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A Fuzzy Logic-Possibilistic Methodology for Risk-Based Inspection (RBI) Planning of Oil and Gas Piping Subjected to Microbiologically Influenced Corrosion (MIC)

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TEK 3901-Master thesis in Technology and Safety in High North – June 2016

Abstract

The oil and gas installations are associated with risk due to different degradation mechanisms. Microbial Influenced Corrosion, commonly known as MIC, is one of them. The failures caused by MIC may have significant impacts on health, safety and environment (HSE). Therefore, to avoid failures regular inspection of the assets and maintenance plans need to be executed. With this on mind, engineers try to develop efficient inspection plans, which could form a basis for saving the assets. The different models so far developed for the assessment of MIC still have shortfalls. This might be due to the complexity of corrosion mechanisms. A model containing all the influential parameters causing MIC is difficult to develop due to the complexity of process and lack of data.

Aim of this project is to develop a simple yet flexible methodology to estimate the time for inspection. The methodology contains four sections: (a) estimation of possibility of MIC initiation and stable pit growth based on a simple flowchart; (b) estimation of rate of corrosion based on Fuzzy Logic; (c) estimation of possibility and necessity of failure in the event of MIC initiation and stable pit growth based on possibilistic framework; and (d) estimation of time for inspection based on matrix.

It is expected that the developed methodology would aid engineers make efficient inspection programs based on the concepts of risk-based inspection (RBI).

Keywords: MIC, Fuzzy Logic, failure, oil and gas pipes, possibilistic approach, reliability, structural integrity

Acknowledgment

This thesis is submitted in fulfillment of Masters Degree in Technology and Safety in High North at The University of Tromsø, Norway.

I would like to thank my advisor, Dr. Maneesh Singh, for guidance during the course of this work.

I would also like to express my gratefulness to the University of Tromsø for providing me all the facilities I needed.

Lastly, I am thankful to my friends and family members for their encouragement and support.

Marshal Pokhrel

June 2016

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Chapter 1
Introduction

1.1 Background

Operating oil and gas installations are subjected to attacks by a number of degrading mechanisms. In order to detect the presence and location of the attacks installations need to be regularly inspection. Unfortunately, comprehensive inspection programs are quite expensive; hence, risk-based inspection (RBI) methodology is often adopted to develop effective and efficient inspection programs. In order to account for a particular degradation mechanism in RBI analysis, inspection engineers need to know its likelihood of taking place and its estimated rate of degradation.

Unfortunately, the complex natures of various degradation mechanisms make accurate prediction of the rates of corrosion in an operating plant rather difficult. Luckily, for developing a risk-based inspection (RBI) program, it is not important to model a degradation process to be able to accurately estimate the degradation rate over a wide range of conditions. Instead the requirement is of a practical model which is simple to use, flexible enough to be modified according to the requirements of different sections of the plant, and able to incorporate field data.

Microbiologically influenced corrosion (MIC) is one of the commonly encountered degradation mechanisms in an offshore or onshore oil and gas installation. As with any other corrosion process, the prediction of likelihood of its initiation and its associated rate of corrosion is difficult to accurately model. A model based on fuzzy logic framework and possibility approach may offer a simple yet flexible tool for engineers to develop their RBI programs.

1.2 Research Purpose

The purpose of this work is to develop a methodology based on fuzzy logic-possibilistic framework to estimate the inspection schedule based on risk based inspection methodology.

1.3 Research Objectives

The research objectives are:

(a) Estimation of possibility of MIC initiation and stable pit growth based on a simple flowchart.
(b) Estimation of rate of corrosion based on Fuzzy Logic.
(c) Estimation of possibility and necessity of failure in the event of MIC initiation and stable pit growth based on possibilistic framework.
(d) Estimation of time for inspection based on matrix.

1.4 Research Questions

To fulfill the research purpose and achieve the research objectives, the following research questions need to be answered:

1. What are the factors that influence the MIC degradation process?
2. How to decide whether corrosion pit initiation and stable pit growth will take place or not?
3. How can the rate of degradation be estimated under an operating plant conditions?
4. How to estimate the possibility and necessity of failure based on the concepts of reliability analysis?
5. How to estimate the time for inspection given the possibility of corrosion initiation and possibility/necessity of failure?

1.4 Scope and Limitations

The factors involved in the degradation mechanism are restricted to a limited number of parameters in this work whose values are known for the modeling procedure.

The limitations are

- The procedure is justified for internal corrosion
- The estimation of MIC rate is limited to Sulfate-Reducing Prokaryotes (SRP) and methanogens.
- The estimation of MIC rate is estimated only in the presence of limited parameters due to limited data.

1.6 Structure of the Thesis

The thesis consists of six chapters.

Chapter 1 introduces the research, after giving a brief background, the chapter discusses research purpose, research objectives, research questions and limitations.

Chapter 2 is an introduction to corrosion and its related phenomena focusing mainly on the MIC and related issues. It also highlights the importance of RBI and its concept. An introduction to expert systems and an outline view of integrating it in to a decision support system is shown.

Chapter 3 describes the important parameters that effect rate of corrosion and their role in the development of predictive model.

Chapter 4 describes the proposed methodology for estimating the time for inspection. It describes the four steps of the methodology: (a) estimation of possibility of MIC initiation and stable pit growth based on a simple flowchart; (b) estimation of rate of corrosion based on Fuzzy Logic; (c) estimation of possibility and necessity of failure in the event of MIC initiation and stable pit growth based on possibilistic framework; and (d) estimation of time for inspection based on matrix.

Chapter 5 shows the results obtained by using the logic model developed for estimation of rate of corrosion.

Chapter 6 describes a proposed procedure for predicting corrosion rates based on Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference system (ANFIS).

Chapter 7 gives conclusion for the whole work.

Chapter 2
Introduction to Corrosion and RBI

2.1 Introduction

This chapter covers the definition of corrosion and its understanding with a focus on MIC. Introduction of RBI and concept of expert systems has also been discussed.

2.2 Definition of Corrosion

There are several definitions and approaches to define corrosion. In a simple terms, corrosion is the gradual destruction of metal by chemical or electrochemical reactions with its environment[1]. The surface disintegration of metals or alloys depends on the chemical constituents of such metals and the nature of ongoing electrochemical reactions. According to International Union of Pure and Applied Chemistry (IUPAC)[2], "Corrosion is an irreversible interfacial reaction of a material (metal, ceramic and polymer) with its environment which results in the consumption of the material or in dissolution into the material of the component of the environment". Another definition by ISO 8044-1986 states "Physiochemical interaction between metal and its environment which results in changes in the properties of metal and which may often lead to impairment of the function of the metal, the environment, or the technical system of which these form a part"[3].

2.3 Microbial Influenced Corrosion (MIC)

This section deals with the definition of MIC, types of bacteria and the process of biofilm formation.

2.3.1 Definition of MIC

MIC is an electrochemical process[4] where micro-organisms may be able to initiate, facilitate or accelerate corrosion reactions through the interaction of the three components that make up this system: metal, solution and micro-organisms. Hence from the definition, micro-organisms are not causing corrosion, but are facilitating in the process either by accelerating or inhibiting the corrosion process [5].

2.3.2 Microbes

Microbes can be distinguished on the basis of different features. There are certain conditions upon which these microbes are categorized. They are

Shape

1. Vibrio: comma shaped cells
2. Bacillus: rod shaped cells
3. Coccus: round shaped cells
4. Myces for filamentous fungi like cells, and so on

Temperature

1. Mesophile: the bacteria that grows at 20-35 degree Celsius
2. Thermophiles: the bacteria that are active above 40 degree Celsius

Oxygen consumption

1. Anaerobic: does not require oxygen to grow
2. Aerobic: requires oxygen to grow
3. Facultative: that have potential to grown in both conditions, either presence or absence of oxygen [4].

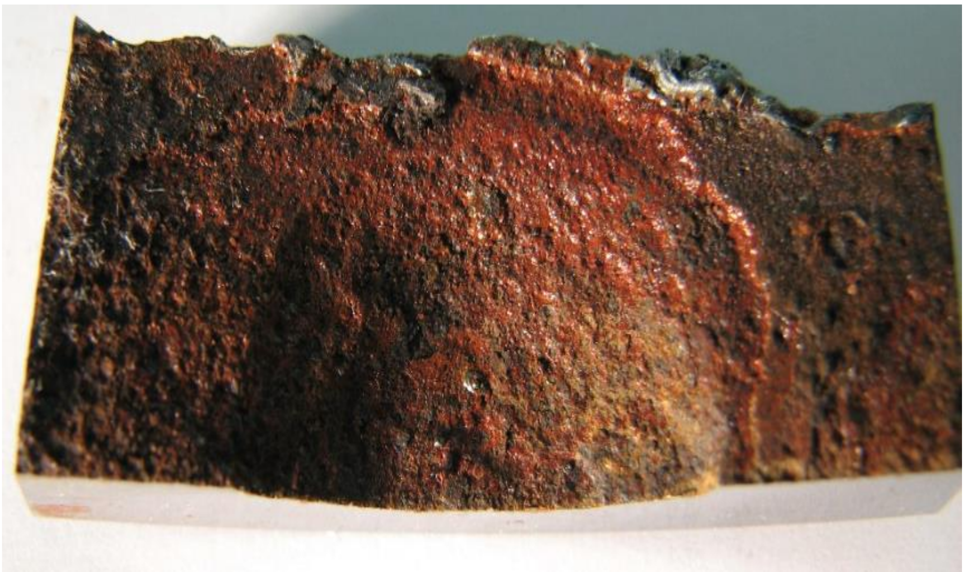

FIGURE 1. Pitting caused due to MIC **[6]**

The presence of bacteria alone does not trigger corrosion. The adhesion of bacteria into metal surfaces incorporated by the formation of bio-films producing the changes in the environment which is different in terms of pH, oxygen ingress, etc. from the bulk metal and hence leading to electrochemical reactions that determines the corrosion behavior.

2.3.3 Biofilm

Biofilm is a ubiquitous, substrate-attached microorganism community confined within a self-developed extracellular polymeric matrix, which is highly structured and resistant to environmental disturbance.
Almost all microorganisms have potential to form biofilm with an ability of adherence to the surface. Understanding of such mechanisms could be helpful in mitigating the cases like corrosion [7, 8].

2.3.4 Role of Biofilm

Biofilms are unwanted formation of deposits, which can affect the equipment in one way or the other. Microbial activity under such films can change the morphology of the materials and affects the redox reactions, thereby promoting or inhibiting corrosion. The characteristic of corrosion is determined by several factors that include physio-chemical environment at the substratum due to change in the concentration of oxygen, salts, pH value, conductivity and potential. Presence of microorganisms actually affects these values and could make a suitable environment for bacterial growth leading to corrosion. For instance, a biofilm with a thickness of 100μm can prevent the diffusion process of the nutrients to the base of the biofilm, while a thickness just of 12μm can make a spot anaerobic enough for the growth of SRB activity in this region, hence promoting corrosion [9].

Hence, to understand the nature of such biofilms, a core understanding of their structure is necessary. In a biofilm, factors like pH, dissolved oxygen, etc. might be different resulting in different concentration gradient of the chemical species along the thickness of biofilm[10].

Broadly, bacteria involved in the MIC process can be divided in to three groups. According to Energy Institute, 2014, ISO, NACE and others, bacterial group can be categorized as follows

- Aerobes
  - ✓ Sulfur-oxidizing bacteria
- Anaerobes
  - ✓ Sulfate-reducing prokaryotes
  - ✓ Methanogens
  - ✓ Acid-producing
  - ✓ Iron-reducing fungi
- Facultative
  - ✓ Iron-oxidizing prokaryotes
  - ✓ Sulfur-reducing prokaryotes
  - ✓ Acid-producing bacteria
  - ✓ Metal-reducing bacteria
  - ✓ Nitrate-reducing bacteria

2.3.5 Sulfate Reducing Prokaryotes and Methanogens

SRP, a collective name given to sulfate reducing archaea (SRA) and sulfate reducing bacteria (SRB), reduces sulfate ion, and methanogens that produce methane as their metabolic activities. Previously, SRB were considered as the only the key factor that cause corrosion; however, recently SRA has also been found as a contributor in causing MIC. The role of methanogens is still not clear because of which its effect has often been neglected, but the recent findings show these microbes can also influence the rate of corrosion. More researches suggest a relation that exists between the presence of methanogens and degradation of iron [11, 12]. Hence on this research basis, this work has been oriented in determining the corrosion rates under the influence of SRB, SRA and methanogens.

2.4 Risk Based Inspection (RBI)

In the scenario where every industry is seeking for an optimized methodology for inspection and maintenance planning of its assets, risk based inspection methodology offers an interesting solution. Risk Based Inspection (RBI) is a methodology that visualizes risk and prioritizes the components to be inspected on three terms

1. When to inspect
2. How to inspect
3. Where to inspect

Any system susceptible to failure needs to be inspected in regular period of time or as scheduled based upon its functionality and criticality [13]. Once the inspections plan is formulated, monitoring techniques are used to detect the failures state and the nature of failure. During RBI, we need data to interpret different parameter of which one is estimating for probability of failure.

Collection of data, interpreting or building logic to the data gives information. However, there is always an uncertainty in collecting data because of various reasons[14-16]. Degradation like corrosion and erosion can reduce the efficiency of the assets, which further brings a risk scenario that needs an eye to look upon. For this, different monitoring techniques and inspection provide the insight of the condition of the assets (like pipeline, pressure vessels, static and dynamic equipment) which is made by using sensors or other applicable methods like visual inspection, Non Destructive Testing (NDT), etc. But, there might be imperfection in data handling as a consequence of which we arrive at improper decision. Imperfection in data will influence the decision making process and could led in degradation of the whole system if optimal steps are not taken in time. At any stage of RBI, the decision-making is inevitable due to which proper decision making system is always a need[17].

2.5 Risk based Inspection Methodology

2.5.1 Introduction

It is a decision-making technique for inspection planning based on risk comprising the consequence of failure (CoF) and probability of failure (PoF) [13]. For RBI analysis, PoF and CoF are separately calculated and combined together to obtain the risk. RBI can be made either quantitative or qualitative. A model based approach where selecting suitable models are used to calculate the numerical values for building a risk picture in quantitative analysis whereas expert judgment based on opinions and experiences is used in qualitative analysis.

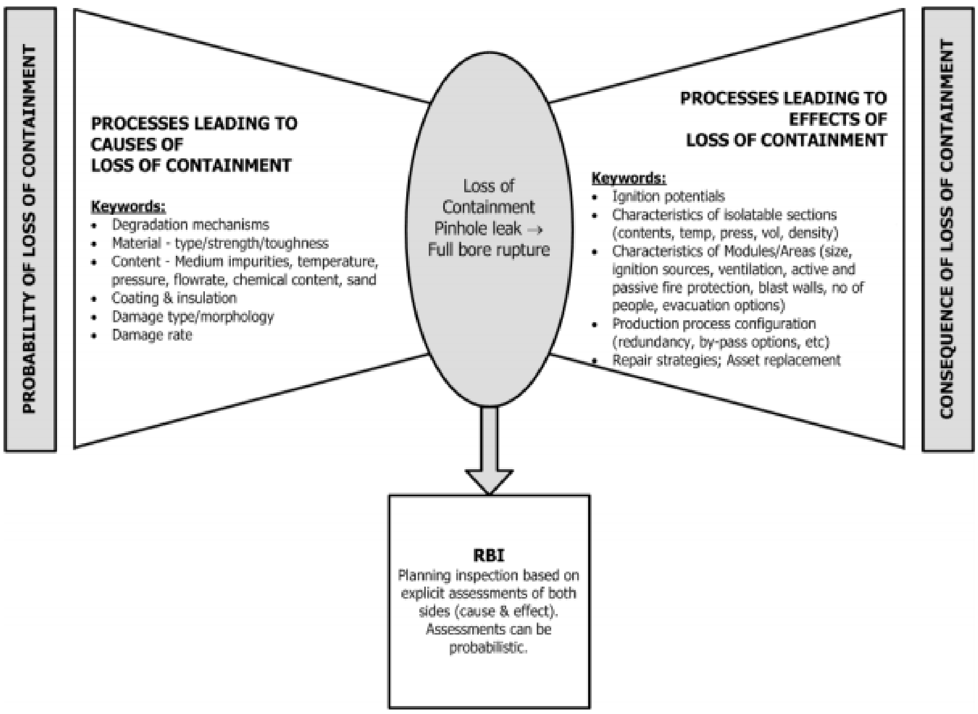

FIGURE 2. RBI Methodology, DNV

2.5.2 Current Methods

Basically RBI consists of 4 stages, which are

- Screening
- Risk assessment
- Inspection interval assessment
- Evaluation and updating

The methodology of RBI is described in DNV-RP-G101 [13]. Here, we are interested in the detailed risk assessment part where data are collected and interpreted. Based upon the findings, a risk scenario is made which provides an insight to a risk picture for determining the inspection intervals. However, it is crucial to understand the nature of data which forms the basis for our decision making process. For the decision support to be effective, it is to be made sure that the data transformation be easily understood and would help in the decision making process for the users.

In order to make an effective decision plan, understanding the nature of data, underlying information and relevant knowledge are needed to be very precise and accurate to formulate the decision structure. In case of RBI, planning of inspection plan is a crucial part of the process where in most of the cases a team of experts makes. A new methodology where computer systems called as Expert systems (ES) that facilitate in making decisions have a great potential if integrated in the existing process, which is discussed in the Section 2.10.

2.6 Data – Information- Knowledge -Decision

Collection of data is important to provide an overview for the prediction of the degradation mechanisms, potential failure modes of the assets (pipeline, pressure vessels, valves, etc.). The hierarchy of data, information and knowledge and its importance are discussed below. For more see [17].

Data:

For any process, collection of simulated or real values is data, which in itself has no meaning. It is then processed to give some information.

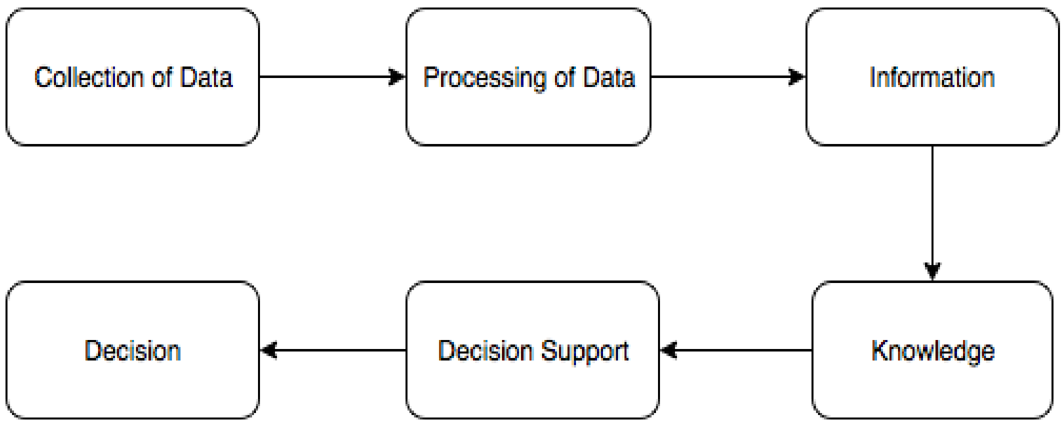

FIGURE 3. Hierarchy of data, information, knowledge and decision support

Information :

Processed data either with some rules or logic gives information about the data. Rules can be either assigned by human or with help of computers.

Knowledge:

Reasoning the information, perception associated with the information or cognition gives knowledge.

Decision support :

After we have knowledge for any process, decision support tools are implemented which could be opinions from experts, decision trees, or some computer based tools to provide the decision with relevant knowledge. In this work, expert systems (ES) has been discussed as a part of decision support tool and recently these systems has proven its efficiency due to its limited domain for problem solving with limited rules and assertions.

2.7 Uncertainty Assessment

Starting from the collection of data in risk assessment, an uncertainty analysis is always recommended for proper decision-making. Uncertainty modeling in determining the probability of failure needs an advanced understanding of the systems where in most of the cases are represented either qualitatively or quantitatively. For example, if the uncertainty is low, it means that the background knowledge is precise and accurate to high extent whereas a high uncertainty means a lot of flaws in understanding the process that might affect the probability calculations and hence the decision that is made might not be accurate. Calculating the probability $P(Z \leq z)$ for any model is a part of the background knowledge which comes from the interpretation of data collected [18].

The information obtained from such uncertainty analysis helps to address the risk involved and weaknesses in the findings. The choice of models can be one of the reasons for the existence of such uncertainties.

2.8 Risk and Uncertainty in Decision Support System

Risk and uncertainty are inherent in any decision making process. A risk scenario developed without considering the uncertainty factors in the assessment process can lead to the chance of quantifying wrong risk picture. Basically risk is interpreted as a combination of probability of event and its consequence. The uncertainty factors involved have a potential to change the probabilities of event and consequences. Hence, a risk picture developed considering all the possible uncertainty factors will provide a better basis for decision-making process. In RBI, the decision for inspection time intervals is crucial. Periodical inspections imply expenses that directly affect the total operational costs. Hence, planning of inspection time could be important in RBI while considering all the possible uncertainty factors [19].

2.9 Decision Under the Uncertainty

The decision making process under the influence of uncertainty factors is a tough task because there will be a range of options in decision process where we have to select the best alternative. It should always be in mind that whatever decision is taken, the best pay off option shall be chosen. For example, determining the inspection time interval in RBI for the same system can be different proposed by different experts based on their knowledge and cognition where choosing the best alternative can be difficult. In such cases, one way to choose the best option is to build a parameter and compare this parameter to the different alternatives. For example, in RBI choosing among the different alternatives can be based upon the cost, which we call as representative value.

Difficulties in decision making can be due to lack in information of a decision maker, hence more clear information can give more precise decision. In case of corrosion of pipelines, the exact process of degradation mechanisms if known, decision related to inspection or preventive maintenance would be more accurate. Relevant knowledge and information used to address the decision making task sharpens the probability and helps to shift our uncertainty towards the deterministic zone. In some cases, decision making can be under pure uncertainty which means that the decision makers has no idea about the consequences and the decision is taken under cognitive bias or with experience.

The corrosion model shown here in this work might not be precise enough. It would not be enough to say that the metal susceptible to MIC corrosions is only due to favorable range of temperature, pH and flow velocity as proposed in this model. There could be so many other factors that might effect the corrosion activity. Without considering these factors, the model so built might not be robust enough to show the real world behavior of corrosion. Hence, the limited data brings uncertainty.

2.10 Expert Decision Support Systems

With an understanding that the decision makers face difficulties while dealing with huge amount of data and information, a need was felt to facilitate the decision makers take more informed decisions. In other words, expert decision support systems can be regarded as a computer version of an expert person. For instance in RBI, such expert systems could help the decision makers by formalizing expert knowledge so that it can be used in any mechanized systems to plan for inspection time. Expert systems can be regarded as outgrowth of Artificial Intelligence oriented system helping in making decisions. In real world, experts while taking decisions could be biased while taking decisions, so to avoid such incidents to a certain extent, the necessity of such expert systems is felt [20].

2.10.1 Definition of Expert System

It can be defined as a problem-solving program that enhances the performance in the particular periphery that needs knowledge and skill to deal with. It can be assumed as an analogy to an expert human being.

The knowledge area of an ES is narrowed down with a proper database of knowledge with certain boundary conditions. The results and decisions made by an ES is based on rules and facts rather than the human intuition and reasoning. ES generally use three kinds of information, which are task-specific, domain-specific and control. Task specific is data relevant needed for ES analysis. Domain-specific is the knowledge base and the rules for solving the problem while control is the inference engine that applies the knowledge for reaching at a solution of any problem [21]. Use of fuzzy logic system is an example of such expert system, which has been discussed in the Section 4.6 of Chapter 4.

2.10.2 Need for Expert Decision Support

Expert systems have been extending its perimeter in various fields such as medical diagnosis, exploration and so on. Using Artificial Intelligence technology for practical use has grown its demand in industries, government and science areas[22]. It’s a challenge to integrate such ES in to existing decision support systems which in fact can give us more effective and convenient way of making decisions[23].

Decision support systems (DSS) functions as a support system for making decisions whereas, ES is a singular performing system which provides expert decision in the fixed problem domain. Integration of DSS and ES can provide some huge advantages in making our managerial tasks more efficient. ES can actually replicate a human expert and can even make its own recommendations where required. ES is considered more effective due to its narrow domain for problem solving with relevant facts and rules and for its explaining capability where it lacks in case for DSS.

Some contributions of ES systems are improvement in database and management systems, improving model management, user friendly interface, acts as a self tutor providing a dynamic approach to problem solving methods and includes computerization of decision making process. In the whole decision making process, ES can be added to any sections not only at the end to make the decision analysis more effective and reliable.

2.11 Expert System as a Part of Decision Support System

A DSS consists of four parts, which are database, model, interface and a user. Integrating ES and AI technologies in to DSS can be viewed as a part of DSS where the output of ES is a part of DSS in building an interface[22].

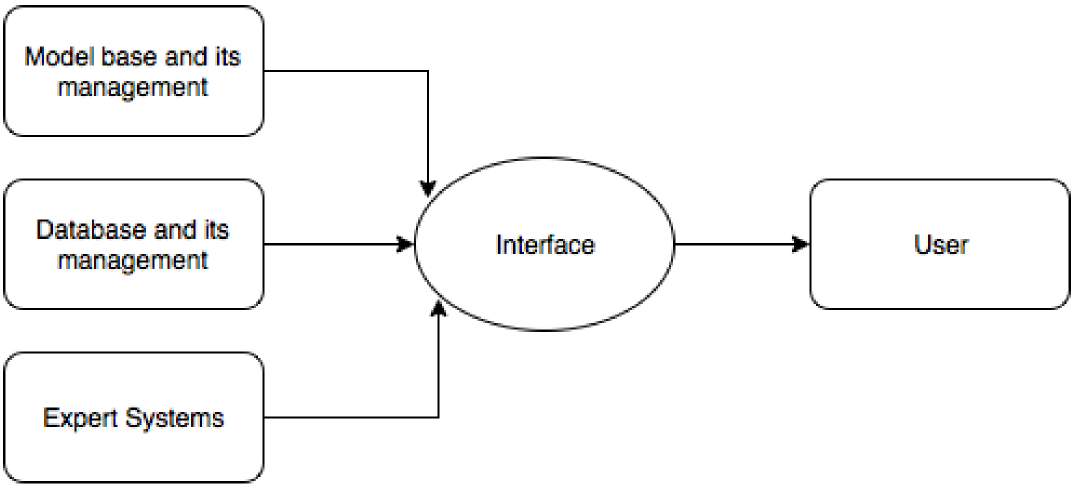

FIGURE 4. Integration of Expert System in Decision Support System

To simply understand, the user of DSS introduce ES at a point where a need is felt in strategy formulation and hence ES can be considered as an expert human who carries a narrow domain of information and relevant background knowledge required for that particular scenario.

On the other hand, some issues might come upon integrating these two systems. For instance, the compatibility of hardware and software could be different which means the programming language might be different which creates difficulty in bringing both in to the same compatible zone.

To facilitate the user in efficient decision-making, integration of ES system in to the conventional DSS can bring a lot of improvements. Cognition bias as in DSS is no more in the system using ES.

Chapter 3
Identification of Important Factors Affecting Microbiologically Influenced Corrosion (MIC)

3.1 Introduction

This chapter highlights the important factors controlling MIC rates. There are number of factors that control MIC. For the proper design and better maintenance plans of an operating plant, it is important to prioritize the factors that could have more potential effects in causing corrosion. A model that includes possible important factors could be more robust and useful for making inspection plans and to avoid unnecessary inspections leading to shutdowns, which thereby increases the cost.

Corrosion takes place as a result of different factors behaving in a complex environment[15]. A whole system is made up of different sub components and the corrosion behavior might be different at different stages of time for these components. But a model that addresses all the factors that results in corrosion might be difficult to propose efficiently because of the limited information about the relationship between the parameters itself. Hence, it brings limitations in defining our model. For example, a comparative study of different models carried out in Institute of Energy Technology (IFE) using the data provided by the participating oil companies gives different predictions for the same field case. So in such case, it is recommended to choose a model based upon the requirements of the plant operating conditions[24, 25].

The next chapter will propose a model that will include certain factors that will show the behavior of corrosion rates at different values of the parameters included in the model for this work.

3.2 Parameters

The environment plays a crucial role in bio-corrosion[26]. By environment, one means suitable range of temperature, pH, oxygen ingress, salinity, and settlement potential that could be some of the factors that can accelerate or inhibit the corrosion process. One should define the boundary conditions under which the system has been defined. This work proposes a corrosion rate model with available data for certain parameters (Section 4.5). The important factors involved in MIC are briefly discussed below.

- **Temperature** : Different literature surveys on microbes focusing on its growth rate associated with temperature range is found different. This creates difficulty in establishing a proper relation between temperature and MIC. From the literature surveys, it has been assumed that SRB grows in a range from 0-65°C, with optimal growth in the range of 25-40 °C [27]. Similarly, SRA grows in a range of 60-95 °C, with an optimal growth between 70-85 °C. Temperature range for methanogens activity is suggested in the range of 4-110 °C [28] with an optimal growth around 35 °C which requires furthermore investigation. Thus it has been assumed that methanogens grows in range of 10-90 °C with optimal growth between 30-70 °C. The temperature range for each microbe in divided in to three linguistic terms as High, Average and Low. The model in this work is flexible enough which can be modified in the presence of more precise information about the temperature range for these microbes.
- **MIC Mitigation Techniques**: MIC mitigation techniques broadly involve two different ways, which can be either direct or indirect. Direct techniques include cleaning, chemical injection and water jetting. While indirect techniques involve some design features and sulfate removal units. In cases where the mitigation technique is effective, the possibility of MIC initiation is low whereas if these techniques are ineffective, then the possibility of MIC initiation is high.
- **Settlement Potential**: The effects of settlement on corrosion rate are indicated by the measure of settlement potential. The ability of microbes to grow, establish a biofilm and to cause under deposit corrosion can be due to various factors like dead legs, geometry of the system and flow velocity. Time when the operation was halted creates suitable environment for biofilm to grow. Factors that bring such corrosion issues are difficult to look over, hence a

subjective knowledge from experts is taken.

- **pH**: Defining the range of pH where these microbes are active is again difficult due to the limited information. NACE suggests a pH range from 6-12 for SRB growth whereas Pots and Energy Institute suggests a range between 5-9.5 for SRB with an optimal growth between 5.5 and 6.5 for SRP. On the other hand, methane-producing microbes was found active in a range from 5.4 to 7.4. Based on these literature surveys, it is assumed that the pH range for both SRP and methanogens is in the range between 3.5 to 12 with optimal growth between 4.5 to 6.5. The pH range for these microbes has been classified in linguistic terms as Acidic, Medium and Basic. Triangular or Trapezoidal shapes are determined for their membership functions in the model.
- **Flow Velocity**: The rate of flow of the process fluid affects the growth of MIC. Issues with design where the settlement is high (e.g., dead legs), the growth of MIC can be affected by the flow rate of the process fluid. In the model, the flow rate has been classified in to three terms as High, Average and Low with triangular of trapezoid membership functions.
- **Oxygen Ingress**: Though anaerobic microbes are unaffected by the presence of oxygen, there are evidence which shows the presence of oxygen can increase the growth of MIC affected by sulfate reduction by 2.5 to 3.5 times higher. According to Beech and Gaylarde [29], the activity of methanogens increases with oxygen ingress. Hence, regardless of the type of microbes being anaerobic, oxygen ingress is believed to have negative impacts on MIC growth. Two linguistic terms, “Yes” or “No” are considered for this parameter.
- **Material:** All metals and metal alloys can be susceptible to MIC. According to ISO, 2010, MIC normally occurs in carbon steel, which is also due to its high use in construction. Different studies has shown it occurrence even in stainless steel and duplex stainless steel. More information on material being more sensible to MIC is required before including this parameter into modeling.
- **Availability of Nutrients**: Microbes need suitable environment for its growth.

However, it is still not clear about the specific contribution from each nutritional group that supports these microbes in its growth. Apparently, SRA and SRB have similar metabolic processes, which therefore can be influenced by the same nutritional group. While the rate of methane production is dependent on the amount of CO_2. The uncertainty of suitable nutritional group for different microbes makes it difficult to integrate in the model and hence has not been considered.

- **Water Breakthrough:** The water injected into the injection well breaks through to one or more production wells that can significantly increase the possibility of MIC. Since, the effect of water in the multiphase (oil-water-gas) system is difficult to quantify, only two *linguistic terms* - “Yes”, and “No” are considered.

	Parameter (Linguistic Variable)	**Linguistic Terms (Fuzzy Variable)**			**Shape of Membership Functions**	**Usage**
1	MIC Mitigation Effectiveness	Effective	Ineffective		Singleton	Possib. of initiation & stable pit growth
2	Water Breakthrough	Yes	No		Singleton	Possib. of initiation & stable pit growth
3	Settlement Potential	Low	High		Singleton	Possib. of initiation & stable pit growth
4	Temperature	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
5	pH	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
6	Flow Velocity	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
7	Oxygen Ingress	Yes	No		Singleton	Calc. corrosion rate
8	Material of Construction	Not accounted				
9	Availability of Nutrients	Not accounted				

TABLE 1. List of parameters in the development of MIC rate model

Chapter 4
Proposed Procedures and Methodology Used for Assessing MIC Rates

4.1 Introduction

The methods and procedures used in the analysis of data for prediction of corrosion rates are discussed in this chapter. The data has been extracted from the previous research papers[4]. The prediction of corrosion behavior can be unpredictable and is difficult to figure out which environment is suitable for its growth. Here the analysis has been focused in determining the corrosion rate for a system in the presence of SRA, SRB and methanogens.

The calculations of corrosion rate in this work show the influence of different parameters considered (temperature, pH, flow velocity and oxygen ingress) to trigger corrosion behavior of the system. The behavior of microorganisms is unpredictable and it is still a matter of interest among scientists, to find out the favorable conditions required for such microbes to grow and enhance the corrosion of the metallic substratum. The simplicity of the model is based upon the idea of adding any other input variables in to a system, once the data is available.

4.2 Overview of the procedure

The procedure begins with identifying a problem. What causes a problem and what can be done to mitigate it is the major concern. When it comes to detecting corrosion rates because of microorganisms, one should not forget the complexity of the environment that corrodes. Keeping all these in mind, this thesis work has tried to justify in finding the corrosion rates in the availability of some parameters whose information is somehow well documented to include in a model[30]. To find the corrosion rates, as discussed in the literature in previous chapters, the effect of temperature, pH and flow velocity has been considered. Amongst many models, rule-based model applying fuzzy logic has been implemented which is discussed in detail in the coming sections.

The work here proposes a methodology with an integration of fuzzy based model to develop an inspection plan. To start with, first the possibility of MIC initiation is discussed followed by the estimation of rate of corrosion using fuzzy logic systems. Estimation of possibility and necessity of failure due to MIC growth is carried out and finally an inspection plan is prepared.

4.3 Estimation of Possibility of MIC Initiation

The efficiency of MIC mitigation techniques has to be well observed for the inspection program to be carried out. Once it is found that the mitigation techniques are effective, it can be concluded that the possibility of MIC growth is low or else high based on expert judgments and opinions. However, if the effect of mitigation procedure is unknown, the process is extended where other influential factors like water breakthrough and settlement potential are taken in to consideration in determining the possibility of MIC growth as shown in Figure 5. Again, it is hard to understand the complex relationship between the parameters that triggers MIC growth due to which it has been assumed that the model proposed in this work is affected only by certain input parameters which is a limitation for this work here.

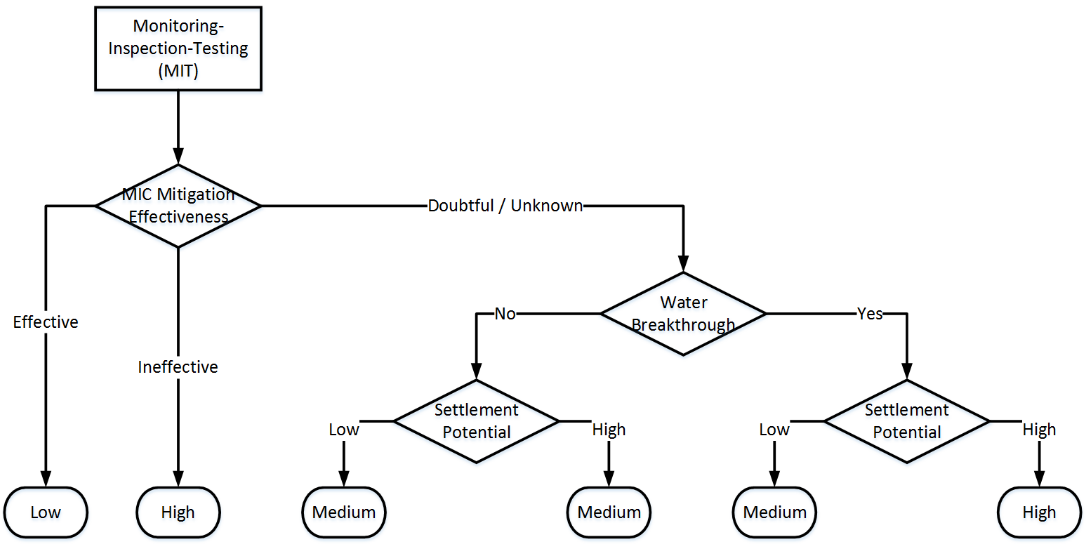

FIGURE 5. Flow chart to show the initiation of MIC

The estimation of possibility of MIC initiation is now followed by finding out the corrosion rates, which is discussed in following sections below.

4.4 Fuzzy Logic Systems

Fuzzy logic (FL) is a logical system, which is an extension of multivalued logic. The logic systems relate the classes of objects with unsharp boundaries where we define the membership degree. In simple understanding, fuzzy logic is a logic system that is capable of handling both numerical data and linguistic knowledge in making a better decision support system. The knowledge base fed by humans have chances of being imprecise with a lot of uncertainties because of which we implement FL as a framework for the management of such uncertainty in expert systems and make it possible to consider a number of issues that cannot be made with conventional techniques. The rules database is based on and/or which gives an output consequence in a way like

```
If X is A then Y is B;
```

where the antecedent, X is A and the consequence Y is B [31, 32] .

4.5 Included Parameters in modeling

The corrosion of the system can be associated with different parameters like temperature, settlement potential, material, pH, and oxygen ingress. Considering all these parameters in to a system can make our work bulky and the correlation between these parameters can be difficult to observe at once. Hence, we have defined our operating system in a certain range of temperature, pH and flow velocity on the basis of which corrosion is predicted using fuzzy logic. Below is the brief description of the parameters taken under considerations. For more details, look in to [33, 34].

1) **Temperature**: We have defined our system which operates between 0-100^{o}C meaning that we have both Mesophiles and thermophiles bacteria active within this given range. A Mesophile is an organism that grows best in moderate temperature typically between 20-45^{o}C whereas a thermophile is an organism that grows best between a range of 40-122^{o}C and typically called as

Archaea. Methanogens growth has been documented between a range of 4 to 110 degree Celsius with an optimal temperature around 35 degree Celsius. Hence, with a range of 0-100°C we have covered almost both SRA, SRB and methanogens [30].

2) **pH**: Optimum growth of SRP has been suggested in between 4.5-6.5 which is almost around neutral range. Hence, it is assumed that the corrosion would be high in this range and low else.
3) **Flow velocity**: We have assumed that the system has dead legs and the section is horizontal where the flow velocities lower than 1m/s would facilitate the growth of bacteria and hence causing high corrosion.
4) **Oxygen Ingress**: As discussed in Section 3.2, the effect of oxygen is crucial to enhance the rate of MIC. The estimation of corrosion rates in the absence and presence of oxygen is shown and compared.

Using these parameters, the model has been prepared to predict the corrosion rate under different values of temperature, pH and flow velocity

4.6 Development of MIC rate model based on fuzzy logic

In this work, a fuzzy expert system has been implemented that uses a collection of fuzzy membership functions and rules in contrast to Boolean logic system, which has only two outcomes. The rules in a fuzzy logic system is similar to something like

```
If A is high and B is low and C is high, then D is medium.
```

Where A, B and C are input variables whereas D is output variable.

Use of fuzzy logic allows the system to have different conclusions and the set of rules in a fuzzy expert system is generally knows as knowledge database. Generally, the fuzzy system proceeds as follows.

1. **Fuzzification**: Here the membership functions defined on the input variables are applied to their actual values in order to determine the degree of truth for each rule premise. Of all the input variables, the most important are selected

which can be based on the availability of data based on previous literatures. Each variable can be classified as “High”, “Average” and “Low”. The accuracy of the model increases while including more input variables but on the same hand, the complexity increases because the relationship between each variables is difficult to judge, thereby increasing the level of difficulty in establishing the rule base.

2. **Inference:** The truth value for the premise of each rule is calculated and is applied to the conclusion part of each rule that results in one fuzzy subset to be assigned to each output variable for each rule.
3. **Composition:** All of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable.
4. **Defuzzification:** It is used to convert the fuzzy output to a numerical value or we can to quantify the fuzzy output. In this work Centre of Gravity (COG) method has been implemented for defuzzification.

To build a fuzzy inference system, the three input variables are defined and has been assigned its membership function as stated above. A membership function for a fuzzy set is defined as μ:X -> [0 ,1], where each element of X is mapped to a value between 0 and 1. This value is called *degree of membership* and quantifies the grade of membership function in X to a given fuzzy set.

Membership function helps to graphically represent a fuzzy set. The x axis (abscissa) represents the range whereas y axis (ordinate) assigns the degree of membership in the interval of [0 1].

Figure 6 illustrates the Mamdani inference system where 3 input variables are fed to give an output. As mentioned already, temperature, pH and flow velocity are the input variables with corrosion rate as an output.

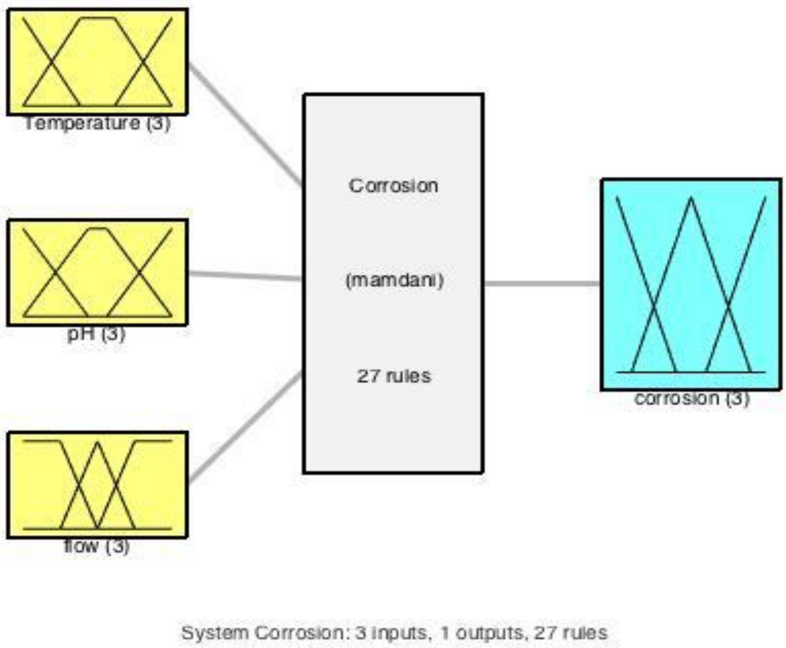

FIGURE 6. A Mamdani inference system

4.7 Membership functions

Connecting the value of input to the degree of truth is determined by the membership function. The range of input variable between which it fluctuates should be well understood to prepare more accurate membership function. In most of the case, this information can be taken from previous researches or expert judgment if necessary. The membership function of the variable can be designed in a number of shapes like triangular, trapezoidal, Gaussian, etc. In this thesis work, often triangular and trapezoidal shapes have been used because of their simplicity. In availability of more precise data and information, other shapes could be used if one could give more justification.

4.7.1 Triangular MFs

A triangular MF is characterized by three parameters [a b c] as follows :

$$\text{Triangle (x; a,b,c)} = \begin{cases} 0, x \leq a \\ \frac{x-a}{b-a}, a \leq x \leq b \\ \frac{c-x}{c-b}, b \leq x \leq c \\ 0, c \leq x \end{cases}$$

The parameters [a b c] determine the x coordinate of the three corners of the underlying triangular MF.

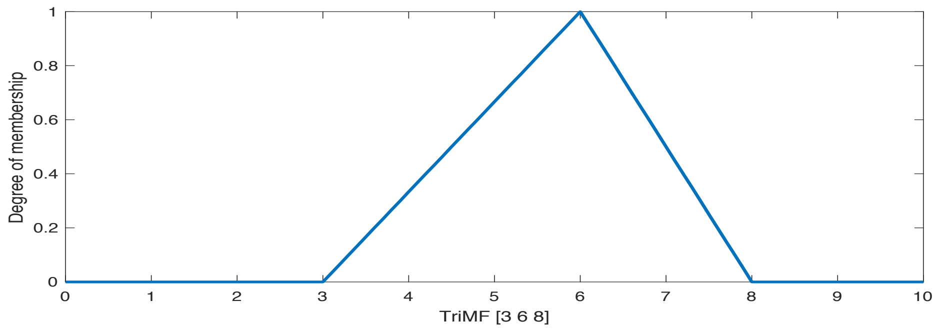

FIGURE 7. A triangular membership function

4.7.2 Trapezoidal MFs

A trapezoidal MF is specified by the four parameters [a b c d] as follows

$$\text{Trapezoid (x; a,b,c,d)} = \begin{cases} 0, x \leq a \\ \frac{x-a}{b-a}, a \leq x \leq b \\ 1, b \leq x \leq c \\ \frac{d-x}{d-c}, c \leq x \leq d \\ 0, d \leq x \end{cases}$$

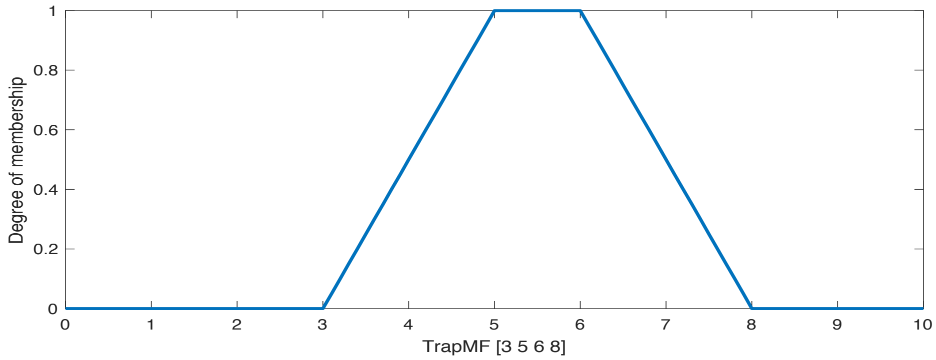

FIGURE 8. A trapezoid membership function

Figure 7 shows the triangular MF with values corresponding to [a b c] as [3 6 8] whereas Figure 8 shows an example of trapezoidal MF with values [a b c d] as [3 5 6 8].

Any sets of continuous probability distribution functions can be used as a specialized MF, provided the set of parameters describing the distribution is provided.

Figure 9 shows the membership functions of the parameters used in the model. It should be noted that the membership functions for pH and flow velocity for SRB, SRA and methanogens remains same.

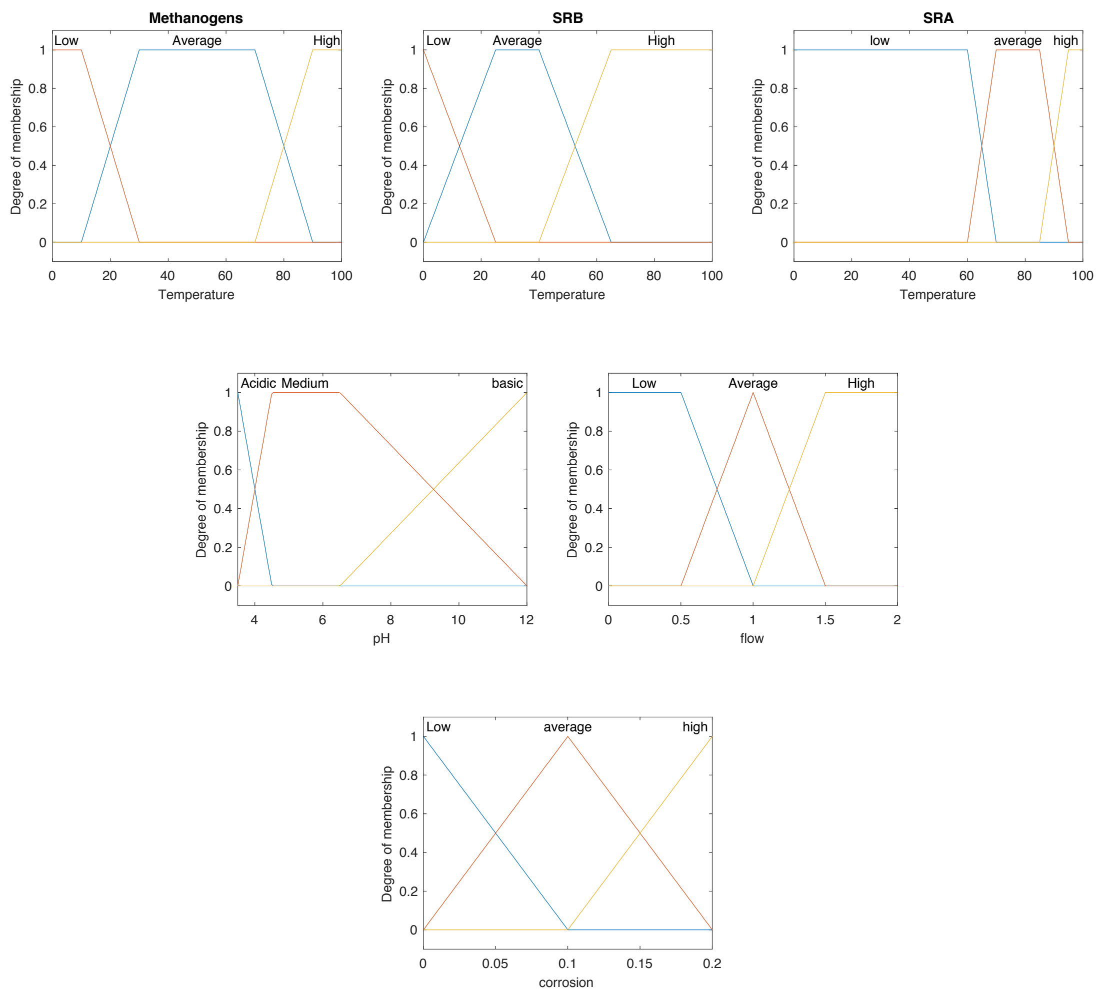

FIGURE 9. Modeling of membership functions

4.8 Rule data base

Generally, the rules are formed based on the previous knowledge about the inter-relation between input variable and output consequence. The rules have been developed using IF-THEN relation between the input and output variables. In this work, since we have included 3 input variables namely temperature, pH and flow velocity, hence it has been assumed, it would give a high corrosion in the favorable condition. However, we have considered an average corrosion where 2 of any 3 variables is favorable for the growth of MIC or low in other cases

Proposed modeling of MIC rates in this work has been based upon interaction of three input variables to give an output corrosion rate as mentioned earlier. The range of these input variables has been categorized in to three sub divisions as shown in Table 2.

Temperature	**pH**	**Flow rate**	**Oxygen ingress**
Low Average High	Acidic Medium Basic	Low Average High	Yes No

TABLE 2. Linguistic terms for the input parameters

The range of input variables has been set in such a way that the favorable condition for the growth of SRP and methanogens causing high corrosion is under average temperature range, medium pH and low flow velocity in the absence of oxygen. The effect of oxygen is accounted in the rule base by assuming that the conditions of temperature, pH and flow rate that gives low corrosion now gives Average corrosion. Similarly, the conditions of temperature, pH and flow rate that gives average corrosion will give high corrosion with oxygen ingress.

Before building a model in fuzzy logic, we require a set of rules where we can feed our knowledge in linguistic based rule to predict the rate of corrosion. Here, it has been assumed that the corrosion would be "**High"** under favorable conditions where the temperature is "Average", pH is "Medium" and flow is "Low" for SRB with "NO" Oxygen Ingress. Similarly, the temperature range where SRA and methanogens are active is made *average* in the rule base while the range for pH and flow rate where these microbes grow remains same. Accordingly, the rules are fed to the system to calculate the output results. It is considered, under any two favorable inputs, the corrosion would be average or else low. The rules for modeling are as follows:

1.If (Temperature is Low) and (pH is Acidic) and (flow is Low) then (corrosion is Low)

2. If (Temperature is Low) and (pH is Acidic) and (flow is Average) then (corrosion is Low)

3. If (Temperature is Low) and (pH is Acidic) and (flow is High) then (corrosion is Low)

4. If (Temperature is Low) and (pH is Medium) and (flow is Low) then (corrosion is average)

5. If (Temperature is Low) and (pH is Medium) and (flow is Average) then (corrosion is Low)

6. If (Temperature is Low) and (pH is Medium) and (flow is High) then (corrosion is Low)

7. If (Temperature is Low) and (pH is basic) and (flow is Low) then (corrosion is Low)

8. If (Temperature is Low) and (pH is basic) and (flow is Average) then (corrosion is Low)

9. If (Temperature is Low) and (pH is basic) and (flow is High) then (corrosion is Low)

10. If (Temperature is Average) and (pH is Acidic) and (flow is Low) then (corrosion is average)

11. If (Temperature is Average) and (pH is Acidic) and (flow is Average) then (corrosion is Low)

12. If (Temperature is Average) and (pH is Acidic) and (flow is High) then (corrosion is Low)

13. If (Temperature is Average) and (pH is Medium) and (flow is Low) then (corrosion is high)

14. If (Temperature is Average) and (pH is Medium) and (flow is Average) then (corrosion is average)

15. If (Temperature is Average) and (pH is Medium) and (flow is High) then (corrosion is average)

16. If (Temperature is Average) and (pH is basic) and (flow is Low) then (corrosion is average)

17. If (Temperature is Average) and (pH is basic) and (flow is Average) then (corrosion is Low)

18. If (Temperature is Average) and (pH is basic) and (flow is High) then (corrosion is Low)

19. If (Temperature is High) and (pH is Acidic) and (flow is Low) then (corrosion is Low)

20. If (Temperature is High) and (pH is Acidic) and (flow is Average) then (corrosion is Low)

21. If (Temperature is High) and (pH is Acidic) and (flow is High) then (corrosion is Low)

22. If (Temperature is High) and (pH is Medium) and (flow is Low) then (corrosion is average)

23. If (Temperature is High) and (pH is Medium) and (flow is Average) then (corrosion is Low)

24. If (Temperature is High) and (pH is Medium) and (flow is High) then (corrosion is Low)

25. If (Temperature is High) and (pH is basic) and (flow is Low) then (corrosion is Low)

26. If (Temperature is High) and (pH is basic) and (flow is Average) then (corrosion is Low)

27. If (Temperature is High) and (pH is basic) and (flow is High) then (corrosion is Low)

TABLE 3. Rule base (“NO” oxygen ingress)

```
IF temperature is average and pH is medium and flow
velocity is High and oxygen ingress is No THEN the
corrosion is High THEN corrosion is Average

IF temperature is average and pH is medium and flow
velocity is High and oxygen ingress is Yes THEN
corrosion is High
```

As stated before, oxygen ingress increases the corrosion rate. Thus, the rule base (with NO Oxygen ingress) is changed such that low corrosion becomes average and average becomes high.

It is to be mentioned that the fuzzy system in this work is valid only when all the three input variables comes in to action since AND logic gate has been used in building the rule base. The modeling is always associated with uncertainties due to the imprecise information regarding input and output data in this work. However, an approach to predict the corrosion rate in a scenario where the three mentioned input variables comes in to play has been shown as Graphics user Interface (GUI) in Mat lab.

4.9 Estimation of Possibility and Necessity of Failure

4.9.1 Fuzzy Arithmetic

Fuzzy membership function can be treated analogous to probability density function and can be interpreted as the possibility distribution function in the possibilistic approach. The α cut for a fuzzy set X abbreviated as X_α can be defined as a crisp set that contains all the elements of X that have membership value greater than or equal to α. Mathematically,

$$X_\alpha = [\underline{x}, \overline{x}]_\alpha = \{x \in X | \underline{x} \le x \le \overline{x}\}$$

Where

$\underline{x} = Lowest\ real\ number\ value\ of\ the\ interval$

$\overline{x} = Highest\ real\ number\ value\ of\ the\ interval$

$\alpha \in [0,1]$

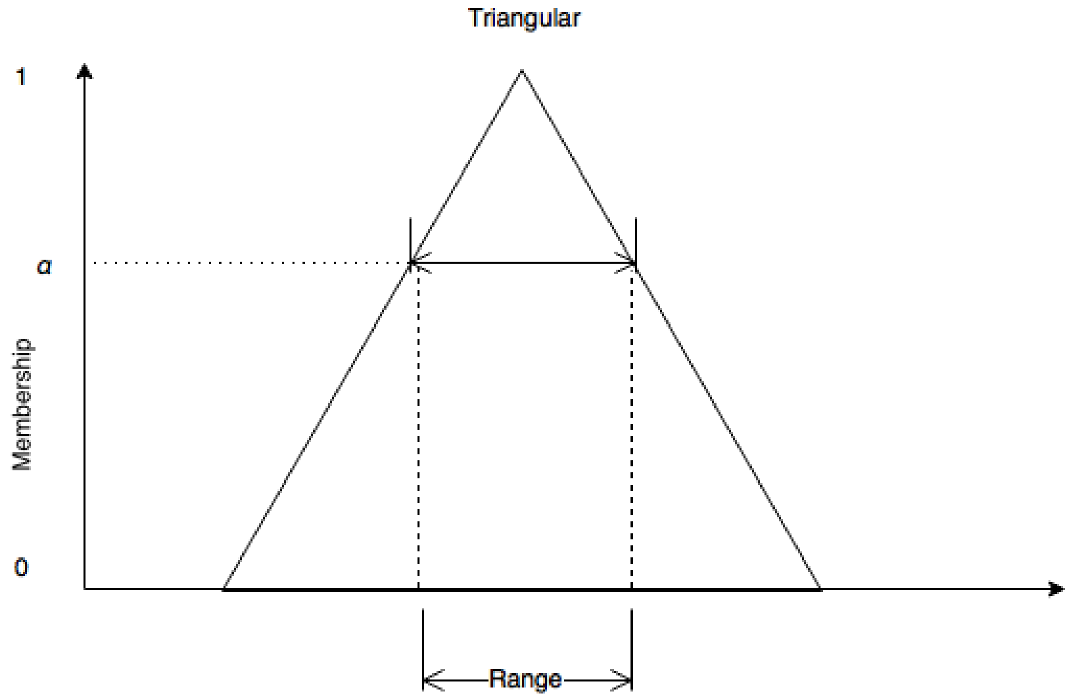

FIGURE 10. Alpha cuts

Each α cut gives a range represented by X_α containing the values whose likelihood is α. With an increase in likelihood, the interval between which the values lie decreases and the certainty that the values would lie within this interval also decreases.

The fuzzy operation between the α-cut of two fuzzy sets A and B, donated by $A_\alpha = [\underline{a}, \overline{a}]_\alpha$ and $B_\alpha = [\underline{b}, \overline{b}]_\alpha$, follows the concept of the interval analysis. The basics of this can be given as[35]:

$$Addition: \quad A_\alpha + B_\alpha = \left[\underline{a} + \underline{b}, \overline{a} + \overline{b}\right]_\alpha$$

$$Subtraction: \quad A_\alpha - B_\alpha = \left[\underline{a} - \overline{b}, \overline{a} - \underline{b}\right]_\alpha$$

$$Multiplication: \quad A_\alpha \times B_\alpha = \left[\min\left(\underline{a}\underline{b}, \underline{a}\overline{b}, \overline{a}\underline{b}, \overline{a}\overline{b}\right), \max\left(\underline{a}\underline{b}, \underline{a}\overline{b}, \overline{a}\underline{b}, \overline{a}\overline{b}\right)\right]_\alpha$$

$$Division: \quad \frac{A_\alpha}{B_\alpha} = \left[\underline{a}, \overline{a}\right]_\alpha \times \left[\frac{1}{\overline{b}}, \frac{1}{\underline{b}}\right]_\alpha \quad if \ 0 \notin \left[\underline{b}, \overline{b}\right]_\alpha$$

$$= \left[\min\left(\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\overline{b}}, \frac{\overline{a}}{\underline{b}}, \frac{\overline{a}}{\overline{b}}\right), \max\left(\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\overline{b}}, \frac{\overline{a}}{\underline{b}}, \frac{\overline{a}}{\overline{b}}\right)\right]_\alpha$$

$$Power: \quad A_\alpha^b = \left[\underline{a}, \overline{a}\right]_\alpha^b = \left[\underline{a}^b, \overline{a}^b\right]_\alpha$$

For this operation, a value of α is selected at first. For this value of α, the $\alpha\text{-}cut$ of each fuzzy number is determined. Considering all the values located in the $\alpha\text{-}cuts$ for every fuzzy number, the minimum and maximum values of the output function are calculated. This step is repeated for all $\alpha\text{-}cuts$ for $\alpha \in [0,1]$. The results of all $\alpha\text{-}cuts$ are combined to build the fuzzy membership function of the output function.

4.9.2 Calculation of reliability

The limit state function (*z*) can be calculated using[36]

$z = ds - dp$, --------------------------(Equation 4.1)

where d_s and d_p are maximum allowed corrosion and predicted corrosion depth respectively.

From the calculated MIC rate, predicted corrosion depth can be calculated by simply multiplying the corrosion rate with time to obtain the values of *dp*. The maximum allowed corrosion can be found from the equipment specification for a particular component. In this work, it is assumed that the maximum allowed corrosion depth (d_s) is 1.5mm. Along with time, the corrosion depth increases until it exceeds the maximum allowed corrosion giving rise to the failure event.

4.9.3 Calculation of Possibility and Necessity Measures of Failure

In the possibilistic framework, the fuzzy membership function $\mu(x)$ of a variable X can be interpreted as the possibility distribution function .The possibility theory uses two different measures – possibility measure and necessity measure – for calculating the limit state function. The possibility and necessity measures describing the truth of the proposition $(d_S \leq d_P)$ are given by Guyonnet [37]:

$$\Pi(d_S \leq d_P) = \underset{d}{Sup}\, max[\alpha_P(d), \alpha_S(d)]$$
$$N(d_S \leq d_P) = \underset{d}{Inf}\, max[1 - \alpha_P(d), \alpha_S(d)]$$

Where:

Π = *Possibility measure*
N = *Necessity measure*
$\alpha_S(d)$ = *Membership function of* d_S *for any value of* d
$\alpha_P(d)$ = *Membership function of* d_P *for any value of* d
min = *Minimization operator*
max = *Maximization operator*
Sup = *Largest value of* d
Inf = *Smallest value of* d

The maximum allowed corrosion can be found from the equipment specification for a particular component. In this work, it is assumed where the maximum allowed corrosion depth (d_s) is already assumed, for example 1.5mm, is discussed. The membership function of allowed corrosion depth (d_S) can be expressed as:

$$\alpha_S(d) = \begin{cases} 0 & d < d_S \\ 1 & d \geq d_S \end{cases}$$

As time progresses the depth of corrosion, characterized by the spread and center of gravity (CoG) of distribution, increases with corresponding increase in the possibility and necessity of failure.

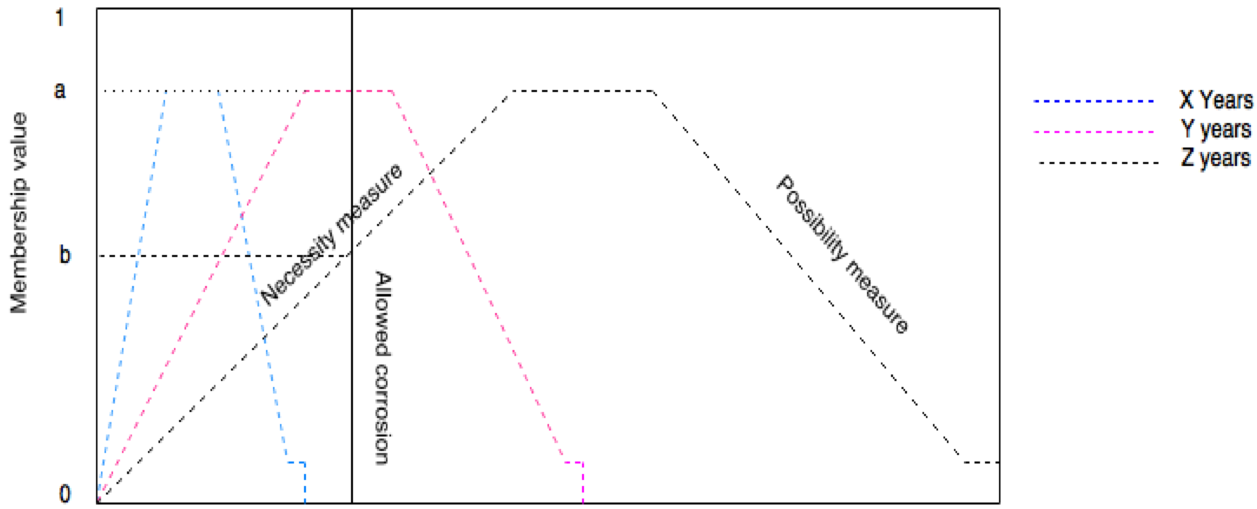

FIGURE 11. The illustration of possibility distribution of the predicted corrosion depth after different time period and of possibility and necessity measures

At X years : Possibility = 0; Necessity = 0

At Y years: Possibility= a; Necessity= 1-a

At Z years: Possibility= a; Necessity= a-b

4.10 Estimation of Inspection time

Proper planning of inspection time of the assets integrity directly influences the operational availability of the integrity. The objective of Risk Based Inspection methodology is to ensure and maintain the required availability of the system. Further, it is important to develop a detailed knowledge about the past, present and future operating conditions of pipelines under different environments that could influence the preparation of inspection schedule. For the time dependent degradation models, a periodic inspection plan can be made based on their failure rate. However, in most of the cases the degradation mechanisms uses semi-probabilistic reliability tools for this purpose. In this work, RBI uses a combination of estimation of MIC and possibility-necessity measure of failure to propose a time of inspection. The possibility measure is less conservative than the necessity measure, hence, the inspection time based on possibility measure is more than the other. In cases, where the zero tolerance is acquired, the possibility-measure based inspection schedule can be used. While, for the case where the failure event is not so crucial with low consequence, the necessity-measure based inspection plan can be executed.

Possibility of failure in the event of MIC initiation (%)	High	10-100	4 years	2 years	1 year
	Medium	1-10	4 years	2 years	2 years
	Low	<1	4 years	4 years	4 years
			Low	Medium	High
			Possibility of MIC initiation		

FIGURE 12 Illustration of inspection time for possibility measure of failure

Necessity measure of failure in the event of MIC initiation (%)	High	10-100	1 year	6 months	3 months
	Medium	1-10	1 year	6 months	6 months
	Low	<1	1year	1 year	1 year
			Low	Medium	High
			Possibility of MIC initiation		

FIGURE 13. Illustration of inspection time for necessity measure of failure

From the Figures 12 and 13, it can be understood that the inspection time with high possibility of MIC initiation and high possibility-necessity of MIC requires more often inspection compared to rest, which is a high risk zone.

Chapter 5
Results and Discussion

5.1 Overview of the results

The data extracted from the previous work has been used to build a fuzzy model in this work. Limited data and information is always an obstacle to build a model, which could precisely reflect the real world behavior of corrosion. With more data, one can propose a model better than this work, which is a part of further research.

Basically, here the model depicts the corrosion rate of a system under the influence of different changing parameters namely temperature, pH, flow velocity and oxygen ingress. The model is able to show the changes in the corrosion of the system with changing values of these input parameters. Computation of data has been facilitated using Matlab fuzzy logic toolbox.

The results obtained for estimation of corrosion rate due to SRB, SRA and methanogens in the absence of oxygen has been shown in the Figures 14-22. Figure 23 shows the comparative results of corrosion rate due to SRB with oxygen ingress and without oxygen ingress.

Oxygen ingress : NO				Oxygen Ingress : YES		
Temperature(°C)	63	45	25	63	45	25
pH	6	4.5	5	6	4.5	5
Flow rate	1	0.5	1	1	0.5	1
Corrosion rate(mm/yr)	0.0483	0.1353	0.1	0.1004	0.1661	0.1673

TABLE 4. Values or corrosion rate due to SRB with and without Oxygen Ingress

5.2 Discussion of the results

The fuzzy based model in this work helps to understand the corrosion behavior under the influence of input variables fed to the system. The complexity of corroding environment makes it difficult to precisely address the nature of corrosion. With the help of fuzzy logic, we can build a model for the estimation of corrosion rate. A fuzzy based model can help in the consequence modeling analysis considering both the available data and expert opinions for those systems, which do not have proper quantitative model. Further, the output from this model can be further extended to make a risk analysis and facilitate the decision makers to identify the major risks and hence give an idea of the understanding of the relative risks associated.

The model formulated in this work has its flexibility to show the corrosion rates with different values of input variables.

The rules database has been formulated according to the knowledge and information provided to predict the corrosion rates. Due to the limited information about the input variables, modeling of their membership functions is made linear to make the work simpler. More precise shapes for their membership functions could have made the results more accurate.

The Chapter 6 will show the proposed procedure for the prediction of corrosion using Artificial Neural Network and Adaptive Fuzzy Inference system. With more data, these models could be an efficient way for predicting corrosion rates.

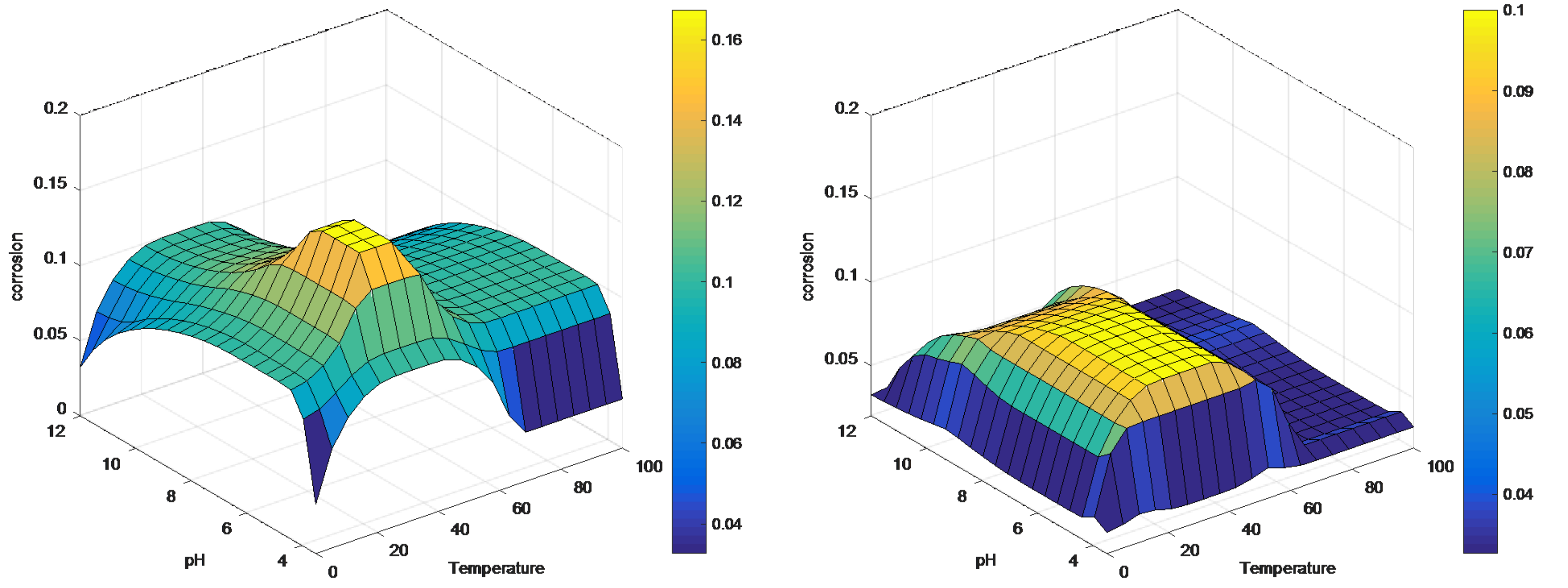

FIGURE 14. Effect of operating Temperature and pH on corrosion rate due to SRB (No oxygen ingress) at flow rate 0.5m/s(Left) and 1.5m/s(Right)

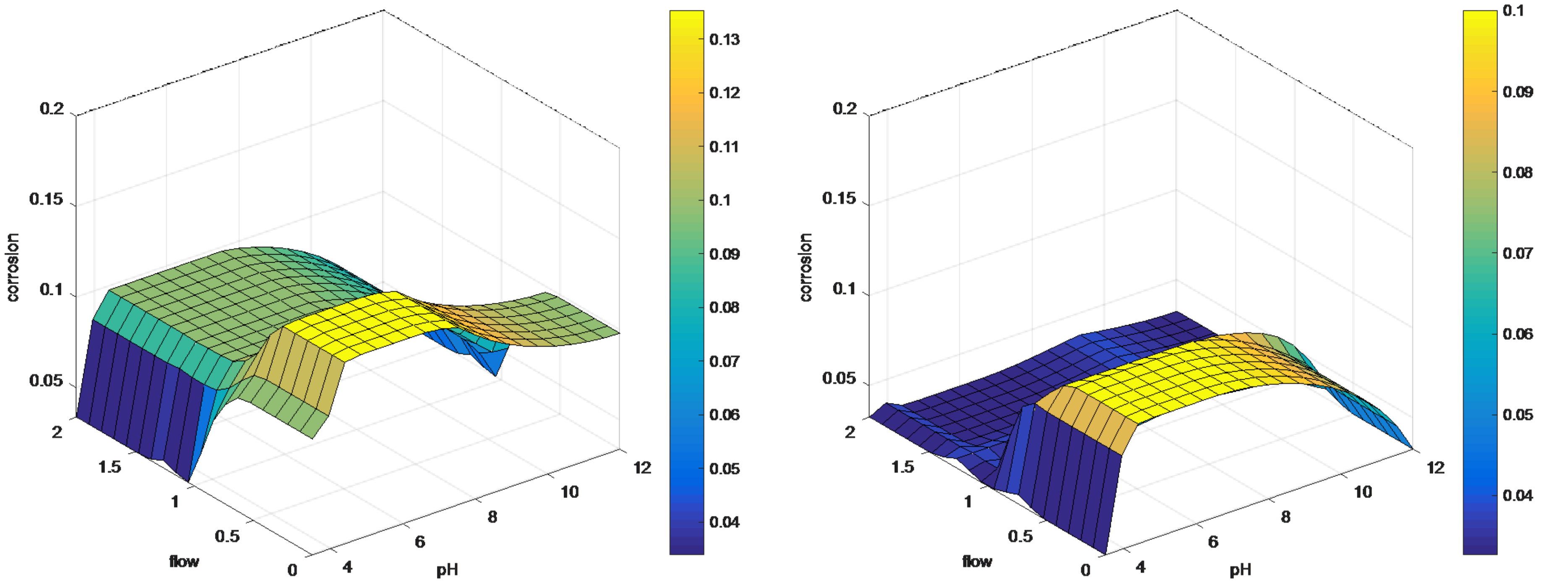

FIGURE 15. Effect of operating pH and flow rate due to SRB (No oxygen ingress) at 20oC(Left) and 80oC(Right)

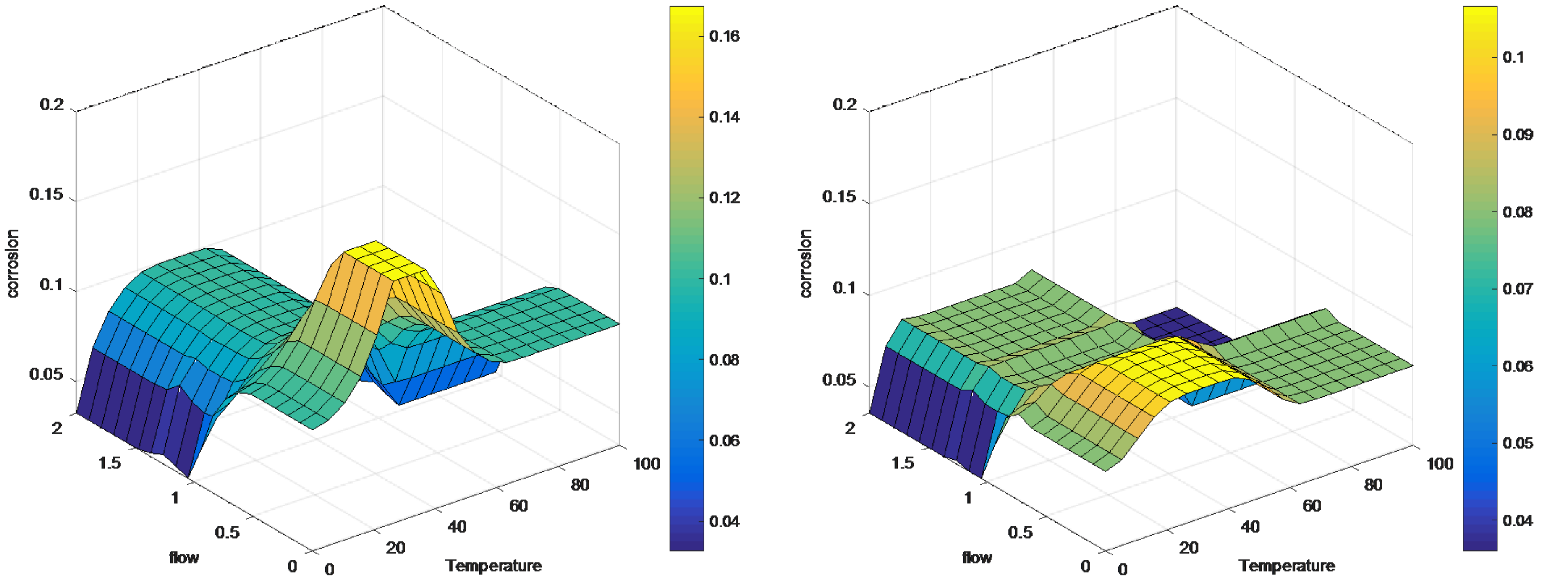

FIGURE 16. Effect of operating Temperature and flow rate due to SRB(No oxygen ingress) at pH 4.5(Left) and 10(Right)

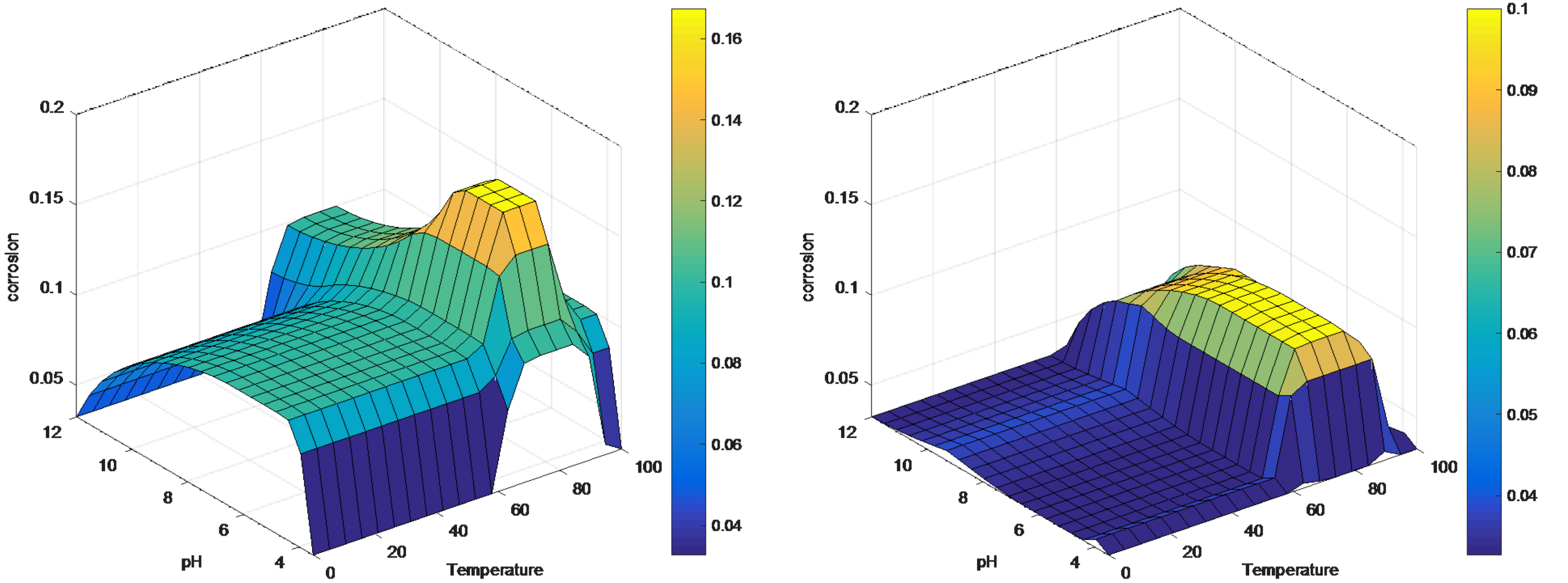

FIGURE 17. Effect of operating temperature and pH due to SRA at flow rate 0.5m/s(left) and 1.5m/s(right)

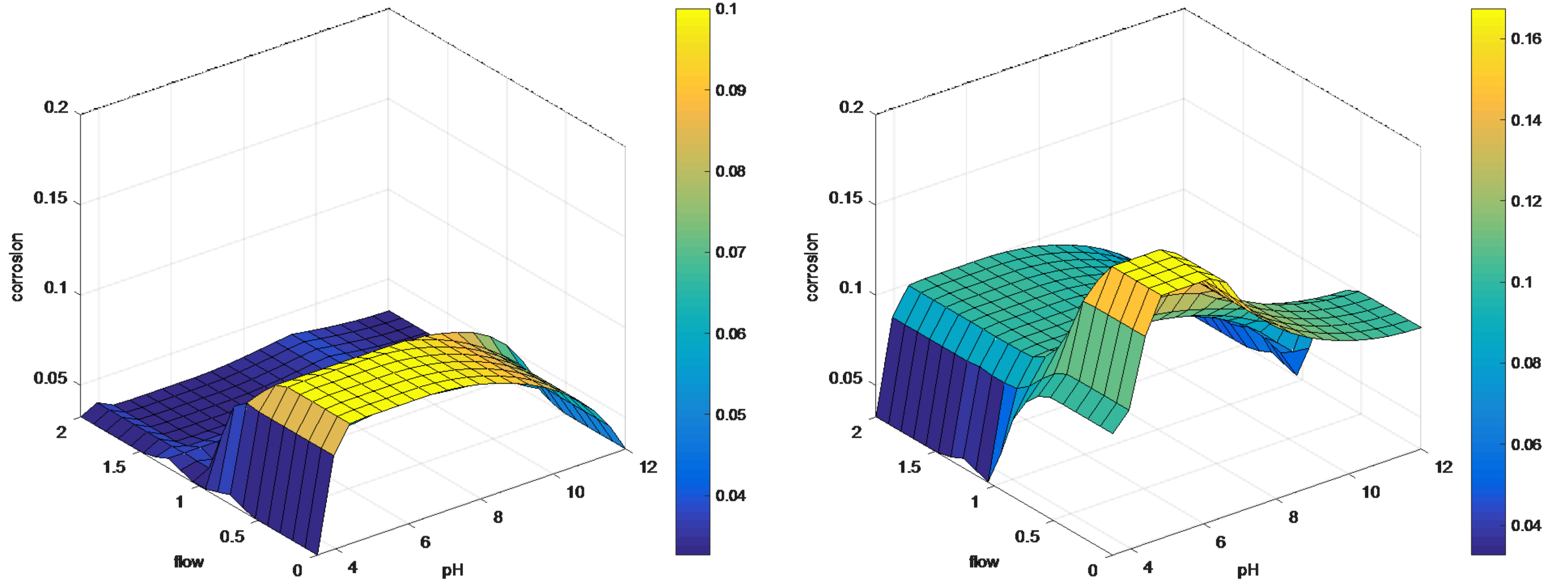

FIGURE 18. Effect of operating flow rate and pH due to SRA at temperature 20ºC(left) and 75ºC(right)

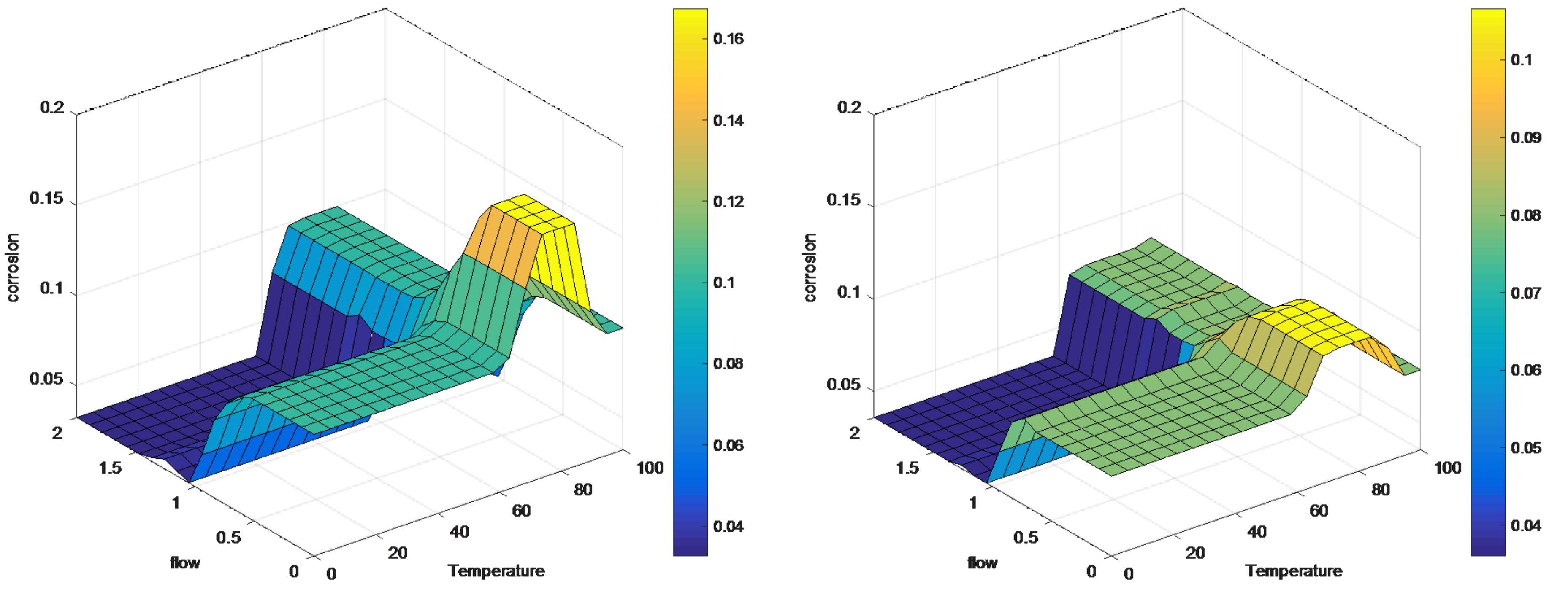

FIGURE 19. Effect of operating temperature and flow rate due to SRA at pH 4.5(left) and 10(right)

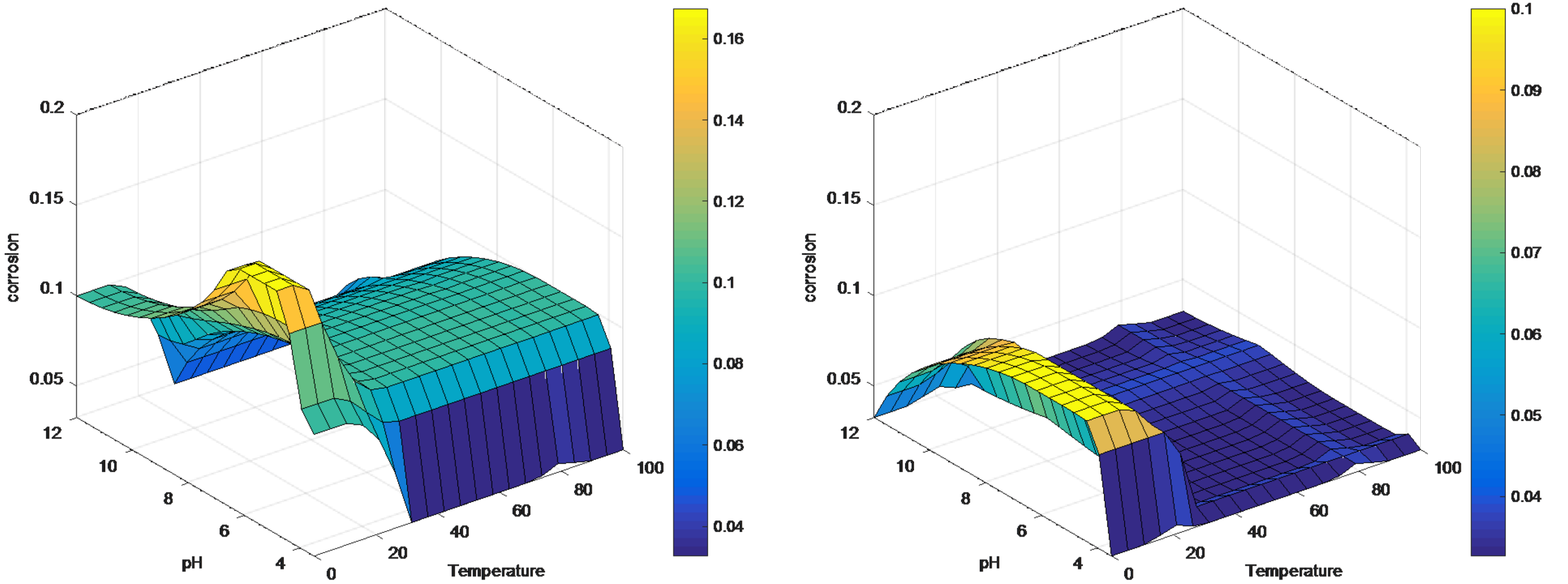

FIGURE 20. Effect of operating temperature and pH due to Methanogens at flow rate 0.5m/s(left) and 1.5m/s(right)

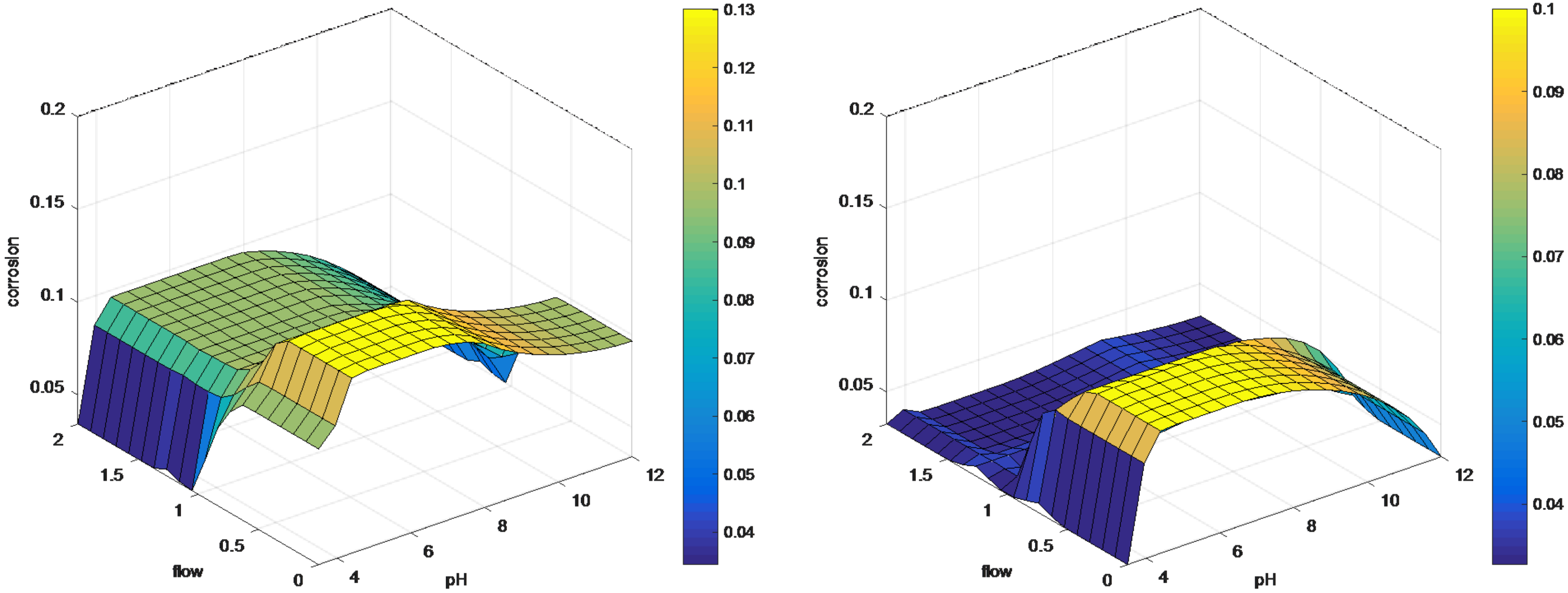

FIGURE 21. Effect of operating flow rate and pH due to Methanogens at temperature 15ºC(left) and 65ºC(right)

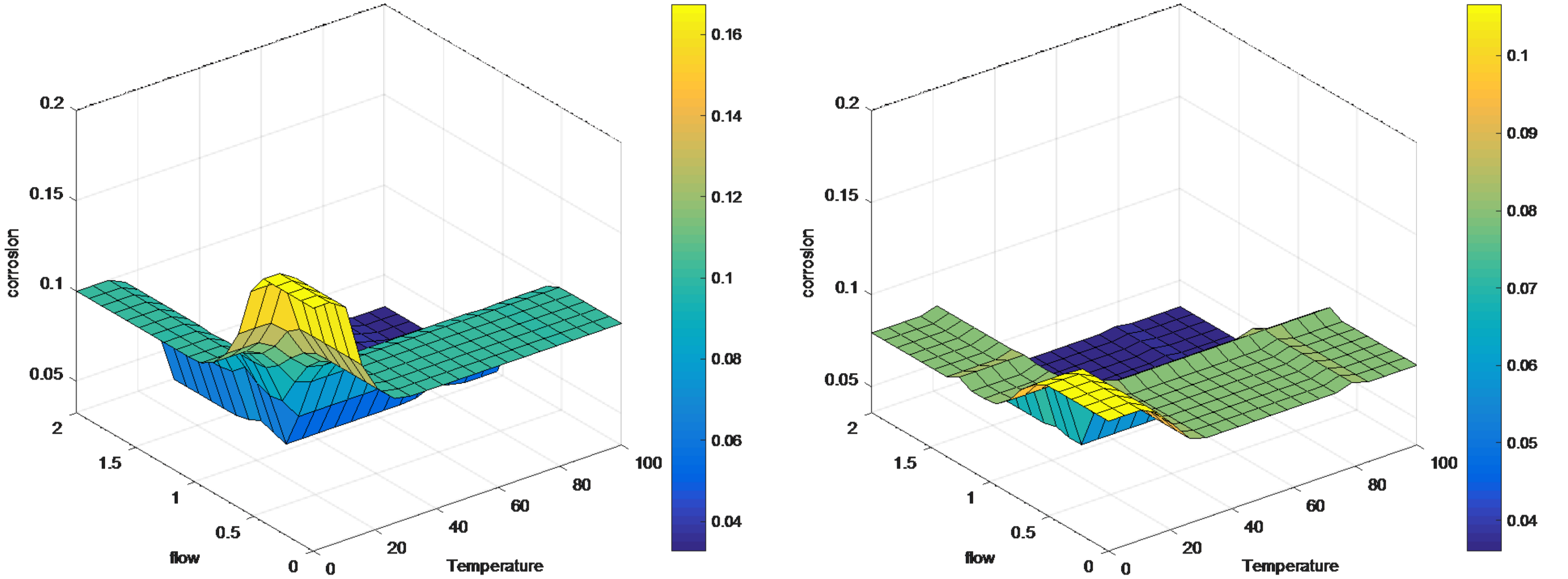

FIGURE 22. Effect of operating flow rate and temperature due to Methanogens at pH 4.5(left) and 10(right)

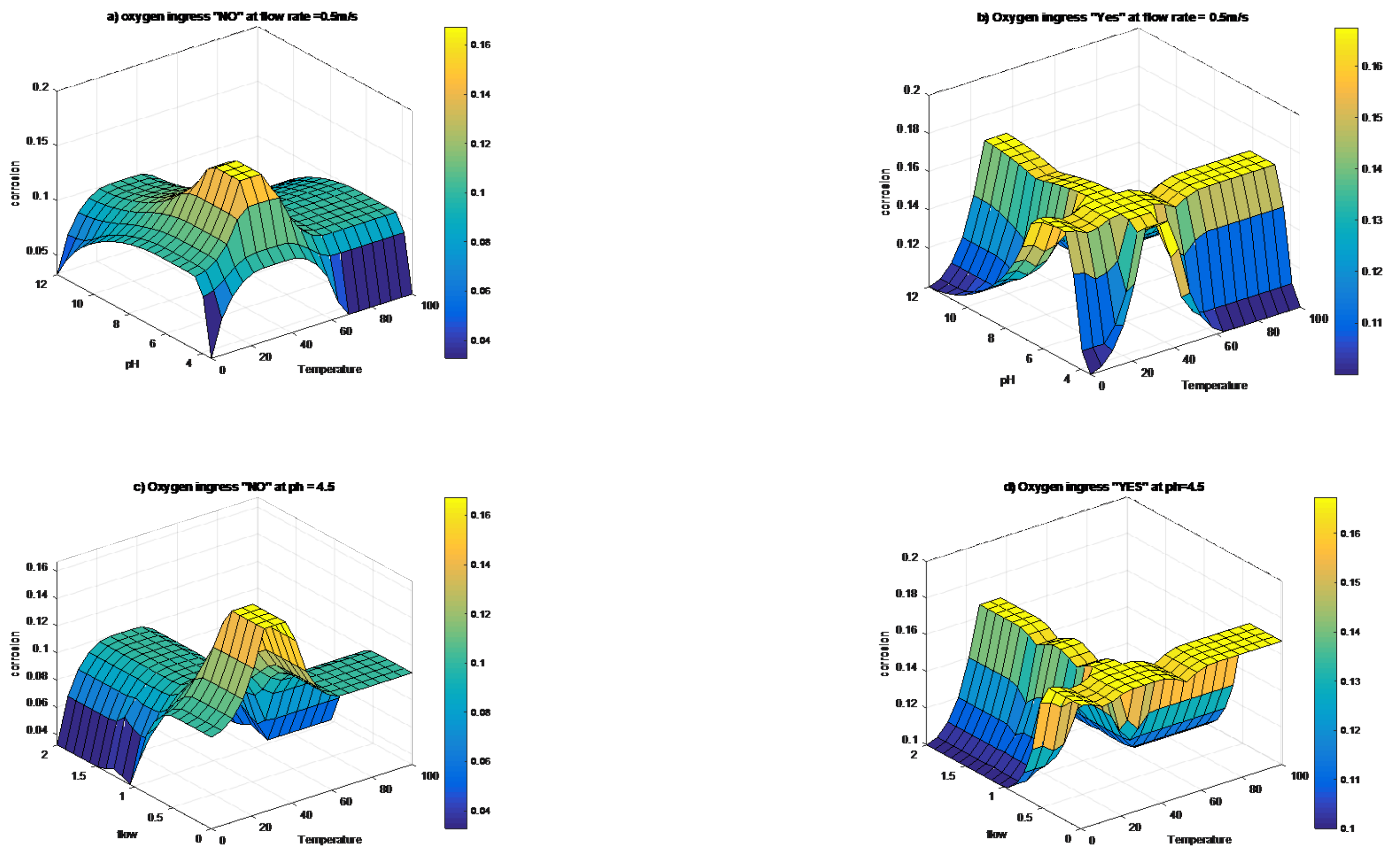

FIGURE 23. Illustration of effect of oxygen ingress due to SRB

Chapter 6
Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy modeling (ANFIS) approach in corrosion prediction

6.1 Artificial Neural Network

6.1.1 Introduction

Artificial neural network (ANN) can be defined as a model equivalent of reasoning based on human brain. Human brain consists of numerous interconnected set of processing units for the given information called as neurons where the information is stored. In ANN such information are processed simultaneously rather than at specific locations. ANN are actually reliable method in which it uses experience to improve the performance output. The neurons are connected by the links, which has got its own weight associated with them. Weights are assigned to measure the importance of the connection and ANN learn through repeated adjustments through these weights[38].

There are certain problems that might not be solved by predefined algorithms. Such problems might be dependent on subtle factors, which could be complex to formulate in the absence of such algorithms. In our case, while detecting corrosion rates, one may not be able to formulate explicit equations that could relate the input variables to give an output. Given a problem, human mind is capable of encoding and solving problems based on their learning. So the question is, how we make computers to learn so that it could function in a similar way as human brain.

6.1.2 Computational method for ANN

The computational methodology of ANN is inspired from the biological structure of neurons and its way of solving and encoding problems. ANN can be divided into two groups: feed forward and feed backwards. In the feed forward, no loops are formed in the network connections. The network signals are processed from a layer of inputs units to an output unit. On the other hand, in feedback networks, the connections are multi-directional to other units.

FIGURE 24. a) Feed forward b) Feedback[39]

6.1.3 Multilayer preceptor (MLP)

One of the common feed forward networks used is MLP. Figure 25 shows a typical MLP where we have three layers: an input layer, an output layer and a hidden layer.

The input signals from the input layer are transferred in the hidden layer. Again each neuron *j* from the hidden layer sums up its value and after weighting with the respective connection w_{ji} and gives its output y_j as a function f of the sum. Here the function *f* can be sigmoidal, hyperbolic tangent or radial basis function.

Mathematically,

$y_j = f\left(\sum_{i=1}^{n} w_{ji}\, x_i\right)$------------------------(Equation 6.1)

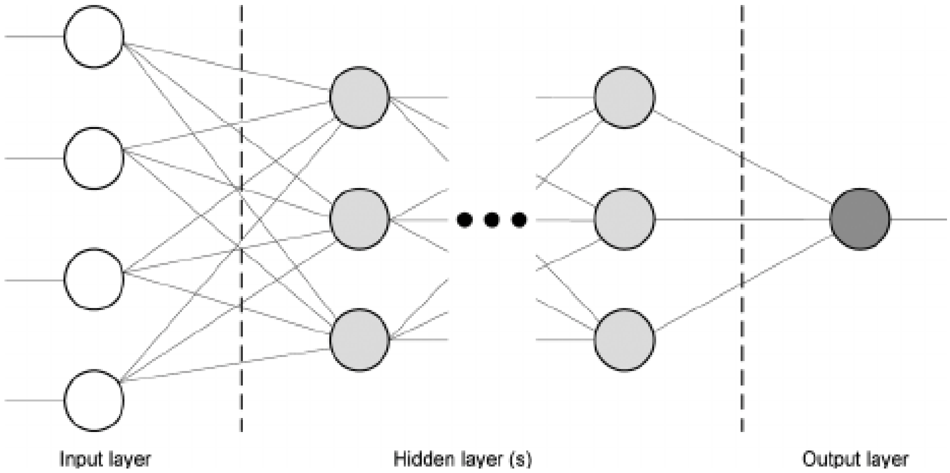

FIGURE 25. A MLP network [40]

6.1.4 ANN model for prediction of corrosion due to MIC

In this work, a proposed methodology has been given to predict the corrosion rate based on ANN. Generally, ANN is trained using real world data to learn the hidden algorithm, which sometimes cannot be described by explicit equations.

Input data in the matrix form of the order 3×n and a output data of the order 1×n is taken, where n is the number of sample points.

Temperature	x	y	z	………n
pH	p	q	r	………n
Flow velocity	l	m	n	……….n
Output corrosion	a	b	c	……….n

TABLE 5. Matrix form of input data

Data collection: From the inspection results, a set on input-output data set is obtained. Generally, these data sets are arranged in a matrix of order 3×n for input and 1× n for output, which is further used in training.

Building a network: Using input data and the target data (desired output) a network is built.

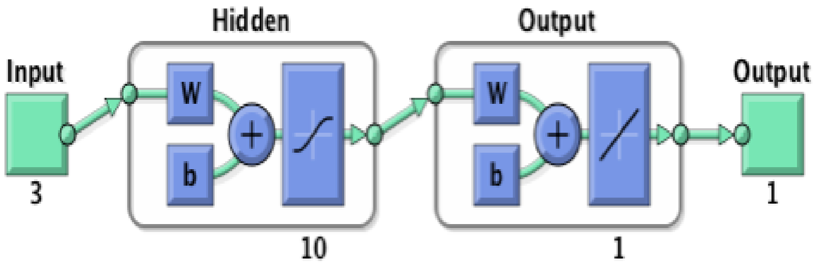

FIGURE 26. Neural network configurations

Training the network: The network is trained using available algorithms. Here, Levenberg Marquardt training algorithms [41]can be been used as a default training algorithm. This algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving, as indicated by an increase in the mean square error (MSE) of the validation samples. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error. Training multiple times will generate different results due to different initial conditions and samplings.

Test performance: When the training in neural network is complete, we can check the network performance and determine if any changes need to be made to the training process, the network architecture, or the data sets.

Once the network has been trained, it can be tested against the input data. A sample data is taken out from the data set and is simulated to see the output results.

6.2 Adaptive Neuro Fuzzy Inference System (ANFIS)

6.2.1 Introduction

ANFIS is architecture and a learning procedure, which is a fuzzy inference system, implemented in the framework of adaptive networks. ANFIS is capable of reproducing input-output mapping using fuzzy (if-then) rules. ANFIS is employed to model the nonlinear functions in a control system, to identify the nonlinearity and predict the output with promising results.

6.2.2 Computational methodology

The acronym ANFIS derives its name from *adaptive neuro-fuzzy inference system*. Using a given input/output data set, the toolbox function *anfis* in matlab constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modeling.

In this work, a fuzzy based model has been proposed to predict the corrosion rates as described in previous chapters. Specified membership functions has been used to model the input parameters which is then combined with a set of rules to give an output. There might be cases, where the shape of membership functions cannot be implemented by just looking the pattern of data. Hence, rather than choosing the membership functions arbitrarily, the membership functions can be tuned so as to give less error in data modeling of the system.

Generally, the input-output data is divided in to three categories: training, testing and checking data. However, if the training data represents the whole feature of the data presented to the model would be enough for the model to work but the case might be where training data might be embedded with noise, which hence could not represent the whole feature of the data. In such scenario, model validation is required. *Model validation* is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values.

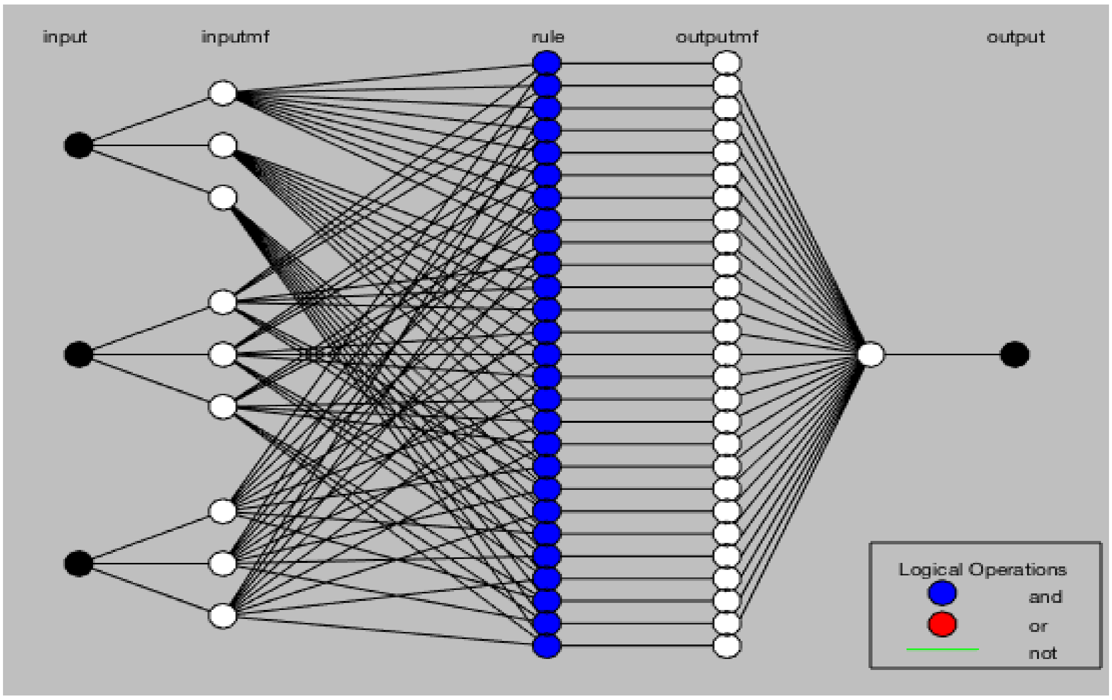

FIGURE 27. ANFIS architecture

The fuzzy model is vague in itself whose results might not be reliable enough to rely upon to make decisions. ANN and ANFIS propose a better methodology for the prediction of MIC facilitating in making more robust decision strategy. Use of either ANN or ANFIS might depend upon the user choice. However, since ANFIS uses a set of rules based on prior knowledge of experts, hence ANFIS might be more reliable method in this process.

Chapter 7
Conclusions

Preparing an inspection schedule is an important step of an effective RBI program. Unfortunately, the unpredictable nature of MIC corrosion makes precise calculation for time to inspect rather difficult, hence, traditionally, the inspection program for MIC has been mostly developed using expert judgement. This thesis presents a methodology for estimating the time for inspection based on the concepts of Fuzzy Logic and possibilistic approach.

The proposed methodology has four steps. In the first step the possibility of MIC initiation and stable pit growth is estimated using a simple flow chart taking into account parameters like water breakthrough and settlement potential. In the second step, the rate of corrosion, in the event of MIC initiation and stable pit growth, is estimated based on the concepts of fuzzy logic. In the third step, the fuzzy membership function of corrosion rate is used to estimate the possibility and necessity of failure as a function of time. Finally, the possibility of MIC initiation and stable pit growth and possibility/necessity of failure are combined using subjectively developed decision matrix to estimate the time for inspection.

As a part of future work, this thesis proposes extending the work using the concepts of ANN and ANFIS.

It is expected that the methodology would help engineers to develop more efficient inspection programs for installations suspected of having MIC.

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Appendix 1

A Fuzzy Logic-Possibilistic Methodology for Risk-Based Inspection (RBI) Planning of Oil and Gas Piping Subjected to Microbiologically Influenced Corrosion (MIC)

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Abstract

Operating oil and gas installations are subjected to attacks by a number of degrading mechanisms. In order to detect the presence and location of the attacks installations need to be regularly inspection. Unfortunately, comprehensive inspection programs are quite expensive; hence, risk-based inspection (RBI) methodology is often adopted to develop effective and efficient inspection programs. In order to account for a particular degradation mechanism in RBI analysis, inspection engineers need to know its likelihood of taking place and its estimated rate of degradation.

Unfortunately, the complex natures of various degradation mechanisms make accurate prediction of the rates of corrosion in an operating plant rather difficult. Luckily, for developing a risk-based inspection (RBI) program, it is not important to model a degradation process to be able to accurately estimate the degradation rate over a wide range of conditions. Instead the requirement is of a practical model which is simple to use, flexible enough to be modified according to the requirements of different sections of the plant, and able to incorporate field data.

Microbiologically influenced corrosion (MIC) is one of the commonly encountered degradation mechanisms in an offshore or onshore oil and gas installation. As with any other corrosion process, the prediction of likelihood of its initiation and its associated rate of corrosion is difficult to accurately model. A model based on fuzzy logic framework and possibility approach may offer a simple yet flexible tool for engineers to develop their RBI programs.

This paper presents a proposed methodology, based on fuzzy logic framework, for estimating the rate of MIC corrosion in carbon steel static equipment, pipes and pressure vessels. The paper also presents a procedure based on possibility approach to calculate the possibility and necessity of failure. Finally the paper presents a methodology to decide time for inspection.

Keywords: MIC, Fuzzy Logic, failure, oil and gas pipes, possibilistic approach, reliability, structural integrity

1 Introduction

Various components that make up an onshore or offshore oil and gas installation are subjected to a number of degrading mechanisms, like corrosion, erosion, fatigue and impacts. As a result, over a period of time, they may lose their structural integrity resulting in leakages, bursts and ruptures. These failures can result not only in economic losses to operators in terms of clean-up operations, reduced production, etc., but more importantly pose significant health, environment and safety (HSE) hazards. Hence, in order to mitigate the problems associated with failures, these components are subjected to regular inspections and maintenance. Since, an installation is made up of thousands of individual components, or tags, the associated costs of inspection and maintenance may be quite high.

An effective asset integrity management (AIM) program intends to maximize the availability of resources at minimum cost without compromising on the safety and legislative standards. One of the ways of developing such asset integrity program is to use the concepts of "risk management". In this case, "risk" is defined as a combination of the probability of failure and its consequence; and "risk management" can be considered as the architecture, including, philosophy, principles, procedures and frameworks, that are used to identify, assess and control risk of accidents in a chemical process installation. Risk management allows the operators to judiciously divide their resources among different assets based on the perceived risk of failure so as to minimize the risks posed by the possibilities of accidents (ISO 31000, 2009; ISO 31004, 2013; ISO Guide 73, 2009; NORSOK Z-008, 2011).

The risk analysis can be carried out qualitatively or quantitatively. In a qualitative risk analysis experts' opinions of individual sections are considered and a subjective score is given to the various factors that are assumed to cause the damage to a pipeline. Based on simple calculations and expert opinion risk associated with various failure modes is estimated. This methodology is very subjective and, hence, inaccurate. In the quantitative risk analysis methods, the probability of leakage and its consequences are calculated based on rigorous inspection and modelling results. These methods often give much more reliable results. Unfortunately, the quantitative calculation of risk is a daunting task because of the difficulties involved in calculating the probability of failure and the effect of the consequence of failure. Thus, a combination of the two is often a good balance between precision and practicality (ABS, 2003; API 580, 2002; DNV-RP-G101, 2010, ISO 17776, 2000).

One of the components in the development of the risk based asset integrity management program is the establishment of a risk based inspection (RBI) plan. RBI has been defined in the following manner in different recommended practices (ABS, 2003; API 580, 2002; DNV-RP-G101, 2010; NORSOK Z-008, 2011):

- **ABS:** Risk-based inspection is a risk assessment and management process that is focused on failure modes initiated by material deterioration, and controlled primarily through equipment and structure inspection.
- **NORSOK Standard Z008:** risk assessment and management process that is focused on loss of containment of pressurized equipment in processing facilities, due to material deterioration

- **API 580:** A risk assessment and management process that is focused on loss of containment of pressurized equipment in processing facilities, due to material deterioration. These risks are managed primarily through equipment inspection.
- **DNV-RP-G101:** A decision making technique for inspection planning based on risk – comprising the probability of failure and consequence of failure.

A closer look into the definitions and the scope highlights the following points: the All of these definitions have the following in common:

1. RBI's purpose is to manage risk, primarily through the inspection of equipment.
2. The RBI is based on risk assessment technique that comprises of assessment of probability of failure, consequence of failure and their combination.
3. The RBI is primarily geared towards the static pressurized process equipment.
4. The main failure mode is the loss of containment.
5. The main failure cause is the material deterioration.

One of the common causes of failure due to material deterioration is the damage to components caused by the internal corrosion which can take place due to a number of factors like the presence of CO_2, humidity, H_2S, microbes, chlorides and sulfates. In order to predict the rate of corrosion due to these factors a number of models have been developed. These models adopt different approaches to account for different components of the complete model. The traditional modelling approaches – semi-empirical and mechanistic – require understanding of the nature and behavior of the corrosion phenomenon. Unfortunately the complex nature of the corrosion process does not make it amenable to modelling. As a result, most of the models have been successful in making accurate predictions only to a limited degree. Luckily, for developing a risk-based inspection program, it is not important to accurately model the whole corrosion process which would be able to predict the rate of corrosion over a wide range of conditions. Instead the requirement is of a practical model which is simple to use, flexible enough to be modified according to the requirements of different sections of the plant, and able to incorporate field data (Singh and Markeset, 2009; Singh et al. 2014).

One of the commonly encountered degradation mechanism in an offshore or onshore oil and gas installation is the microbiologically influenced corrosion (MIC). In order to prevent the corrosion extensive amount of research has gone into understanding the fundamental principles behind it. Unfortunately, the complex nature of the phenomenon, caused by a wide range of microbes that operate over a wide range of conditions, makes understanding and mitigation of the problem rather difficult.

In order to predict the rate of corrosion due to MIC a number of models have been developed (Allison et al., 2008; Maxwell, 2006; Maxwell and Campbell, 2006; Sørensen et al., 2012; Taxèn et al., 2012). These models adopt different approaches to account for different variable parameters and components of the complete model. Unfortunately, the complex nature of the corrosion process makes it unamenable to modeling. As a result, most of the models have been successful in making accurate predictions only to a limited degree. Different models give different predictions for the same case and no particular model is expected to outperform others under all conditions. Hence, the selection of model should depend upon the empirically found correlations between the predicted and actual results.

An important feature of plant operation is the availability of a considerable amount of information regarding the corrosion of pipelines as a qualitative and imprecise knowledge. This subjective expert knowledge cannot be easily used by the traditional mathematics based on differential and algebraic equations. Hence, there is a requirement for a technique that can incorporate the subjective knowledge along with the objective information to develop a practical model which is simple to use, flexible enough to be modified according to the requirements of different sections of the plant, and able to incorporate field data (Singh and Markeset, 2009).

Fuzzy logic is a mathematical tool suitable for handling imprecise information in the real world. The benefit of this approach lies in its ability to include personal experiences along with acceptable deterministic models in the calculation. The structure of the model also allows easy calibration of the model to suit a particular condition. This approach can thus help to reduce the dependence upon the precise data, allow modelling even when a phenomenon is incompletely understood, and reduce the difficulties arising due to the complex computation required by more traditional methods (Singh and Markeset, 2009).

The fuzzy logic approach is an attractive option when (a) the available data is not precise enough to allow conventional methods of computing; (b) there is a significant tolerance to the imprecision, allowing the development of a simple and robust model; (c) the available information is too incomplete to allow the development of a proper model; and (d) the model is too difficult to allow easy computation (Zadeh 2002; Ross 2009).

In an ongoing research project, a methodology based on fuzzy logic is being developed for establishing a risk-based inspection schedule for oil and gas pipes. It is hoped that the methodology will allow the maintenance or inspection engineers to develop an optimal inspection plan considering various sources of information like the recommended models, standards and their own experience of the plant.

This paper presents a proposed semi-Q (semi-quantitative or semi-qualitative) methodology based upon the concepts of fuzzy logic for developing inspection schedule for static equipment subjected to possible MIC attack. The methodology contains four sections:

1. Estimation of possibility of MIC initiation and stable pit growth
2. Estimation of rate of corrosion
3. Estimation of possibility and necessity of failure in the event of MIC initiation and stable pit growth
4. Estimation of time for inspection.

2 Description of Input Variables

Microbiologically influenced corrosion (MIC) can be caused by different types of microbes. These microbes are characterized based on their biological features. The significant groups among the microbes are the (a) prokaryotes, which includes bacteria and archea; and (b) eukaryotes, which includes algae, fungi and protozoa.

Microbes can also be divided according to the environment they live in. Aerobic microbes can survive and grow only in the environment containing oxygen; whereas anaerobic microbes do not require oxygen for growth. A facultative microbe can survive and grow in both conditions, presence or absence of oxygen.

MIC takes place due to the metabolic activities of various types of microbes. Due to the unpredictable nature of microbes there is no unanimity regarding which type of microbes cause MIC, but there is a broad consensus that MIC is mostly caused by anaerobic microbes. Among the anaerobic microbes, eukaryotes seem to cause almost negligible MIC (Schlegel and Jannasch, 2006). Anaerobic microbes that are most commonly encountered can be categorized as:

- sulfate reducing prokaryotes (SRP),
- methanogens,
- iron reducing fungi, and
- acid reducing fungi falls

Out of these microbial groups, SRP and methanogens are considered to be the primary contributors to the MIC (Larsen et al., 2008, Mitchell et al., 2012). SRP is a collective name given to sulfate reducing archaea (SRA) and sulfate reducing bacteria (SRB). As a result of their metabolic process SRP reduces sulfate ($SO_4{}^{2-}$) resulting in the generation of H_2S. The H_2S released by the microbes reacts with the component iron to form iron sulfide (FeS), resulting in degradation of the component (Maxwell, 2006, Maxwell and Campbell, 2006; NACE, 2012, Sørensen et al., 2012, Rodrigues and Akid, 2014; Skovhus and Whitby, 2011).

While developing a model, selecting the most important input parameters and understanding of the complex relationship between these parameters is of vital importance. This listing helps to optimize between the accuracy and complexity of the system by incorporating the important variables and leaving out the less important ones. Too many variables increase the complexity of the model, hence, add to the noise in the calculated results; and too few variables result in erroneous results due to the disregard of important parameters. The selection of the variables can be based on the sensitivity analysis backed by the laboratory and plant data (IEC-1131 1997; Singh and Markeset, 2009; Singh et al. 2014).

While developing the model a number of parameters that may affect the rate of corrosion have been considered, some of these are operating temperature, settlement potential, material of construction, pH, and oxygen ingress. Out of all these variables, more important variables have been judiciously selected and described as *linguistic variables* (IEC-1131, 1997; Ross, 2004; Singh and Markeset, 2009).

Each of the linguistic variables (example "Temperature", "pH", "Flow Velocity", "MIC Mitigation Effectiveness", "Settlement Potential", etc.) has a number of *linguistic terms or fuzzy variables* (example "High", "Medium", "Low", etc.). The collection of all the fuzzy variables of a linguistic variable constitute the *term set*. The decision regarding the number of fuzzy variables in each linguistic variable is quite important. As the number of fuzzy variable in a linguistic variable increases, the accuracy of the model also increases but so does the complexity of the model because it entails increase in the number of rules in the rule base. On the other hand, too few terms will make the model coarse. The determination of the number of fuzzy variables in a linguistic variable has been carried out by first conducting the sensitivity analysis of the linguistic variable. The number of fuzzy variables in a linguistic variable increases with the increase in the sensitivity of the linguistic variable (IEC-1131, 1997; Ross, 2004; Singh and Markeset, 2009).

In the fuzzy logic framework, a fuzzy variable X can be described by its membership function $\alpha(x)$. The membership function $\alpha(x)$ connects the value of input to the degree of compatibility or truth. While developing the membership functions, a number of factors are taken into account, like the extreme values between which the values oscillate the expert opinion of the maintenance engineers, etc. The accuracy of prediction of a model falls with increase in the range of input variables. Hence, it is advantageous to model individual components with the variables within the range it is expected to operate in. The membership functions of the variables can be adapted to a number of shapes, like sigmoidal, Gaussian, bell, etc., but the shape should be justified by the available information. In this work, the triangular and trapezoidal fuzzy sets have been mostly used because they were the most common, easy to use and adequately reflect most of the processes. At this conception stage there is no justification for using any other more complex functions, but in future if the need arises then these functions can be adapted to reflect the available information (IEC-1131, 1997; Ross, 2004; Singh and Markeset, 2009).

Thus, first the number and shapes of each fuzzy variable (also called linguistic terms) in a linguistic variable are determined. Then the variable input value is fuzzified by determining the membership of each fuzzy variable of the corresponding linguistic variable.

Brief description of these parameters is given below.

1. **MIC Mitigation Effectiveness.** In an oil and gas installation, a number of MIC mitigation techniques are implemented. These techniques can be preventive, like injection of biocides, or corrective, like cleaning and water jetting. Based on the experience, plant engineers can subjectively decide if these techniques have been effective or not. For this parameter two linguistic terms – "Effective", and "Ineffective" are considered. The shape of membership functions for this parameter is Singleton.
2. **Water Breakthrough.** In the early life of a field the gas pressure pumps out oil from the well, but in the later stage large volumes of water are injected into the well to displace the remaining oil in the reservoir. Often the water injected into the injection well breaks through to one or more production wells. The introduction of water into the production can significantly increase the possibility of MIC. Since, the effect of water in the multiphase (oil-water-gas) system is difficult to quantify, only two linguistic terms – "Yes", and "No" are

considered. The shape of membership functions for this parameter is Singleton.

3. **Settlement Potential.** Settlement potential indicates the ability of microbes to adhere to the walls and grow. This is dependent upon a number of factors like, periods of low activities due to downtime, presence of dead legs, unfavorable geometries (out of service sections, upstream/downstream sections near a closed valve, U sections, bends, T joints, blocked pipe segments, etc.) and low velocities. Since it is difficult to quantify the effect of these parameters, subjective evaluation by experts taking into account the operational history may be a good approach. For this parameter two linguistic terms – "High" and "Low" are considered. The shape of membership functions for this parameter is Singleton.
4. **Temperature.** While there is considerable uncertainty regarding the temperature range at which MIC takes place, fuzzy logic offers an easy way of customizing the model based on the actual plant data. Hence, to initialize the model it has been assumed that SRB, grows in moderate temperature range of 0-65°C, with optimal growth in the range 25-40°C. Similarly it is assumed that SRA, grows best in the temperature range 60-95°C, with optimal growth in the range 70-85°C. For methanogens, the assumption is that they grow in the range 10-90°C, with the optimum in the range 30-70°C (Andersen 2014). For this parameter three linguistic terms – "High", "Medium", and "Low" for each type of microbe (SRA, SRB and methanogens) are considered. The shape of membership functions for this parameter is Triangular or Trapezoidal (**Figure 1)**.
5. **pH.** Due to the conflicting reports regarding the effect of pH on MIC it is difficult to establish the pH range in which MIC takes place. Based on survey, it is assumed that the MIC can take place in the pH range 3.5-12, with an optimal range of 4.5-6.5 (Andersen, 2014). For this parameter three linguistic terms – "High", "Medium", and "Low" have been considered and the shape of membership functions for this parameter is Triangular or Trapezoidal (**Figure 1)**.
6. **Flow Velocity.** Once microbe colony has developed on the surface of a pipe or equipment it cannot be flushed out just by the flow of the process fluid, but the flow velocity of process fluid can affect the rate of growth of MIC. The effect of velocity on the rate of growth depends also upon the geometry of the plant, hence, the effect has to be studied on the plant to plant basis. In the proposed model three linguistic terms – "High", "Medium", and "Low" have been considered and the shape of membership functions for this parameter is Triangular or Trapezoidal (**Figure 1)**. The shape of the membership functions has been guessed but can be easily modified on availability of more data.
7. **Oxygen Ingress.** While MIC causing microbes are mostly anaerobic in nature, plant observations have shown a significant increase in MIC in the sections that have experienced oxygen ingress in the system. While in a well designed and operated plant oxygen is not expected in the system, there may be a possibility of ingress due to leakages from imperfectly sealed parts, like valves, flanges, pumps, and compressors. The increase in MIC due to the presence of oxygen may be due to existence of both aerobic and anaerobic microbes in biofilms. The aerobic microbes generate conditions that are conducive to MIC attacks by anaerobic microbes (Andersen 2014). Since it is difficult to relate

degree of oxygen ingress on the rate of corrosion, hence, for this parameter only two linguistic terms – "Yes", and "No" are considered. The shape of membership functions for this parameter is Singleton. The effect is accounted for in the rule base by stepping up the corrosion rate to the next linguistic term. Hence, for conditions of temperature, pH and flow velocity if the expected rate of corrosion without oxygen ingress is "Low" then with oxygen ingress it will be "Medium". Similarly, for the conditions of temperature, pH and flow velocity if the expected rate of corrosion without oxygen ingress is "Medium" then with oxygen ingress it will be "High".

8. **Material of Construction.** Most of the metals are susceptible to MIC attacks. MIC has been observed in equipment made of different types of carbon steels, stainless steels, aluminum, etc. (Andersen 2014). Unfortunate, the current knowledge of the role of material on MIC attacks is rather limited, hence, this model has been developed taking into account only the information for carbon steel system.
9. **Availability of Nutrients.** Like any other living organism, microbes require nutrients to survive and grow. Due to the diversity in the types of microbes what constitutes as nutrient is difficult to list, hence, the parameter is not considered in the model and it is assumed that sufficient nutrients are available for them to grow.

Table 1 summarizes list of various parameters that have been considered in the development of the model.

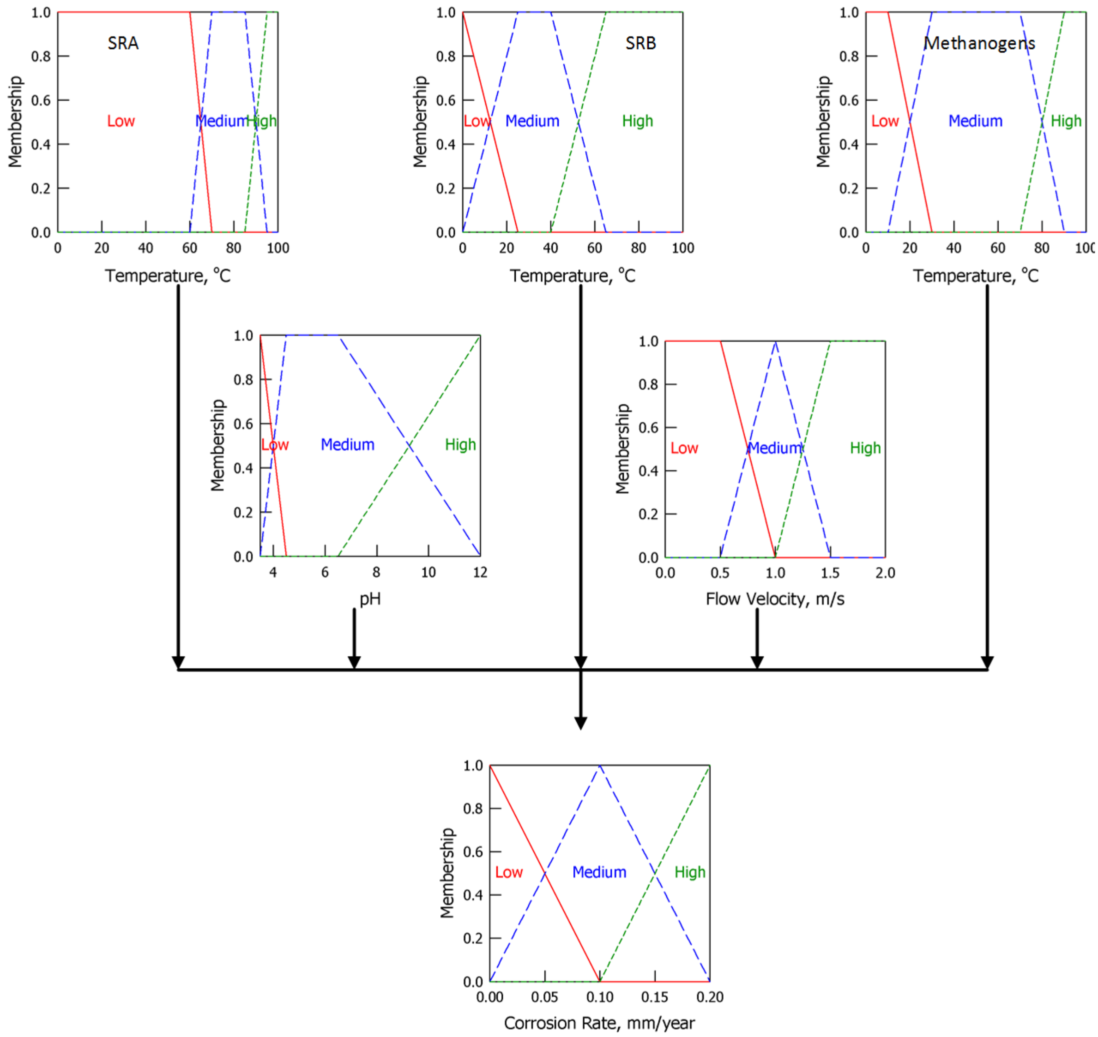


FIGURE 1. Membership functions of inputs and output for the calculation of the corrosion rates.

TABLE 1. List of parameters considered for the development of the MIC corrosion rate model.

	Parameter (Linguistic Variable)	Linguistic Terms (Fuzzy Variable)			Shape of Membership Functions	Usage
1	MIC Mitigation Effectiveness	Effective	Ineffective		Singleton	Possib. of initiation & stable pit growth
2	Water Breakthrough	Yes	No		Singleton	Possib. of initiation & stable pit growth
3	Settlement Potential	Low	High		Singleton	Possib. of initiation & stable pit growth
4	Temperature	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
5	pH	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
6	Flow Velocity	Low	Medium	High	Triangular / Trapezoidal	Calc. corrosion rate
7	Oxygen Ingress	Yes	No		Singleton	Calc. corrosion rate
8	Material of Construction	Not accounted				
9	Availability of Nutrients	Not accounted				

3 Estimation of Possibility of MIC Initiation and Stable Pit Growth

Initiation of corrosion pit may take place soon after the first exposure to corroding environment; but not all the initiated pits will grow or continue to grow. Some of the initiated pits will not grow at all or others will cease to grow after some time. The pits that either do not grow or cease to grow after some time are called "metastable" pits. These metastable pits may meet pit "death" or may re-activate to become stable pits at later stage. It is difficult to identify the pits that would be the stable pits and continue to grow (Melchers, 2005).

While early identification of stable pit may be desirable, it may not be possible to do so. In the proposed model for developing an inspection program, first step is to estimate the possibility of MIC initiation and stable pit growth. Since, it is difficult to develop a reliable quantitative model for the task, hence, a qualitative flow chart based model has been proposed **(Figure 2)**.

If the regular monitoring-inspection-testing (MIT) activities do not identify presence of MIC and the operator is confident regarding the effectiveness of MIC mitigating actions that have been taken then the possibility of MIC initiation and stable pit growth is assumed to be "Low". On the other hand, if the inspection monitoring-inspection-testing (MIT) activities identify the ineffectiveness of MIC mitigating actions then the possibility is considered as "High". For doubtful or unknown cases, the possibility is decided according to the flowchart based on the factors like water breakthrough and settlement potential. More factors may be included in the decision-making flowchart based on the specific installation design and operating conditions.

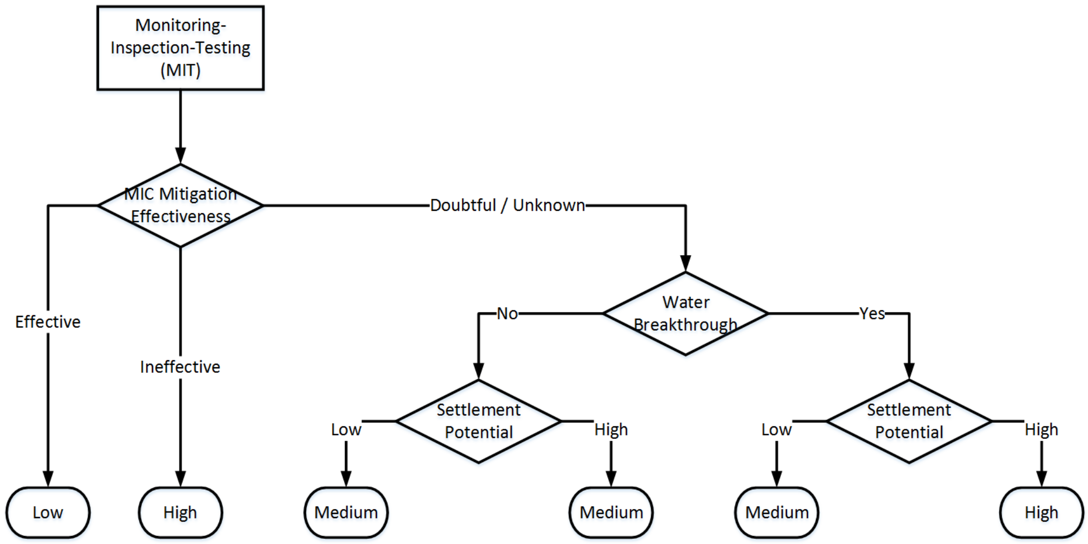


FIGURE 2. Flow chart showing the decision making process for estimation of possibility of stable MIC pit growth.

4 Estimation of Rate of Corrosion

4.1 Development of Rule Base

Linguistic rule base contains the empirical knowledge used by a model. It comprises of a set of linguistic IF-THEN rules. In this work, the rule base is a MISO (Multiple Input Single Output) system consisting of a number of rules linking many inputs with a single output (IEC-1131, 1997; Ross, 2004).

A *linguistic rule* comprises of *linguistic statements* connected by *AND* and a *conclusion*. A linguistic statement consists of a simple basic structure "Linguistic variable – Symbol of Comparison – Linguistic term". An example of a linguistic statement is $temperature\ is\ low\_temperature$. A rule is thus of the form (IEC-1131, 1997; Ross, 2004):

`Rule` R_i : `IF` (linguistic statement or antecedent proposition P_{i1}) `AND` (linguistic statement or antecedent proposition P_{i2}) `THEN` (conclusion or consequent proposition C_i);

For example:

RULE 1 :	IF temperature is medium_temperature AND pH IS medium_pH AND flow_velocity is high_flow_velocity AND oxygen_ingress is no_oxygen_ingress THEN corrosion is medium_corrosion;
RULE 2 :	IF temperature is medium_temperature AND pH IS medium_pH AND flow_velocity is high_flow_velocity AND oxygen_ingress is yes_oxygen_ingress THEN corrosion is high_corrosion;

The truth value of a linguistic statement (a real number between 0 and 1) depends upon the degree of match between the linguistic variable $(temperature)$ and the linguistic term $(medium\_temperature)$ (IEC-1131, 1997; Ross, 2004).

Having decided the structure of the rules, the next step is to generate the rules. The number of rules depends upon the number of linguistic variables and the number of linguistic terms in each variable.

In order to develop the rules for a fuzzy model, information can be collected in two ways: (a) expert opinion of the responsible persons; and (b) measured data. In the first case, the expert knowledge is expressed as a set of linguistic IF-THEN rules. These rules are then fine-tuned using the available input-output data. In the second case, the rules are formulated by clustering the input-output data by dividing the data into the required number of fuzzy partitions and then fine-tuning using the expert knowledge.

Based on the information collected from literature, discussed in **Section 2**, and opinion of experts a set of rules were developed to correlate the rate of corrosion with the variables – temperature, pH, and flow velocity.

4.2 Design of an Inference Engine

The inference engine relates the consequences of the linguistic rule base with membership function values to deduce the output for the corresponding input values. Depending upon the type of operator used in the individual step, different inference engines can be obtained. This model works on the commonly used Mamdani inferencing scheme and uses the MaxMin Inference engine, which uses maximum (MAX) for accumulation and minimum (MIN) for activation. The inference engine consists of three sub-functions (IEC-1131, 1997; Ross, 2004).

Aggregation

In this step, if a rule consists of only one condition (antecedent) then the condition is identical to the rule, however, if the rule consists of a combination of several conditions (antecedents), then all the conditions are aggregated using AND fuzzy logic operator to determine the final degree of accomplishment.

Activation

In this work the first-infer-then-aggregate (FITA) scheme has been adopted, in which the inferences are first made from individual rules, and then these inferences are aggregated together. The degree of membership value of each rule is determined on the basis of the degree of accomplishment of the rule, and then the minimum (MIN) of each element of the Cartesian product of the input and output sets is taken.

Accumulation

The results of all the rules are accumulated (combined) to give the overall result using the maximum (MAX) algorithm.

4.3 Selection of Appropriate Defuzzification Process

In the defuzzification process a representation of the information contained in the output fuzzy set is obtained in the form of a crisp value. While there are a number of techniques for defuzzification, in this model the Centre of Gravity centroid method has been used for calculating the crisp output value from the accumulated membership functions.

4.4 Results of Calculations for Predicting the Rate of MIC Corrosion

Figure 3 shows an example of results of calculation carried out to estimate the rate of corrosion. The input parameters for the calculation were: temperature = 63^{o}C, pH = 6, flow velocity = 1m/s, oxygen ingress = "No". The three curves are the results obtained after accumulation of membership rules that have been satisfied by the input parameters.

Figures 4-6 show the effects of temperature, pH and flow velocity on the estimated MIC corrosion rate for "No" oxygen ingress condition. The MIC corrosion rates were estimated by taking the Centre of Gravity of the accumulated membership functions for different input parameters. The results shown in the figures reflect the intention of the model regarding the effect of the operating conditions on the estimated MIC corrosion rate.

As desired, **Figure 4** shows that the optimum temperatures for MIC corrosion due to SRA, SRB and methanogens depends upon the operating temperature. For SRA the optimum temperature is in the range 70-85^{o}C, for SRB it is 25-40^{o}C and for methanogens it is 30-70^{o}C.

Figure 5 shows that, as modelled, the MIC corrosion rate is high at low flow velocities; and beyond 0.5m/s the corrosion rate decreases with increase in the flow velocity.

Reflecting the intentions of the model, **Figure 6** shows that the optimum range of pH for MIC corrosion to take place is 4.5-6.5; beyond this range on the either side the rate of corrosion decreases.

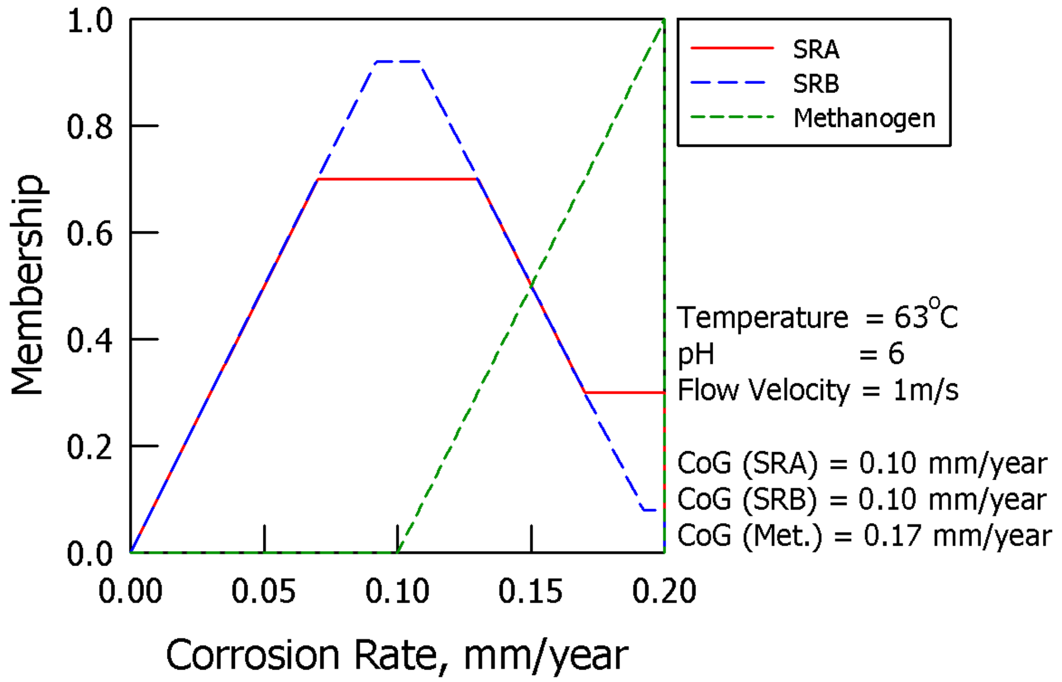


FIGURE 3. Example of results of calculation carried out to predict the rate of corrosion due to SRA, SRB and methanogens for "No" oxygen ingress condition.

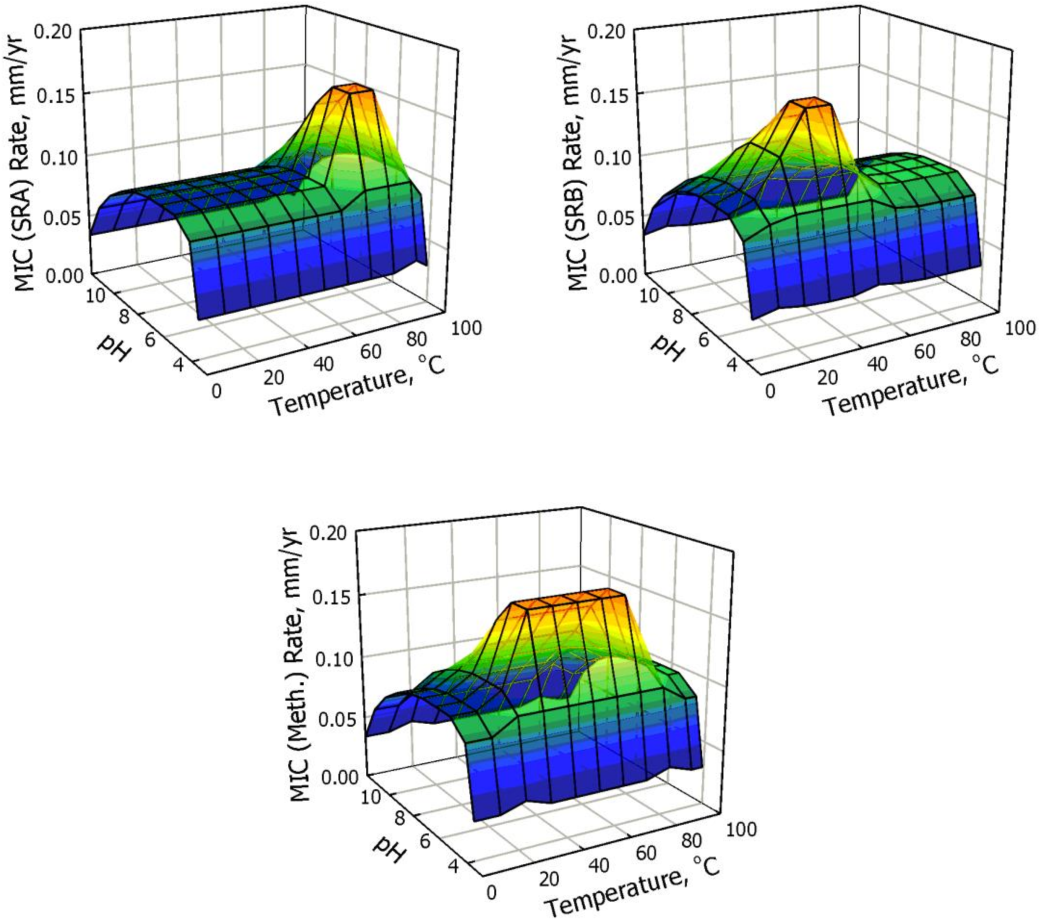


FIGURE 4. Effect of operating temperature and pH on the calculated MIC corrosion rate due to SRA, SRB and methanogens at flow velocity = 0.4m/s and oxygen ingress = “No”.

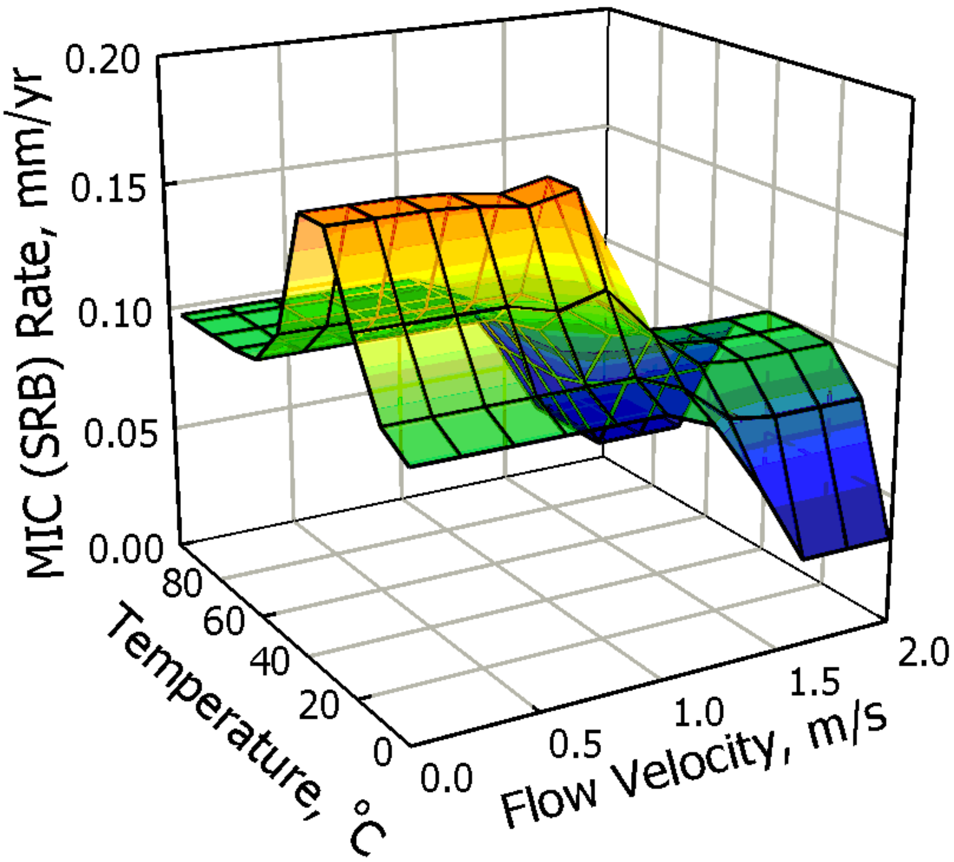


FIGURE 5. Effect of operating temperature and flow velocity on the calculated MIC corrosion rate due to SRB at pH = 6 and oxygen ingress = “No”.

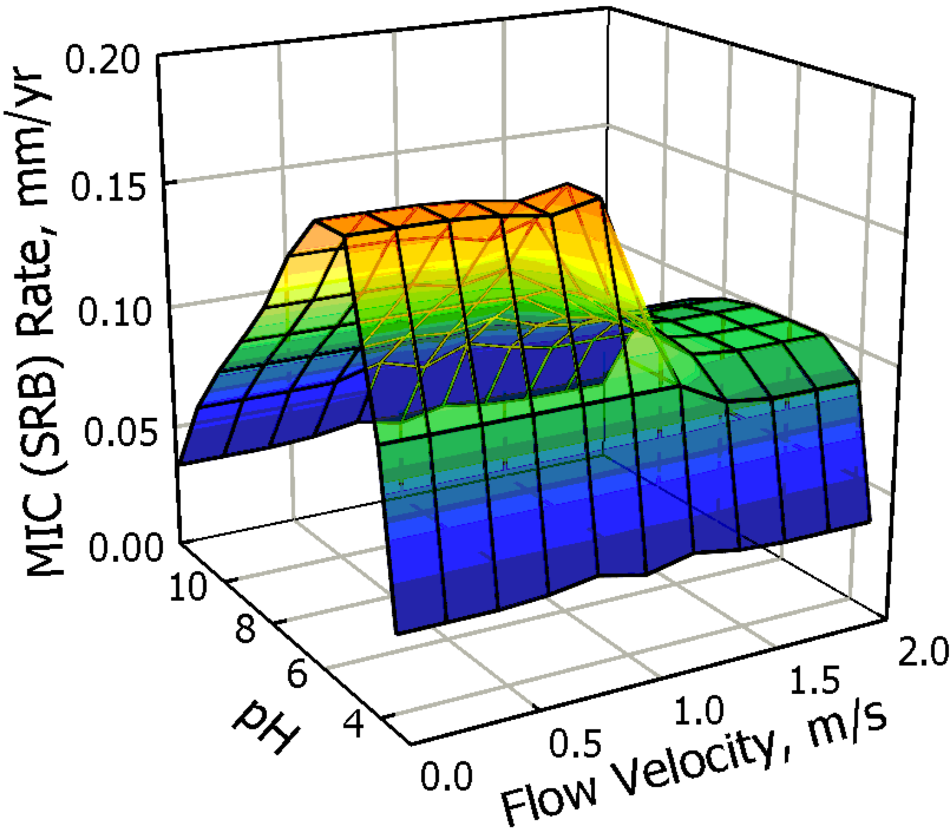


FIGURE 6. Effect of pH and flow velocity on the calculated MIC corrosion rate due to SRB at temperature = 40°C and oxygen ingress = "No".

5 Estimation of Possibility and Necessity of Failure

5.1 Fuzzy Arithmetic

In the possibilistic approach the fuzzy membership function can be interpreted as the possibility distribution function. The α-cut of a fuzzy set X, donated by X_α, is a crisp set that consists of all elements of X having membership value greater than or equal to α (Ayyub and Klir, 2006; Ross, 2004).

The α-cut for a fuzzy set can be represented by (Ayyub and Klir, 2006):

$$X_\alpha = [\underline{x}, \overline{x}]_\alpha = \{x \in X | \underline{x} \le x \le \overline{x}\} \tag{1}$$

Where

$\underline{x} = Lowest\ real\ number\ value\ of\ the\ interval$

$\overline{x} = Highest\ real\ number\ value\ of\ the\ interval$

$\alpha \in [0,1]$

The value of α can be in the range $[0,1]$. The set of all α-$cuts$ of a fuzzy set always forms a nested family of sets and can be formed by incrementally changing the value of α. This α-cut representation of fuzzy sets allows extension of the various properties of crisp sets into fuzzy sets. The properties of the crisp sets that can be extended to the fuzzy sets are called *cutworthy properties* (Ayyub and Klir, 2006).

In other words, according to the possibilistic interpretation, α-cut of the membership function can be considered to be the *fuzzy interval* $[\underline{x}, \overline{x}]$, containing the values whose *likelihood* is α. Thus, as the likelihood increases, the interval between which the values lie decreases, but the certainty that the values will lie within this interval also decreases. Thus, according to **Figure 3** the expected MIC corrosion rate due to SRB certainly lies in the range 0-0.2 mm/year. When the value of α is 0.92, the expected MIC corrosion rate due to SRB lies in the range 0.09-0.11 mm/year, which is the most likely range but is also the least certain range.

The fuzzy operation between the α-cut of two fuzzy sets A and B, donated by $A_\alpha = [\underline{a}, \overline{a}]_\alpha$ and $B_\alpha = [\underline{b}, \overline{b}]_\alpha$, follows the concept of the interval analysis. The basics of this can be given as [Ayyub and Klir, 2006; Ayyub and Chao, 1998]:

$$Addition: \quad A_\alpha + B_\alpha = [\underline{a} + \underline{b}, \overline{a} + \overline{b}]_\alpha \tag{2}$$

$$Subtraction: \quad A_\alpha - B_\alpha = [\underline{a} - \overline{b}, \overline{a} - \underline{b}]_\alpha \tag{3}$$

$$Multiplication: \quad A_\alpha \times B_\alpha = [\min(\underline{a}\underline{b}, \underline{a}\overline{b}, \overline{a}\underline{b}, \overline{a}\overline{b}), \max(\underline{a}\underline{b}, \underline{a}\overline{b}, \overline{a}\underline{b}, \overline{a}\overline{b})]_\alpha \tag{4}$$

$$Division: \quad \frac{A_\alpha}{B_\alpha} = [\underline{a}, \overline{a}]_\alpha \times \left[\frac{1}{\overline{b}}, \frac{1}{\underline{b}}\right]_\alpha \quad if\ 0 \notin [\underline{b}, \overline{b}]_\alpha \tag{5}$$

$$= \left[\min\left(\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\overline{b}}, \frac{\overline{a}}{\underline{b}}, \frac{\overline{a}}{\overline{b}}\right), \max\left(\frac{\underline{a}}{\underline{b}}, \frac{\underline{a}}{\overline{b}}, \frac{\overline{a}}{\underline{b}}, \frac{\overline{a}}{\overline{b}}\right)\right]_\alpha$$

$$Power: \quad A_\alpha^b = [\underline{a}, \overline{a}]_\alpha^b = [\underline{a}^b, \overline{a}^b]_\alpha \tag{6}$$

To apply these concepts of interval analysis, first a value of α is selected. For this value of α the $\alpha\text{-}cut$ of each fuzzy number is determined. Considering all the values located in the $\alpha\text{-}cuts$ for every fuzzy number, the minimum and maximum values of the output function are calculated. This step is repeated for all $\alpha\text{-}cuts$ for $\alpha \in [0,1]$. The results of all $\alpha\text{-}cuts$ are combined to build the fuzzy membership function of the output function (Ayyub and Klir, 2006).

It is relatively easy to apply these rules in the current example. Having found the MIC corrosion rate according to the methodology describes in the previous section **(Section 4)**, estimated depth of corrosion can be found by multiplying the corrosion rate with time. Instead of taking the Center of Gravity (CoG), it is the complete interval that is considered for the calculation according to the **Equation 4**. The results of the calculations are shown in **Figure 7**.

5.2 Calculation of Reliability

In the structural reliability analysis, first of all the limit state function (z) is calculated using (Melchers, 2001):

$$z = d_S - d_P \tag{7}$$

Where

$d_S = Maximum\ allowed\ corrosion\ depth, mm$

$d_P = Measured\ corrosion\ depth, mm$

As the corrosion takes place, the corrosion depth increases; and finally, the failure event (F_i) occurs when the predicted corrosion depth exceeds the maximum allowed corrosion depth $(d_P \geq d_S)$. Thus, to calculate the limit state function, two values are needed: (a) the maximum allowed extent of corrosion (d_S); and (b) the predicted extent of corrosion (d_P). Having decided upon the correlations for d_S and d_P, an appropriate approach for calculating the limit state function is selected.

In this study, the possibility distribution functions of the predicted extent of corrosion (d_P) after different time periods can be obtained according to the MIC rate model described in the **Section 4** and an example of which is shown in **Figure 3**. The maximum allowed extent of depth (d_S) can be obtained from the piping or equipment specification sheet, under the section on maximum allowed corrosion depth, or calculated using the models like those recommended in ASME B31G and DNV RP-F101. In this paper, a simple case wherein the maximum allowed corrosion depth (d_s) is already provided, example 1.5mm, is discussed.

5.3 Calculation of the Possibility and Necessity of Failure

In the possibilistic framework, the fuzzy membership function $\alpha(x)$ of a variable X can be interpreted as the possibility distribution function (**Figure 2**).

The possibility theory use two different measures – possibility measure and necessity measure – for calculating the limit state function (**Equation 1**). The possibility and necessity measures describing the truth of the proposition $(d_S \leq d_P)$ are given by (Guyonnet *et al*., 1999):

$$\Pi(d_S \leq d_P) = \underset{d}{Sup}\, max[\alpha_P(d), \alpha_S(d)] \tag{8}$$

$$N(d_S \leq d_P) = \underset{d}{Inf}\ max[1 - \alpha_P(d), \alpha_S(d)]$$

Where:

Π = *Possibility measure*

N = *Necessity measure*

$\alpha_S(d)$ = *Membership function of* d_S *for any value of* d

$\alpha_P(d)$ = *Membership function of* d_P *for any value of* d

min = *Minimization operator*

max = *Maximization operator*

Sup = *Largest value of* d

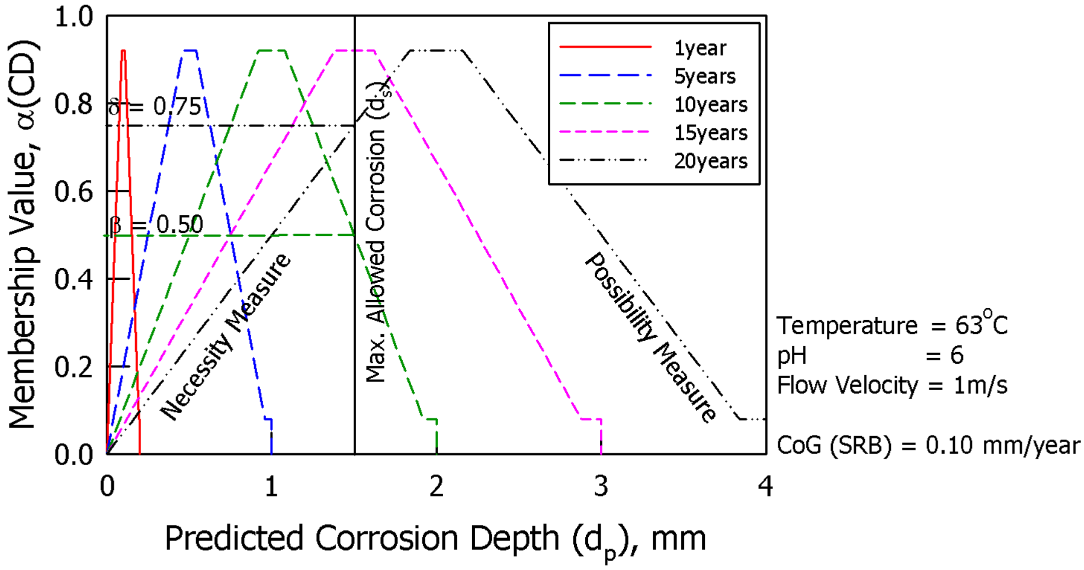
Inf = *Smallest value of* d

The membership function of allowed corrosion depth (d_S) can be expressed as:

$$\alpha_S(d) = \begin{cases} 0 & d < d_S \\ 1 & d \geq d_S \end{cases} \tag{6}$$

The concept is illustrated in **Figure 7**. As time progresses the depth of corrosion, characterized by the spread and Center of Gravity (CoG) of distribution, increases with corresponding increase in the possibility and necessity of failure.

After 1 year	: Possibility = 0;	Necessity = 0.
After 5 years	: Possibility = 0;	Necessity = 0.
After 10 years	: Possibility = 0.5;	Necessity = 0.
After 15 years	: Possibility = 0.92;	Necessity = 0.08.
After 20 years	: Possibility = 0.92;	Necessity = 0.25.



Time 5years	: Possibility = 0;	Necessity = 0.
Time 10years	: Possibility = β;	Necessity = 0.
Time 20years	: Possibility = 0.92;	Necessity = (1-δ).

FIGURE 7. The illustration of possibility distribution of the predicted corrosion depth after different time periods and of possibility and necessity measures.

6 Estimation of Time for Inspection

Having estimated the possibility of MIC initiation **(Section 4)** and the possibility-necessity of failure due to MIC **(Section 5)**, the two need to be combined to obtain time for inspection. Since the two parameters are difficult to combine using any mathematical operator, hence, a system based on matrices has been proposed. **Figure 8** illustrates examples of proposed decision matrices. The values shown in each box can be changed depending upon the operator company's philosophy taking into account the criticality of the equipment. Since, the possibility measure is less conservative than the necessity measure, hence, the matrix based on possibility measure gives more time for inspection.

After modifying the values for time for inspection, the two matrices can also be used separately for different types of systems. For example, possibility measure may be a useful tool for implementing the philosophy of zero-tolerance of accidents, where any possibility of failure has to be eliminated. This would be more suitable for hydrocarbon systems. On the other hand, the necessity measure may be used when the failure of the equipment does not have any significant consequence, for example in case of open drain system.

Possibility of Failure in the Event of MIC Initiation, %					
	High	10-100	4 years	2 years	1 year
	Medium	1-10	4 years	2 years	2 years
	Low	<1	4 years	4 years	4 years
			Low	Medium	High
			Possibility of MIC Initiation and Stable Pit Growth		

Necessity of Failure in the Event of MIC Initiation and Stable Pit Growth, %					
	High	>1	1 year	6 months	3 months
	Medium	0.1-1	1 year	6 months	6 months
	Low	<0.1	1 year	1 year	1 year
			Low	Medium	High
			Possibility of MIC Initiation and Stable Pit Growth		

FIGURE 8. Examples of decision matrices for combining estimation of possibility of MIC initiation and stable pit growth **(Section 4)** with estimation of possibility and necessity of failure due to MIC **(Section 5)** for estimating time for inspection.

7 Conclusions

Preparing an inspection schedule is an important step of an effective RBI program. Unfortunately, the unpredictable nature of MIC corrosion makes precise calculation for time to inspect rather difficult, hence, traditionally, the inspection program for MIC has been mostly developed using expert judgement. This paper presents a methodology for estimating the time for inspection based on the concepts of Fuzzy Logic and possibilistic approach.

The proposed methodology has four steps. In the first step the possibility of MIC initiation and stable pit growth is estimated using a simple flow chart taking into account parameters like water breakthrough and settlement potential. In the second step, the rate of corrosion, in the event of MIC initiation and stable pit growth, is estimated based on the concepts of fuzzy logic. In the third step, the fuzzy membership function of corrosion rate is used to estimate the possibility and necessity of failure as a function of time. Finally, in the fourth step possibility of MIC initiation and stable pit growth and possibility/necessity of failure are combined using subjectively developed decision matrix to estimate the time for inspection.

It is expected that the methodology would help engineers to develop more efficient inspection programs for installations suspected of having MIC.

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