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Prediction models for remaining life assessment of pressure vessels: A comparative analysis of inspection-based and chemical approaches

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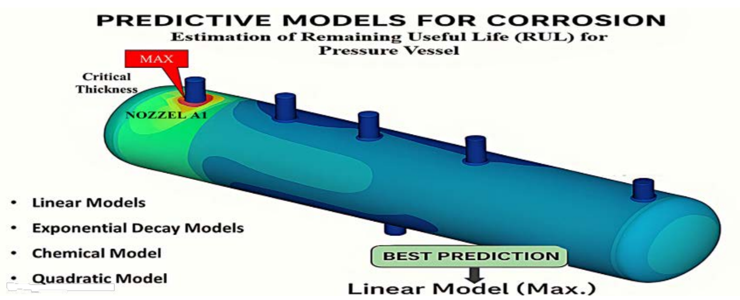
Article



ABSTRACT This study examines the effectiveness of various predictive models for estimating the remaining useful life (RUL) of low-alloy steel pressure vessels subjected to corrosion-induced metal loss. Using API 579-1/ASME FFS-1 standards, linear, nonlinear (quadratic, exponential decay), and chemical models were applied to ultrasonic thickness data collected between 2002 and 2008. The linear model (max.) provided conservative estimates, predicting faster degradation compared to the linear model (avg.), while the quadratic model indicated an accelerating corrosion rate unsuitable for most scenarios. Power and logarithmic models suggested negligible thickness changes over time, potentially underestimating real-world corrosion risks. The chemical model balanced simplicity and accuracy with moderate degradation predictions. Exponential decay models (max. and avg.) demonstrated decreasing corrosion rates over time, with the maximum variant offering more conservative predictions. Results indicated that model selection significantly impacts RUL estimates: linear and chemical models are effective for short-term predictions, while exponential decay models are more accurate for long-term assessments. Critical sections such as Nozzles A1 and A2 were identified as high-risk areas requiring immediate attention. Finite Element Analysis (FEA) is recommended to assess structural integrity further, incorporating stress analysis to guide maintenance and repair strategies. This work provides a comprehensive framework for integrating inspection data, predictive modelling, and structural analysis to enhance safety and optimise maintenance in high-risk industries.

Keywords: Structural Integrity, Corrosion Rate Prediction, Fitness-for-service, Degradation Mechanisms, Pressure vessel

INTRODUCTION

The general corrosion rate and the remaining life assessment of a pressure vessel are some of the main concerns in relation to fitness-for-service. Several methodologies and techniques that offer a wide overview of parameters on the structural integrity and safety operation of pressure vessels have been developed.[1] Fitness-for-Service (FFS) assessments, as outlined in API 579, are commonly used to evaluate the mechanical integrity of pressure vessels and piping systems. These assessments involve quantitative evaluations, often using nondestructive testing methods such as ultrasonic thickness testing, to measure wall thickness and calculate corrosion rates.[2] The corrosion rate, which can vary over time, serves as a benchmark for predicting the remaining life of a component, allowing for the establishment of inspection intervals and maintenance schedules.[3] For instance, in a study involving a pressure vessel at the Basra Oil Company, ultrasonic testing was used to determine wall thickness at multiple locations, leading to a calculated remaining life of over 50 years under current conditions.[4] Similarly, the use of finite element analysis in FFS assessments can provide detailed insights into the structural impacts of corrosion, allowing for more accurate predictions of remaining life and necessary safety measures.[5] The integration of probabilistic approaches in FFS assessments further enhances decision-making by evaluating the reliability of components with metal loss, thus supporting rational decisions regarding repair or continued operation.[6] These methodologies not only improve the accuracy of life assessments but also help in optimizing maintenance schedules, ultimately leading to cost savings and enhanced safety in operations.[7]

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FITNESS FOR SERVICE (FFS)

Fitness-for-service (FFS) is recognized as a qualitative engineering assessment methodology, which is systematically used to evaluate the ongoing operational viability of pressure vessel equipment or, conversely, to ascertain the necessity for its retirement from service.[8] In the year 2000, the American Petroleum Institute (API) took a significant step by publishing the API 579 document, which subsequently laid the groundwork for the endorsement of the fitness-for-service evaluation protocols.[9] However, in a collaborative effort in 2007, the American Society of Mechanical Engineers (ASME) joined forces with API to create a new standardized document that delineates the FFS method; this document is now commonly referred to as API 579-1/ASME FFS-1. The assessment focused on the structural integrity of pressure vessel components that are subjected to local hot spots, and this evaluation adopted a variation of plasticity theory to better understand the implications of thermal stress.[10] Furthermore, to facilitate the quantification of the remaining strength of pressure vessels, an empirical formula known as the Remaining Strength Factor (RSF) was proposed, which utilizes decay shell length as a critical parameter for identifying reference volumes necessary for this assessment.[11]

This work aims to provide an explanation of the procedures involved in assessing local metal loss, specifically focusing on the methodologies outlined in the API/ASME FFS standard and incorporating numerical validation analysis and finite element analysis results that are pertinent to the overall assessment of fitness-for-service.[12,13] The API 579/ASME FFS-1 standard is a widely used methodology for conducting FFS assessments, providing a structured approach to evaluating equipment integrity under various damage mechanisms.[13]

The primary intent of conducting a fitness-for-service assessment is to systematically evaluate the functionality and integrity of numerous structural components, including but not limited to pressure vessels, storage tanks, and piping systems, to ascertain their safety and suitability for continued operational use in an industrial setting.[13] This process not only involves a meticulous examination of the current state of these assets but also requires a thorough analysis of their anticipated reliability and performance over a predetermined duration, such as the timeframe leading up to the next scheduled maintenance shutdown, thus ensuring that any potential risks are identified and mitigated proactively.[14,15] Furthermore, such assessments allow stakeholders to make well-informed decisions regarding the operational status of their equipment, allowing them to determine whether to continue operation, initiate repairs, modify the equipment's rating, implement alterations, or ultimately decommission the assets, while also evaluating the remaining operational lifespan of the equipment to strategically plan future inspection intervals and effectively manage budgeting for associated capital expenditures, thereby minimizing downtime and enhancing the efficiency of any necessary remediation efforts, all while obtaining specialized recommendations regarding any corrective actions that may be warranted.[7,16]

FFS assessments are typically conducted at multiple levels, with increasing complexity and data requirements at each level. For instance, Level 1 assessments involve basic screening using tables and screening curves, while Level 2 and Level 3 assessments involve more detailed analyses and advanced engineering calculations. These assessments are crucial for maintaining asset integrity and optimizing maintenance costs in industries such as oil and gas.[17]

Assessment Techniques

The assessment of local metal loss is organized into a series of systematic steps that include data collection, analysis, and evaluation against established acceptance criteria. The following techniques are commonly used:

A. Data Collection

Accurate measurement of wall thickness is paramount in assessing local metal loss. Techniques such as ultrasonic testing (UT) and radiographic inspection are frequently utilized to obtain precise data on the extent and depth of material loss. These methods help in identifying the extent of metal loss, which is crucial for further analysis.[18]

B. Level 1 Assessment

Level 1 assessment focuses on whether the local metal loss condition exceeds predefined limits based on empirical data and the standard code API 579-1. If it passes this preliminary assessment, further evaluations may be warranted. Level 1 assessment depend on simplified criteria to determine if more detailed assessment is needed.[8]

C. Evaluation Methodology

The below flowchart clarifies the methodology for evaluating the equipment condition

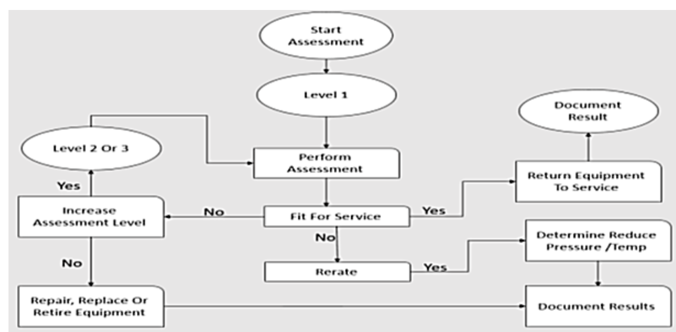

Figure 1. Fitness for service evaluation assessments levels

To connect the gap between the theoretical basis and the practical application, this section transitions from the methodology to a detailed case study. The methodology outlined gives the basis for understanding the predictive models used in assessing the remaining useful life (RUL) of pressure vessels, including linear, nonlinear, and chemical approaches developed to tackle corrosion-induced degradation. The following case study includes the mentioned models to evaluate the structural integrity of a carbon steel pressure vessel under corrosion. This practical example not only validates the theoretical concepts but also focuses on the challenges of ensuring pressure vessel operation safety in industrial environments.

CASE STUDY

A case study of a corroded horizontal pressure vessel manufactured from low-alloy steel. Non-destructive Examination (NDE) and Ultrasonic Testing (UT) were used to inspect a horizontal pressure vessel over a four-year period from 2002 to 2008, focusing on determining the thickness values at 24 different inspection points. The UT technique involved continuous measurements of these predefined grid points, ensuring accurate and detailed data collection, as illustrated in Figure 2 and summarized in Table 1.

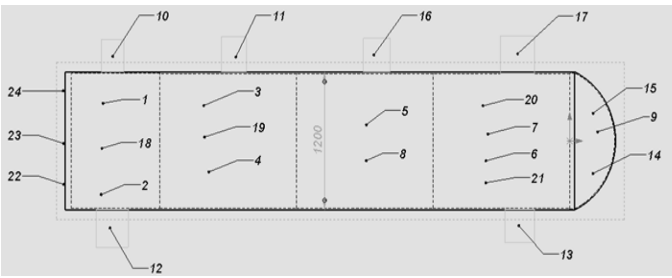

Figure 2. Vessel inspection points

Table 1 Vessel thickness readings

Inspection Points	Year/ thickness value (mm)			
	2002	2004	2006	2008
1	11.5	11.4	11.2	11.1
2	11.6	11.5	11.3	11.3
3	16.2	16	15.9	15.9
4	16.2	16	15.9	15.9
5	16.1	15.7	15.6	15.5
6	16	16	16	15.9
7	16.2	16.1	16	15.9
8	16	15.5	15.4	15.3
9	9.6	9.5	9.4	9.3
10	8.7	8.6	8.5	8.5
11	11	11	10.8	10.8
12	8.3	8.2	7.9	7.9
13	11.4	11.3	11.3	11.2
14	9.5	9.5	9.4	9.3
15	9.7	9.5	8.9	8.6
16	11.5	11.2	11.2	11.1
17	11.3	11.2	11.1	10.8
18	11.9	11.6	11.5	11.4
19	16.2	16.1	15.9	15.8
20	15.9	15.6	15.5	15.4
21	16	15.9	15.7	15.6
22	60	59.7	59.6	59.5
23	60	59.5	59.4	59.3
24	60	59.8	59.7	59.5

Each inspection point was accurately monitored from 2002 to 2008, with thickness readings recorded annually to track material degradation due to corrosion. For instance, Inspection Point 1 showed a gradual decrease in thickness from 11.5 mm in 2002 to 11.1 mm in 2008, while other points, such as Points 22, 23, and 24, demonstrated more significant variations, starting at 60 mm and reducing to approximately 59.3–59.5 mm by 2008. Using the collected data, the corrosion rate for different sections of the vessel was calculated using the formula Corrosion Rate (mm/yr) $=\Delta T/t$, where ΔT represents the change in thickness (mm) and t the time period of observation (years). Based on the analysis, the average corrosion rate across all inspected areas was determined to be 0.065 mm/year, while the maximum corrosion rate reached up to 0.15 mm/year, showing localized areas of accelerated degradation.

MATHEMATICAL MODELS FOR CORROSION PREDICTION IN PRESSURE VESSELS

The assessment of remaining useful life (RUL) for pressure vessels is a critical task to ensure their safe and reliable operation, particularly in environments prone to corrosion-induced degradation. To address this challenge, mathematical models have been developed to predict the rate of material loss over time, enabling engineers to make informed decisions regarding maintenance, inspection, and replacement schedules.[19] Among these models, linear and nonlinear approaches are widely used due to their ability to capture varying degrees of complexity in corrosion behaviour.[20]

A. Linear models

Linear corrosion rate models, assume a constant rate of material loss over time, making them simple and suitable for short-term predictions or scenarios where corrosion rates remain fairly stable.[21] These models rely on basic equations like Remaining Thickness=T0−CR·t, where T0 is the initial thickness, CR is the corrosion rate, and t is time. While linear models provide quick estimates, they often fail to account for real-world complexities, such as variations in environmental conditions or non-uniform corrosion patterns.[22]

In contrast, nonlinear models are essential for capturing the complexities of corrosion behavior, particularly in scenarios where corrosion rates vary over time. The quadratic model (y=a·t^2+b·t+c) is used to represent accelerating corrosion, making it suitable for situations where degradation increases with time. This type of model is particularly relevant in environments where the corrosion rate accelerates over time due to factors like increased exposure to corrosive substances.[23]

B. Power model

The power model (y=a·t^b) describes exponential increases in corrosion, reflecting environments where degradation accelerates rapidly, which may be critical in high-corrosion environments such as chemical plants or marine structures. This model is effective in capturing the rapid degradation observed in such environments, where the corrosion rate can significantly impact structural integrity. Studies have shown that nonlinear models like the power model are crucial for predicting corrosion in complex environments, where linear models may not accurately capture the dynamics of degradation.[24]

C. Logarithmic model

The logarithmic model (y=a·ln(t)+b) accounts for slower corrosion rates as time progresses, ideal for cases where degradation slows down over extended periods, as seen in certain materials that develop protective oxide layers over time. This model is beneficial for predicting long-term corrosion behaviour in materials that exhibit self-limiting corrosion processes.[25] For instance, probabilistic models of corrosion have been developed to account for the stochastic nature of pitting corrosion, which often follows a logarithmic trend.[26]

D. Exponential Decay model

The exponential decay model (y=T0·e^(-kt)) reflects decreasing corrosion rates, providing accurate predictions for scenarios where material loss diminishes over time, offering balanced predictions for long-term assessments.[27] This model is particularly useful in situations where protective coatings or environmental changes lead to reduced corrosion rates over time. Nonlinear models, such as those proposed for AC-induced corrosion and corrosion fatigue, demonstrate the importance of accounting for the complex interactions between environmental factors and material degradation.[28]

Both linear and nonlinear models play essential roles in fitness-for-service (FFS) evaluations, which are governed by standards such as API 579-1/ASME FFS-1 (2016). These standards emphasize the importance of selecting appropriate models based on the specific conditions and time horizons of interest. Furthermore, advancements in computational tools and experimental techniques continue to enhance the accuracy and applicability of these models, paving the way for improved life assessment methodologies.[29] The following section was selected as a base for conducting the linear and nonlinear models as per Figure 3.

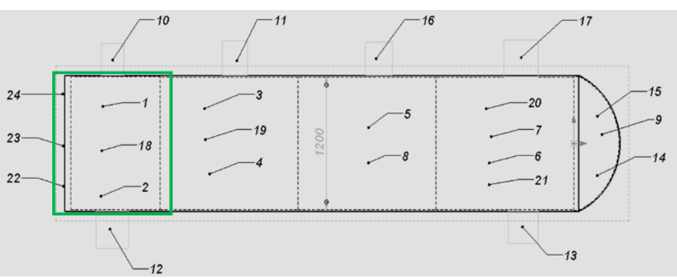

Figure 3. Pressure Vessel Section 1

Table 2 Pressure vessel section 1 thickness

Inspection Points	Year/thickness value (mm)			
	2002	2004	2006	2008
1	11.5	11.4	11.2	11.1
2	11.6	11.5	11.3	11.3
18	11.9	11.6	11.5	11.4

Mathematical models are applied to predict the thickness of a material over time under corrosion. These models include both linear and nonlinear approaches for two different corrosion rates: CR=0.065 mm/year and CR=0.15 mm/year. The choice of model depends on whether the corrosion process is assumed to occur at a constant rate (linear) or if it varies with time (nonlinear). Each model is derived and presented below, along with its significance.

Inspection-Based Models

A. Linear Model

The linear mathematical model is a straightforward and widely used approach for predicting the remaining life of pressure vessels based on uniform corrosion rates.[30] In this case, two linear models are considered: one for the average corrosion rate of 0.065 mm/year and another for the maximum corrosion rate of 0.15 mm/year. The general equation for the linear model is expressed as

$$\mathrm{T(t)} = \mathrm{T_0} - \mathrm{CR.t} \quad [1]$$

where T0 represents the initial thickness, CR is the corrosion rate, and t is the time. This model assumes that the material thickness decreases uniformly over time at a constant rate, making it particularly suitable for scenarios where corrosion progresses consistently without significant variation.

For this analysis, the initial thickness (T0) is assumed to be 11.5mm as per table 1. The equations for the linear model are derived based on the given corrosion rates:

- For the average corrosion rate of 0.065 mm/year, the equation is

$$\mathrm{Tavg(t)} = 11.5 - 0.065.\mathrm{t} \quad [2]$$

- For the maximum corrosion rate of 0.15 mm/year, the equation is

$$\mathrm{Tmax(t)} = 11.5 - 0.15.\mathrm{t} \quad [3]$$

B. Non-Linear models

Nonlinear models are essential for capturing the complexities of corrosion behavior, particularly in scenarios where corrosion rates vary over time. The following models will be used.

The quadratic model (*y*=*a*·*t*^2+*b*·*t*+*c*) is used to represent accelerating corrosion, making it suitable for situations where degradation increases with time.[31] The power model (*y* =*a*·*tb*) describes exponential increases in corrosion, reflecting environments where degradation accelerates rapidly, which may be critical in high-corrosion environments such as chemical plants or marine structures. The logarithmic model (*y*=*a*·ln(*t*)+*b*) accounts for slower corrosion rates as time progresses, ideal for cases where degradation slows down over extended periods, as seen in certain materials that develop protective oxide layers over time.

The exponential decay model T(t)=T0e−kt, where k is the decay constant that controls the rate of thickness loss, the decay constant k is related to the corrosion rate (CR) through the following relationship:

CR=ΔT/Δt,

ΔT=T0−T (∞),

ΔT is the total thickness lost over the total time Δt

The model reflects decreasing corrosion rates, providing accurate predictions for scenarios where material loss diminishes over time, offering balanced predictions for long-term assessments.[32] Together, these nonlinear models offer more precise and flexible assessments of remaining life compared to linear approaches, especially for long-term predictions or complex environmental conditions, as highlighted in comparative studies of pressure vessel life assessment methodologies.

Chemical Corrosion Rate Model

Corrosion is a complex electrochemical process that leads to the degradation of metallic materials when they come into contact with their environment. This process involves the transfer of electrons from metal atoms to suitable electron acceptors, such as oxygen or acids, often facilitated by water acting as a medium for ion transport.[33] The rate at which corrosion occurs is influenced by a variety of factors, including material properties, environmental conditions, and external influences such as temperature, pH, ion concentrations, flow velocity, and microbial activity.[34]

Accurate prediction of corrosion rates is crucial for designing durable structures, ensuring safety, and optimizing maintenance schedules in industries such as oil and gas, water treatment, and infrastructure development.[35] Electrochemical techniques, including polarization diagrams and impedance measurements, are commonly used to analyse and predict corrosion processes. Understanding the detailed electrochemical mechanisms and the effects of environmental factors on corrosion kinetics is essential for developing effective corrosion prevention strategies.[36]

To model corrosion rates, empirical equations based on the Arrhenius relationship and modified by environmental factors are widely used.[37] These models incorporate key parameters such as activation energy (Ea) for moderate aggressive water, pre-exponential factor (K), and correction factors for pH, dissolved oxygen, chloride concentration, pressure, flow velocity, and microbial activity. For instance, the general form of the corrosion rate equation can be expressed as:

$$\mathrm{CR} = \mathrm{K}.\,\mathrm{e}^{\left(\frac{\mathrm{E_a}}{\mathrm{RT}}\right)}.\,\mathrm{f(pH)}.\,\mathrm{f(ion\ concentration)} \cdot \mathrm{f(pressure)} \cdot \mathrm{f(flow)} \cdot \mathrm{f(MIC)} \qquad [4]$$

where CR represents the corrosion rate, R is the universal gas constant, T is the absolute temperature, and the various f terms account for specific environmental influences. In the context of low-alloy steel**,** commonly used for pipelines and structural applications, understanding the impact of water environments is particularly important. Water systems often contain dissolved oxygen, chlorides, sulfates, and other ions that accelerate corrosion processes. Additionally, microbiologically influenced corrosion (MIC) caused by sulfate-reducing bacteria (SRB) or iron-oxidizing bacteria (IOB) can significantly enhance localized corrosion rates. Flow velocity also plays a crucial role by affecting mass transfer rates and oxygen availability at the metal surface. A detailed comparison has been made comparing the proposed model to other models used for corrosion rate prediction based on several factors in Table 3.

The following equations to calculate the corrosion rate of low-alloy steel 09G2S with an industrial water environment inside the vessel, the environmental conditions for the chemical model are assumed constant over the study period, based on average field measurements, validated against LPR data to ensure accuracy. The below table includes the operating parameters and water analysis as per the operating conditions and project specifications as per Table 4.

Table 4 Input Data

Parameter	Symbol	Value	Unit
Temperature	T	60	°C
pH	pH	5.5	-
Chloride Concentration	$[Cl^-]$	150	mg/L
Dissolved Oxygen	$[O_2]$	8	mg/L
Sulfate Concentration	$[SO_4^{2-}]$	50	mg/L
Pressure	P	10	bar
Flow Velocity	v	2.0	m/s
Activation Energy	Ea	$6\text{x}10^4$	J/mol
Pre-exponential Factor	K	$6\text{x}10^6$	mm/year
Microbial Activity Factor	f(MIC)	3	

1.Arrhenius equation[37]

$$\mathrm{CR} = \mathrm{K}.\,\mathrm{e}^{\left(\frac{\mathrm{E_a}}{\mathrm{RT}}\right)} \qquad [5]$$

where E is $E_a$effective activation energy, R gas constant, K Pre-exponential Factor and T the temperature

2.pH-Dependent Factor f(pH):

For mildly acidic (industrial) water with a pH of 5.5:

$$\mathrm{f(pH)} = 1 + \alpha \cdot (\mathrm{pH} - 7)2 \qquad [6]$$

Where α is the pH coefficient

3.Ion Concentration Factor f (ion concentration):

$$\mathrm{f(ion\ concentration)} = 1 + \beta \cdot [\mathrm{O2}] + \gamma \cdot [\mathrm{Cl}] + \zeta \cdot [\mathrm{SO42}] \qquad [7]$$

Where: β is the Oxygen Coefficient, γ Chloride Coefficient, ζ Sulfate Coefficient.

4.Pressure-Dependent Factor f(pressure):

At a pressure of 10 bar

$$\mathrm{f(pressure)} = 1 + \delta \cdot (\mathrm{P} - 1) \qquad [8]$$

Where: δ is the Pressure Coefficient

5.Flow Velocity Factor f(flow):

For a moderate flow velocity of 2 m/s:

$$\mathrm{f(flow)} = 1 + \epsilon \cdot \mathrm{vf} \qquad [9]$$

Where: ϵ is the Flow Coefficient

6.Microbial Activity Factor f(MIC):

Table 3: Chemical Prediction Models Comparison

Feature	Proposed Chemical Model	Linear Regression Model	Empirical Models	Arrhenius-Based Model	Machine Learning Models	Non-Linear Exponential Decay Model [41]	Polynomial Regression Model [42]
Mathematical Basis	Combines Arrhenius equation with functional dependencies for pH, ion concentration, pressure, flow, MIC, etc.	Assumes a linear relationship between corrosion rate and time [first-order approximation] [43]	Derived from experimental data; uses polynomial, power-law, or exponential relationships [env ironment specific] [4445]	Based on the Arrhenius equation to model temperature-dependent reaction rates [46]	Uses algorithms like ANN, decision trees, or SVMS [data-driven approach] [4748].	Based on exponential decay to model corrosion rate as a function of pH and immersion time.	Uses polynomial equations (e.g., quadratic) to fit non-linear experimental data.
Key Equation	CR=K.e^((E_a/RT)). F(pH). F (ion concentration) ·f(pressure)·f(flow)·f(MIC)	CR=β0+β1t+ϵ	CR=a·tb or CR=a·e−bt.	CR=A·e−rtea, where A is the pre-exponential factor [49]	No fixed equation; depends on training data and algorithm (e.g., ANN weights).	CR=a·e−bt+u, where u account s for random error.	CR=a·t2+b·t+c
Independent Variables	Temperature (T), pH, Ion concentration, Pressure, Flow, MIC Factors	Time (t)	Time (t) Environmental factors (e.g., pH, chloride concentration).	Temperature (T)	pH, temperature, pressure, flow velocity, material properties.	pH of medium Immersion time (t).	Time (t) Operational parameters (e.g., flow rate, pressure).
Input Parameters	Material properties (K ,Ea), environmental factors (pH, ions, MIC), operational factors.	Minimal: initial thickness, time, and material loss [50].	Experimentally derived constants (e.g., a, b) for specific environments.	Activation energy (Ea), temperature (T), and pre-exponential factor (A).	Large datasets with features like pH, temperature, and material properties [high -dimensional].	A,b,u (from experimental fitting), immersion time, pH.	A,b,c (polynomi al coefficients), operational parameters (e.g., flow rate).
Accuracy	High: Captures complex environmental interactions and effects accurately.	Moderate: Suitable for stable environments but fails in dynamic conditions.	Moderate to High: Depends on experimental data quality.	Moderate: Accurate for temperature-driven reactions only.	Very High: Captures non-linear relationships and variable interactions.	High: Effective for systems following exponential decay trends.	High: Captures non-linearities but risks overfitting without validation.
Data Requirements	Extensive: Requires detailed environmental and operational parameters as inputs.	Minimal: Time-series thickness measurements.	Moderate: Experimental data for specific environments/mat erials.	Minimal: Requires temperature and activation energy.	High: Diverse datasets (lab/field) for training.	Moderate: pH and immersion time data.	Moderate: Operational parameters (e.g., flow rate, pressure).
Predictive Capability	Excellent for dynamic environments with multiple interacting factors (e.g., oil & gas pipelines).	Suitable for short-term predictions in stable conditions but inaccurate over long periods or dynamic settings.	Good within the range of experimental conditions but poor extrapolation outside those ranges	Limited to systems where temperature is the dominant factor influencing corrosion rates.	Excellent for complex systems with non-linear relationships but depends heavily on dataset quality	Excellent for predicting corrosion in acidic environments for materials like mild steel, with limited data	High Predictive Capability in specific environments, but can be unstable if not properly applied

Assuming moderate microbial activity

$$CR = K.e^{\left(\frac{E_a}{RT}\right)}.f(pH).f(ion\ concentration)\cdot f(pressure)\cdot f(flow)\cdot f(MIC)$$

CR = 0.074 mm/year

The proposed corrosion rate model values were consistent with existing literature, which reports similar corrosion rates for mild steel in water environments. To validate the model, the corrosion of steel in the permeates was benchmarked against the corrosion of steel in industrial water used in daily refinery operations. Using the linear polarization resistance (LPR) method, the corrosion rate of steel in the permeates was found to range from 0.053 ± 0.006 mm/y to 0.123 ± 0.011 mm/y under aerated conditions, demonstrating a comparable corrosion behavior to that observed in the refinery's industrial water.[38] Future studies could incorporate dynamic environmental data to enhance model robustness, especially for long-term predictions.

MATHEMATICAL MODELS RESULTS

The results of the inspection-based model and chemical-based model are illustrated in Figure 4

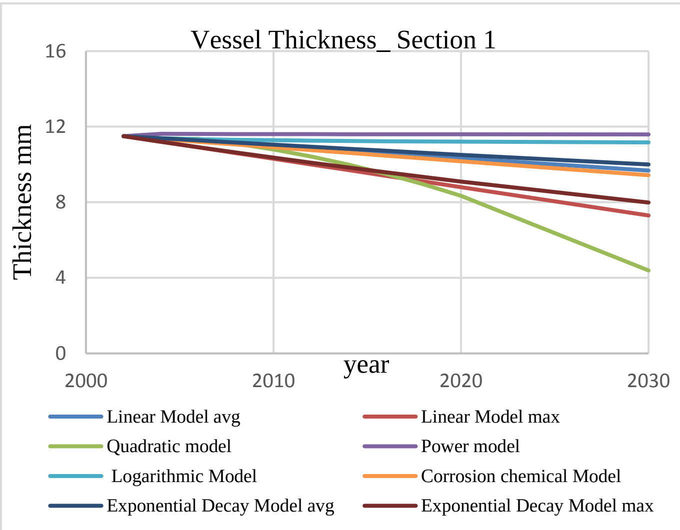

Figure 4. Models output

- The Linear Model (Max.) predicts more rapid degradation compared to the Linear Model (Avg.), reflecting a conservative estimate.
- Quadratic Model: Shows accelerating degradation, with the remaining thickness decreasing rapidly after 2020.
- Power Model and Logarithmic Model: Predicts almost no change in thickness over time, suggesting minimal corrosion. This may not reflect real-world scenarios where corrosion rates typically increase or decrease.
- Chemical Model: Combines aspects of both linear and nonlinear models, showing moderate degradation over time. Provides a balance between simplicity and accuracy.
- Exponential Decay Models (Average and Maximum): Show decreasing corrosion rates over time, with the remaining thickness approaching a stable value. The exponential decay (max.) model provides a more conservative estimate, predicting lower remaining thickness compared to the average model.

Remaining Life Assessment: Thickness Approach

The remaining life of a component can be determined based upon computation of a minimum required thickness for the intended service conditions.[8] The results are shown in Figure 5 for corrosion rate values and Figure 6 for remaining life for each model.

$$\textbf{Remaining life} = \frac{\textbf{Tintial} - \textbf{Tmin}}{\textbf{Corrosion Rate}} \quad [10]$$

$$\textbf{Corrosion Rate} = \frac{\textbf{Tintial} - \textbf{Tmin}}{\textbf{Years}} \quad [11]$$

Where:

T initial: Initial thickness measured of the material (mm).

T min: Minimum allowable thickness (mm)

CR: Corrosion rate (mm/year).

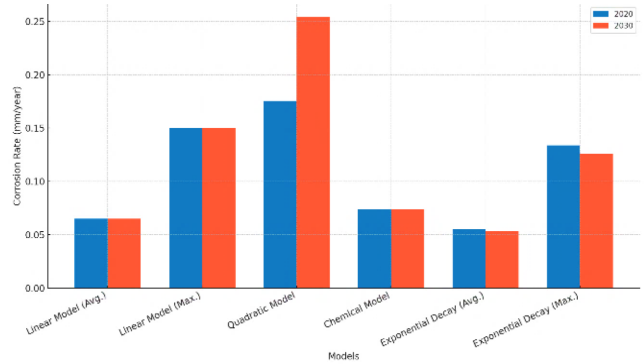

Figure 5. Corrosion Rate Comparison (2020 vs 2030)

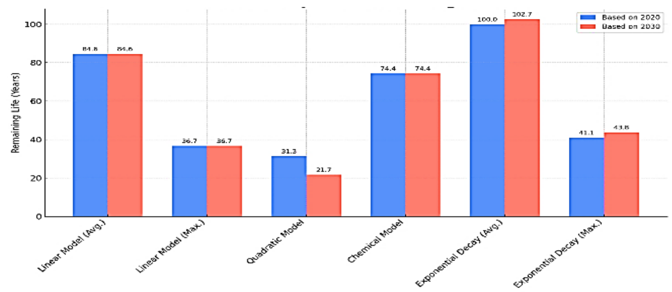

Figure 6. Remaining Life Comparison (2020 vs 2030)

The selection of model significantly impacts the estimated remaining useful life (RUL). For short-term assessments, linear and chemical models are suitable, while for long-term predictions, exponential decay and chemical models offer better accuracy. Conservative estimates, particularly important for critical systems, can be achieved using the linear model (max.) or exponential decay (max.). The quadratic model predicts rapid failure, making it unsuitable for most scenarios unless accelerating corrosion is confirmed. Power and logarithmic models may overestimate remaining life in environments with significant corrosion.

INSPECTION-BASED MODELS

To further validate the accuracy of the inspection-based models (linear model avg., linear model max., exponential decay avg., and exponential decay max.), a comparative analysis was conducted using thickness measurement data from three pressure vessels over the period from 2006 to 2011, as reported in the pervious study.[39] The validation focused on comparing the predicted thickness values from each model against the actual measured thickness data as per Figure 7,with the total absolute error used as the metric for accuracy as per Figure 8.

Validation Results

a. Vessel 1:

The linear model (max.) outperformed all other models, achieving the lowest total absolute error of 0.11. This suggests that the linear model (max.) is particularly effective for vessels exhibiting higher corrosion rates or more aggressive degradation patterns.

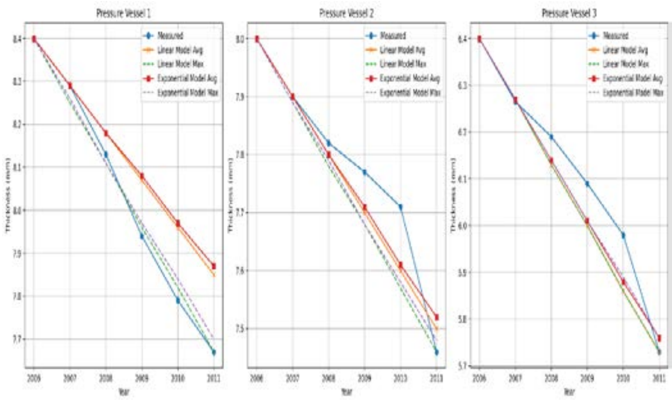

Figure 7. Inspection based models' validation

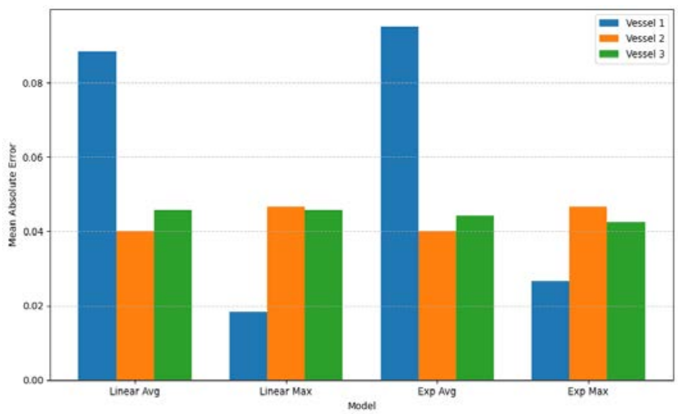

Figure 8. Models Mean absolute error

b. Vessel 2:

Both the linear model (avg.) and exponential decay model (avg.) performed equally well, with the lowest total absolute error of 0.24. This indicates that these models are suitable for vessels with moderate and consistent corrosion behaviour.

c. Vessel 3:

The exponential decay model (max.) provided slightly better predictions than the other models, with the lowest total absolute error of 0.255. This demonstrates the model's ability to capture more complex corrosion dynamics, particularly in environments where corrosion rates vary over time.

Overall Findings:

- The validation results highlight that the accuracy of the models varies depending on the vessel and its specific corrosion behaviour.
- The linear model (max.) and exponential decay model (max.) tend to provide more accurate predictions in most cases, particularly for vessels with higher or accelerating corrosion rates.
- These findings align with the conclusions drawn from the case study, further reinforcing the importance of selecting the appropriate model based on the operational conditions and corrosion characteristics of the vessel.
- For short-term assessments or vessels with stable corrosion rates, the linear model (avg.) and exponential decay model (avg.) are suitable choices due to their simplicity and reasonable accuracy.
- For long-term predictions or vessels with more aggressive corrosion behaviour, the linear model (max.) and exponential decay model (max.) are recommended, as they provide more conservative and accurate estimates.

LEVEL 1 ASSESSMENT FOR THE VESSEL

In evaluating the corrosion rate across the entire vessel's different sections, two distinct models will be applied: the linear model and a nonlinear model (excluding quadratic, power, and logarithmic models). The analysis will utilize specific corrosion rate values as outlined below. For the linear model and nonlinear model, the following corrosion rate values will be used:

- Linear model max. with corrosion rate: 0.15 mm/year
- Exponential Decay model maximum will be used with the corrosion rate (0.15 mm/year) to calculate the decay constant in the exponential decay model.

A. Step 1 Determine the minimum required shell wall thickness at the circumferential and longitudinal planes.

$$\mathbf{T^{c}_{min}} = \frac{\mathbf{P\,R}}{\mathbf{(SE-0.6P)}} \qquad [12]$$

$$\mathbf{T^{L}_{min}} = \frac{\mathbf{P\,R}}{\mathbf{(2SE+0.4P)}} \qquad [13]$$

The minimum wall thickness calculations for other vessel sections (nozzles, head, etc.) are as per pressure vessel design code ASME Section VIII and API 579-1 Annex 2C.

B. Step 2: Remaining Thickness Ratio

Minimum Required Thickness

$$t_{min} = \max\left(\mathrm{t^{c}_{min}}, \mathrm{t^{L}_{min}}\right) \qquad [14]$$

C. Step 3: Level 1 Acceptance criteria for Minimum Measured Thickness

$$t_{mm} - FCA \geq \max[0.5t_{min}, t_{\mathrm{lim}}] \qquad [15]$$

$$t_{min} = \max\left(\mathrm{t^{c}_{min}}, \mathrm{t^{L}_{min}}\right) \qquad [16]$$

$$t_{\mathrm{lim}} = \max\left[\,0.2t_{nom}\,, 2.5\ \mathrm{mm}\right] \qquad [17]$$

Use the formula for future corrosion allowance (FCA), which is typically the product of the corrosion rate and the future service period.[40]

FCA=Corrosion Rate x Future Service Period [18]

D. Step 5 Calculating remaining life

Table 5: Linear Model max results, FCA = 3 mm

Sections	Measured thickness t_{mm}	t_{min}	year	Minimum predicted thickness (mm)	Corrosion Rate mm/year	Remaining life	$t_{\lim}$	$\max[0.5t_{min}, t_{\lim}]$	$t_{mm} - FCA \geq \max[0.5t_{min}, t_{\lim}]$
Shell 1	11.5	6.0		8.8		37	2.5	3	PASS
Shell 2,3,4	16.1	8.5		13.4		50	2.8	4,265	PASS
elliptical head 5	9.5	4.5		6.8		34	2.5	2.5	NOT PASS
Nozzles N1, N2, N3, N4	11	7.0	2020	8.3	0.15	27	1.6	3.5	PASS
Nozzle A1	8.3	5.0		5.6		22	1.4	2.5	NOT PASS
Nozzle A2	8.7	5.0		6		25	1.4	2.5	NOT PASS

Table 6: Exponential Decay Model max, FCA = CR * 20 years

Sections	Measured thickness t_{mm}	t_{min}	year	Minimum predicted thickness (mm)	Corrosion Rate mm/year	Remaining life	$t_{\lim}$	$\max[0.5t_{min}, t_{\lim}]$	$t_{mm} - FCA \geq \max[0.5t_{min}, t_{\lim}]$
Shell 1	11.5	6.0		9.09	0.13	41	2.5	3	PASS
Shell 2,3,4	16.1	8.5		13.63	0.14	55	2.8	4,265	PASS
elliptical head 5	9.5	4.5		7.15	0.13	39	2.5	2.5	NOT PASS
Nozzles N1, N2, N3, N4	11	7.0	2020	8.61	0.13	30	1.6	3.5	PASS
Nozzle A1	8.3	5.0		6	0.13	26	1.4	2.5	NOT PASS
Nozzle A2	8.7	5.0		6.28	0.13	28	1.4	2.5	NOT PASS

Where:

t^c_{min}	Minimum Thickness At The Circumferential	t^L_{min}	Minimum Thickness At The Longitudinal
P	Design pressure	t_{mm}	Minimum thickness reading
Rc	Pressure Vessel Radius	FCA	Future Corrosion Allowance
S	Material allowable stress	$t_{\lim}$	Limiting thickness
E	Weld efficient factor	T initial	Thickness reading of the material (mm).
t_{min}	Minimum Required Thickness	CR	Corrosion Rate (mm/year).

E. Final Results

The results for the linear model and the exponential decay model are illustrated in table 5 and table 6

RESULTS ANALYSIS

Both models consistently identify Nozzles A1 and Nozzles A2 as critical sections requiring attention, though the exponential decay model predicts slightly longer remaining lives for these sections compared to the linear model.

The exponential decay model provides more realistic predictions for sections with non-linear corrosion behaviour, while the Linear Model offers simplicity and ease of use for stable corrosion trends.

The analysis highlights the need for action on Section 5 and Nozzles A1 and A2, which are at risk of failure due to corrosion. Finite Element Analysis (FEA) is recommended to further evaluate the structural integrity of these components and guide mitigation efforts. By incorporating corrosion effects and stress analysis, FEA will provide a comprehensive understanding of the risks and support informed decision-making for maintenance and repair.

LEVEL 3 ASSESSMENT: FINITE ELEMENT ANALYSIS (FEA)

Level 3 assessments involve detailed stress analysis techniques to assess components with general or local metal loss. These advanced methods are crucial for evaluating the integrity of pressure vessels, piping, and tanks under various loading conditions.[11] In the case of the Level 3 analysis, methods for numerical stress analysis, such as the finite element analysis (FEA), are preferred to ensure accurate evaluation of the remaining strength. Using FEA, the limitations associated with Level 1 and Level 2 analyses with respect to defect handling and remaining strength estimation can be eliminated. Further, the results obtained from finite element analysis based on the actual three-dimensional (3D) profile of the local thin area should be considerably reliable.[41]

RESULTS AND DISCUSSION

The minimum and maximum thicknesses of the vessel walls and nozzles are taken according to the values of linear model max, as it shows the lowest thickness predictions, and the vessel modelling results are shown in Figure 9 and Figure 10.

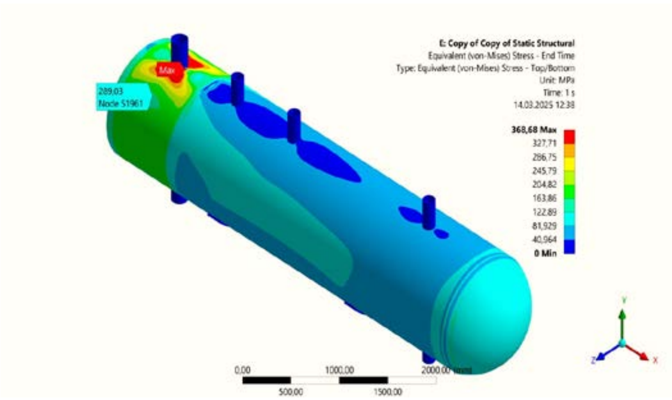

Figure 9. Vessel finite element model

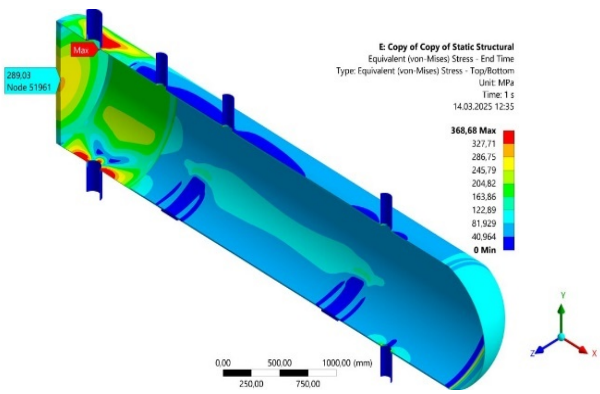

Figure 10. Vessel finite element cross section

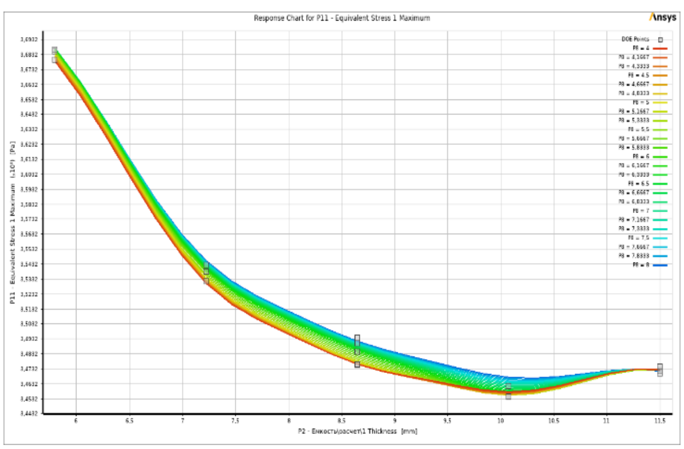

Figure 11. Stresses at the joint of the vessel body Section 1 (shell 1).

Figure 11 shows the maximum stresses were 368 MPa with a yield strength of 345 MPa. Localization of maximum stresses at the joint of the nozzle and the body with a vessel wall thickness of t ≈ 5.8 mm, and a pipe thickness of t ≈ 6.5 mm

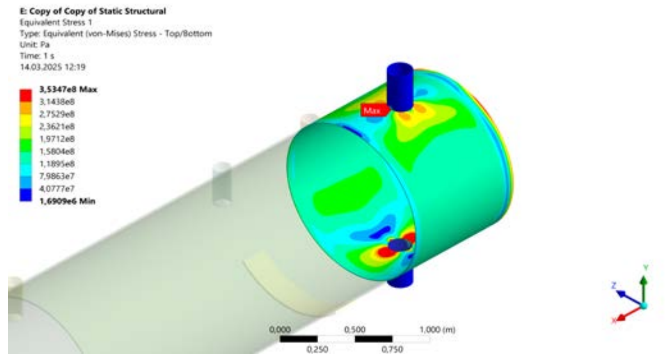

Figure 12. Stress in the first section with a nozzle A1 thickness of 6 mm

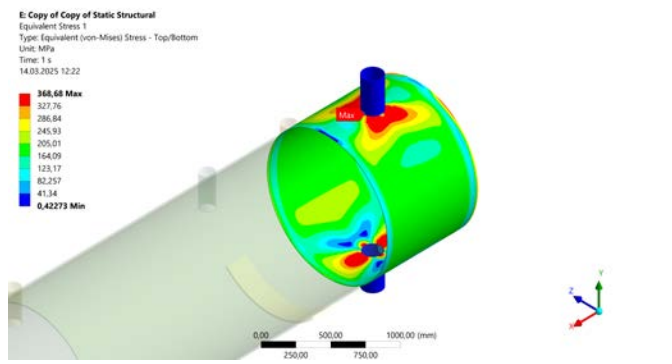

Figure 13. Stresses in the first section with a nozzle A2 thickness t ≈ 5.6 mm

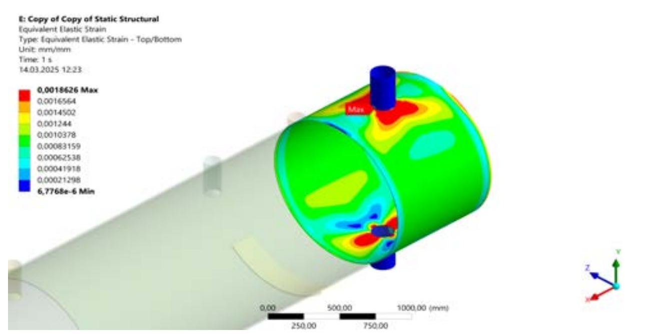

Figure 14. Residual plastic deformations

For this structure, the yield point is the critical stress as per Figure 13 and Figure 14, necessitating cyclic fatigue calculations under cyclical loading. Local defects or stress concentrations lead to fatigue-induced crack formation as per Figure 14. Fatigue calculations require actual stresses to be significantly lower than the yield point, considering corrosion-related thinning. The results indicate that the first section is the most critical due to the highest stress levels.

CONCLUSION

This study assesses the remaining useful life (RUL) of a corroded low-alloy steel pressure vessel by using both inspection-based and chemical modelling methods. A detailed analysis of linear, nonlinear, and chemical corrosion models to highlight their strengths and limitations; for instance, the linear model (maximum) showed fast degradation, offering a conservative estimate that is suitable for systems with considerable corrosion conditions, while the linear model (average) provided more moderate predictions under low-to-moderate corrosion conditions; however, the quadratic model showed accelerating degradation, making it suitable for cases with confirmed high corrosion conditions, but it's less applicable for general cases. The chemical model, which includes the main factors in various environmental conditions, shows a high accuracy in complex environments. The exponential decay models (both average and maximum) showed decreasing corrosion rates over time; finally, the exponential decay (maximum) model presented more conservative estimates for long-term evaluations.

Validation of the inspection-based models was achieved by thickness measurement data from three pressure vessels collected from 2006 to 2011, further strengthening the reliability of the proposed models. Validation of the proposed chemical model against the linear polarisation resistance (LPR) method showed that the proposed model provides corrosion rate values within acceptable limits.

The pressure vessel integrity for critical sections, mainly at the nozzles, was assessed using finite element analysis (FEA). A likelihood of failure was identified, especially under cyclic loading conditions, with localised stress concentrations at the nozzles with corrosion-induced wall thinning. The residual plastic deformations highlight the requirement for maintenance and repair techniques to reduce fatigue-induced crack formation to prevent catastrophic failures.

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Declaration of Conflict

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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