated is found to be like what was seen in the past, further proving that the model is over fitted which can be seen in Figure 4.31. there is a need to find other measures and techniques to ensure that the model's accuracy can be increased over time which will ensure that it will detect the rate of corrosion with ease.

The only changes to this model are the dropout rate and the number of epochs through which the model will be trained. As previously stated, reducing epochs results in a less likely scenario, which reduces the likelihood of overfitting the model, which can degrade its accuracy rate. This has reduced the epoch to around 25, as seen in the previous graphs, where the accuracy for both the training phase and the test was the same when it reached 25 epochs. After that, checked that how these can change depending on how many times the dataset has been exposed to the model. Along with that, the dropout rate will need to be changed to 60% and 40%, as there are two dropouts for different layers.

Examine that the accuracy of this new model is around 92 percent, which, while lower than previous models, is found to be pretty accurate than what was found in previous models as the testing accuracy is found to be 88 percent, which is close to the accuracy found in the training stage, indicating that the model can be pretty accurate at detecting the rate of corrosion.

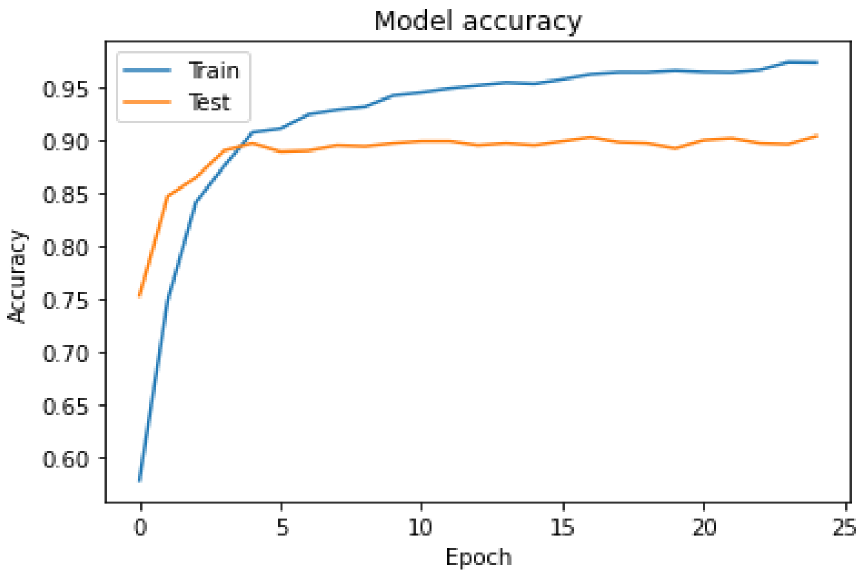

Figure 4.32 Accuracy of the revised model

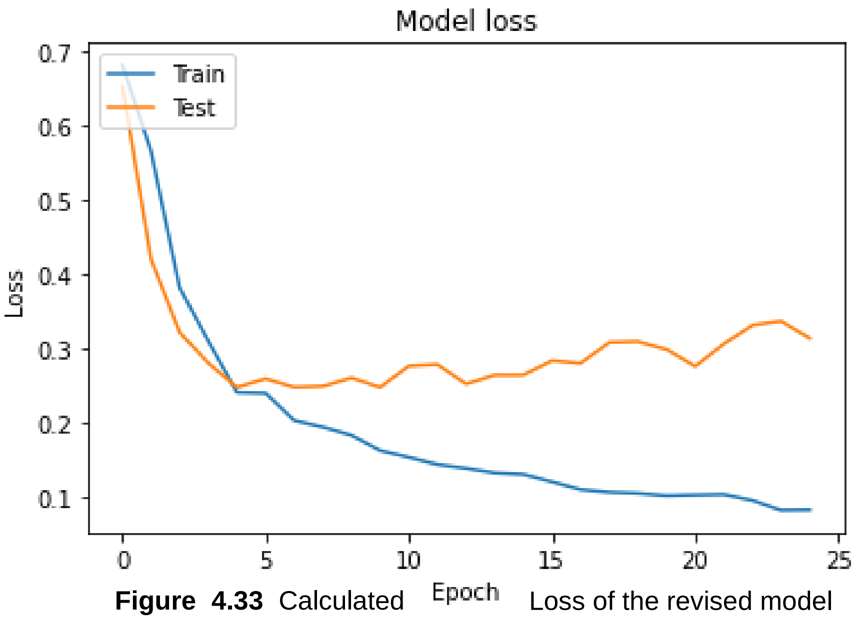

Figure 4.33 Calculated Loss of the revised model

From the graphs that are shown in Figures 4.32 and 4.33, this new model is a significant upgrade over the initial model along with a substantial improvement over the previous one. The accuracy that is found in the testing stages is comparatively the same as during the training stages, indicating that the model will be able to accurately detect the corrosion rate of the steel pipes. The loss metric indicates the same thing as the training loss is small, however the loss metric of the testing stage.

4.7.1. The Virtual Reality Environment Results

This section will be used to detail and highlight the findings that were found from conducting the experiment using the VR environment. It will be used to provide an insight on how it was made, what factors and considerations were made along with what was found when the experimentations were conducted. In the case of the latter, the experiments that will be conducted will be used to simulate how the model will perform in a real setting. In this case, the real setting will be a VR environment built using BIM and Unity VR. BIM is used to build the equipment inside the virtual environment that will be used to illustrate how the model will perform under real world setting.

4.8. Summary

This section presented how the VR study produced its results. These are: The Key data from the survey. The study measured participants' abilities in Revit and VR. These findings will enable the analysis of current VR use in the AEC industry and the possible role it plays.

All survey participants were between 21 and 29 years old and from diverse backgrounds volunteers from Loughborough university. Participants ranged from none to five years in the construction industry and had varying levels of Revit experience. This sample represents the future workforce within and outside the construction industry. A total of 14 people participated in this experiment.

Participants rated varying quantities of the statements on a Likert scale from 1 to 5, with 5 being strongly agree and 1 strongly disagree.

S1: I like and had fun using Revit.

S2: I like and had fun using VR.

S3: I understand a space better in VR than in Revit.

S4: Gamified Systems such as VR are more intuitive than Revit.

S5: I would like to use VR at work in the future.

S6: These systems could help with my interactions with other users/ friends/ colleagues.

S7: These systems could facilitate decision making in AEC.

S8: VR allows for the identification of unsatisfied social needs

Figure 4.34 represents the statement and overall value on a scale of 1 to 5, where a higher value represents a more frequent agreement.

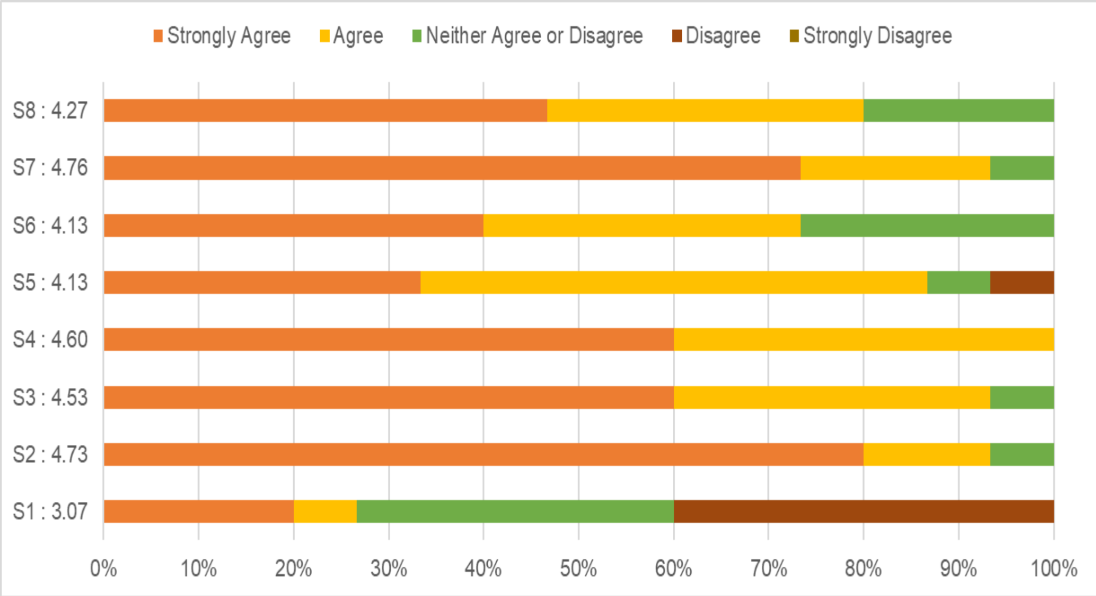

Figure 4.34 Likert scale of statements experiment outcome

S1 (3.07) was the outlier among these statements, indicating that when users compared their experiences in Revit and VR over a short time frame, there was a clear preference for VR, as demonstrated by statement S2 (4.73). Statements S8 (4.27), S7 (4.76), S4 (4.60), and S3 (4.53) all show a favourable view of VR's potential to improve construction learning and decision making. A lack of communication tools was noted among the S6 results once a participant was immersed in VR. S5 (4.13) demonstrates a broad range of responses, with the majority agreeing that using VR at work can be beneficial.

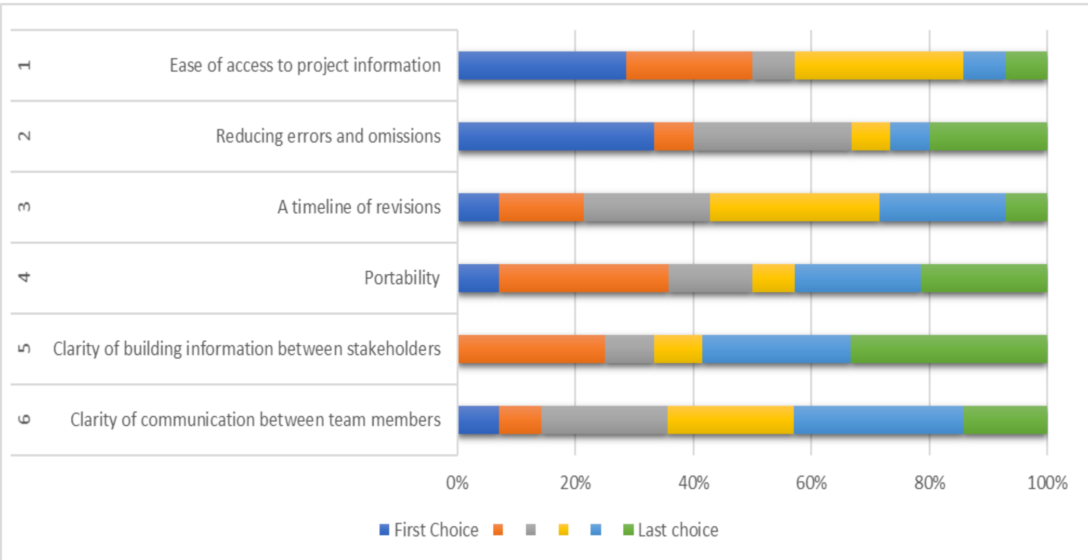

Figure 4.35 Use of a VR system for construction Participant’s ranking

In Figure 4.35, participants were asked to rank statements (as seen in Appendix question 30) in order of importance. Statements like "A high level of communication among team members" and "Clarity of communication between stakeholders" were ranked sixth and fifth, respectively. The options with the highest ratings were "Accessing project information," "Avoiding errors and omissions," and "Accessing the revision timeline." “Portability” came in fourth place, trailed by three statements with higher scores. At the end of their respective tutorials, students will have gained confidence in using Revit and Virtual Reality.

Figure 4.36 Participant confidence related to using Revit or VR after tutorial

Figure 4.36 depicts participants' confidence in using Revit and VR at the end of their respective tutorials on a scale of 1 to 5, with 1 being very confident and 5 being extremely confident.

Participants' levels of confidence ranged from "Not at all confident" to "Somewhat confident," with "Extremely confident" being the outlier for Revit. VR displayed a range of confidence levels ranging from "Not so confident" to "Very confident." Despite the fact that the Revit tutorial was more tailored and relevant to the experiment's content, the VR tutorial and associated game instilled more confidence in participants.

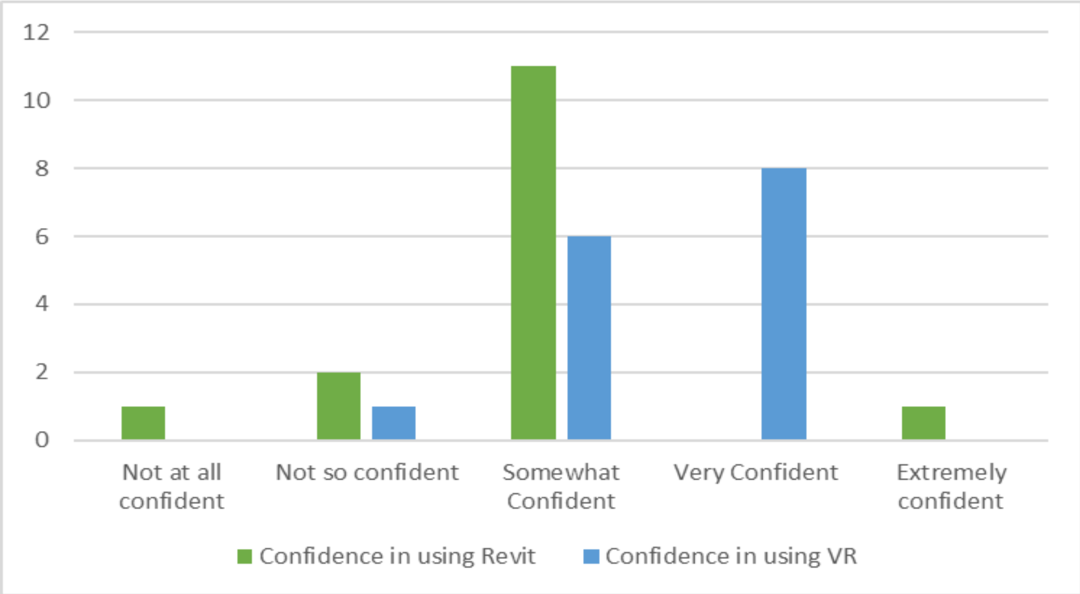

Figure 4.37: Participant confidence related to using Revit or VR after tutorial

4.9. Confidence in having found all the errors in a model

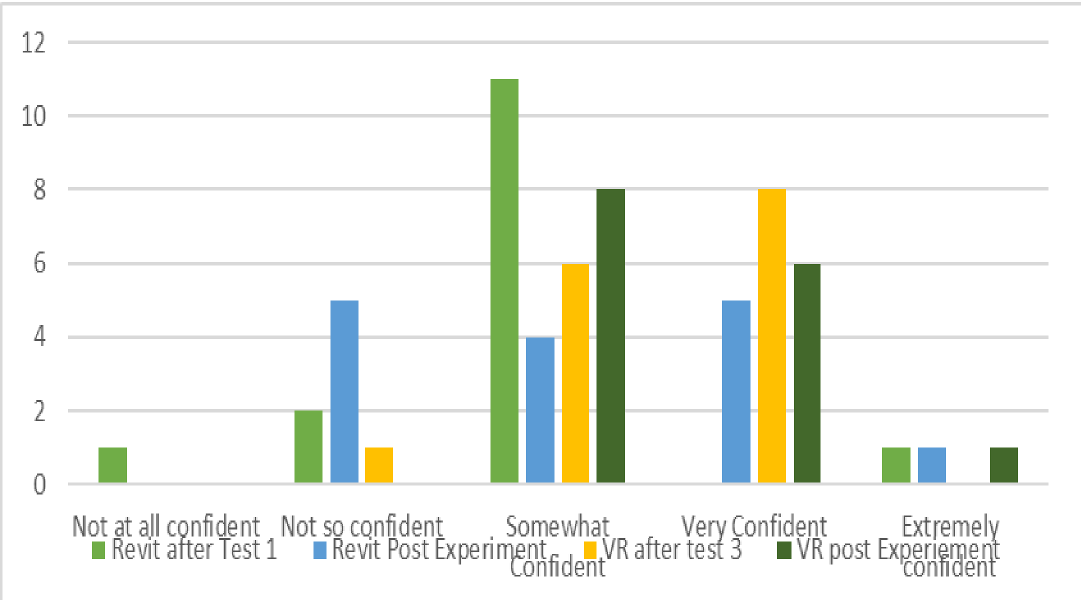

Figure 4.38 Error finding in a Revit and in a VR model and Participant confidence.

Participants were generally confident in their Revit skills, as shown in Figure 4.37, with a peak in confidence at "Somewhat confident." VR responses ranged from "I am not confident" to "I am extremely confident," with "I am somewhat confident" and "I am very confident" peaking at "I am somewhat confident" and "I am very confident."

From pre-test to post-test, participants' confidence in Revit and VR increased. Following the completion of the contest, the Revit average score increased from 2.87 to 3.13, while VR increased from 3.49 to 3.53.

4.10. Number crunching

Following the identification of a qualitative factor, quantitative results were computed. Revit or VR was found to have fewer errors in a building model by categorising participant data. For each grouping, an analysis of the time taken, total errors, intentional errors, and found errors (due to an imperfect model) was performed. It enabled simultaneous evaluation of both groups' performance in Revit and VR.

4.11. Virtual reality versus Revit

Table 4.3 shows how long it took each study participant to complete the error finding task.

Table 4.3 Time comparison of participant performance in Revit and VR

	Time				
	Mean	Median	Min.	Max.	Total
Revit	08:16.2	07:02.0	00:13.0	29:27.0	16:32.8
VR	04:50.3	04:07.0	00:04.0	17:17.0	10:51.2
Δ	03:25.9	02:55.0	00:09.0	12:10.0	05:41.6

Overall, immersion speed in VR was faster across all measures. The minimum virtual reality time was 31% of the real-world counterpart, and the mean, median, and maximum all improved similarly.

Table 4.4 shows that the mean, median, minimum, and maximum number of errors discovered at the end of each Revit and VR task were nearly equal.

Table 4.4 Comparison of participant performance in Revit and VR in terms of total errors

	Errors Total			
	Mean	Median	Min.	Max.
Revit	12.3	12	6	19
VR	16.1	17	8	21
Δ	3.8	6	2	2

Overall error rates have decreased across all measures, with Revit averaging 131 percent more accurate than VR. The median average (148%), minimum average (133%), and maximum average (111%) indicate that more errors were discovered in VR across all participants.

The table below provides an overview of the types of errors that each participant discovered more frequently and less frequently in Revit and VR.

A similar pattern emerges when errors are divided into intentional model manipulation errors and unintentional model manipulation errors. However, intentional errors discovered using virtual reality are more significant than unintentional errors.

Table 4.5 Comparison of participant performance in Revit and VR in terms of intentional and found errors

	Errors Intentional				Errors Found			
	Mean	Median	Min.	Max.	Mean	Median	Min.	Max.
Revit	10.2	10	5	15	2.1	2	1	4
VR	13.2	14	7	17	2.9	3	1	5
Δ	3.0	4	2	2	0.8	1	0	1

The data support these conclusions, which are supported by the experiment's standard deviations.

- Duration: 4:49.3 minutes.
- Time spent on Revit: 05:35.6 minutes.
- VR Duration: 03:28.9 minutes.

VR results demonstrated less variability than Revit data, indicating greater data coherence. This, combined with a lower number of errors omitted by using VR, suggests that the VR process is more efficient than Revit.

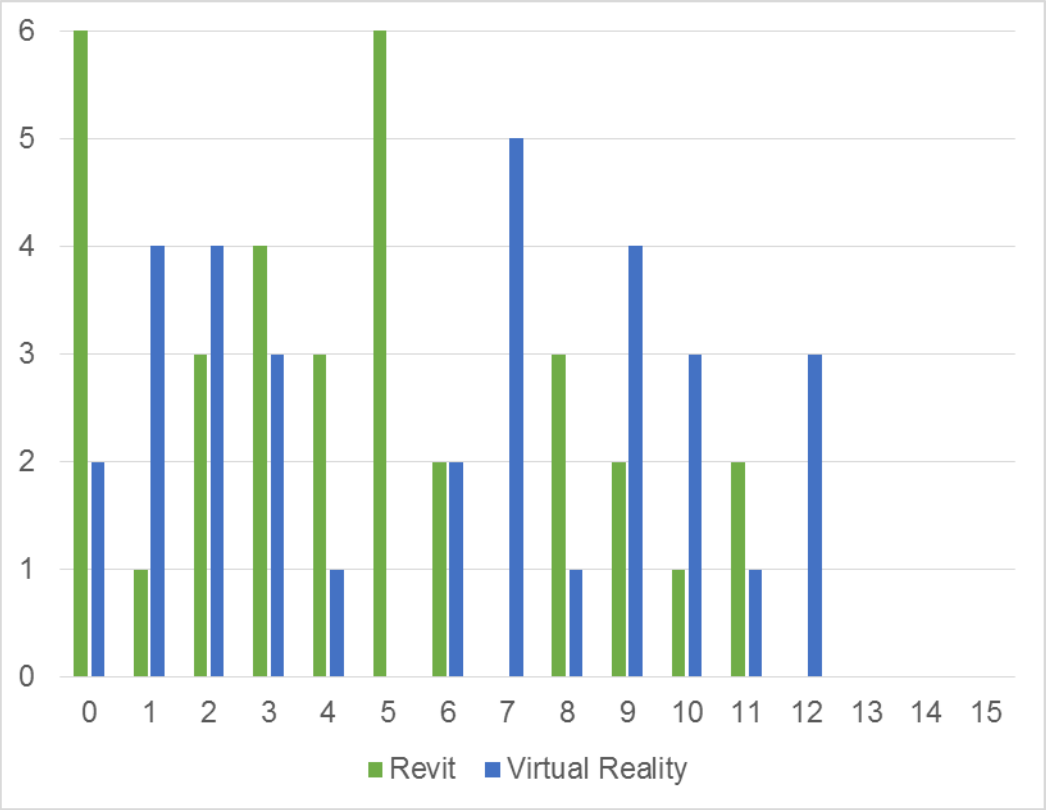

Figure 4.39 Spread of Total Errors found, as given in Section 3.4, in Revit and VR, along with their polynomial trend lines (Poly.)

The number of errors that occurred in various Revit and VR files is depicted in Figure 4.38. The Revit trend lines show a linear decrease in the number of errors discovered. VR has peaks in the 0-9 range and a low point around 4. This denotes clusters of errors that appeared in specific areas of the text.

4.12. Revit and virtual reality tutorial times

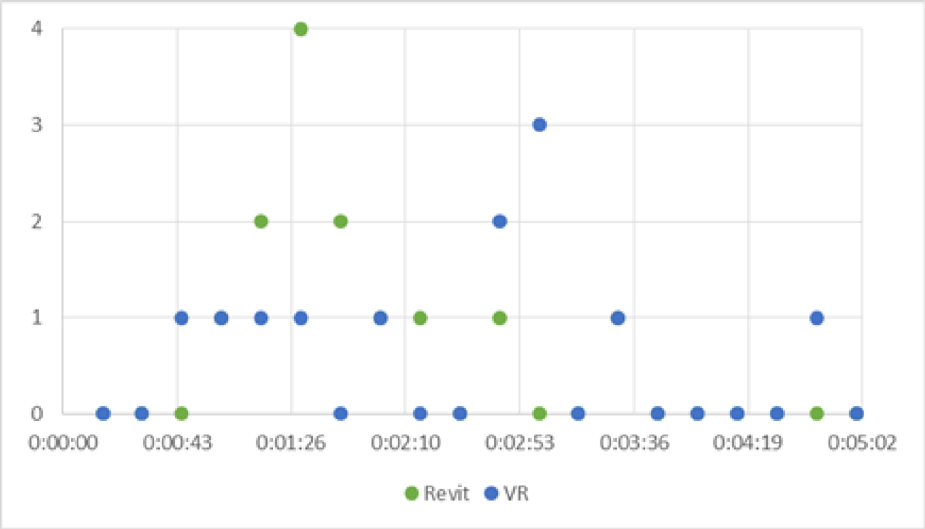

Figure 4.40 Spread of Revit and VR tutorial times (with a count at 15 second intervals) with associated polynomial trend lines (Poly.)

According to the experiment supervisor's instructions, participants attempted to complete the shortest and longest VR tutorials possible. The trend lines in Figure 4.39 show that Revit produces more consistent results than VR. This would imply that Revit has a consistent learning curve, whereas results for VR ranged from 50 seconds to just under 5 minutes, indicating a less consistent experience.

4.13. Spread of error times in Revit and Virtual Reality

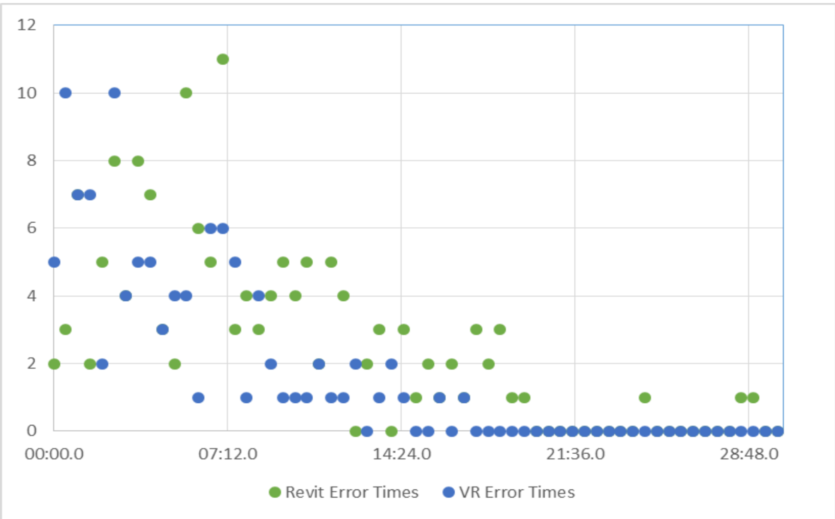

Figure 4.43 Spread of times at which errors were found by the participants in Revit and VR (with a count of errors at 30 second intervals) with associated polynomial trendlines (Poly.)

According to Figure 4.40, when using VR, participants' errors decrease over time. Revit displays a steady increase for approximately thirty to forty minutes, followed by a gradual decrease. Near zero volume, the trend line flattens out.

The findings suggest that virtual reality (VR) has a future in the AEC industry. The experiment emphasises the problems associated with existing software, Revit, particularly in terms of movement and model manipulation. This study identifies the areas where VR still needs to be improved.

4.14. Summary

Corrosion rates are faster at higher temperatures, and pH levels at lower temperatures may vary. The information gathered during the experiment in the same steel, BISPA corrosion, and process temperature is used. In a short period of time, the corrosion efficiency is measured and observed. The study's goal is to determine what factors contribute to increased corrosion rates in hot-finished steel tubes, and to collect data for an Al study.

As shown in the figure, the data was retrieved with a probe and cleaned as needed (Figure 4.4). At the start of the period, the temperature was 8°C, and the corrosion rate was 5 mil/year. The corrosion rate rises faster than the pH level. The relationship between pH value and corrosion rate is not as steep as in (Fig. 4.1), but it is softer than in (Fig. 4.1). Corrosion rates typically increase slowly at the beginning of a period, but rapidly when the temperature exceeds 20 degrees Celsius.

After the inhibitor was introduced into the pipe system, the corrosion rate was reduced to less than a millimetre per year. The data was collected using the probe after it was cleaned and washed in cold water. The rate of corrosion in the (Figure 4.9) decreased from 15.0 mils/year to 14.5 mils between June 23rd and June 27th, 2018. The system's corrosion rate is relatively stable at 5.5 mils per year and is now faster than before. The inhibitor is used to keep pipes larger than 5cm in diameter from corroding.

The pH level gradually increased in the experiment, but the rate of increase slowed as the experiment progressed. The concentration and corrosion rate of the system remain constant at 5.5 mils/month and 9.7, respectively. The relationship between pH value and corrosion rate is flatter than that between temperature and corrosion rate in (Figure 4.14). The data was collected on July 27, 2018, and analysed with a probe that had been cleaned, a set-point temperature of 10.2°C, and a running time of more than one month.

Increased oxygen and oxidizers have a corrosion effect, allowing for an increase in corrosion. As the temperature rises and the pH falls, the corrosion rate increases. When the temperature rises above 16°C, the rate of corrosion increases rapidly at the start of the cycle and then drops sharply. It demonstrates that corrosion takes place throughout the lifetime of a steel pipe network.

The corrosion rate increases as the temperature rises, peaking at 32°C before levelling off. It will be reduced by one million dollars per year beginning this year. The trend in the following stage is the same as it was four weeks ago, but the accelerated velocity performance is different. The thickness reduction can be accelerated over two years, lowering the rate of reduction from 14 mils to 11 mils per year. The information presented above was gathered during the first year of monitoring.

The growing influence of corrosion by oxygen and oxidizers is widely acknowledged to be increasing the corrosion seen in the review. As the temperature rises and the pH value falls, the rate of corrosion increases. The corrosion rate in the control experiment was 5.5 mils/year. This rate remained constant at 5.5 percent per year after a month of continuous service. The experiment data for the first test run is approximately 3 millimetres per year. When the results of the two operations are compared, it is discovered that the second operation of the corroded and no corrosion rate in this test is 2 mils per year higher than the initial test data.

The study concluded that, while the situation in both tests in two test rounds is comparable, the commitment of the tubes and the water is different, resulting in a higher corrosion rate in the second year of service of the corrosion than in the first year. The findings of the study are presented in such a way that they enable rapid control of the rate of corrosion. The operation of the cooling system is as follows: the flow rate and temperature must be constant, and the system must be able to maintain the set point value for an extended period of time.

They used a dataset created by combining two data sets from laboratory experiments. It consists of BISPA laboratory tests and Hevasure laboratory tests, which are used to analyse and determine the factors that can contribute to steel pipe corrosion. The results of these tests will be used to evaluate the key variables that will aid in determining the rate of corrosion in subsequent sections. This could lead to the creation of an ANN model capable of accurately predicting pipe condition.

Chapter 5 Enhancement and validation of ANN model

5.1. Introduction

This section will primarily be used to describe the model's limitations and how to overcome them. This will be done to gain an understanding of what limitations exist in the ANN model itself, how each of these will impact how the model performs in the given circumstances and the impact it has on the building's HVAC Pipe network. Despite the fact that the training was stopped earlier and dropouts were used to reduce the likelihood of the model overfitting. The new ANN modelling approach was implemented in MATLAB to develop and test two different Neural Network methods, Comparison of ANN model vs. Optimized ELM model for predicting corrosion rate in steel pipe.

5.2. New model

This section will primarily be used to detail the model's limitations to how they can be overcome. This will be done to gain an understanding of what limitations exist in the ANN model itself, and also focus to how each of these will impact how the model performs in the given circumstances and the impact it will have on the HVAC Pipe network in the building. Understanding these will allow user to investigate and investigate alternatives that can be considered, meanwhile the measures and techniques that can be used to not only improve the existing model, but also to build a new one that can overcome the limitations of the current one and expand or improve on its functionality. This will aid in gaining an understanding of what methods or algorithms can be used to further improve the model's performance, and how the process and accuracy can be improved.

According to the assessment and previous sections, Black Box models are efficient in handling prediction and predicting data because these are data-driven in nature, which black box models excel at. Statistical methods and techniques can be used to fit well because they can capture the correlation and relationship that exists between the data, in this case the rate of corrosion and the metal loss that exists in the environment of the steel pipes. These models typically require Lab and Field measurements data to be collected over a specific time period in order to train the model and predict building operations, which can be used in a variety of operations such as developing strategies to reduce energy consumption and costs, monitoring and assessing the performance of the pipes. The parameters in a black box model are automatically generated and calibrated, which can be advantageous over other models such as white box models.

Another disadvantage discovered during the initial model training phase was that the model was over-fitted most of the time. Though overfitting was overcome after a while, it did play a role in drastically decreasing its accuracy (Ying, 2019). The reason this may have caused a problem is that overfitting causes the model to memorise the entire data set rather than identify it, which can lead to it considering noisy data, resulting in a drastic decrease in its accuracy when it is passed through the testing stage (Ying, 2019). Despite stopping the training earlier and using dropouts to reduce the likelihood of the model overfitting, when testing the model on field data, it is clear that the accuracy was significantly lower than what was found during the training stages and in the testing stage, indicating that the model over-fitted before the training was stopped; this has been confirmed after tuning the model. It is clear that using the most common solutions to overcome the possibility of overfitting is not the best solution for this. As a result, the model would need to determine different methods to reduce the likelihood of model overfitting so that it can be used to understand how it can be used to improve or increase the accuracy of the model itself, which is why the ELM model was developed.

5.3. Justification of ELM-GHS

In this study, the authors used intelligence ANN models, specifically global harmony search (GHS) combined with extreme learning machine (ELM), to model steel pipe corrosion prediction. The GHS was used to extract the significant influential attributes on the EAC dependent variable. The effectiveness of ELM as a novel predictive model for the investigated application, on the other hand, was demonstrated. To validate the new ELM model in terms of prediction accuracy, a classical artificial neural network (ANN) was developed as a benchmark model. The predictive models were developed using both laboratory and field data related to steel pipe corrosion from an HVAC pipe network system.

ELM is made up of a collection of neural network (NN) models that rely on a fast-training algorithm and randomization of hidden layer weights. In the ELM, the hidden layer is randomly initialised rather than using an iterative algorithm such as back propagation to optimise the output weights. ELM training entails solving the linear system defined by the hidden layer's outputs and targets. Despite the randomness of its hidden layer weights, the ELM has been shown to be capable of universal non-constant piecewise continuous function optimization. The ELM has become a popular framework over the last decade due to its speed and universal acceptance. The term ELM popularised the concept of randomization in the hidden layer of NN; the term has also been associated with a variety of models and extensions of NN with randomised weights.

Due to the shortcomings of traditional machine learning models (e.g., ANN), the ELM was proposed as a new technique to address these shortcomings. In this context, the term "extreme" refers to the algorithm's ability to mimic the behaviour of the human brain in a short amount of time. Because the hidden neurons do not require any tuning during the learning phase, the ELM has a simple and unique learning process. Human intervention, on the other hand, is required in traditional learning methods such as ANN or SVM, particularly in determining the most appropriate model parameters. Because of its role in developing data-intelligent expert systems for use in real-world situations, the ELM has an advantage over the traditional data-intelligent models framework. Over the last five years, the ELM has been used to solve a variety of problems such as clustering, feature learning, classification, and regression with a high level of performance and learning capacity.

Harmony search (HS) is a meta-heuristic search algorithm that attempts to mimic the improvisation process used by musicians to find a pleasing harmony. HS has received a lot of attention in recent years due to a variety of benefits. HS is easy to implement, quickly converges to the optimal solution, and finds a satisfactory solution in a reasonable amount of time. Because of the benefits of the HS algorithm, it has been applied to optimization problems in a wide range of engineering disciplines. This chapter discusses the HS algorithm's concepts and performance, as well as some engineering applications. HS has been found to perform well when solving difficult optimization problems, and several variants of this algorithm have been developed. As a result, the authors used ELM-GHS to solve real-world optimization problems like corrosion prediction in HVAC steel pipe network systems.

5.4. New ANN Model vs. Optimized ELM model

The ANN modelling approach was further developed in MATLAB to develop and test two different algorithm methods, Comparative analysis of ANN model vs. Optimized ELM model for predicting corrosion rate in steel pipe.

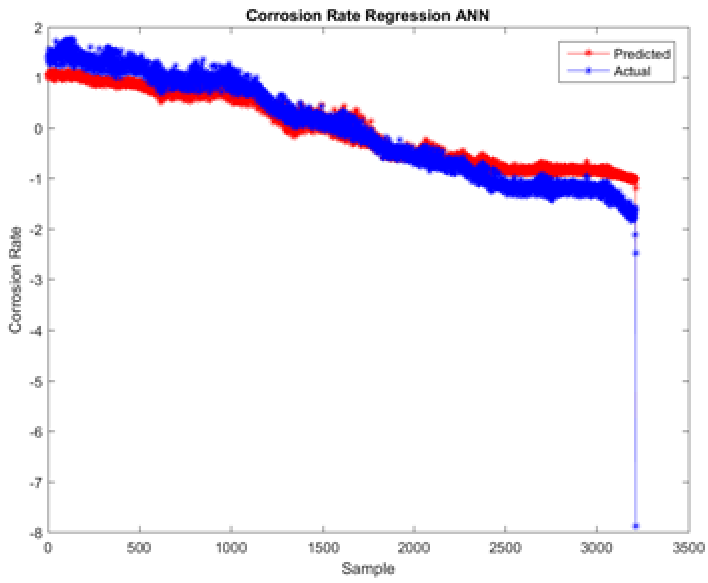

Figure 5.1 Sample vs. Corrosion Rate using Regression based ANN

Figure 5.1 depicts the difference between the training input for a 3,000-point sample and the actual output for 3,000 points. In the other extraction-based ANN model, the predicted values tend to be lower near the beginning of the dataset, but much higher at the end of the learning. It has been observed that the values of "both" are becoming more similar. This could indicate that the model is functioning properly.

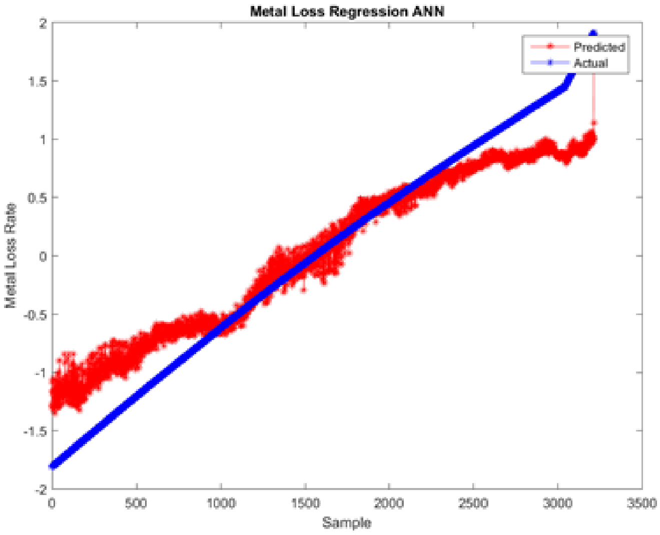

Figure 5.2 Metal Loss Prediction using Regression based ANN

The above graph in figure 5.2 depicts the most accurate metal loss prediction using Regression-based ANN, but it is easy to see the deviated values because most of that deviation will produce a difference. However, the same increasing outcome is considered a good wording model, but the error being higher than intended for further improvement is to be noted.

Data analysis for corrosion. The majority of the sample was used as training data, with the remainder being used as test input. The quantitative models are evaluated using a number of numerical indicators that attempt to quantify the overall goodness of the predictive model, best-goodness (the closest to one), and error evaluation (the closest to zero). In this manner, studies can be conducted to confirm the optimal model that produces the greatest number of outputs. The root mean square error, or RMSE, the mean absolute error, or MAE, and the mean relative error are all numerical indicators (MSE). The mathematical problem is summarised in equations 5.1 and 5.2.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(\text{Predicted}_i - \text{Actual}_i)^2}{\text{n}}} \qquad (5.1)$$

$$\text{MAE} = = \frac{\sum_{i=1}^{N}(\text{Predicted}_i - \text{Actual}_i)}{\text{n}} \qquad (5.2)$$

Were:

Predicted_i = The predicted value for the i observation.

Actual_i = The observed(actual) value for the i observation

N = Total number of data points.

RMS = Root Mean Square Error

MAE = Mean absolute error

Table 5.1 Regression based ANN model Performance metric

Regression based ANN	RMSE	MSE	MAE
Corrosion Rate	0.2486	0.0847	0.246
Metal loss Rate	0.2496	0.1080	0.2496

Table 5.1 shows how the ANN model performs in terms of error values and the range of error mean. The RMSE result showed the highest error performance in the experiment, while the MSE result showed the lowest.

ELM with Harmony Search optimization model was developed to obtain the optimum composition in the neural network of it. The theory model would assign different weight values and use the best optimum value that results in the least amount of error.

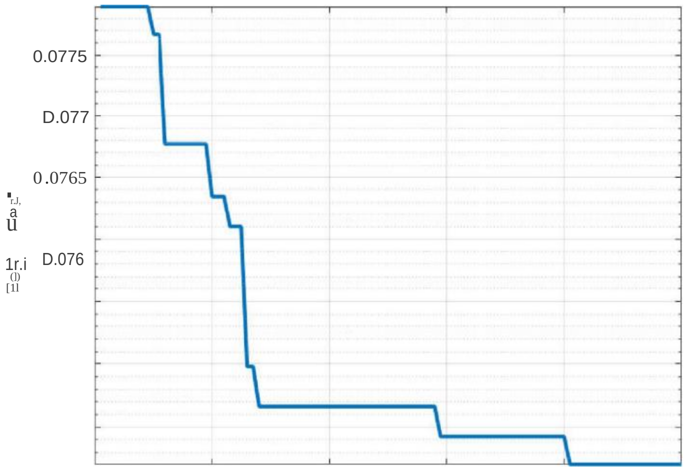

Figure 5.3 Harmony search optimization

The graph in figure 5.3 shows that the optimization is working because the error value is higher at the start of the model and decreases to zero as it develops. The Corrosion rates are shown in this graph using the Harmony Search optimised ELM model. Because both the predicted and actual values are at the same level, it is difficult to see clearly. This explains why the model is correct in every way. However, tests show that the data has less than 0.01 errors. This is visible when the graph is zoomed in.

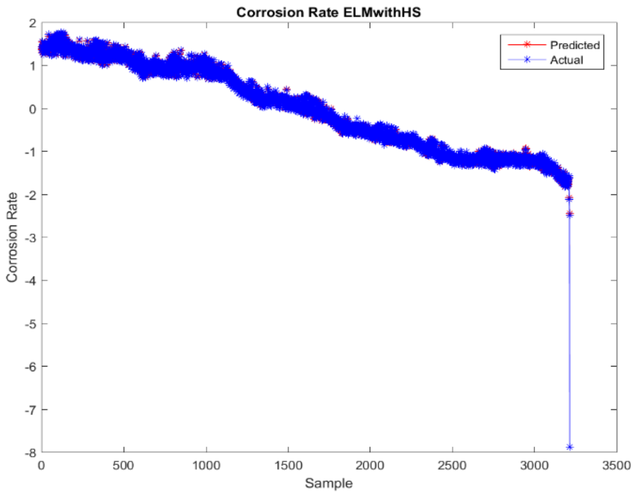

Figure 5.4 Sample vs. Corrosion Rate By using Harmony Search optimized ELM

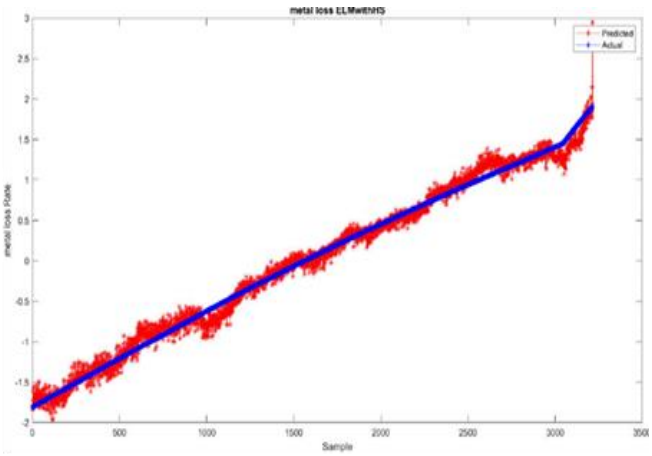

Figure 5.5 Sample vs. Metal loss Rate By using Harmony Search optimized ELM

The graph above in figure 5.5 shows the metal loss rate performance for the model using the Harmony Search optimized ELM model algorithm. The prediction model has a remarkably close level of accuracy for the actual.

Table 5.2 Table of comparison Corrosion Rate and Metal Loss Rate

ELM-GHS	RMSE	MSE	MAE
Corrosion Rate	0.0100	0.0002	0.0100
Metal loss Rate	0.0807	0.0108	0.0807

Table 5.2 shows how the Harmony Search optimised ELM mode in terms of error values. This model outperforms the regression-based ANN model significantly. The MSE of the ELM-GHS Corrosion Rate is less than 0.0002. This is clearly demonstrated in the graph on the following page.

5.5. Performance analysis

The graphs on the next page examine the RMSE. MSE and MAE are calculated for both models. (ANN and ELM based on regression with Harmony Search optimization model). The blue dotted line: The best prediction is produced by the ELM-HS model. Based on the results of the ELM and ANN-based models, the ELM model outperformed the average ANN in the study.

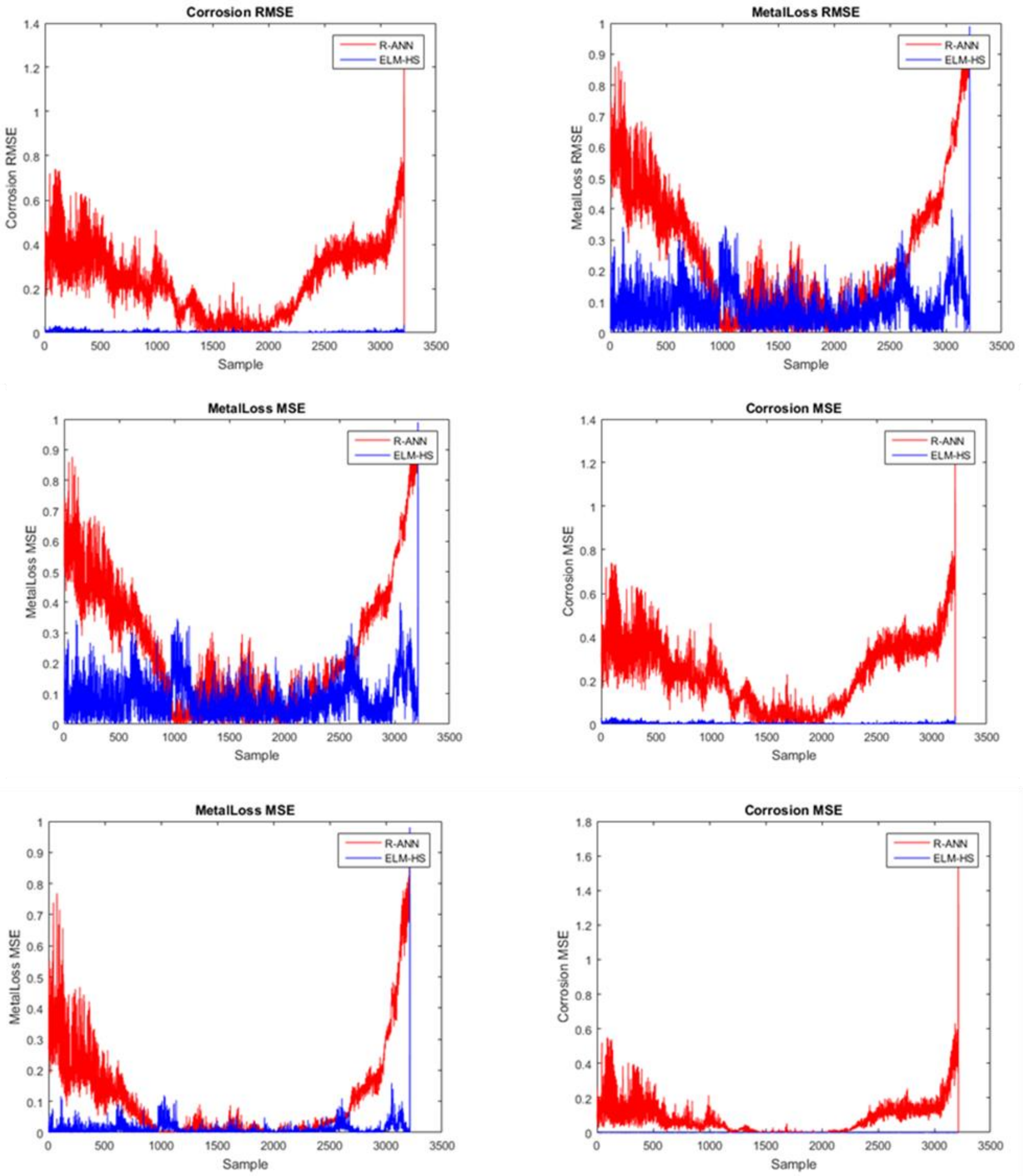

Figure 5.6 Performance of Regression based ANN and ELM-GHS, show the actual versus predicted

5.6. Summary

OB1: In order to predict the performance of the pipe, we developed a system that uses artificial neural networks. Using ANN, I built a system that predicts the performance of a pipe.

OB2: Actual BISPA Lab experiments and Hevasure data collection were used to collect data. Following that, a MATLAB Blackbox model was created and used to implement the ANN Technique.

OB3: The investigation into implementing morden technology, such as virtual reality, has been carried out in order to gain a better understanding of its applicability in the BIM environment. The study of implementing morden technology, such as VR, has been carried out in order to form an understanding of its applicability in the BIM environment.

OB4: Due to the large and diverse nature of the ANN study, this OB was met by examining the most relevant technique and emphasising the accuracy rate in particular. The ELM- with Harmony Search optimization model was the most successful of the models tested thus far.

This section will discuss the model's limitations over and above how to overcome them. It will be carried out in order to gain insight into what methods or algorithms can be used to improve the model's performance further. Based on the assessment and the preceding sections, it is possible to conclude that Black Box models are capable of performing their tasks and predicting data. These are data-driven problems that black box models excel at. A black box model’s parameter is generated and calibrated automatically, which has advantages over other models such as white box models. Another drawback discovered during the initial model training phase was that the model was frequently over-fitted. Overfitting did play a role in significantly lowering its accuracy, but this was overcome after a while.

When the model was tested using real-world data, it was clear that the accuracy was much lower than what had been discovered during the training and testing stages. Using the most commonly used solutions to avoid overfitting is not the best option. As can be seen, in order to reduce the likelihood of model overfitting, the model would need to determine different methods. The ELM model was created in order to improve the model's accuracy. The new ANN modelling approach was implemented in MATLAB to develop and test two different algorithm methods, the ANN model and the Optimized ELM Model. The same increasing outcome is considered a good wording model, but the error is higher than intended for further improvement.

To obtain the best neutral network composition, regression-based ANN and ELM were combined to optimise the objective function, Corrosion rate, by highlighting decision variables such as dissolved oxygen and galvanic current with the Harmony algorithm. Model for search engine optimization The theory model would assign various weight values and use the best optimum value with the least amount of error. The RMSE result demonstrated the best overall performance in the experiment, while the MSE result demonstrated the worst. The prediction model has a remarkably high level of accuracy when it comes to the actual. The ELM-GHS Corrosion Rate MSE is less than 0.01. This explains why the model is correct in all aspects. The ELM model outperformed the average based on the results of the ELM and ANN-based models.

Chapter 6 Conclusion and Recommendations

6.1. Summary of key research results

This chapter presents the study's conclusion, which develops a model to improve HVAC pipe network system performance and efficiency by utilising a novel way of visualising a BIM model. The study also investigates how an AI-PPM model and visualisation on a next-generation VR platform can improve the detection of steel pipe performance issues.

The study objectives were met, and three primary research questions were addressed. The first model called for research into the use of artificial neural networks to control HVAC pipes. The evaluation's success was determined by comparing the neural network system to the targets in laboratory and field experiments. This research resulted in the creation of the Black Box model in MATLAB, which aided the understanding of how the pipes corroded.

Using a novel approach to incorporating artificial intelligence-machine learning into a long-running HVAC pipe corrosion performance issue and a novel approach to using a visual platform to provide insight on how one's neural network model can improve HVAC performance. Long-term improvement can be obtained by performing continuous modifications with the assistance of a visualisation model. In this way, it can also provide users with complex information.

6.1.1. BISPA lab experiment

The results in this section are from BISPA Lab corrosion experiments. The experiment results show that the most corrosion occurs when pipes are new and have no corrosion protection. As the new pipe metal corrodes, a scale forms on the inside surface, acting as a barrier against corrosion and causing the corrosion rate to decrease to a steady-state value.

When the industry-standard coupon method was compared to the relatively new Linear Polarisation Resistance (LPR) method, the results revealed that both techniques had a mean difference of 8.3 percent, which equates to approximately 3 months over the pipe network's 50-year service life. As a result, both the coupon and LPR methods produce comparable results, but the LPR method has the added benefit of displaying real-time corrosion rates when compared to the coupon method. Based on the weight loss method, the coupon method was vulnerable to how the coupons were installed/removed from the rig and transported to/from the lab. The coupons are less expensive than the LPR probe, but each coupon can only be used once, whereas the LPR probe can be used for up to 750 days, according to this study. The LPR probe was further investigated in four different scenarios using simulation to determine the effects of the LPR probe on corrosion rate. A dirty pair of LPR electrodes was deposited with corrosion debris; the result shows that the corrosion rate differs by 20% when compared to clean/new electrodes. In addition, an LPR probe was tested two months after it was cleansed, and the results show a 44 percent difference in corrosion on average when compared to a newly cleansed LPR probe. Finally, a pipe network dosed with an inhibitor reduced corrosion rate by 50% at lower temperatures (around 10 °C) and 25% at higher temperatures (around 30 °C). This means that, while the LPR probe is more dynamic than coupons, it is extremely sensitive to the conditions to which it is subjected. This highlights the limitations of LPRs, as they cannot be installed in HVAC systems for extended periods of time and must be maintained and calibrated. Otherwise, the LPR Probe's efficiency decreases in direct proportion to the rate of corrosion and the amount of deposits covering the element.

6.1.2. Field work experiment

This study looks into the linear polarisation resistance and localised corrosion caused by linear corrosion on steel. Because the electrodes have similar electrochemical kinetic parameters at the anode and cathode sites, the linear polarisation resistance could be used as a general corrosion rate measurement. The well-matched corrosion rate measurements performed using the BISPA - LPR method, the Hevasure Galvanic Current sensor method, and the gravimetric method at measured temperature, galvanic current, and PH validate the derivation further. The results of the characterization show how the electrochemical parameters remain stable under various conditions.

The section discusses the fieldwork experiment's findings. The experiment results show that when exposed to the same dissolved oxygen and flow conditions, the two galvanic current sensor designs produce the same output. Because of the current configuration of Hevasure Rig 2, increasing the flow increases the measured galvanic current while decreasing the dissolved oxygen. The difference in results between Coupon tests #07 and #08, where there was an increase in galvanic current for similar coupon corrosion rates found on results, was not due to the use of a different design of galvanic current sensor validate the profound data accumulated by the testing process.

6.1.3. Black box model

Corrosion is a common deterioration process that reduces the life of an HVAC steel pipe network. Corrosion behaviour is a highly nonlinear process that is influenced by a wide range of factors. This study used artificial intelligence (AI) techniques to predict the rate of corrosion in carbon steel pipes. Two well-known machine learning algorithms were used in the prediction, including artificial neural networks (ANNs) and global harmony search (GHS)

Practical Regression techniques based on Elman simple recurrent neural Network (SRN) and Probabilistic Neural Network (PNN) Regression were presented in the black box model experiment. To address the issues, a semi-parametric scheme for learning the mixture model was developed. The proposed methods were applied to the corrosion severity level of Galvanic Current (GC) signals obtained from TATA steel corrosion. The performance of conventional Modified Elman Neural Network (SRN) - Simple Recurrent Network and Probabilistic Neural Network (PNN) was compared in the competition. The results show that the proposed methods resulted in significantly lower classification-error rates and significantly lower classifier variances. As a result, BISPA Lab experiments were carried out in order to obtain a meaningful data set and to use field study data to train and build the AI-PPM.

6.1.4. BIM to VR model

The significance of VR in relation to its introduction into the construction industry was determined by weighing the technology's benefits and drawbacks. It has been demonstrated that integration of this technology is possible in its current state, with enough room for the industry to extend and develop existing technologies.

VR's dominance over current industry applications has been demonstrated in terms of intuitiveness and ease of use in the context of an industry striving to incorporate innovations. To maximise optimum potential, the benefits of existing BIM applications, such as Revit, and their incorporation into VR, other than methods of optimising the HVAC pipe designing approach, have been addressed.

VR's potential to improve pipe design collaboration, operation management, and waste prevention, among other applications, may be an invaluable asset in the BIM design process for resolving issues unique to the AEC industry. Though still in its early stages, virtual reality (VR) is a highly valued technology that requires information dissemination to ensure its long-term viability and continuous development in pipe network design and visualisation in AEC.

6.2. Implications and conclusion

6.2.1. Implications and strength of the study

This study looks into a new data-intelligence predictive model called Elman Network, which is a neural network that can help current Galvanic corrosion growth in pipe for accurate Corrosion Rate Performance (CRP) predictions. Monitoring and predicting are ongoing issues in the HVAC pipe network industry, particularly in building services pipe systems, and have been a difficult area of study for decades. The variety of data available through PPM methods is critical in the training of AI models. As an example, standard types of AI use mathematical techniques to solve interest problems, such as traditional gradient-based optimisation methods. The successful application of certain types of gradient-based optimisation methods in modelling, such as the Levenberg-Marquardt algorithm, could be applied because this method worked on other modelling problems. Attempting to address uncertainty analysis using a novel hybrid double feed forward neural network model for accurate prediction.

The study was divided into two phases: the attribute-based variable selection phase, in which the GHS algorithm was used to determine the related variables that could influence the prediction task, and the prediction task phase. The predictive ELM model for the CRP was implemented in the second phase. The proposed ELM model was validated against the classical ANN model for reliability purposes by using the same hybridisation process for input selection. At that point, another input selection approach in the form of variable assortment was used to analyse the GHS algorithm. The strength of this study is based on how the model was created and is capable of detecting and analysing the health and condition of the pipes. This solution would allow the user to monitor the health of HVAC pipes and predict when they will corrode in the future. This is significant because it would allow for the construction of energy-efficient buildings. Also, the HVAC system performs as expected; if any of the pipes fail, building maintenance workers are notified to replace the pipes sooner than previously. The study's strengths include energy-efficient steel pipes that can maintain a constant temperature and pressure for an extended period of time. This would result in greater efficiency because corroding pipes could be detected in time for building management to replace them, saving money.

The study's implications are that building workers should pay attention to the temperature, applied pressure, and dissolved oxygen levels to determine the current galvanic being produced on the metal. This can aid in determining whether or not the pipes can corrode. According to the study, understanding how the pipe material is made can help determine when the pipe will corrode quickly, and such understanding provides an in-depth understanding of how the model works to better analyse the pipe condition.

6.2.2. Limitation of the study

To begin, the limitations of this study relate to data collection because steel pipe system failures were not reported and drew negative attention to corporate companies, along with a lack of data due to inefficient practise, which kept inaccuracy and faults data away from other authorities.

As a result, BISPA Lab experiments were carried out in order to obtain a meaningful data set for use in the field study data to train and build the AI-PPM.

Another identified limitation of the study was applying each method in consideration of the differences between the best result and the best available result because the first gives the closest result to the actual one and the second gives the best result by using fewer data.

The LPR probe's limitation suggests a corrosion rate value. This value may not represent material loss on all pipe surfaces (uniform corrosion), which may be insignificant, or it may be focused on a specific region (pitting corrosion), which may cause rapid pipe failures. LPR is assumed to represent uniform corrosion and is not a reliable indicator of pitting. When a relationship between temperature and corrosion was established, it was discovered that for each degree 1°C increase in temperature, the corrosion rate increased by 3.5 percent on average. This demonstrates the importance of understanding how a rise in water temperature in an HVAC system can affect the corrosion rate of the pipe network during the design stage. At this point, it should be noted that predicting an exact corrosion rate should not be the goal because these methods have inherent uncertainty; however, it has provided validity data to develop an AI-PPM.

Because the model was limited to six months between January and June of 2019, this study can be improved by using more data from the defined model. The ANN model can be strengthened by incorporating a larger set of data.

6.2.3. Future research direction

This research has resulted in findings that add to the body of knowledge on HVAC system development. This research is also paving the way for future opportunities.

Future research should look into other ANN architecture models, but this paper shows that GHS-ELM and BF-ELM ANN outperform traditional and hybridised artificial intelligence models. Further advancements are unavoidable as more clean data becomes available.

Such research approach could lead to more efficiency in addition to make it a self-learning agent. Future research must use a large and accurate dataset to train the model that can better predict the health of steel pipes based on varying temperatures and pressures, plus the dissolved oxygen found in the environment throughout the year. In line with this, future work should be done to expand on this study and try to find new methods and techniques that will be used to assess and identify how the HVAC system training process can be further improved to overcome any limitations of the black-box model in order to significantly improve the train.

This work can also be expanded to provide a better model that can improve the analysis and predict better by gaining insight into what other algorithms and models to improve to further improve model performance. To build the new model, an algorithm based on reinforcement learning should be used. This is significant because reinforcement learning has enabled researchers to create new algorithms and strategies for developing a model that can learn or improve from the data itself via various parameters and processes for better prediction based on the environment and data.

More research is needed to analyse and assess other metals, alloys, or variations of steel pipes commonly used in HVAC systems in order to understand how the model can be trained to analyse their corrosion rate. This is due to the fact that the experiments in this study were conducted using Q235 steel pipes, which are commonly used in HVAC systems. However, other steel pipes can be used in place of HVAC systems, which can pose a challenge in terms of how the pipe is monitored by building management to detect corroded pipes.

To support the wide range of pipe network systems and environments used in building services, future research should broaden the parameter scale by incorporating other sources of variation. Comparing corrosion data CFD models to laboratory and field data will undoubtedly reveal performance gaps.

This research can be expanded to investigate the uncertainty of error that exists in other types of corrosion such as pitting corrosion, galvanic corrosion, and erosion Corrosion.

6.3. Conclusion

Finally, this research has discussed the key findings of this thesis. The study's limitations and strengths were also discussed, and a future research direction was proposed. Through the findings of this study, the study contributes to knowledge in a variety of ways. According to the theoretical proposition, the laboratory experiments performed for the study yielded an accuracy of 80%, and the ANN model gathered all of the elements to form a prediction validated by 30% of the data. In addition, applying field data yields 99 percent accuracy in word prediction. The study demonstrates that a successful framework of connecting BIM metadata to VR and manual correlation with AI is formed, and the result also predicts tool using VR platform of user satisfaction successful predictive tool was tested and visualisation framework was formed. The predictive models were built using monitoring data collected while building steel pipe rigs and field study monitoring data. Based on the results of the ELM and ANN-based models, the ELM model outperformed the classical ANN. However, incorporating the input selection algorithm significantly improved the predictability of the ELM model. Finally, the AI-PPM predictability demonstrated more reliable and accurate results.

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