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Numerical Validation and Multiphysics Characterization of Progressive Degradation in Oil Pipelines Using a Simulation-Driven Virtual Twin

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Abstract—Pipeline integrity assessment requires reliable representation of the interacting hydraulic, thermal, mechanical, and corrosion processes associated with progressive degradation. In environments where extensive real-time sensing is limited, physics-based simulation provides an alternative means of generating virtual measurements; however, the reliability of such information depends on the numerical stability and physical consistency of the underlying model. This study evaluates a COMSOL Multiphysics-based virtual pipeline under normal operation, partial blockage, corrosion hotspot, and leak-induced pressure-drop conditions. A one-meter carbon-steel pipeline section was modelled using a two-dimensional axisymmetric representation. Parametric and transient simulations generated 2,000 operating cases containing inlet pressure, outlet pressure, flow rate, temperature, wall shear stress, and corrosion rate. Numerical reliability was evaluated through solver convergence, mesh refinement, parameter-bound verification, and physical-consistency checks. All retained simulation cases met the specified solver tolerance, while peak wall shear stress and maximum temperature varied by less than 0.9% between the two finest mesh configurations, indicating practical mesh independence for the selected observables. Correlation analysis showed strong associations between corrosion rate and inlet pressure (r=0.84), wall shear stress (r=0.72), and temperature (r=0.72). Mutual-information analysis ranked corrosion rate highest at 0.46, followed by temperature at 0.41, inlet pressure at 0.37, outlet pressure at 0.35, wall shear stress at 0.28, and flow rate at 0.22. The findings demonstrate that the developed simulation environment provides numerically stable and physically interpretable operating states suitable for virtual sensing and simulation-driven pipeline-integrity assessment.

Keywords—Virtual Twin, COMSOL Multiphysics, Pipeline Integrity, Numerical Validation, Corrosion, Wall Shear Stress, Virtual Sensing.

I. INTRODUCTION

Oil and gas pipelines are important infrastructure for transporting crude oil, natural gas, and refined petroleum products between production facilities, processing plants, storage terminals, and consumers. Despite their operational importance, pipeline systems are subjected to corrosion, pressure variation, thermal effects, material ageing, mechanical stress, and other degradation processes capable of reducing their structural and operational integrity [1]. Prolonged deterioration may eventually result in leakage, rupture, interruption of production, environmental contamination, and increased maintenance requirements.

Pipeline integrity remains particularly important in Nigeria, where corrosion and infrastructure deterioration occur alongside operational and environmental challenges. Studies of pipeline degradation in the Niger Delta have identified corrosion as an important integrity concern [2], while recent reliability investigations have continued to report ageing infrastructure and pipeline failure as significant issues within the Nigerian oil and gas sector [3]. These conditions create a need for monitoring methods capable of characterising deterioration before severe failure occurs.

Predictive maintenance provides an alternative to relying exclusively on periodic inspection and reactive intervention. Rather than waiting until a fault becomes obvious, predictive maintenance uses operating information and analytical models to evaluate equipment condition and support earlier intervention [4]. Its effectiveness nevertheless depends on the availability of reliable information concerning the physical behaviour of the asset.

Digital-twin technology has consequently attracted attention for engineering monitoring and lifecycle management. Digital twins combine virtual representations, data, computational models, and analytical functions to support monitoring, diagnosis, and prediction [5]. Within the oil and gas sector, digital and virtual twins have been proposed for pipeline monitoring, integrity assessment, operational optimisation, and maintenance planning [6].

A simulation-driven virtual twin is particularly useful when continuous physical-to-digital connectivity is not available. Instead of relying completely on real-time sensors, representative operating states can be reproduced through physics-based simulation. Such an approach is relevant where field-failure data are scarce or where installation of extensive sensing infrastructure is impractical.

Pipeline degradation is inherently multiphysical. Pressure and flow describe the hydraulic condition of the transported fluid, temperature influences fluid and material behaviour, while corrosion progressively alters the integrity of the pipe wall. These phenomena may interact rather than evolve independently. Coupled modelling of underground pipeline corrosion has demonstrated the importance of accounting for interacting physical and environmental conditions when evaluating degradation [7].

Physics-based computational modelling provides a controlled means of examining these interactions. Operating parameters can be systematically varied without intentionally creating hazardous conditions in a physical pipeline. The broader development of physics-informed computational methods has similarly emphasised the value of constraining engineering models using known physical relationships [8].

Recent pipeline applications demonstrate the increasing integration of simulation and virtual representations. Al-Ammari *et al.* developed a digital/visual twin for real-time leak detection in gas pipelines under multiphase-flow conditions [9]. Ganesh *et al.* similarly investigated a digital-twin approach incorporating machine learning for pipeline leak detection [10]. These studies demonstrate the growing relevance of virtual pipeline representations for integrity monitoring.

However, producing simulation data does not automatically establish that the underlying numerical model is reliable. Spatial discretisation, time-step selection, solver configuration, material assumptions, and boundary conditions can influence the generated outputs. Numerical credibility should therefore be examined before simulation-generated information is treated as a substitute or supplement for physical measurements.

A previous study from this research programme used the COMSOL-generated pipeline dataset for machine-learning fault classification. Logistic Regression, Random Forest, and Long Short-Term Memory models were compared using predictive-performance metrics and model-specific feature importance [11]. That study demonstrated the analytical usefulness of the generated dataset but did not make detailed numerical verification of the COMSOL environment its central research contribution.

The present paper addresses this complementary problem. It evaluates whether the underlying virtual pipeline demonstrates numerical stability and physically interpretable multiphysics behaviour across normal operation, partial blockage, corrosion hotspot, and leak-induced pressure-drop conditions. Solver convergence, mesh refinement, physical-consistency checking, correlation analysis, and mutual information are used to assess the simulation environment. The emphasis is therefore placed on the credibility of the virtual pipeline itself rather than another comparison of machine-learning classifiers.

II. RELATED WORK

2.1 Pipeline Degradation and Integrity Assessment

Pipeline degradation results from interacting chemical, mechanical, hydraulic, and environmental processes. Corrosion progressively reduces material integrity, while pressure variation, cyclic loading, flow behaviour, and thermal conditions can modify the operating stresses experienced by the pipeline [1]. Corrosion is particularly important because sustained material loss can reduce wall thickness and increase susceptibility to leakage and structural failure.

Obaseki investigated corrosion behaviour in oil and gas pipelines within the Niger Delta and emphasised the relevance of allowable corrosion rates in pipeline diagnosis and prognosis [2]. Oni and Opara also examined pipeline reliability in Nigeria and identified ageing infrastructure and failure trends as continuing concerns within the oil and gas sector [3].

Corrosion behaviour may also depend on surrounding physical conditions. Azoor *et al.* developed a coupled electrochemical-soil model for underground pipe corrosion and demonstrated the influence of environmental variation on corrosion behaviour [7]. This supports the use of multiphysics approaches where degradation is analysed together with operating and environmental conditions.

Hydraulic variables are equally important in pipeline integrity assessment. Leakage, obstruction, and other abnormal states can produce changes in pressure and flow behaviour. Lu *et al.* reviewed pipeline leakage-detection approaches and identified pressure-, flow-, acoustic-, and model-based techniques as important methods for pipeline monitoring [12].

2.2 Digital Twins and Virtual Sensing

Digital twins provide computational representations of physical assets and can integrate physical information, operational data, analytical models, and decision-support functions [5]. In oil and gas systems, virtual representations have been investigated for monitoring pipelines, assessing degradation, and supporting maintenance decisions [6].

Pipeline digital-twin applications have increasingly focused on leak detection and condition monitoring. Al-Ammari *et al.* developed a digital/visual twin for pipeline leakage assessment [9], while Ganesh *et al.* integrated digital-twin concepts with machine-learning-based leak detection [10]. These systems illustrate how virtual representations can extend conventional monitoring beyond individual sensor signals.

Virtual sensing is particularly important where a physical quantity cannot be measured continuously or where sensors are installed only at selected points. Computational models can estimate inaccessible variables from available operating information. Data-driven smart monitoring has similarly been investigated as a means of improving pipeline-integrity assessment using available condition information [13].

A virtual-sensing model nevertheless depends on the reliability of its computational representation. If the underlying simulation contains excessive numerical sensitivity or physically inconsistent operating conditions, the resulting virtual measurements may provide misleading information. Numerical assessment is therefore an important stage before virtual sensing is incorporated into an operational monitoring system.

2.3 Multiphysics Simulation of Pipeline Degradation

Multiphysics modelling is suitable for pipeline integrity because flow, thermal behaviour, wall interaction, and material degradation occur simultaneously. Physics-based simulation allows these variables to be studied within a controlled environment where normal and abnormal states can be reproduced without intentionally damaging a physical pipeline.

Azoor *et al.* demonstrated the value of coupled modelling for corrosion analysis [7]. Such computational approaches provide information about spatial and operational relationships that may be difficult to obtain through conventional inspection alone.

Simulation also provides a means of generating structured operating data when real failure records are limited. Instead of producing arbitrary numerical samples, physics-based simulation generates results from governing equations, model geometry, boundary conditions, and specified material parameters. This principle is consistent with physics-informed modelling approaches that use known physical behaviour to constrain computational solutions [8].

The resulting model can therefore serve as a virtual experimental environment in which pressure, temperature, corrosion severity, flow, and other parameters are systematically varied. However, the reliability of the generated information depends on the stability of the numerical solution.

The reviewed studies demonstrate different applications of simulation, digital twins, and data-driven monitoring in pipeline integrity assessment. However, their primary emphasis is generally corrosion modelling, leak detection, or predictive performance rather than numerical verification of the simulation environment. A comparative summary of the most relevant studies and their limitations in relation to the present work is presented in Table 1.

Table 1: Selected Related Studies on Pipeline Monitoring and Virtual Modelling

Study	Approach	Application	Main Contribution	Limitation Relevant to Present Study
Azoor *et al.* [7]	Coupled electrochemical model	Underground pipe corrosion	Models' interaction of corrosion and environment	Not developed as a pipeline virtual-sensing framework
Zhang and Elsayed [6]	Digital/virtual twin review	Oil and gas	Establishes twin applications in energy systems	Limited emphasis on numerical verification
Al-Ammari *et al.* [9]	Digital/visual twin	Gas pipeline	Real-time leak detection	Focuses mainly on leak detection
Ganesh *et al.* [10]	Digital twin + ML	Pipeline leakage	Intelligent pipeline monitoring	Main emphasis on predictive performance
Giunta *et al.* [13]	Data-driven monitoring	Pipeline integrity	Continuous integrity assessment	Limited physics-based virtual modelling

2.4 Numerical Reliability of Virtual Pipeline Models

The usefulness of simulation-generated data depends on the numerical behaviour of the computational model. Mesh resolution may influence quantities with large spatial gradients, particularly near pipeline walls. Time-step selection and solver tolerances may also affect transient solutions.

A virtual pipeline intended to generate engineering information should therefore demonstrate that important outputs do not change excessively under reasonable numerical refinement. Solver convergence is equally relevant because unresolved parameter combinations should not be treated as valid operating observations.

Numerical verification should, however, be separated from field validation. A computational model may demonstrate stable numerical behaviour while still requiring calibration against measurements from an actual pipeline. For this reason, the present study considers mesh stability and solver convergence as evidence of computational reliability rather than proof of complete physical equivalence.

2.5 Predictive Maintenance and Research Gap

Predictive-maintenance research has increasingly combined condition data with statistical and machine-learning methods for equipment-health assessment [4]. Digital-twin architectures offer an additional mechanism through which simulation and analytical functions can be integrated into maintenance systems [14].

Pipeline failures remain especially important in the Niger Delta because of their environmental and operational consequences [15]. Simulation-driven monitoring therefore provides a potentially useful development pathway where continuous real-time measurements are not yet available.

The previous study associated with the present research concentrated on machine-learning classification using COMSOL-generated data [11]. The unresolved question is whether the underlying simulation environment itself demonstrates sufficient numerical stability and physically interpretable behaviour to support its use as a virtual-sensing platform. This study addresses that gap by evaluating mesh behaviour, solver convergence, physical operating limits, multiphysics scenario characteristics, correlation structure, and mutual-information relationships.

III. METHODOLOGY

3.1 COMSOL Virtual Pipeline Model

A simulation-driven virtual pipeline was developed using COMSOL Multiphysics 6.1. The model consisted of a one-metre carbon-steel pipeline section represented through a two-dimensional axisymmetric computational domain. The model incorporated fluid-flow, thermal, and degradation-related behaviour to generate representative pipeline operating conditions.

The physical configuration provided a controlled environment in which pressure, temperature, flow, wall shear stress, and corrosion-related conditions could be varied systematically. The principal geometric, material, and operating parameters used to configure the virtual pipeline are summarised in Table 2

Table 2: Principal Pipeline Model Parameters

Parameter	Value
Pipeline length	1 m
Internal diameter	0.25 m
Wall thickness	6 mm
Steel density	7,850 kg/m³
Dynamic viscosity	0.001 Pa·s
Specific heat capacity	460 J/kg·K
Nominal inlet pressure	2 MPa
Nominal outlet pressure	1 MPa
Temperature range	35–75 °C
Representative flow velocity	1–2 m/s

The COMSOL Multiphysics environment used to construct and configure the pipeline simulation is shown in Figure 1. The environment provided the platform for defining the pipeline geometry, material properties, boundary conditions, multiphysics interactions, and simulation studies.

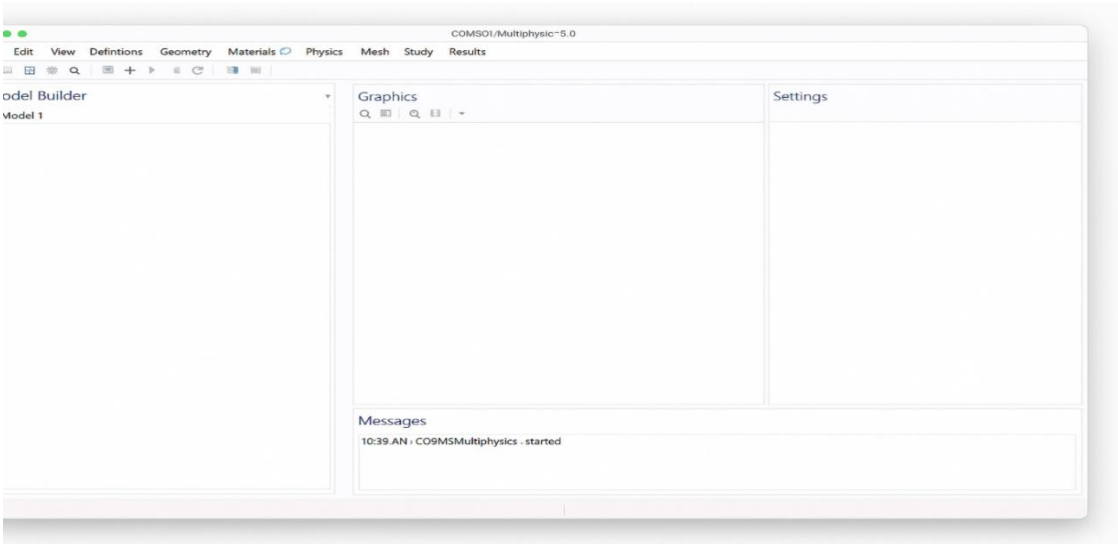

Figure 1: COMSOL Simulation Environment

3.2 Governing Physical Relations

The fluid-flow component was represented using conservation of mass and momentum. For incompressible flow, continuity is expressed as

$$\nabla \cdot \mathrm{u} = 0 \tag{1}$$

where (u) represents the velocity field.

Momentum conservation is represented as

$$\rho\left(\frac{\partial \mathrm{u}}{\partial t} + \mathrm{u} \cdot \nabla \mathrm{u}\right) = -\nabla p + \mu \nabla^2 \mathrm{u} + \mathrm{F} \tag{2}$$

where (ρ) is fluid density, (p) is pressure, (μ) is dynamic viscosity, and (F) represents body forces.

Thermal behaviour was represented using the energy equation

$$\rho C_p\left(\frac{\partial T}{\partial t} + \mathrm{u} \cdot \nabla T\right) = \nabla \cdot (k \nabla T) + Q \tag{3}$$

where (T) represents temperature, (C_p) is specific heat capacity, (k) is thermal conductivity, and (Q) represents heat generation.

Wall shear stress provides an indication of the interaction between the transported fluid and the internal pipeline surface. Under idealised pipe-flow conditions,

$$\tau_w = \frac{4\mu Q_v}{\pi R^3} \tag{4}$$

where (τ_w) is wall shear stress, (Q_v) is volumetric flow rate, and (R) is the internal pipeline radius.

Corrosion behaviour was represented using the weight-loss relationship

$$CR = \frac{KW}{At} \tag{5}$$

where (CR) represents corrosion rate, (W) is material loss, (A) is exposed area, (t) is exposure duration, and (K) is the unit-conversion coefficient.

The COMSOL solution was used to obtain the corresponding pressure, thermal, flow, and wall-related outputs under the specified operating conditions.

3.3 Simulation Scenarios

Four representative pipeline operating states were considered: normal operation, partial blockage, corrosion hotspot, and leak-induced pressure drop. The reference pressure, temperature, and corrosion-rate conditions associated with the four scenarios are summarized in Table 3.

Table 3: Pipeline Simulation Scenarios

Scenario	Description	Pressure (MPa)	Temperature (°C)	Corrosion Rate (mm/yr)
Normal	Steady-state operation	2.0	40	0.01
Fault 1	Partial blockage	3.0	55	0.04
Fault 2	Corrosion hotspot	1.8	65	0.08
Fault 3	Leak-induced pressure drop	1.2	70	0.10

The normal condition represented moderate operating pressure, low temperature, and low corrosion severity. Partial blockage was represented using increased pressure and temperature. The corrosion-hotspot condition combined increased temperature with high corrosion severity, while the leak-induced condition represented the lowest reference pressure and the highest corrosion and temperature values.

Pressure, temperature, and corrosion parameters were also varied around the reference scenario conditions to generate multiple operating combinations.

The COMSOL simulation interface through which the operating conditions were generated and prepared for data extraction is illustrated in Figure 2.

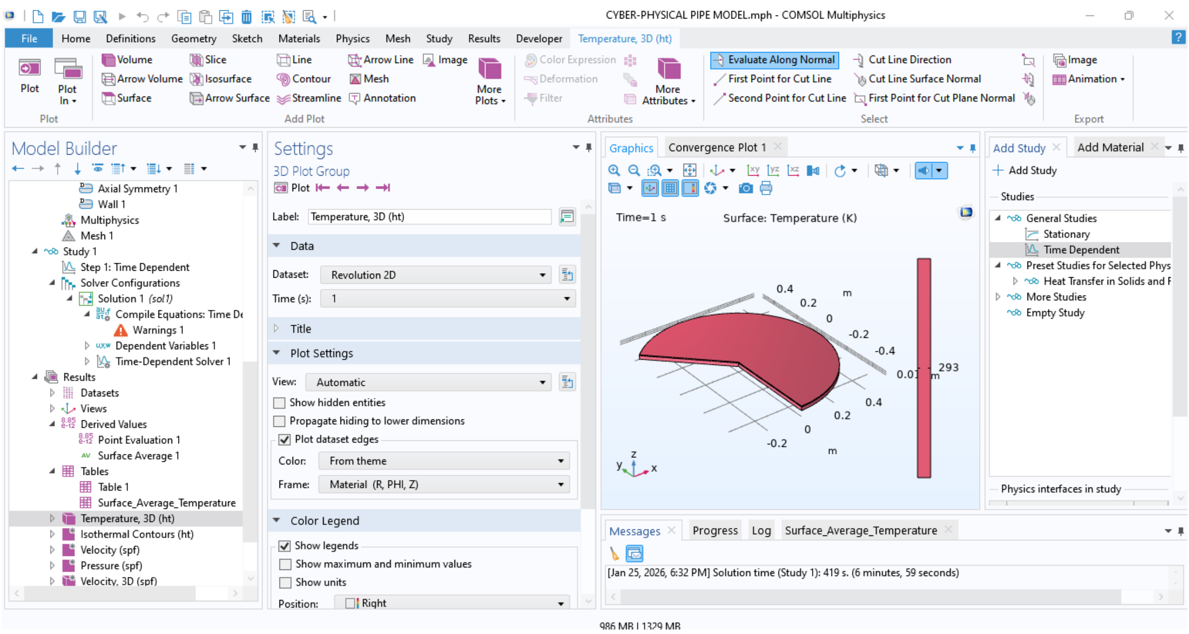

Figure 2: Data Simulation from COMSOL

3.4 Parametric and Transient Simulation

A total of 2,000 simulation cases were generated using the COMSOL Parametric Sweep and Time-Dependent Study modules.

Each simulation contained 30 discrete time points with a fixed increment of

$$\Delta t = 0.1s \quad (6)$$

giving a total simulated duration of approximately 3 s per case.

The principal parameters were varied around their scenario reference values. Pressure and temperature were perturbed around their specified operating conditions, while the corrosion parameter was varied to represent changes in degradation severity.

The principal exported variables were:

i. Inlet pressure
ii. Outlet pressure
iii. Flow rate
iv. Average temperature
v. Wall shear stress
vi. Corrosion rate

Simulation results were exported from COMSOL through Derived Values tables and stored in CSV format. Each record therefore represented a distinct set of virtual pipeline operating conditions.

3.5 Mesh and Solver Configuration

The computational domain was discretised using an adaptive finite-element mesh. Finer spatial resolution was applied near the pipeline wall because this region contains high-gradient quantities associated with wall shear stress and thermal behaviour. The principal mesh and solver configurations used for the simulations are presented in Table 4.

Table 4: Mesh and Solver Configuration

Parameter	Configuration
Mesh strategy	Adaptive finite-element mesh
Near-wall element scale	Approximately 2 mm
Bulk-fluid element scale	Approximately 10 mm
Degrees of freedom	Approximately 1.2 x 106
Study type	Time-dependent
Solver	PARDISO direct solver
Time step	0.1 s
Relative tolerance	1 x 10^{-6}
Absolute tolerance	1 x 10^{-8}

The mesh was successively refined by reducing the maximum element size. Peak wall shear stress and maximum temperature were selected for assessment because both quantities are sensitive to near-wall and thermal discretisation.

Percentage variation between two mesh solutions was evaluated using

$$\delta_{\phi} = |\frac{\phi_f - \phi_c}{\phi_f}| \times 100\% \quad (7)$$

where (ϕ_f) represents the value obtained using the finer mesh and (ϕ_c) represents the corresponding value from the preceding mesh.

3.6 Numerical and Physical Validation

Numerical verification consisted of solver-convergence checking, mesh-refinement assessment, and physical-bound verification. The PARDISO solver was required to achieve the specified relative tolerance for each retained simulation. Physical consistency was additionally assessed using the expected forward-flow pressure relationship and predefined thermal and corrosion limits. Table 5 summarizes the complete numerical and physical validation criteria adopted in the study.

Table 5: Numerical and Physical Validation Criteria

Validation Item	Criterion
Solver convergence	Relative tolerance (1\times10^{-6})
Mesh behaviour	Small change between refined meshes
Pressure condition	$P_{in} > P_{out}$
Temperature range	35–75 °C
Corrosion-rate range	0.01–0.10 mm/yr
Parameter consistency	Values within predefined operating limits

Only simulation cases satisfying these numerical and physical requirements were retained for subsequent analysis.

3.7 Statistical Characterization

Pearson correlation was used to characterize linear relationships among the simulated variables. The correlation coefficient is expressed as

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (8)$$

where (r) ranges from (-1) to (+1).

Mutual Information was used to determine the statistical dependency between each simulated variable and the corresponding binary operating/degradation state. It is generally defined as

$$I(X;Y) = \sum_{x,y} p(x,y)\, log\left(\frac{p(x,y)}{p(x)p(y)}\right) \quad (9)$$

where higher MI values indicate greater information concerning the target state.

Correlation was used to evaluate relationships among the physical variables, while MI was used to determine the relative information contained by each variable regarding the defined pipeline condition.

IV. RESULTS AND DISCUSSION

4.1 Numerical Validation

All 2,000 retained simulation cases successfully attained the specified PARDISO solver tolerance, and no non-convergent case was reported within the final simulation dataset. Mesh refinement also demonstrated stable behavior, with peak wall shear stress and maximum temperature changing by less than 0.9% between the two finest mesh configurations. The principal numerical-validation outcomes are summarized in Table 6

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Table 6: Numerical Validation Results

Validation Parameter	Result
Total retained simulation cases	2,000
Successfully converged cases	2,000
Non-convergent cases	0
Relative convergence tolerance	(1\times10^{-6})
Absolute tolerance	(1\times10^{-8})
Mesh variation between two finest meshes	<0.9%
Mesh observables	Peak WSS and maximum temperature

The convergence of the complete simulation set indicates that the selected operating conditions remained numerically solvable within the adopted model configuration.

The mesh-refinement result also indicates that further spatial refinement produced limited changes in the selected quantities. Because wall shear stress is calculated close to the pipe surface and maximum temperature is influenced by spatial thermal gradients, both provide useful indicators of mesh sensitivity.

The <0.9% value should be interpreted as evidence of practical mesh independence for the selected observables rather than as a direct estimate of physical error. Mesh convergence demonstrates stability with respect to spatial discretization; it does not establish that the model differs from an actual field pipeline by less than 0.9%.

4.2 Pressure and Temperature Distribution

The COMSOL post-processing environment was used to examine the spatial behavior of pressure and temperature within the pipeline domain. The resulting pressure and temperature distributions are presented in Figure 3.

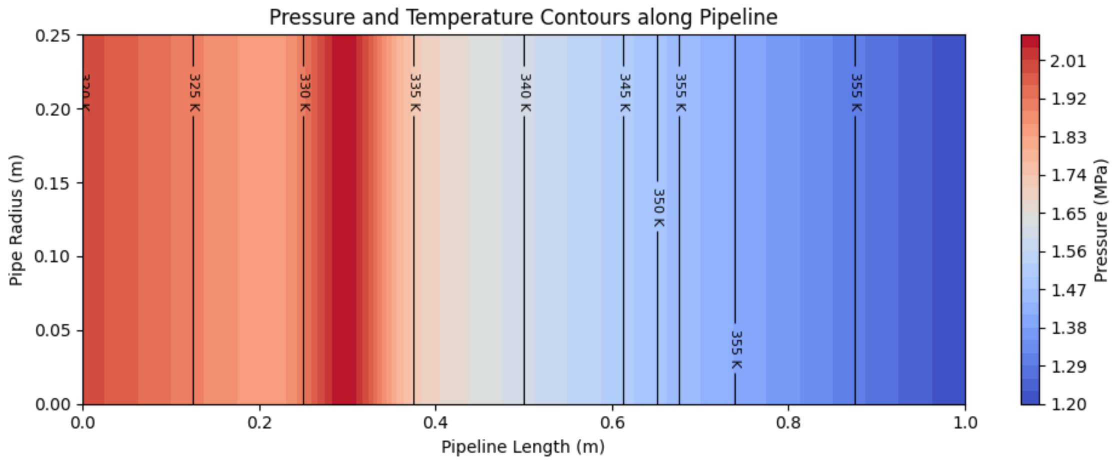

Figure 3: COMSOL Simulation Results Showing Pressure and Temperature Distributions

As observed in Figure 3, the pressure distribution shows a gradual reduction along the direction of flow, reflecting hydraulic losses within the simulated pipe section. The temperature field also exhibits spatial variation across the computational domain.

The thermal field similarly showed variation along the pipeline section. The spatial temperature distribution provides additional information beyond a single average temperature value because it indicates how thermal conditions vary across the computational domain.

The availability of spatial information demonstrates one advantage of the virtual model. A physical pressure or temperature sensor normally records information only at its installed location, whereas the simulation provides estimates throughout the model domain.

4.3 Multiphysics Behavior Across Operating Conditions

The four simulated operating states produced distinct combinations of hydraulic, thermal, and degradation behavior. To provide a direct comparison, the principal characteristics and engineering interpretation of each condition are summarized in Table 7

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Table 7: Multiphysics Characteristics of Simulated Pipeline Conditions

Scenario	Hydraulic Condition	Thermal Condition	Corrosion Condition	Interpretation
Normal	Moderate pressure	Low	Low	Healthy reference operation
Partial blockage	Elevated pressure	Moderate	Moderate	Increased hydraulic resistance
Corrosion hotspot	Moderate/lower pressure	High	High	Localized material degradation
Leak-induced condition	Reduced pressure	Highest	Severe	Advanced abnormal condition

The normal condition established the reference pipeline state. At 2.0 MPa, 40 °C, and 0.01 mm/yr corrosion rate, the condition represented moderate operation with relatively low degradation.

Partial blockage produced the highest reference pressure at 3.0 MPa. This condition represents increased hydraulic resistance within the flow path. The corresponding temperature and corrosion values were also higher than those of the normal operating state.

The corrosion-hotspot condition was characterized by a corrosion rate of 0.08 mm/yr and a temperature of 65 °C. Its dominant characteristic was therefore material deterioration under increased thermal severity rather than the high-pressure behavior associated with blockage.

The leak-induced pressure-drop condition combined the lowest reference pressure, 1.2 MPa, with the highest reference temperature, 70 °C, and corrosion rate, 0.10 mm/yr. This produced a distinct severe degradation condition.

The results demonstrate that the simulated faults were represented through combinations of physical variables rather than changes in one quantity alone. This is important because similar changes in a single parameter may arise from different pipeline conditions. A lower pressure, for example, may not independently identify the physical mechanism responsible for the disturbance.

A Multiphysics virtual environment therefore provides additional information by considering hydraulic, thermal, and degradation characteristics simultaneously.

4.4 Correlation and Variable Interaction

Pearson correlation analysis was performed to examine how the simulated physical variables varied relative to one another. The complete pairwise correlation structure of the generated variables is shown in Figure 4.

Figure 4: Feature Correlation Matrix

As shown in Figure 4, corrosion rate exhibits strong positive relationships with several operating variables. The strongest reported association was between corrosion rate and inlet pressure, with r=0.84. Corrosion rate also showed correlations of r=0.72 with wall shear stress and r=0.72 with temperature.

For clarity, the three strongest corrosion-related relationships identified from the correlation matrix are summarized in Table 8.

Table 8: Major Corrosion-Related Correlations

Variable Paired with Corrosion Rate	Correlation Coefficient
Inlet Pressure	0.84
Wall Shear Stress	0.72
Temperature	0.72

The value of 0.84 indicates that inlet pressure and corrosion severity exhibited a strong positive association across the generated operating conditions. This does not establish that increasing pressure independently causes a proportional increase in corrosion. Several parameters were varied jointly within the simulated scenarios, and the observed correlation therefore also reflects the structure of the sampled operating states.

The relationship between corrosion and wall shear stress is important because wall shear stress describes near-wall fluid interaction. The positive correlation indicates that changes in simulated degradation severity were accompanied by corresponding variation in the hydraulic interaction between the transported fluid and the pipe surface.

Temperature displayed an equally strong relationship with corrosion at 0.72. This result demonstrates that thermal behaviour forms an important component of the simulated degradation environment.

The combined relationships indicate that the dataset does not represent pipeline degradation as an isolated corrosion variable. Instead, corrosion severity changes together with other hydraulic and thermal quantities, providing a multivariate representation of degraded operating states.

4.5 Mutual-Information Analysis

Mutual Information was used to determine how much information each simulated feature contained about the binary normal/fault operating state.

Table 9: Mutual-Information Scores

Variable	MI Score
Corrosion Rate	0.46
Temperature	0.41
Inlet Pressure	0.37
Outlet Pressure	0.35
Wall Shear Stress	0.28
Flow Rate	0.22

Corrosion rate obtained the highest MI score of 0.46, indicating that it contained the strongest individual statistical dependency with the target operating state. Temperature ranked second with an MI score of 0.41. This result reinforces the importance of thermal information observed in the correlation analysis.

Inlet and outlet pressures produced MI scores of 0.37 and 0.35, respectively. These values show that hydraulic pressure information remained important in distinguishing the operating/degradation states represented within the simulation.

Wall shear stress recorded a score of 0.28, while flow rate produced 0.22. Although lower than corrosion, temperature, and pressure, both variables retained useful complementary information.

The MI results are important because they provide a model-independent description of feature relevance. No particular classification algorithm is required to obtain the scores. The results therefore describe the information structure of the generated virtual-pipeline dataset rather than the behaviour of a particular trained model.

Taken together, correlation and MI show that corrosion is strongly associated with several physical parameters and also contains the greatest individual information regarding pipeline condition. Temperature and pressure provide additional information, while flow and wall shear contribute complementary physical behaviour.

4.6 Virtual-Sensing and Engineering Implications

The numerical and statistical results support the use of the COMSOL model as a simulation-driven virtual-sensing environment.

Conventional pipeline monitoring normally uses measurements such as pressure, temperature, and flow at selected physical locations. Quantities such as distributed wall shear stress or localised degradation state may be more difficult to observe continuously.

The virtual pipeline provides a mechanism for evaluating these variables throughout a defined computational region. Under a future hybrid implementation, available physical measurements could be supplied to a calibrated model while the simulation provides estimates of quantities that are not directly measured.

The current model should therefore be viewed as a foundation rather than a replacement for physical sensing. Its principal role is to provide a controlled environment for analysing degradation scenarios, testing parameter relationships, and identifying variables that may be useful during future field monitoring.

The numerical-verification results are particularly important in this context. Virtual measurements should not be generated from a model that is excessively sensitive to mesh resolution or unable to converge across the required operating range. The successful solution of all 2,000 retained cases and the <0.9% mesh variation provide computational support for the stability of the virtual environment.

The correlation and MI results also indicate that multiple sensing variables should be considered jointly. Corrosion rate provided the strongest information, but temperature, pressure, wall shear stress, and flow also contributed to the representation of pipeline condition.

Consequently, a future field-calibrated system could combine conventional sensor measurements with physics-based virtual quantities to provide a broader representation of pipeline condition than either approach would provide independently.

4.7 Limitations

The developed model represents a simplified one-meter pipeline section and therefore does not reproduce all characteristics of a complete field-scale pipeline system. Actual networks may contain bends, valves, pumps, branches, elevation changes, welds, variable wall thickness, and changing external environmental conditions.

The four operating scenarios also represent controlled simulation conditions rather than individually validated field-failure events. They provide a structured environment for studying degradation behaviour but should not be interpreted as exact representations of every real blockage, corrosion hotspot, or leakage event.

The corrosion formulation represents degradation at a simplified level. A more detailed corrosion model could additionally account for variables such as pH, dissolved gases, microbial activity, coating condition, fluid composition, local surface chemistry, and electrochemical behaviour.

Although the mesh-refinement procedure demonstrated less than 0.9% variation between the two finest meshes for the selected quantities, a formal discretisation-uncertainty assessment was not performed. Further work could apply additional refinement levels and uncertainty measures to quantify numerical discretisation error more rigorously.

Finally, numerical convergence and consistency with predefined operating ranges do not constitute complete experimental validation. Calibration against laboratory measurements or operational pipeline data remains necessary before the virtual model is used for direct field decision-making.

V. CONCLUSION

This study evaluated the numerical reliability and multiphysics behaviour of a COMSOL-based simulation-driven virtual pipeline under normal operation, partial blockage, corrosion hotspot, and leak-induced pressure-drop conditions. A total of 2,000 parametric simulation cases were generated containing inlet pressure, outlet pressure, flow rate, temperature, wall shear stress, and corrosion rate.

All retained simulation cases achieved the specified PARDISO convergence tolerance. Mesh refinement showed less than 0.9% variation in peak wall shear stress and maximum temperature between the two finest mesh configurations, supporting practical mesh independence for the selected observables. Pressure and temperature contours further demonstrated spatially resolved hydraulic and thermal behaviour across the computational domain.

Correlation analysis showed that corrosion rate had strong positive relationships with inlet pressure (($r=0.84$)), wall shear stress (($r=0.72$)), and temperature (($r=0.72$)). Mutual-information analysis also identified corrosion rate as the most informative individual variable with a score of 0.46, followed by temperature at 0.41, inlet pressure at 0.37, outlet pressure at 0.35, wall shear stress at 0.28, and flow rate at 0.22.

The findings establish that the developed simulation environment produces numerically stable and physically interpretable operating states. The principal contribution of the study is therefore the numerical verification and multiphysics characterisation of the underlying virtual pipeline rather than another comparison of machine-learning classifiers.

The model provides a foundation for virtual sensing, degradation studies, scenario testing, and future integration with physical pipeline-monitoring systems. Further work should include field or laboratory calibration, formal discretisation-uncertainty assessment, expanded sensitivity analysis, and more detailed spatial corrosion modelling.

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