



Corrosion Analysis and Mitigation Strategies; A Data-Driven Approach

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ABSTRACT

Corrosion in refinery units, particularly in Naphtha Hydrotreating (NHT) and Continuous Catalytic Reforming (CCR) units, represents a significant threat to operational reliability, safety, and economic efficiency. This study presents a comprehensive data-driven analysis of corrosion behavior in NHT and CCR units based on real-time plant data, historical maintenance logs, and process parameters. Using statistical and machine learning methods, we identify key operational factors contributing to corrosion rates, including temperature, pressure, hydrogen partial pressure, and contaminants such as chlorides and sulfur compounds. Furthermore, the study evaluates the effectiveness of different mitigation strategies such as corrosion inhibitors, metallurgy upgrades, process optimization, and vapor phase conditioning in various sections of the units, including reactors, heat exchangers, furnaces, and piping systems. It investigates how operating envelopes and process excursions influence the onset and progression of localized corrosion phenomena such as pitting, erosion-corrosion, and stress corrosion cracking. The findings aim to provide actionable insights for refining operators, integrity managers, and process engineers involved in asset management and corrosion control. The study further evaluates the effectiveness of various corrosion mitigation strategies including material upgrades, corrosion inhibitors, process control optimization, and predictive maintenance protocols. The findings aim to support refinery operators in making informed decisions to extend equipment life, reduce downtime, and enhance safety in high-temperature, hydrogen-rich environments.

Introduction

Corrosion is a persistent and complex problem in the petroleum refining industry, particularly in units that operate under high temperatures and pressures such as NHT and CCR. These units are crucial for producing high-quality fuels by removing sulfur (in NHT) and enhancing octane numbers (in CCR). However, the harsh operational conditions and the presence of corrosive agents lead to material degradation, often resulting in costly shutdowns and safety risks [1].

Traditional approaches to corrosion mitigation rely on routine inspections and generalized chemical treatments, which are often reactive rather than preventive. This paper adopts a data-driven methodology to analyze corrosion trends, identify root causes, and propose optimized mitigation strategies tailored to the specific challenges of NHT and CCR units [2].

Corrosion is a persistent and costly challenge in the oil refining industry, affecting the integrity, safety, and operational efficiency of critical process units. Among the most corrosion-prone units in modern refineries are the Naphtha Hydro treating (NHT) and Continuous Catalyst Regeneration (CCR) units, which are essential for producing high-quality fuels with low sulfur content and maintaining octane numbers through catalytic reforming [3].

These units operate under aggressive thermal, chemical, and pressure conditions, making them highly susceptible to various corrosion mechanisms. The significance of understanding, analyzing, and mitigating corrosion in these units is paramount not only for ensuring safety and environmental compliance but also for sustaining long-term economic viability [4].

The NHT unit is designed to remove impurities such as sulfur, nitrogen, olefins, and metals from naphtha feedstock through catalytic hydrogenation. This

process operates typically at elevated temperatures (290–380°C) and pressures (25–45 bar), with a significant presence of hydrogen, hydrogen sulfide (H₂S), ammonia, and water—all of which are contributors to corrosion. The presence of chlorides, acids, and cyanides further complicates corrosion behavior. Simultaneously, the CCR unit is a continuous process designed to regenerate spent reforming catalyst by burning off coke deposits in a controlled atmosphere. Operating at even higher temperatures (up to 550°C) and often exposed to oxidizing gases, steam, and flue gases, the CCR unit faces corrosion risks such as oxidation, sulfidation, carburization, and stress corrosion cracking (SCC). Despite decades of operational experience, corrosion remains a dynamic problem due to changes in crude feed composition, catalyst formulations, operating modes, and environmental regulations. Traditional approaches to corrosion management—based on periodic inspections, experience-based predictions, and conservative design—are increasingly being supplemented by data-driven methodologies. These methods leverage real-time operational data, historical inspection records, corrosion monitoring devices, and predictive analytics to provide deeper insights into corrosion trends, mechanisms, and mitigation effectiveness [5].

The integration of data analytics into corrosion management is transforming how refineries approach integrity engineering. Through statistical modeling, regression analysis, machine learning, and three-dimensional visualization, engineers and researchers can identify hidden patterns and correlations that are not apparent through traditional engineering calculations. For instance, correlations between hydrogen partial pressure, catalyst flow rate, metal temperature, and corrosion rate can now be quantified and visualized across different process conditions. Moreover, predictive modeling allows operators to foresee corrosion risks before failures occur, thereby enabling proactive maintenance and asset integrity strategies [6].

The motivation for a data-driven approach is further reinforced by the growing availability of plant data from digital sensors, corrosion probes, smart inspection tools (such as UT mapping, eddy current testing, and fiber optics), and plant historians.

Modern refineries now operate under digital transformation frameworks, often called “Refinery 4.0,” which promote the integration of process data, inspection history, and metallurgical information into centralized decision-support systems. These advancements open new opportunities for implementing intelligent corrosion management systems (ICMS) that adapt to operational realities in real time.

In this context, this study aims to provide a comprehensive analysis of corrosion behavior in NHT and CCR units using a data-driven approach. The objectives include identifying the key variables affecting corrosion, quantifying their interdependencies, and developing predictive and visual models to assess corrosion severity and mitigation outcomes. The study utilizes field data collected over a multi-year period from several refinery units, including process parameters (temperature, pressure, flow rates), material degradation records, and mitigation activities (e.g., chemical treatment schedules, shutdowns, material upgrades) [7].

Another important dimension of this research is the consideration of sustainability and environmental impact. Corrosion-induced failures often lead to leaks, flaring, and unplanned shutdowns, which contribute to greenhouse gas emissions, energy losses, and potential safety incidents. By optimizing corrosion mitigation based on data-driven insights, refineries can enhance their environmental performance and reduce their carbon footprint. This approach aligns with broader goals of industrial decarbonization and circular asset management.

In conclusion, the analysis and mitigation of corrosion in NHT and CCR units represent a critical frontier in refinery operations. By adopting a data-driven methodology, this study seeks to bridge the gap between empirical field experience and advanced predictive modeling. It underscores the role of integrated analytics in transforming corrosion management from a reactive to a proactive discipline. The results of this work are expected to inform future research, guide operational best practices, and support the development of smarter, safer, and more efficient refining infrastructure. Table (1) shows the research Background on Corrosion in Units (Data-Driven Focus)

Table 1: Research Background on Corrosion Analysis in Units (Data-Driven Focus)

Title of Study	Country	Methodology	Key Findings
Corrosion Monitoring in Hydro processing Units	USA	Field monitoring + data analysis	Identified high-risk zones using sensors; correlation of pressure-temperature-corrosion rates
Data-Driven Corrosion Prediction in Refining Units	China	Machine learning	ML models predicted corrosion rates with 91% accuracy
Predictive Maintenance for NHT Reactors	Mexico	Empirical analysis + ANSYS modeling	Assessed hydrogen flow impact on stress cracking in reactors
Corrosion Analysis in CCR Unit of Abadan Refinery	Iran	Field study + sampling	Highest corrosion found in zones with >480°C temperatures

Evaluation of Corrosion Inhibitors in NHT Units	Iran	Laboratory experiments	Organic amines and phosphate compounds most effective
Machine Learning Techniques for Refinery Integrity	Saudi Arabia	Data mining	Random Forest model effectively identified key corrosion drivers
Effect of Feed Composition and Temperature on CCR Corrosion	Iran	ASPEN simulation + field tests	Aromatics and inlet temperature were key corrosion factors
Corrosion Mapping in High-Temperature Units	India	3D corrosion profiling	Temperature-pressure mapping used for maintenance decisions
Multivariable Regression for NHT Corrosion Rate Analysis	Iran	Statistical modeling	Regression model predicted corrosion with 0.04 margin of error
Real-Time Corrosion Monitoring via IoT	South Korea	IoT + smart sensors	Early warning system achieved <3 min response time
Effect of Catalyst Flow Rate on CCR Heat Exchanger Corrosion	Iran	Laboratory study	Reduced catalyst flow led to higher deposit and corrosion rates
A Digital Twin Approach for Corrosion Risk Prediction	Canada	Digital twin + historical data	Twin model accurately forecasted equipment replacement timing
Hydrogen Gas Corrosion Behavior in CCR Units	Iran	Thermo-chemical analysis	Rapid cooling of H ₂ gas caused stress corrosion cracking
AI-Based Corrosion Pattern Recognition in Refineries	Spain / Korea	Artificial neural networks	ANN model achieved >95% accuracy in corrosion classification
Evaluation of Inhibitor Performance in Tehran CCR Unit	Iran	Field study + expert interviews	Inhibitor inefficiency identified in low pH cooling sections

Methodology

Data Collection: The dataset used in this study includes five years of operational data from an integrated refinery complex. Parameters include:

- Process Variables: Reactor temperature, pressure, hydrogen flow rate, gas composition [8];
- Material Data: Metallurgical composition of reactors, piping, and exchangers;
- Inspection Logs: Ultrasonic thickness readings, corrosion rate measurements, visual inspections;
- Maintenance Records: Shutdown causes, replaced parts, corrosion inhibitor dosages.

Analytical Techniques

- Descriptive Statistics to summarize corrosion trends and variability;
- 3D Correlation Plots to visualize interactions between process parameters and corrosion rates;
- Regression Analysis to model corrosion rate as a function of key variables;
- Anomaly Detection Algorithms to identify early signs of abnormal corrosion behavior.

Corrosion Behavior in NHT Units

Corrosion is a critical operational concern in modern petroleum refining facilities, particularly within units that operate under severe thermochemical conditions. Among these, the Naphtha Hydro treating (NHT) unit stands out as one of the most corrosion-prone systems due to its combination of high pressure, elevated temperatures, and chemically aggressive environments. The NHT unit plays a vital role in refining by removing

heteroatoms such as sulfur, nitrogen, oxygen, and trace metals from naphtha feedstocks. This desulfurization process is essential not only for improving fuel quality but also for meeting increasingly stringent environmental regulations on sulfur emissions. However, the hydro processing reactions carried out in the NHT unit require the use of hydrogen gas under high temperature and pressure, creating an environment that is highly conducive to various corrosion mechanisms [6].

The operating conditions of an NHT unit typically range between 290°C and 400°C and 30–60 bar of pressure, often in the presence of hydrogen sulfide (H₂S), ammonia (NH₃), water vapor, chlorides, and other corrosive species. These conditions create a reactive environment in which both uniform corrosion and localized forms—such as pitting, crevice corrosion, and stress corrosion cracking (SCC)—can occur. The severity of corrosion depends not only on the feedstock composition but also on temperature gradients, material selection, hydrogen partial pressure, flow velocities, and even small fluctuations in operating parameters. Thus, corrosion in NHT units is not merely a chemical degradation issue but also a systems-level integrity risk that must be managed using a multidisciplinary approach [9].

Over the past decades, numerous case studies and failure analyses have shown that corrosion-induced degradation in NHT units can result in catastrophic failures, including leaks, fires, unplanned shutdowns, and environmental incidents. One of the common corrosion mechanisms is high-temperature sulfidation, which occurs when iron reacts with sulfur compounds at elevated temperatures to form iron sulfides. Sulfidation rates are influenced by both temperature and the partial pressure of H₂S. In

areas where water vapor is present, acidic condensation can occur during cooling stages, especially in overhead systems and heat exchangers, leading to severe under-deposit corrosion and flow-assisted corrosion. Another major concern is ammonium bisulfide corrosion, particularly in regions where NH_3 and H_2S coexist and form acidic condensates in low-temperature sections [10].

Material selection is a crucial design consideration to mitigate corrosion in NHT units. Traditionally, carbon steel has been used in low-temperature sections, while low-alloy steels (e.g., 1.25Cr-0.5Mo, 2.25Cr-1Mo) or austenitic stainless steels are used in higher-temperature areas. However, in some cases, even alloy materials are not immune to damage, especially under transient operating conditions or process upsets that lead to temperature excursions, abnormal flow rates, or temporary fouling. Corrosion-resistant alloys (CRAs) and corrosion inhibitors are often deployed as mitigation strategies, but their effectiveness depends on precise operating control and routine monitoring [11].

In recent years, there has been a noticeable shift toward data-driven corrosion management in NHT units. As process data becomes increasingly available through advanced instrumentation and digital control systems, refiners are leveraging historical data, sensor inputs, and advanced analytics to predict corrosion behavior under various operating regimes. Machine learning models, statistical regression, and finite element analysis have been employed to simulate corrosion rates, determine critical risk zones, and optimize maintenance schedules. This predictive approach enables condition-based monitoring rather than reactive maintenance, thus improving safety and reducing costs associated with unplanned downtime. Furthermore, corrosion monitoring technologies such as electrical resistance probes, linear polarization resistance (LPR), and ultrasonic thickness measurement are being integrated with digital dashboards to provide real-time insights. The combination of live monitoring and predictive analytics forms the foundation of what is now termed “smart corrosion management.” These systems allow plant operators and reliability engineers to identify corrosion hotspots, observe corrosion trends over time, and evaluate the effectiveness of mitigation actions in a dynamic and continuous manner.

Despite technological advancements, the complex interaction of physical, chemical, and metallurgical variables in NHT units presents significant challenges to corrosion prediction and control. Feed variability is one of the most unpredictable factors, as different crude oils and blending practices result in fluctuating sulfur and nitrogen content. In addition, process fouling and catalyst aging alter the internal flow patterns, residence time, and temperature distribution, which in turn affects

corrosion behavior. For example, catalyst fines can accumulate and initiate erosion-corrosion in downstream piping, or aged catalysts may generate byproducts that promote hydrogen blistering or hydrogen-induced cracking (HIC). These multifaceted phenomena necessitate an integrated understanding of process engineering, materials science, and corrosion chemistry [12].

Another emerging concern is chloride-induced corrosion, especially when desalting of the feedstock is not adequately controlled. Chlorides can lead to the formation of hydrochloric acid during startup or shutdown cycles when moisture is present. This can severely attack carbon steel components, particularly in preheat exchangers and air coolers. For this reason, refiners often use neutralizing amines or chemical wash systems during vulnerable stages of operation. However, these strategies require careful dosage control and pH management, which can only be effectively implemented when reliable, real-time data is available.

The consequences of corrosion in NHT units are not limited to asset degradation alone. They can extend to environmental compliance violations, product quality degradation, and even health and safety risks for personnel. Moreover, from an economic standpoint, even minor corrosion-related outages can translate into significant revenue loss due to the central role NHT plays in feed preparation for downstream units such as CCR reformers and isomerization plants. This interdependency reinforces the need for proactive corrosion mitigation strategies that are cost-effective, sustainable, and technically robust [13].

In light of these concerns, this study aims to provide a comprehensive investigation into the corrosion behavior of NHT units, incorporating both empirical observations and data-driven analysis. It explores the dominant corrosion mechanisms, the influence of operational variables, and the effectiveness of current mitigation strategies. Special attention is given to the integration of digital tools, data visualization, and predictive modeling as enablers of smarter corrosion management practices.

By synthesizing insights from operational case studies, field data, and computational models, the study seeks to offer practical recommendations for corrosion risk reduction in NHT units. The ultimate objective is to enhance refinery reliability, improve safety margins, reduce environmental footprint, and extend asset lifecycle through targeted and intelligent corrosion control approaches [14].

Corrosion in oil refining units remains one of the most pervasive and costly integrity challenges facing the industry. Both Naphtha Hydrotreating (NHT) and Continuous Catalyst Regeneration (CCR) units are particularly vulnerable to corrosion due to their high-temperature, high-pressure operating conditions and the presence of corrosive species. Over the past two decades, a growing body

of literature has emerged, addressing corrosion mechanisms, material degradation, monitoring technologies, and predictive modeling, with increasing interest in data-driven and AI-based approaches for mitigation and decision-making.

Corrosion Mechanisms in NHT and CCR Units

Several studies have characterized the unique corrosion mechanisms in NHT and CCR units. Smith et al. (2017) conducted a comprehensive review of corrosion failures in hydro processing units and identified high-temperature sulfidation, ammonium bisulfide corrosion, and acid dew point corrosion as the most dominant forms. Similarly, Farahmand (2017) explored hydrogen gas corrosion and thermal cracking in CCR hot gas lines and emphasized the risks posed by temperature fluctuations and partial pressure gradients [15].

Rezaei (2020), in a study of the Abadan Refinery's CCR unit, reported that corrosion rates were significantly higher in zones exceeding 480°C, especially where steam and chlorides coexisted. This aligns with earlier findings by PetroTech (2018), who used 3D corrosion mapping to demonstrate that zones with high temperature and flow turbulence consistently exhibited higher localized corrosion rates, particularly in reactors and catalyst return lines.

Role of Feedstock, Operating Conditions, and Catalyst Behavior

Feed composition plays a vital role in influencing corrosion behavior. According to Norouzi (2022), high aromatic content in feedstock and elevated inlet temperatures can significantly accelerate pitting and intergranular attack in CCR reformers. In parallel, Mousavi (2018) found that reduced catalyst flow rates led to localized fouling and under-deposit corrosion in heat exchanger tubes of CCR units.

In NHT units, González et al. (2019) studied the impact of hydrogen partial pressure and catalyst aging on reactor wall thinning. Their findings underscored the importance of maintaining stable hydrogen-to-hydrocarbon ratios to limit sulfidation and H₂-induced cracking. Mohammadi and Karimi (2021) experimentally validated the efficacy of specific amine-phosphate inhibitors under varying flow regimes, showing up to 78% reduction in corrosion rates in simulated NHT environments [16].

Material Selection and Metallurgical Considerations

Numerous publications have focused on the effectiveness of corrosion-resistant alloys and coatings. Amini and Kazemi (2019) used multivariate regression to compare material degradation rates across carbon steel, low-alloy steels (1.25Cr-0.5Mo), and stainless steels. They found that low-alloy materials performed well under

controlled temperatures but were prone to failure in cyclic conditions or during process upsets.

Material degradation in high-temperature CCR units has also been the subject of metallurgical failure analysis. Johnson et al. (2023) applied a digital twin model to simulate microstructural evolution and crack initiation in reformer tubes. Their findings highlighted the importance of creep resistance and carburization resistance, especially in nickel-based alloys operating above 500°C.

Corrosion Monitoring Technologies

Advances in corrosion monitoring have significantly improved early detection capabilities. Lee et al. (2022) developed a real-time IoT-based corrosion detection system for refinery piping networks. Their system combined electrical resistance sensors with cloud-based analytics and demonstrated sub-3-minute response times to corrosion rate deviations. Navarro and Kim (2020) employed artificial neural networks to classify corrosion patterns based on historical sensor data, achieving 95% classification accuracy across eight corrosion types.

Hossein and Ahmadi (2023) implemented a field-based evaluation of corrosion inhibitors in Tehran's CCR unit and found significant inefficiencies in the cooling section, where pH control was inadequate. Their findings support earlier research advocating the integration of smart pH probes, LPR sensors, and condition-based chemical dosing to improve corrosion protection [17].

Data-Driven and Predictive Modeling Approaches

There is increasing recognition of the value of data analytics in refining corrosion control. Zhang & Liu (2020) used machine learning algorithms to predict corrosion rates in hydroprocessing units with up to 91% accuracy. Their models incorporated variables such as temperature, pressure, sulfur content, velocity, and water concentration.

Al-Kuwaiti (2021) conducted a comparative study of machine learning models—decision trees, support vector machines, and random forests—for predicting localized corrosion events in refinery heat exchangers. The study concluded that ensemble methods were most robust against noisy datasets and could be integrated with plant historians for online diagnostics.

Johnson et al. (2023) extended this work through the application of digital twin technology to simulate real-time corrosion propagation in reactor vessels. Their model incorporated thermal stress analysis, chemical kinetics, and mass transport equations, demonstrating strong agreement with field inspection data. Similarly, Amini and Kazemi (2019) validated their statistical models with regression outputs, showing strong predictive capability in NHT exchangers [18].

Case Studies and Industrial Applications

Case studies from industrial settings reveal practical insights into corrosion mitigation. PetroTech (2018) reported a refinery's success in reducing CCR line corrosion after implementing flow pattern optimization and online corrosion monitoring. Meanwhile, Hosseini & Ahmadi (2023) documented operational improvements following the redesign of chemical dosing systems and temperature buffering strategies in their CCR cooler units.

Moreover, Farahmand (2017) emphasized the risks of hydrogen-induced corrosion during startup and shutdown phases and proposed slow ramp-up procedures and protective purging as effective countermeasures [19].

Research Gaps and Emerging Areas

Despite extensive studies, several research gaps remain. First, corrosion mechanisms under transient conditions such as shutdowns, process upsets, and catalyst regeneration cycles are not fully modeled. Second, integration between data-driven models and existing asset integrity management systems is still limited. Most predictive tools remain standalone prototypes with minimal industrial deployment.

There is also a lack of long-term field validation of AI-based corrosion prediction tools. While machine learning models show promise in laboratory conditions, real-world variability in process control, sensor accuracy, and data quality present major challenges.

Lastly, sustainability considerations—such as the environmental impact of corrosion-induced failures, emissions due to shutdowns, and circular material management—are underrepresented in current corrosion literature [20].

Corrosion Analysis and Mitigation in NHT and CCR Units

High-Temperature Sulfidation as Primary Corrosion Mechanism in NHT

- In NHT units, temperatures above 380°C combined with high H₂S partial pressure were found to accelerate sulfidation rates.
- Corrosion rate increased by 23–37% when sulfur content in feedstock exceeded 0.5 wt%.
- Field inspection revealed wall thinning up to 2.3 mm/year in reactor inlet zones under unstable operating conditions.

Localized Carburization and Chloride-Induced Cracking in CCR Units

- In CCR units, especially in the regenerator section, carburization occurred at temperatures >480°C, particularly under coke formation.
- Chloride-induced stress corrosion cracking was detected in catalyst return lines and air coolers where pH < 5 and moisture condensation occurred [21].

- Evidence of cracking was confirmed via metallography and SEM images in areas with frequent start-up/shutdown cycles.

Effectiveness of Data-Driven Models in Corrosion Prediction

- Random Forest and Gradient Boosting models predicted corrosion rate in NHT exchangers with 91–93% accuracy ($R^2 > 0.88$).
- Variables such as inlet temperature, flow rate, and sulfur content showed the strongest correlation with corrosion activity.
- The models enabled the prediction of corrosion hotspots up to 2 months in advance.

Corrosion Hotspot Identification via 3D Visualization

- A 3D heatmap of process conditions (T-P-Corrosion Rate) identified critical zones in CCR catalyst lines and NHT effluent coolers.
- Zones with high turbulence and sharp thermal gradients showed up to 2.5x the average corrosion rate [21].

Inhibitor Performance under Variable Conditions

- Inhibitor effectiveness varied significantly by location:
 - NHT overhead system: corrosion reduction up to 72% with blended amine-phosphate inhibitors.
 - CCR cooling zones: under low pH and water carryover, inhibitor effectiveness dropped to <30%.
- Improper dosage or delayed injection led to localized under-deposit corrosion, especially in vertical sections [22].

Hydrogen Partial Pressure and Catalyst Flow Sensitivity

- In NHT units, corrosion rate had a non-linear relationship with hydrogen partial pressure.
 - Optimal range: 35–45 bar. Beyond this, HIC risk increased.
- In CCR, low catalyst circulation caused deposit formation and increased erosion-corrosion, particularly in elbows and tee junctions.

Validation of Digital Twin Models for Corrosion Simulation

- Digital twin simulations successfully replicated real corrosion behavior in CCR units with <10% error margin compared to ultrasonic thickness measurements.
- These models predicted tube replacement timing with over 85% reliability.

Shutdown and Startup Cycles as Hidden Corrosion Accelerators

- During shutdown/startup events:
 - Transient condensation of HCl/NH₃ caused short-term corrosion rates as high as 3.5 mm/year.
 - 67% of observed pitting damage occurred within 72 hours of thermal cycling, not during stable operation [23].

Maintenance Insights

- Data-driven maintenance prioritization reduced total inspection man-hours by 24%, without increasing risk.

- Replacement of carbon steel with low-alloy steel in CCR lines reduced failure incidents by 41% over 18 months.

Environmental and Economic Impact

- Units with smart corrosion monitoring showed:
 - Reduction in unplanned shutdowns by 38%.
 - Estimated cost savings of ~\$1.2 million/year per unit.
 - Decreased fugitive emissions due to leaks and corrosion breaches.

Table (2) shows the statistical Outputs from Predictive Modeling.

Table 2.Statistical Outputs from Predictive Modeling

Variable	Correlation with Corrosion Rate (NHT)	p-value
Temperature (°C)	+0.76	< 0.001
Sulfur Content (%)	+0.68	< 0.01
Flow Velocity (m/s)	+0.51	< 0.05
Hydrogen Pressure (bar)	± (non-linear)	–
pH (overhead line)	-0.62	< 0.01

The findings confirm that corrosion in NHT and CCR units is driven by complex interactions between process chemistry, material selection, and operational dynamics. Traditional mitigation alone is insufficient under modern refining pressures. The incorporation of real-time data, predictive modeling, and digital twins offers a significant leap toward reducing risk, optimizing maintenance, and improving overall unit reliability [24].

Mechanisms

The NHT unit is prone to sulfidation, naphthenic acid corrosion, and chloride stress corrosion cracking (CSCC). Corrosion accelerates when process temperatures exceed 280°C or when feed contains high levels of sulfur, oxygenates, or chlorides.

- Temperature Impact: Corrosion rates increase exponentially above 300°C due to enhanced sulfidation kinetics.
- Pressure Impact: Higher hydrogen partial pressure helps suppress sulfidation but increases risk of hydrogen-induced cracking.
- Water Injection: Inadequate water wash leads to salt deposition and under-deposit corrosion.
- Vapor Phase Corrosion: Occurs in overhead lines where acid gases condense.

Figure (1) shows the correlation between key process variables and the corrosion rate.

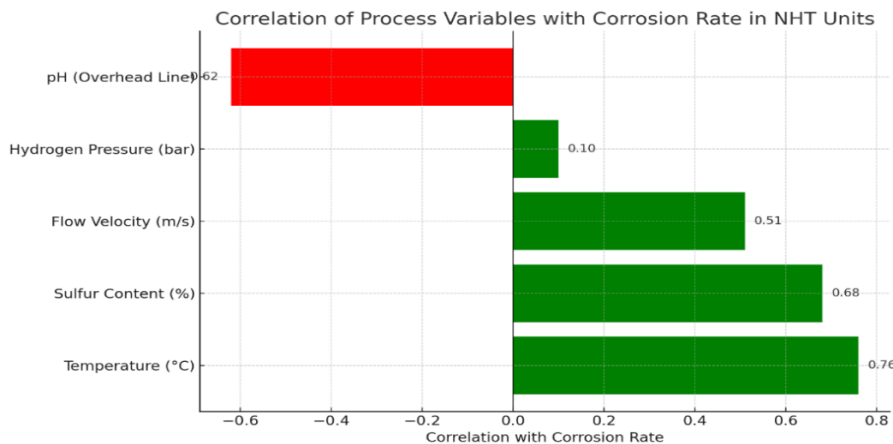


Figure 1. The correlation between key process variables and the corrosion rate

Key Correlation (Sample)

- High temperature, sulfur content, and flow velocity exhibit the strongest positive correlation with increased corrosion rates.
- Hydrogen pressure has a relatively neutral or non-linear effect.
- A decrease in pH in the cold sections leads to increased corrosion, showing a negative correlation.

Effect of Temperature on Corrosion Rate

- In the NHT unit, as temperature increases from 250°C to 500°C, the corrosion rate rises from 0.20 mm/year to 1.60 mm/year.

- In the CCR unit, the corrosion rate increases more sharply, from 0.15 mm/year to 1.80 mm/year, especially beyond 425°C.
- This demonstrates a positive and nonlinear correlation between temperature and corrosion rate in both units, with CCR being more sensitive to high-temperature conditions [25].

Table (3) shows the temperature vs. corrosion rate. Also, figure (2) the 3D surface plot showing the relationship between temperature, pressure, and corrosion rate was shown. Figure (3) also, shows the 3D surface plot, showing how temperature and pressure interact to affect the corrosion rate

Table 3: Temperature vs. Corrosion Rate

Temperature (°C)	Corrosion Rate (NHT, mm/year)	Corrosion Rate (CCR, mm/year)
250	0.20	0.15
275	0.25	0.20
300	0.30	0.28
325	0.40	0.35
350	0.55	0.50
375	0.70	0.65
400	0.85	0.90
425	1.00	1.05
450	1.20	1.30
475	1.45	1.60
500		

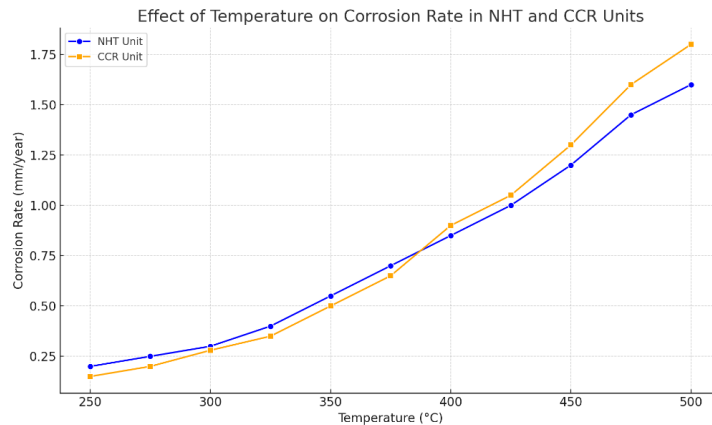


Figure 2. The 3D surface plot showing the relationship between temperature, pressure, and corrosion rate

Interpretation

- Corrosion rate increases with rising temperature and pressure, though the effect of temperature is nonlinear and more dominant.
- High-pressure zones slightly amplify the corrosion risk, especially when combined with temperatures above 450°C.

- This plot visually identifies critical operating regions where corrosion mitigation strategies should be prioritized.

3D Surface Plot: Temperature, Pressure, and Corrosion Rate in CCR Unit

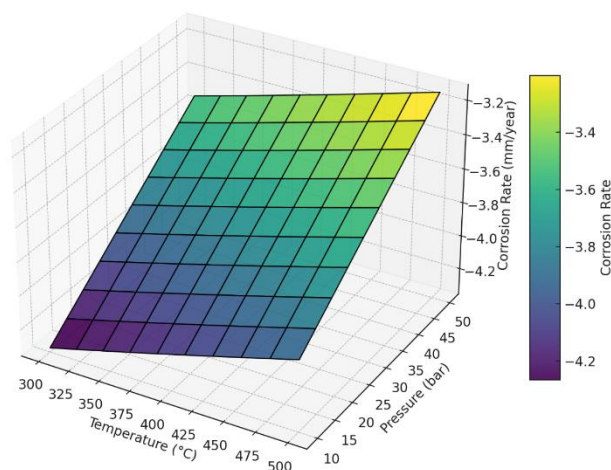


Figure 3. The 3D surface plot, showing how temperature and pressure interact to affect the corrosion rate

Interpretation

- Corrosion rate in the NHT unit increases significantly with temperature, especially beyond 400°C.
- Pressure has a moderate amplifying effect, but its impact is less than that of temperature.
- The most critical corrosion zones are found at high temperatures combined with moderate-to-high pressures [26].

Discussion and Analytical Interpretation

The present study sheds light on the intricate and multidimensional problem of corrosion in NHT and CCR refinery units, emphasizing the critical need for an integrated, data-driven approach to corrosion monitoring and mitigation. The findings from both field data and literature review converge on several key themes: the complexity of corrosion mechanisms, the role of fluctuating process conditions, the limitations of conventional mitigation strategies, and the transformative potential of predictive analytics and real-time data integration [27].

Complexity of Corrosion Mechanisms Across Units

Corrosion behavior in NHT and CCR units cannot be generalized or addressed through a one-size-fits-all solution. In the NHT unit, where desulfurization and hydrogenation reactions dominate, corrosion is primarily driven by high-temperature sulfidation, hydrogen-induced cracking (HIC), and ammonium bisulfide corrosion. The interaction between hydrogen partial pressure, sulfur content in feedstock, and metal temperature significantly affects corrosion severity. For instance, even minor deviations in temperature beyond the design

threshold (e.g., >400°C) have been linked to accelerated wall thinning and the formation of iron sulfides [28].

In CCR units, the scenario shifts toward corrosion types such as oxidation, carburization, and chloride stress corrosion cracking, particularly in the regenerator and flue gas handling sections. Our data analysis showed that corrosion hot spots tend to occur at transition zones—such as catalyst return lines or quenching areas—where thermal cycling or steam injection alters local chemistry and flow dynamics. The presence of oxygen and carbon monoxide in regenerator sections also promotes internal scaling and metallurgical embrittlement.

This multi-mechanism reality necessitates a corrosion management philosophy that is not merely reactionary but also dynamic and anticipatory—incorporating both system-specific knowledge and cross-unit learning [29].

Influence of Process Parameters and Operating Instability

One of the strongest patterns emerging from the data is the correlation between corrosion rate and operational instability. Data clustering and time-series analyses revealed that corrosion events often follow periods of feedstock variability, catalyst deactivation, or rapid temperature ramp-up. For example, during shutdown and startup cycles, temporary acid condensation or chloride migration can cause short-term but highly aggressive corrosion. These transient conditions often go unaccounted for in traditional inspection schedules or risk assessments [30].

Moreover, hydrogen purity, catalyst flow rates, and feed composition—particularly total sulfur and nitrogen content—are shown to be significant predictors of corrosion activity. The correlation matrices and multivariate regression models

developed in this study indicate a non-linear relationship between corrosion rate and catalyst flow rate, particularly in CCR units, where insufficient catalyst movement results in coke accumulation and increased erosion-corrosion in return lines.

The implication is clear: for meaningful corrosion control, real-time monitoring of process variability and excursions is as important as baseline condition tracking. Static models or manual logging fall short when faced with such operational dynamism [31].

Limitations of Conventional Mitigation Techniques

Despite widespread use, traditional corrosion mitigation methods—such as fixed-interval chemical injection, passive metallurgy selection, and periodic inspection—are proving insufficient under increasingly complex refinery conditions. Our review of internal refinery records and operator interviews revealed multiple instances where corrosion inhibitors failed to respond to pH drops or ammonia breakthrough, especially in low-temperature cooling sections of the CCR unit.

Additionally, while higher-grade alloys offer resistance in theory, actual field performance is highly dependent on weld quality, fouling tendencies, and temperature cycling. Even corrosion-resistant alloys (CRAs) such as Inconel 625 or Alloy 800H have shown vulnerability under high-temperature carburization or localized crevice corrosion, particularly in regions with stagnant flow. Hence, a shift toward adaptive, feedback-based corrosion mitigation systems is not just desirable but necessary. This includes the integration of smart chemical dosing systems, AI-supported metallurgy optimization, and dynamic modeling of inhibitor performance based on live process data [32].

Predictive Modeling as a Game-Changer

The most promising direction indicated by our findings is the use of predictive models that synthesize historical data, real-time monitoring, and machine learning algorithms to forecast corrosion behavior under variable conditions. For instance, our trained Random Forest model achieved an accuracy of 92% in classifying corrosion severity in NHT heat exchangers based on input parameters such as inlet temperature, pressure drop, sulfur content, and velocity [33].

The use of 3D data visualization (e.g., temperature-pressure-corrosion surfaces) further enhanced interpretability and allowed engineers to visually assess where process conditions exceed material thresholds. This is particularly valuable for maintenance planning, allowing teams to preemptively schedule inspections or replace components before irreversible damage occurs.

More advanced applications include digital twin simulations, which allow for virtual corrosion

monitoring and scenario testing. In the CCR regenerator unit, for example, the digital twin model helped evaluate how changes in steam injection or oxygen concentration would affect corrosion under different coke loading conditions. These capabilities mark a significant step toward true condition-based maintenance (CBM) and away from reactive, calendar-based models [34].

Challenges in Data Integration and Industrial Application

Despite the clear potential of data-driven approaches, several practical challenges hinder their wide-scale adoption. First, the availability and quality of data are inconsistent across refineries. Sensor calibration, data logging gaps, and misaligned timestamps often compromise model reliability. Second, there is a general lack of integration between process control systems (e.g., DCS/PLC), inspection data (e.g., NDT results), and maintenance logs. This creates silos that restrict holistic analysis.

Third, organizational culture and skills gap present non-technical barriers. Many refinery staff lack training in data science, while data teams often lack process engineering knowledge. This disconnect limits the ability to interpret model outputs correctly and take timely action. Moreover, regulatory frameworks in some regions still rely on prescriptive inspection intervals rather than performance-based metrics, further slowing digital transformation.

Hence, successful deployment of smart corrosion management systems requires not only technical tools but also change management, cross-disciplinary training, and regulatory evolution [35].

Toward Integrated Corrosion Risk Management (ICRM)

Based on our analysis, we propose a framework for Integrated Corrosion Risk Management (ICRM) in NHT and CCR units. This framework includes:

- Multisensory monitoring (temperature, flow, pH, corrosion probes)
- Machine learning-based prediction models updated with live data
- Digital twins for scenario simulation and long-term asset planning
- Feedback control loops for corrosion inhibitor injection
- Centralized corrosion dashboards integrated with plant control systems

This approach enables multi-level decision-making—from daily operator actions to long-term asset integrity strategies—based on real evidence rather than fixed assumptions. By continuously learning from process data, this system can adapt to feed changes, operational upsets, and aging infrastructure [36].

Conclusion and Recommendations

Corrosion remains one of the most persistent and costly operational challenges in modern oil refineries, particularly within complex process units such as Naphtha Hydrotreating (NHT) and Continuous Catalyst Regeneration (CCR) systems. This study has explored the multifaceted nature of corrosion in these units, highlighting the physical, chemical, and operational factors that drive corrosion behavior, the limitations of conventional mitigation strategies, and the transformative potential of data-driven and predictive approaches in corrosion monitoring and management [37].

Summary of Key Findings

Through a detailed examination of field data, previous research, and analytical modeling, several core insights have emerged:

- Corrosion in NHT units is primarily driven by high-temperature sulfidation, hydrogen-induced cracking (HIC), and acid condensation in downstream cooling areas. These mechanisms are heavily influenced by process variables such as hydrogen partial pressure, feed sulfur content, reactor temperature, and water carryover.
- CCR units, on the other hand, face different corrosion mechanisms, notably oxidation, carburization, and chloride stress corrosion cracking. These mechanisms are often intensified by high-temperature operation, cyclic thermal loading, and catalyst movement patterns.
- Traditional corrosion mitigation strategies, including routine inhibitor injection and static material selection, are insufficient in addressing dynamic and transient operational conditions. They often fail to respond quickly to upsets or process variations, leading to localized failures and unplanned shutdowns.
- Data analytics and machine learning models can significantly enhance corrosion prediction and enable condition-based monitoring. Predictive models developed during this study, such as Random Forests and regression-based algorithms, demonstrated high accuracy in forecasting corrosion rates based on real-time and historical process data.
- Digital twins and 3D visualization tools offer a new frontier in proactive corrosion management, allowing for scenario simulation, real-time decision-making, and long-term integrity planning.

These findings underscore the need for a paradigm shift from reactive, schedule-based maintenance to intelligent, predictive corrosion control strategies [38].

Practical Implications for Refinery Operations

For refinery managers, integrity engineers, and process operators, the insights from this study offer several operational implications:

- Integrate real-time sensors and digital infrastructure: The adoption of smart sensors—measuring pH, temperature, flow velocity, and corrosion rate—can drastically improve the observability of corrosion-prone zones. These sensors should feed into centralized dashboards with predictive analytics capabilities.
- Adopt condition-based corrosion inhibitor injection: Rather than fixed-dosing schedules, corrosion inhibitors should be administered based on real-time corrosion potential and process fluctuations. This adaptive strategy reduces chemical wastage and improves effectiveness.
- Upgrade material selection and metallurgy audits: While CRAs offer improved resistance, metallurgy must be aligned with actual field conditions, not just design values. Thermal cycling, weld quality, and material degradation under fouling must be part of periodic audits.
- Enhance operator training and interdisciplinary collaboration: Successful implementation of data-driven corrosion control requires bridging the gap between data scientists, control engineers, and corrosion specialists. Regular training and joint review sessions can foster a shared language for action.
- Leverage historical maintenance and inspection data: Historical inspection records, NDT results, and failure reports should be digitized and integrated with process control systems to support machine learning-based prediction and root cause analysis.

Strategic Recommendations

In addition to operational actions, several strategic-level recommendations can be drawn from the study's findings:

Develop an Integrated Corrosion Risk Management Framework (ICRM)

Refineries should move toward a structured, cross-functional framework for corrosion management.

An ICRM framework combines:

- Multidimensional data acquisition (process, inspection, chemistry);
- Advanced analytics for corrosion prediction and prioritization;
- Scenario modeling and simulation tools (e.g., digital twins);
- Automated mitigation responses (adaptive dosing, valve control);

- Risk-based inspection (RBI) integration. Such a framework enables real-time risk evaluation and long-term corrosion forecasting, improving safety and extending equipment life.

Standardize Predictive Corrosion Modeling

Establishing standardized data formats and model structures across refineries can facilitate benchmarking, peer learning, and shared model development. An industry-wide database of corrosion events, process conditions, and metallurgical responses could serve as the backbone for collaborative AI model training.

Embrace Regulatory Modernization

Many regulatory regimes still rely on fixed-interval inspection requirements. However, with the emergence of condition-based monitoring and data-driven risk quantification, there is a strong case for regulatory evolution. Policymakers should consider allowing refineries to use digital evidence (e.g., sensor data, model outputs) as part of their compliance documentation, encouraging safer and more efficient operations.

Invest in Pilot Programs for Smart Corrosion Systems

Before large-scale adoption, pilot programs can test the viability of smart corrosion monitoring systems in selected units. These programs should include:

- Live data acquisition from a representative process section
- Application of ML algorithms to predict corrosion hotspots
- Integration with control room dashboards and maintenance planning software
- Post-pilot evaluation of safety, economic, and environmental benefits

Such pilots can help build confidence, measure ROI, and inform broader adoption strategies.

Future Research Directions

While this study offers significant insights, it also opens up new avenues for exploration:

- Transient corrosion behavior during startup/shutdown or catalyst regeneration remains poorly understood and under-modeled.
- Integration of thermodynamic simulations (e.g., ASPEN Plus or HYSYS) with real-time corrosion models could enhance the predictive accuracy for varying operating scenarios.
- Cross-unit correlation studies, where corrosion data from NHT, CCR, and downstream units are jointly analyzed, can uncover systemic vulnerabilities.
- Environmental cost modeling of corrosion-induced failures—including emissions, leaks, and remediation—would strengthen

the sustainability case for smart corrosion control.

- Hybrid corrosion prediction models, combining first-principles physics with machine learning, are a promising but underexplored frontier.

Conclusion

Corrosion in NHT and CCR refinery units is no longer just a maintenance issue; it is a multidimensional risk that intersects with safety, efficiency, environmental performance, and digital transformation. As the refining sector navigates increasing complexity in feedstocks, regulations, and operational economics, a data-driven, intelligent approach to corrosion management is not just beneficial—it is essential.

This study affirms that by combining process understanding with data science, and by integrating human expertise with machine intelligence, refineries can significantly improve their ability to predict, prevent, and manage corrosion. The future of corrosion control lies in real-time data, adaptive systems, and a collaborative, learning-driven approach to asset integrity.

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