Scientific Contributions Oil & Gas, Vol. 49. No. 2, June: 487 - 507

SCIENTIFIC CONTRIBUTIONS OIL AND GAS

Testing Center for Oil and Gas
LEMIGAS

Journal Homepage:http://journal.lemigas.esdm.go.id
ISSN: 2089-3361, e-ISSN: 2541-0520

Predictive Modeling of Pipeline Erosion in Multiphase Flow Using OLGA Simulation and Response Surface Methodology (RSM)

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Manuscript received: February 25th, 2026; Revised: April 03th, 2026
Approved: May 12th, 2026; Available online: June 19th, 2026; Published: June 19th, 2026.

ABSTRACT - Pipeline erosion is a significant issue in the oil and gas production sector, especially in multiphase flow systems. Predicting erosion in the lab is expensive and time-consuming because it requires elaborate flow loops. This study developed a hybrid modeling framework integrating OLGA multiphase flow simulation with Response Surface Methodology (RSM) to predict the erosional velocity ratio (EVR) under clean service gas condensate flow conditions. The EVR was determined using the API RP 14E erosional velocity approach available in OLGA. A Box–Behnken design with 46 simulation cases was used to examine the influence of superficial gas velocity, superficial liquid velocity, pipe diameter, pressure, and temperature on EVR behavior. The results demonstrated that pipe diameter dominates EVR variation (75.28%), followed by superficial liquid velocity (18.38%) and gas velocity (6.59%), while temperature (0.31%) and pressure (0.03%) are negligible. An ANOVA (analysis of variance) also confirmed the OLGA simulation results by developing a robust quadratic model, achieving an R^2 of 0.9937 and validation R^2, RMSE, and MAE values of approximately 0.9904, 0.016, and 0.011, respectively, indicating that the model accurately forecasts EVR across a range of operating conditions. This model could aid in pipeline design optimization and enable rapid monitoring of erosion to enhance flow pipeline safety and service life.

Keywords: erosional velocity ratio, flow assurance, surrogate modeling, superficial fluid velocity, OLGA, DOE, ANOVA.

How to cite this article:

Bilal Ahmed, Syed Mohammad Mahmood, Mysara Eissa Mohyaldinn, Muhammad Jawad Khan, and Fahd Saeed Alakbari, 2026, Predictive Modeling of Pipeline Erosion in Multiphase Flow Using OLGA Simulation and Response Surface Methodology (RSM), Scientific Contributions Oil and Gas, 49 (2) pp. 487-507. DOI org/10.29017/scog.v49i2.2078.

INTRODUCTION

Reservoir fluids are most often transported through pipelines in the oil and gas sector due to their operational efficiency and cost-effectiveness (OBIOMAH 2025). However, pipeline erosion has become a widespread concern since it reduces the lifespan of pipelines by damaging the surface of their interior walls (Chen et al., 2006; Osman et al., 2025). The risk is magnified in multiphase flow systems where solid particles accelerate internal degradation (Othman et al., 2024). The erosional velocity ratio (EVR) is a key parameter in erosion prediction, where values above 1 typically indicate an elevated risk of pipeline wear (Peters et al., 2022; Khor et al., 2023a: Khor et al., 2023b; Al Wardi 2020; Peters et al., 2022). Controlling EVR through production and design parameters is essential to ensuring long-term pipeline reliability and safety.

A complementary technique for reducing erosional damage is operational control, which regulates the production velocities of particle-laden production fluids (Vieira 2014). Many scholars have spent many years focusing on this very determination. The American Petroleum Institute (API) issued the API RP 14E paper in 1975, which provided recommendations on the permitted velocity of solid-free, non-corrosive production fluids to minimize erosion damage; it has been revised five times since its first release (Shirazi et al., 2025). According to these recommendations, (Grant & Tabakoff 1975; Bashir et al., 2024, Pleshkov et al., 2022, Deng et al., 2013) serious erosion should not occur if production velocities are kept below the erosional velocity determined by Equation 1,

$$V_e = \frac{C}{\sqrt{\rho_m}} \tag{1}$$

where Ve is the erosional velocity in feet per second, ρm is the carrier fluid density in pounds per cubic foot, and C is a constant. The API guidelines specify that C = 100 for continuous service and 125 for intermittent service. API RP 14E states that less-dense fluids may experience greater erosion. However, experimental evidence shows that this is not the case. Furthermore, this rule does not account for several factors that influence erosion, including particle characteristics, particle geometry, impact angle, and the mechanical properties of the wall material. Several researchers concluded that API RP 14E was inapplicable when sand was present, and efforts were started to develop alternative erosion models.

Despite offering a commonly used empirical limit for erosional velocity, API RP 14E does not specifically account for geometric complexity, multiphase interactions, or sand production. Rather than serving as a complete erosion prediction model, API RP 14E is used in this study solely as a reference threshold for determining the erosional velocity ratio (EVR). Researchers such as Salama & Venkatesh (1983), Bourgoyne (1989), and Svedeman & Arnold (1993) attempted to improve these limitations by introducing modified empirical relationships that incorporated pipe diameter, impact angle, and erosion constants (Salama & Venkatesh 1983; Bourgoyne Jr, 1989; Svedeman & Arnold 1993).

In recent years, research has progressed toward high-fidelity numerical methods. For example, X. Chen et al. and B. Hong et al. (Chen et al., 2006; Hong et al., 2021) used Computational Fluid Dynamics (CFD) to simulate erosion in elbows and tees under multiphase conditions. These models demonstrated high accuracy in geometry-specific predictions but required significant computational resources. More recent work by (Othman et al.,

2024) integrated CFD with artificial neural networks (ANN) to predict erosion rates, achieving enhanced precision but introducing dependency on extensive datasets and calibration. Further (Parsi et al., 2017) proposed a new dimensionless parameter derived from CFD analysis to estimate solid particle erosion in elbows. While these models are effective, their applicability is often limited to specific pipeline geometries or flow regimes, making it difficult to generalize or deploy in field operations.

Although previous studies have applied CFD, ANN, and empirical methods for pipeline erosion prediction, most focus on direct erosion rate estimation using particle tracking, impact angle modeling, or geometry-specific simulations. CFD models provide high accuracy but are computationally intensive, while ANN approaches require large datasets and often have limited interpretability (Chang et al., 2025; Nadeem et al., 2025).

It is essential to clarify that solid-particle effects are not considered in this study, which focuses primarily on fluid-induced erosion under clean-service conditions. Therefore, rather than particle-wall impact mechanisms, hydrodynamic and multiphase flow parameters drive erosional behavior.

The objectives of the study are: 1). To develop an RSM-based surrogate model for predicting EVR using OLGA simulations; 2). To evaluate the effects of superficial gas velocity, superficial liquid velocity, pipe diameter, pressure, and temperature on EVR under clean-service conditions; 3). To establish operational guidelines for minimizing EVR; 4). To validate the predictive accuracy and statistical reliability of the developed surrogate model (code-to-code validation).

METHODOLOGY

OLGA model development

This section describes the step-by-step methods used to conduct parametric research on the erosional velocity ratio (EVR) with OLGA multiphase simulation software (OLGA 2021.2.0). OLGA has significant benefits for modeling long-distance and energy storage pipelines (Liang et al., 2023a, Venriza & Wahyuni 2024, Tony et al., 2025). It specifically provides a technique for optimizing design and evaluating system performance while considering critical elements such as EVR, pipeline length, and height, and pressure (George et al., 2024). OLGA can model a wide range of fluid characteristics, including single - and multiphase flow and sediment transport. Furthermore, OLGA enables rapid computation and accurate forecasting of complex flows, dynamic changes, and transient responses within the pipeline (Liang et al., 2023b; Auni et al., 2023). In the OLGA simulation setup, the erosional velocity threshold was guided by API RP 14E, which is defined by Equation 2,

$$EVR = \frac{1}{C}(EVR_{VACTUAL})(EVR_{RHOMIX})^{1/2} \tag{2}$$

where, $EVR_{VACTUAL}$= |Usg| + |Usl| + |Usd| EVR_{RHOMIX}= [ρg|Usg| + ρl(|Usl| + |Usd|)]/ (|Usg|+|Usl| + |Usd|) and C = 100 for U in ft/s and ρ in lb/ft^3, C = 121.99 for U in m/s and ρ in kg/m^3. Here |Usg|, |Usl| and |Usd| denote the absolute value of the superficial velocity for gas, liquid film and liquid droplets respectively. Similarly, ρg and ρl denote gas and liquid density.

The OLGA simulation model represented a 2000 m horizontal pipeline operating under steady-state multiphase flow conditions. The pipeline was discretized into 200 computational sections to ensure sufficient spatial resolution for pressure and velocity calculations along the pipeline length.

A parametric simulation strategy was adopted in which operating conditions were varied according to the Box–Behnken experimental design matrix. The investigated operating ranges included superficial gas velocities between 5 and 30 m/s, superficial liquid velocities between 0 and 4 m/s, pipe diameters between 4 and 18 inches, operating pressures between 500 and 1500 psi, and temperatures between 25 and 100 °C.

The EVR values were extracted directly from OLGA using the API RP 14E-based erosional-velocity formulation implemented in the simulator. The present work focused specifically on EVR prediction under clean-service conditions;

therefore, explicit sand particle tracking, particle-wall impact modeling, and erosion-rate calculations were not included in the simulations.

Each DOE design point corresponded to one independent OLGA simulation run. The identified influential residual points observed during statistical diagnostics were associated with physically meaningful extreme operating conditions rather than numerical instability or simulation failure. The pipe roughness is constant (5×10^{-5} m) throughout the simulation. In realistic systems, roughness changes over time resulting from erosion, corrosion, and deposition. Such alterations may affect wall shear stress and flow behavior; however, these impacts are outside the scope of the present study. A list of independent variables considered in the current study has been presented in the Table 1.

Moreover, three operating pressures, such as 500, 1000, and 1500 psi, and an operating temperature ranging from 25 °C to 100 °C were considered. The composition of the gas condensate considered is presented in Table 1 (Su et al., 2003).

In the OLGA simulations, the flow conditions were controlled using gas and liquid mass flow rates. These flow rates were subsequently converted on superficial gas velocity (Vsg) and superficial liquid velocity (Vsl) using the pipe cross-sectional area for response surface methodology (RSM) modeling and statistical analysis. Therefore, the discussion of parametric effects in the RSM section is presented in terms of superficial velocities rather than direct mass flow rates.

Assumptions and Limitations

- The study focused only on EVR prediction under clean-service multiphase flow conditions using OLGA and RSM approaches.
- The developed model is based on API RP 14E erosional velocity criteria and does not directly predict the actual erosion rate.
- Explicit sand particle tracking, particle-wall interaction, and particle impact angle effects were not modeled.
- Simulations were limited to a straight horizontal pipeline configuration.
- Complex pipeline components such as elbows, tees, valves, and fittings were not considered.
- Localized turbulence and severe erosion regions associated with fittings were outside the scope of the study.
- Wax deposition, hydrate formation, and heat transfer effects were neglected.
- Flow regime identification and analysis were not explicitly performed.
- Pipe roughness was assumed constant throughout the pipeline (5×10^{-5} m).
- Pressure drop and phase behavior were calculated using OLGA's built-in governing equations but were not independently validated.
- Validation was limited to computational agreement between OLGA simulations and the RSM surrogate model.
- Additional calibration with real operational or experimental data is required before industrial application of the model.

This methodology ensures a comprehensive assessment of gas-condensate multiphase flow dynamics under the given pipeline conditions using OLGA.

Design of experiments (DOE):

A Design of Experiments (DOE) method was employed to effectively explore the parameter range. To ascertain how various input factors

Table 1. Ranges of parameters

Parameter	Min.	Max.	Unit
Superficial Gas Velocity	5	30	m/s
Oil Superficial Velocity	0	4	m/s
Pipe Diameter	4	18	inches
Pressure	500	1500	psi
Temperature	25	100	°C

impact the process's output, Sir R.A. Fisher created the Design of Experiments approach in the 1920s (Ghomian 2008; Ghorbani 2008; Al Shalabi 2014). Identifying the input or independent elements is the first and most crucial phase in the use of RSM as it has a big impact on the whole process, including the desired responses as outputs (Veza et al., 2023).

In order to determine the optimum target, the RSM uses a low-order polynomial equation to identify a certain region of the predictor variables, which is further evaluated to determine the best possible values of the predictor variables (Ceylan et al., 2008). Compared to conventional methodologies and a time-consuming one-factor-at -a-time approach, optimization employing the RSM speeds up the collection of experimental study outcomes (Alim et al., 2008. Central Composite Design (CCD), D-optimal designs, Box–Behnken, and historical data design are the most used forms in the RSM (Asghar et al., 2014).

A randomized Box–Behnken Design (BBD) under Response Surface Methodology (RSM) was employed to systematically evaluate the effects of five independent variables on the erosional velocity ratio (EVR). The selected predictor variables were superficial gas velocity (Vsg), superficial liquid velocity (Vsl), pipe diameter, operating pressure, and temperature. The Box–Behnken approach was selected because it provides efficient quadratic model development with fewer simulation runs compared to full factorial designs while minimizing extreme combinations of variables.

The experimental design consisted of 46 OLGA simulation runs generated using Design-Expert software. Each simulation run corresponded to one unique combination of operating parameters within the selected design space. The predictor variables were coded into three levels (−1, 0, and +1), representing low, center, and high operating conditions, respectively. The ranges of the investigated variables are summarized in Table 1.

The generated DOE matrix was directly mapped to OLGA simulations, with each design point simulated independently under steady-state conditions. The resulting EVR values obtained from OLGA were then used as the response variable for regression model development and statistical analysis.

The suggested response surface methodology (RSM) model, which forecasted the EVR in the pipeline, was constructed using the block diagram displayed in Figure 1. The elements of the block diagram were (1) gathering data, (2) developing an EVR model, (3) assessing the RSM model, and (4) investigating how the predictors affected EVR. EVR was utilized as a target response in the RSM for variables including fluid velocities, pipe

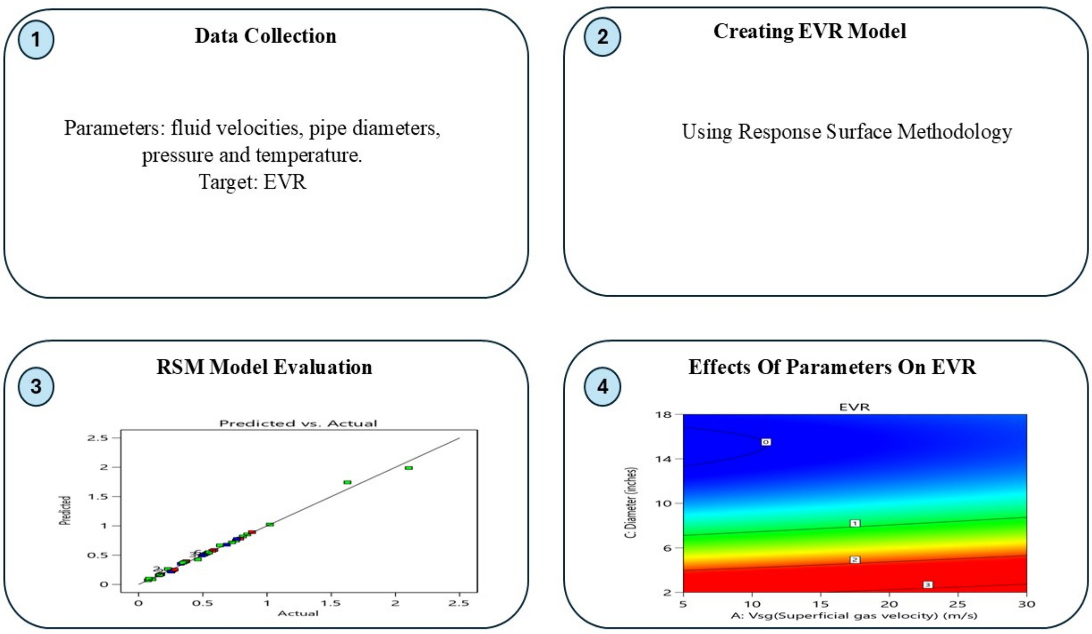

Figure 1. Block diagram

diameters, pressure, and temperature after the parameter ranges were first specified from the literature and run in OLGA to produce EVR.

The developed RSM model was then assessed using a variety of methods, such as fit statistics, diagnostic plots, Pareto charts, and analysis of variance (ANOVA). The next step was to apply the EVR model's contour and 3D surface response plots in Design-Expert software to assess the interactions between predictors and the target. From an engineering perspective, the developed OLGA-RSM surrogate model enables rapid EVR assessment without repeatedly performing computationally intensive multiphase simulations. This makes it useful for preliminary pipeline design, operational screening, flow assurance analysis, and production optimization. Compared with detailed CFD-based erosion models, the proposed approach provides a practical balance between physical representation and computational efficiency for rapid engineering evaluations under clean-service multiphase flow conditions.

EVR correlation development using response surface methodology (RSM)

RSM, also known as the response surface methodology, is a well-known approach to experimental design (DOE). RSM was employed to determine the relationship between goal variables (output variables) and predictor variables (input variables) to enhance the process. In addition, mathematical models of RSM were developed to investigate the impacts of the predictor factors. Equation 3 below represents the connection between the predictor and the target variables (Myers et al., 2016, Alakbari et al., 2025).

$$\eta = f\,(x1, x2, \dots x_n) + \mathcal{E} \tag{3}$$

where η: in this study, the response is indicated by a specific EVR, f: the unknown function of response, x1, x2, . . . xn: the predictor variables.

The objective was to identify the relationship between the inputs (Vsg, Vsl, diameter, pressure, and temperature) and the response EVR. Table 3 shows how Design-Expert was used to generate new empirical correlations for EVR forecasts based on Vsg, Vsl, diameter, pressure, and temperature. In addition to using Design-Expert tools, regression analysis was employed to find the best fit to the data (Dawud and Shakya, 2019. (Satiyawira et al., 2025 used RSM as a tool for the optimization of drilling fluid. A mathematical model that supports

Table 2. Fluid composition

Component	Mole Percent	Mole Weight (g/mol)	Component	Mole Percent	Mole Weight (g/mol)
Water	0.057	18.015	Iso Pentane	0.108	72.151
Nitrogen	0.081	28.014	Normal Pentane	0.089	72.151
Carbon Dioxide	0.251	44.01	Hexanes	0.101	86.178
Methane	94.388	16.043	Heptanes	0.076	96
Ethane	3.207	30.07	Octanes	0.048	107
Propane	1.069	44.097	Nonanes	0.01	121
Iso Butane	0.241	58.124	C10+	0.003	134
Normal Butane	0.272	58.124			

Table 3. Data range and statistical

Parameters	Min.	Max.	Mean	Std. Dev.	Skewness
Vsg (m/s)	5	30	17.5	7.372098	3.86E-17
Vsl (m/s)	0	4	2	1.179536	0
Diameter (inch)	4	18	11.47	3.645957	0.819777
Pressure (psi)	500	1500	1000	285.3131	0.002654
Temperature (°C)	25	100	60	22.66539	0.029593
EVR	0.0723	2.1034	0.5218	0.371485	2.117483

the relationship of the objective functions with the test factor group is obtained by regression analysis, assisting in developing a common relation between the predictor and the target parameter (Deng & Cai 2010; Marbun et al., 2025). In addition, the regression approach is utilized to examine response surface behavior.

The extent to which the variable predictors Vsg, Vsl, diameter, pressure, and temperature affect the target variables and the EVR in the regression analysis is further evaluated using analysis of variance (ANOVA). ANOVA was used in statistical analyses to evaluate the contributions of predictor variables to response, i.e., the EVR (Adalarasan et al., 2015; Derdour et al., 2018).

RESULT AND DISCUSSION

OFAT for Parameters in OLGA simulation.

Diameter

In Figure 2, the Erosion Velocity Ratio (EVR) and pipe diameter have a strong inverse relationship, based on the one-factor-at-a-time (OFAT) study.

As the diameter increases, the EVR decreases markedly, a trend effectively modeled by power-law regression curves. Reducing the pipeline diameter increases EVR because it drives the fluid to move faster to maintain the same flow rate. This promptly increases the risk of erosion.(Supmea, 2023 The chart shows that while larger diameters lead to lower EVR values, the rate of decrease varies with the specific settings of the other variables (Min, Mean, Max). Under all operating conditions, smaller diameters show noticeably higher EVR values. In particular, the 4" and 8" pipes exhibit higher erosion risk, especially when temperature, pressure, and mass flow rate are at their highest, while pipes with diameters of 12" and larger consistently have low EVR levels under all operating situations. As the diameter increases, the influence of other parameters becomes negligible.

Effect of mass flow when varying diameter

In Figure 3, for varying diameters, the OFAT analysis for mass flow reveals a strong linear relationship between mass flow rate and EVR across all test conditions, with R^2 values of 0.9973 to 1.0 indicating an excellent fit. As the flow rate increases, EVR rises steadily, with the rate of increase (slope m) being highest under Min conditions due to the lower-diameter effect and varying across Mean and Max settings. As mass flow increases from 10 to 30 kg/s, EVR consistently increases, with the steepest rise observed at the minimum setting. This suggests that mass flow has a predictable and proportional impact on EVR, making it a reliable parameter for tuning system performance. The linear trend also implies that incremental increases in mass flow result in a steady increase in EVR.

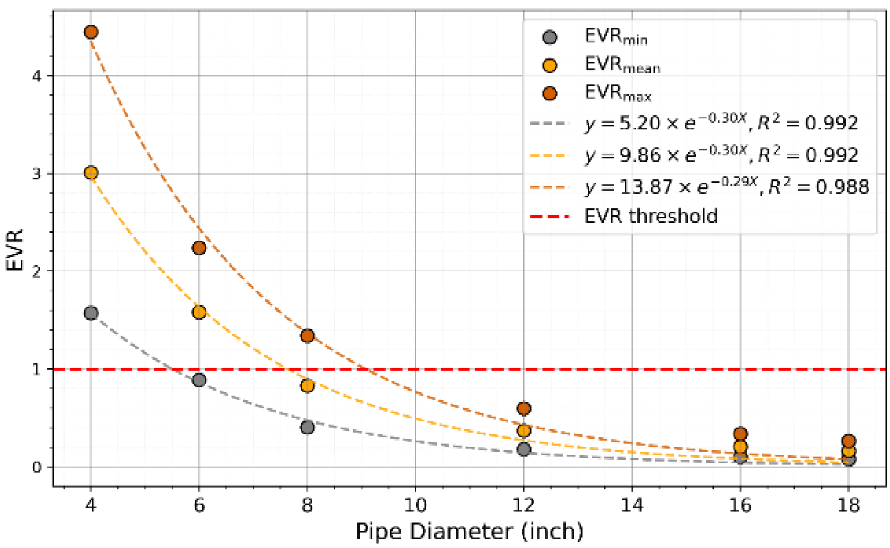

Figure 2. OFAT of diameter for EVR while keeping other variables constant at their Min, Mean and Max.

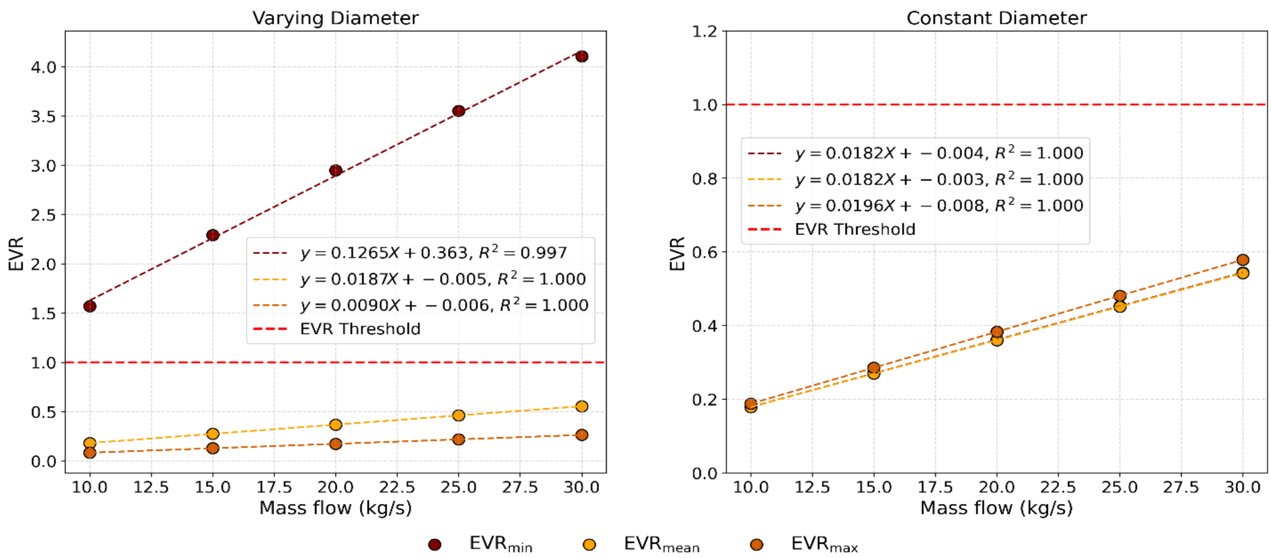

Figure 3. Effect of Mass Flow on EVR for constant and varying diameters

Effect of mass flow when the diameter is constant, 12 inches

In Figure 3, for Constant Diameter as mass flow increases from 10 to 30 kg/s, the EVR demonstrates a linear and proportional increase for all three cases (Min, Mean, and Max). The slopes of the regression lines are nearly identical, indicating that increasing mass flow predictably and consistently enhances erosional velocity across all scenarios. This linearity suggests that EVR is directly dependent on flow rate under constant pipe diameter, and that increasing the mass flow rate in a pipeline (without increasing the diameter) immediately increases EVR and the risk of erosion. (Othman et al., 2023).

Temperature

Figure 4 illustrates how the Erosional Velocity Ratio (EVR) varies with temperature (25–100 °C) under two conditions: varying diameter (left) and constant diameter (right). In the varying-diameter case, EVR_{min}, EVR_{mean}, and EVR_{max} all increases linearly with temperature, with EVR max showing the steepest rise and exceeding the critical EVR threshold, suggesting a higher risk of erosion at elevated temperatures due to increased velocity imbalances. Conversely, the constant diameter yields lower, more stable EVR values, all of which remain below the threshold over the temperature range. As the temperature increases, the gas density drops due to expansion. Lower density (at constant mass flow) leads to higher gas velocity, which raises the actual velocity component of EVR. With small-diameter pipes, the velocity increase is greater, so EVR rises faster.

Pressure

Figure 5 shows the effect of pressure (500–1500 psi) on the Erosional Velocity Ratio (EVR) under varying (left) and constant (right) diameter conditions. In the varying-diameter case, all EVR values (min, mean, max) decrease slightly with increasing pressure, as indicated by negative slopes, yet EVR max consistently exceeds the critical threshold, indicating ongoing erosional risk. In contrast, the constant-diameter configuration shows nearly flat trend lines with negligible slopes, and all EVR values remain well below the threshold, reflecting excellent flow stability. At constant temperature, increasing pressure increases gas density. For a fixed mass flow, higher density lowers the velocity, which in turn reduces EVR. However, the effect is marginal because gas compressibility at these moderate pressures (500–1500 psi) doesn't cause significant velocity drops. Overall, Figure 5 suggests that pressure has minimal impact on EVR, and maintaining a constant diameter is key to reducing erosional risk.

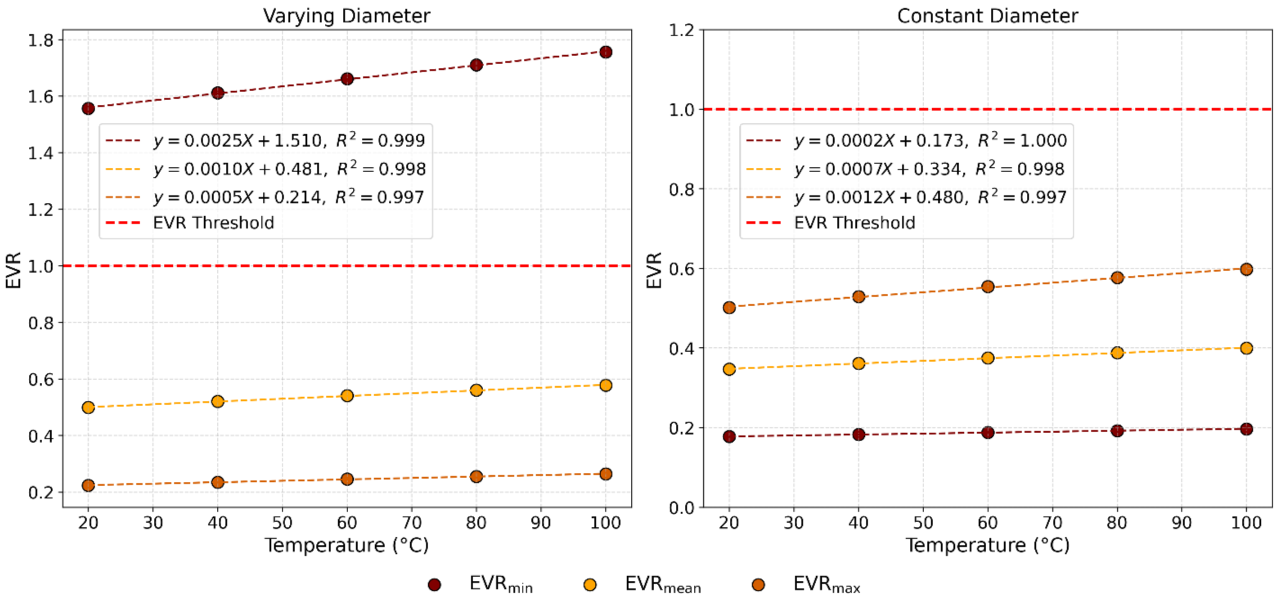

Figure 4. Effect of Temperature on EVR for constant and varying diameters

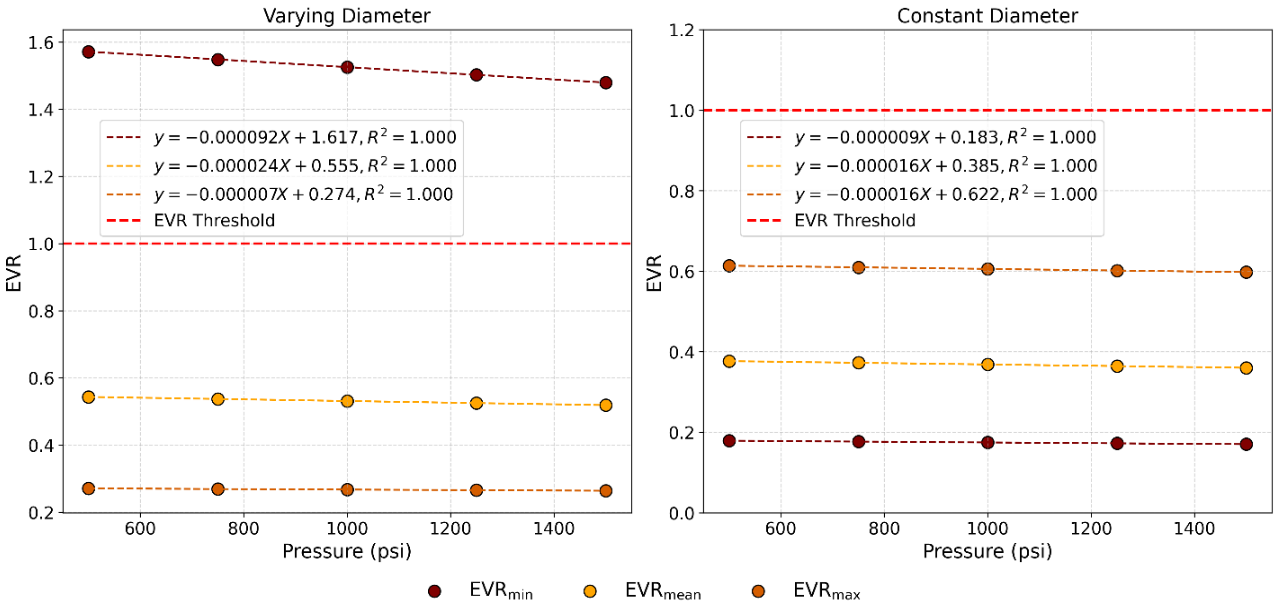

Figure 5. Effect of Pressure on EVR for constant and varying diameters

EVR correlation

The results of this study suggest that the developed RSM model for EVR prediction is satisfactory. The empirical relationship between EVR and the process variables was represented in equation 4 using the complete quadratic regression obtained from the Box–Behnken Response Surface Methodology. The final regression model in terms of actual factors is expressed as follows in Table 4.

$$\begin{aligned} EVR = {} & 2.99325 + 0.020240(A) + 0.293276(B) \\ & - 0.462939(C) + 0.000695(D) \\ & - 0.000031(E) + 8.54291 \times 10 - 6(AB) \\ & - 0.000914(AC) + 0.000032(AD) \\ & - 7.05612 \times 10 - 7(AE) - 0.014814(BC) \\ & + 0.000290(BD) - 6.32577 \times 10 - 6(BE) \\ & - 0.000089(CD) + 2.00876 \times 10 - 6(CE) \\ & + 2.26686 \times 10 - 7(DE) + 0.000052(A2) \\ & - 0.002070(B2) + 0.016596(C2) \\ & - 1.58185 \times 10 - 6(D2) - 2.01434 \times 10 \\ & - 10(E2) \end{aligned} \tag{4}$$

where *A* superficial gas velocity, Vsg (m/s), *B* superficial liquid velocity, Vsl (m/s), *C* pipe diameter (inches), *D* temperature (°C), and *E* pressure (psi) using Equation 4.

The EVR model has been evaluated through ANOVA, diagnostics plots, and fit statistics.

Analysis of variance

An analysis of variance (ANOVA) was performed at the 5% significance level to evaluate the influence of various process factors on the EVR response. The relative importance of each factor and interaction in the model is shown by the F-values and p-values in Table 5.

Table 4. Coefficients of actual quadratic Equation

Term	Coefficient	Term	Coefficient
Intercept	2.99325	BD	0.000290
A (Vsg)	0.020240	BE	-6.32577E-06
B (Vsl)	0.293276	CD	-0.000089
C (Diameter)	-0.462939	CE	2.00876E-06
D (Temperature)	0.000695	DE	2.26686E-07
E (Pressure)	-0.000031	A^2	0.000052
AB	8.54291E-06	B^2	-0.002070
AC	-0.000914	C^2	0.016596
AD	0.000032	D^2	-1.58185E-06
AE	-7.05612E-07	E^2	-2.01434E-10
BC	-0.014814		

Table 5. ANOVA For EVR

Source	Sum of squares	df	Mean square	F-value	P-value	
Model	6.31	20	0.3154	196.01	< 0.0001	significant
A-Vsg (Superficial gas velocity)	0.4157	1	0.4157	258.36	< 0.0001	
B-Vsl (superficial liquid velocity)	1.16	1	1.16	722.37	< 0.0001	
C-Diameter	4.75	1	4.75	2951.22	< 0.0001	
D-Temperature	0.0193	1	0.0193	11.98	0.0019	
E-pressure	0.0016	1	0.0016	0.9731	0.3334	
AB	1.83E-07	1	1.83E-07	0.0001	0.9916	
AC	0.0215	1	0.0215	13.35	0.0012	
AD	0.0009	1	0.0009	0.5717	0.4567	
AE	0.0001	1	0.0001	0.0483	0.8278	
BC	0.1443	1	0.1443	89.69	< 0.0001	
BD	0.0019	1	0.0019	1.18	0.288	
BE	0.0002	1	0.0002	0.0995	0.7551	
CD	0.0012	1	0.0012	0.7727	0.3877	
CE	0.0001	1	0.0001	0.0695	0.7943	
DE	0.0001	1	0.0001	0.0449	0.8339	
A^2	0.0006	1	0.0006	0.3575	0.5553	
B^2	0.0006	1	0.0006	0.3748	0.5459	
C^2	1.95	1	1.95	1213.96	< 0.0001	
D^2	0	1	0	0.0256	0.8741	
E^2	2.14E-08	1	2.14E-08	0	0.9971	
Residual	0.0402	25	0.0016			
Lack of Fit	0.0402	16	0.0025			
Pure Error	0	9	0			
Cor Total	6.35	45				

The Model F-value of 196.01 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. P-values less than 0.0500 indicate model terms are significant. In this case, A, B, C, D, AC, BC, and C^2 are significant model terms. Values greater than 0.1000 indicate the model terms are not significant. If there are many insignificant model terms (excluding those required to support the hierarchy), model reduction may improve the model. These factors are statistically significant and have a considerable impact on the model response. However, E ($p = 0.3334$) is not statistically significant at the 95% confidence level, indicating that it has no major impact on the EVR under the conditions investigated. With a Residual Mean Square of 0.0016 and a Lack of Fit score of 0.0025, suggesting a good model fit.(Zabeti et al., 2010. Given the significance of several key terms, the model is refined for greater accuracy and confidence, ensuring a robust predictive response for the EVR quadratic model.

The developed quadratic regression model satisfies the hierarchy principle, as all significant interactions and quadratic terms were retained together with their associated main effects. The lack-of-fit test was statistically insignificant ($p > 0.05$), indicating that the model adequately represents the relationship between the operating parameters and EVR within the investigated design space. In addition, a Box–Cox transformation analysis was performed to evaluate the need for response transformation. The optimal lambda value was close to unity, indicating that no significant transformation of EVR was required. Therefore, the ANOVA and regression analyses were conducted using the original EVR response values.

Fit statistics

Table 6 shows the fit statistics for the developed model, indicating its excellent accuracy and reliability in forecasting EVR responses. The model has a good coefficient of determination ($R^2 = 0.9937$), explaining 99.37% of the variability in the response. The adjusted R^2 (0.9886) and predicted R^2 (0.9539) are closely aligned, indicating that the model is not overfit and can accurately predict new data. Furthermore, the standard deviation (0.0401) and coefficient of variation (7.69%) show minimal residual variability and high accuracy.

An initial quadratic RSM model containing linear, interaction, and quadratic terms was established and later simplified via backward elimination based on the statistical significance of the model terms, while preserving the hierarchical structure. Several diagnostic tests were then conducted to assess the suitability of the developed regression model. The Box–Cox analysis suggested that transformation of the response was unnecessary, indicating that the original EVR data were appropriate for model development. Examination of the residual plots showed a random scatter around the zero line without any noticeable pattern, which indicates stable variance and acceptable model behavior.

In addition, the predicted values were in close agreement with the OLGA simulation results, demonstrating the surrogate model's strong predictive performance. The Cook's distance results also showed that most runs had minimal influence on the regression fit, with only a few points showing comparatively stronger influence due to extreme response values. Overall, the statistical diagnostics confirmed that the developed EVR model is reliable, stable, and capable of accurately representing the simulation data.

The model's suitable signal-to-noise ratio and appropriateness for navigating the design space are demonstrated by its Adequate Precision value of 70.6829, which is significantly greater than the minimum requirement of 4. These statistical analyses validate the regression model's validity and robustness, making it an effective tool for examining and refining the factors influencing the EVR response.

Table 6. FIT statistics analysis of RSM model

Parameter	R^2	St. D.	Mean	COV (%)	Adj. R^2	Predicted R^2	Ad. Precision
Value	0.9937	0.0401	0.5219	7.69	0.9886	0.9539	70.6829

EVR model verification

To further evaluate the predictive capability of the developed RSM model, an external validation study was conducted using additional OLGA simulation cases outside the original DOE dataset. Ten independent operating conditions were selected and simulated separately in OLGA under clean-service multiphase flow conditions. This is a code-to-code validation in which the simulation tool's numerical behavior is replicated by the surrogate model.

The predicted EVR values obtained from the RSM model were compared to the corresponding OLGA simulation results. The comparison demonstrated excellent agreement between predicted and simulated EVR values, confirming the generalization capability of the developed surrogate model outside the original design space.

The developed model achieved high predictive accuracy with R^2, RMSE, and MAE values of approximately 0.9904, 0.016, and 0.011, respectively, as shown in Figure . These results indicate that the proposed OLGA-RSM framework can reliably predict EVR within the investigated operational range while significantly reducing computational effort compared to repeated full multiphase simulations.

Effect of the Predictor Variables on EVR

To assess the interactions among predictor variables, Design-Expert was used to interpret the contour and 3D surface response plots of the EVR model, including Vsg, Vsl, diameter, pressure, and temperature. i.e., the EVR, as Figures. From 7 to 8.

Effect of Vsl and Vsg on EVR

This graph Figure (a) shows the relationship between superficial gas velocity (Vsg) on the x-axis (ranging from 5 to 30 m/s) and superficial liquid velocity (Vsl) on the y-axis (from 0 to 4 m/s), with EVR represented by contour lines. The contour lines labeled 0.2, 0.4, 0.6, 0.8, and 1.0 show that EVR increases as both Vsg and Vsl increase, indicating a positive correlation. The diagonal trend of the lines from bottom-left (low Vsg and Vsl) to top-right (high Vsg and Vsl) means that combinations like Vsg = 10 m/s and Vsl = 0.5 m/s yield EVR ≈ 0.2, while Vsg = 25 m/s and Vsl = 3 m/s correspond to EVR ≈ 0.8. This implies that, to keep EVR constant, an increase in one velocity must be offset by decreases in the others.

3D effect of Vsg and pipe diameter on EVR

The combined effects of pipe diameter and superficial gas velocity (Vsg) on the Erosional Velocity Ratio (EVR) are shown in the 3D surface graphic Figure (b). The graphic demonstrates that EVR rises as Vsg increases, emphasizing how Vsg increases EVR, although pipe diameter remains the dominant factor. However, as pipe diameter increases, the EVR tends to decrease, indicating that larger pipe diameters reduce velocity gradients, which in turn decrease EVR. The gradient flattens for larger diameters and is steeper for smaller ones, indicating that EVR's sensitivity to Vsg decreases with increasing pipe diameter.

Contour effect of Vsg and pipe diameter on EVR

Figure (c) shows the relationship between superficial gas velocity (Vsg) on the x-axis and pipe diameter on the y-axis, with EVR (Erosional Velocity Ratio) represented by color-coded contour lines. The contour lines trend mostly horizontally, indicating that EVR is highly sensitive to changes in pipe diameter, whereas changes in Vsg have a smaller effect than changes in diameter. Specifically, EVR increases as pipe diameter decreases the red zone at the bottom (small diameters) shows higher EVR values (e.g., 2 and 3), while the blue zone at the top (larger diameters) shows lower EVR values (e.g., 0 and 1) (Onyegiri et al., 2020. This means that for a given Vsg, a smaller pipe diameter significantly increases the risk of erosion. The nearly horizontal lines suggest that diameter is the dominant factor influencing EVR in this scenario.

Effect of Vsl and Pipe Diameter on EVR

This graph Figure (d), displays how EVR (Erosional Velocity Ratio) varies with superficial liquid velocity (Vsl) on the x-axis (ranging from 0 to 4 m/s) and pipe diameter on the y-axis

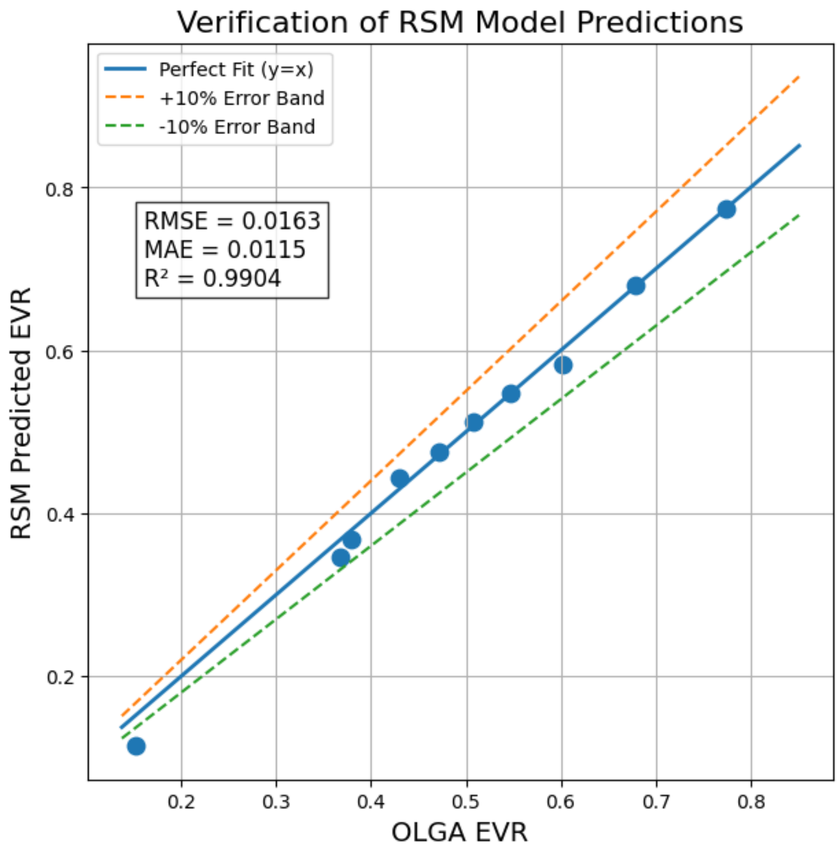

Figure 6. External validation of RSM model vs OLGA for EVR at different operating conditions.

(ranging from 2 to 18 inches). The contour lines, marked with EVR values 0, 1, 2, and 3, show that EVR increases significantly as diameter decreases, while increasing Vsl also causes a moderate rise in EVR. For instance, at a 2.5-inch diameter and Vsl = 3 m/s, the EVR is about 3, indicating a high erosion risk. In contrast, at a 14-inch diameter and at the same Vsl = 3 m/s, the EVR is close to 0, reflecting a much lower erosion potential. The mostly horizontal contour lines suggest that pipe diameter has a stronger influence on EVR than liquid velocity in this scenario.

Effect of Vsg and temperature on EVR

The EVR contour plot Figure (a) illustrates the relationship between superficial gas velocity (Vsg) and temperature, highlighting regions of potential erosional risk. Results indicate that EVR increases with Vsg, whereas higher temperatures slightly increase EVR. The contour line at EVR = 1.0 serves as a critical threshold, distinguishing safe (EVR < 1) and unsafe (EVR > 1) operational zones.

Effect of diameter and temperature on EVR

Figure (b) shows the effect of diameter (C: inches) and temperature (D: °C) on the response EVR using a contour plot. EVR values decrease from 3 to below 1 as the diameter increases from around 2 to 8 inches, as shown by vertical contour lines that transition from red to blue. The near-vertical contour lines indicate that EVR is strongly influenced by diameter, while temperature (25°C to 100°C) has minimal effect. This confirms diameter as the primary factor affecting EVR in this system.

Effect of Vsl and Temperature on EVR

Figure (c) shows EVR increases as superficial liquid velocity (Vsl) increases, whereas temperature has only a slight impact, according to the EVR contour plot for Vsl versus temperature. The safe and critical zones are indicated by the EVR <1 contour line, which shows that higher Vsl values make the system more vulnerable to erosion. This implies that regulating EVR requires controlling Vsl, with temperature also affecting EVR in these scenarios.

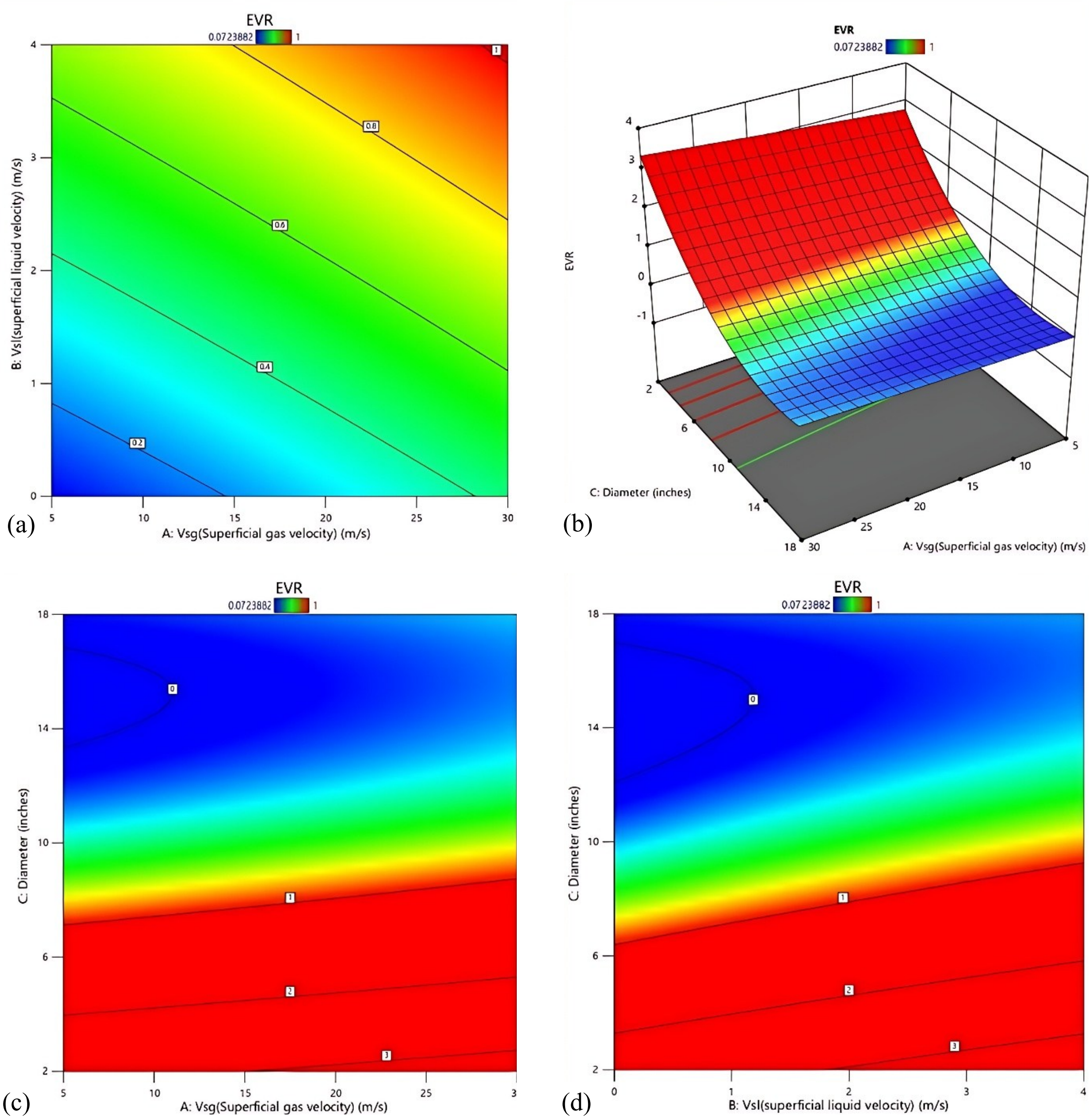

Figure 7. Response surface and contour plots illustrating the interaction effects of process parameters on EVR. Contour plot in RSM (a) Vsg vs Vsl, (b) 3D plot for Vsg vs Pipe Diameter, (c) Vsg vs Pipe Diameter, (d) Vsl vs Pipe Diameter

The strong effect of pipe diameter on EVR is primarily due to its influence on flow velocity and turbulence inside the pipeline. For a constant mass flow rate, reducing the pipe diameter decreases the flow area, which increases fluid velocity, wall shear stress, and turbulence intensity, thereby increasing EVR. In multiphase flow, smaller diameters also intensify phase interactions and local velocity fluctuations, further increasing the tendency toward erosion. Conversely, larger diameters reduce turbulence and flow velocity, leading to lower EVR values and reduced erosion risk, which explains the dominant contribution of diameter observed in the ANOVA analysis. Despite having relatively little impact, temperature and pressure have an indirect relationship with fluid characteristics. Temperature increases cause condensate viscosity to decrease, which can change flow profiles and shear stress distribution and affect erosion behavior.

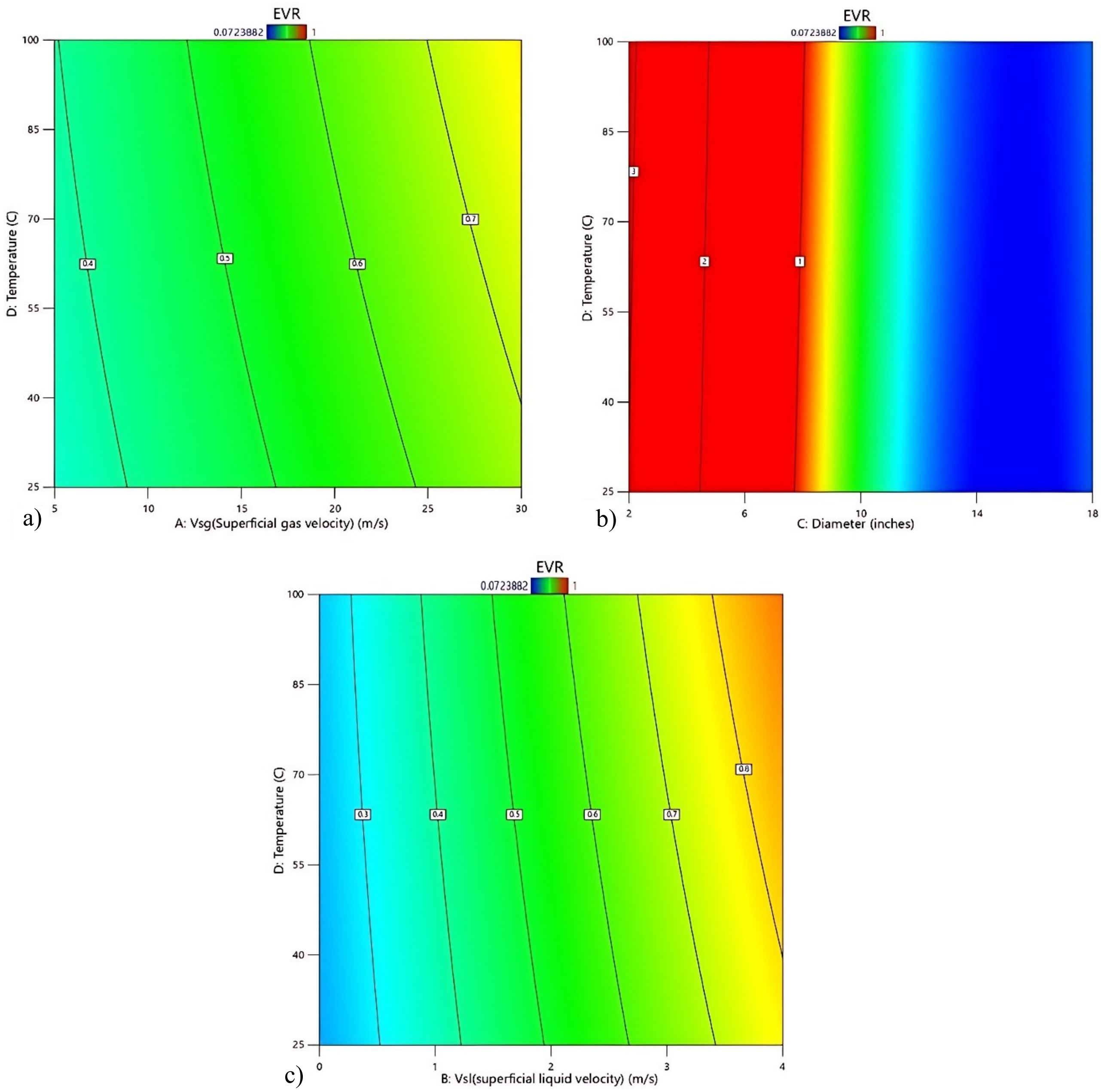

Figure 8. EVR contour plot illustrating the interaction effects of parameters.
a). Vsg vs temperature, b). diameter vs temperature, c). Vsl vs temperature.

The statistical insignificance of pressure in the ANOVA indicates that it contributes minimally to EVR variation within the investigated operating range. Physically, increasing pressure increases gas density, which may slightly reduce gas velocity for a fixed mass flow rate. However, within the investigated pressure range of 500–1500 psi, the resulting velocity variation was insufficient to significantly affect EVR relative to dominant parameters such as pipe diameter and superficial velocity. This finding suggests that pressure may potentially be excluded from simplified future EVR surrogate models under similar clean-service operating conditions without substantial loss of predictive accuracy.

Engineering implications and practical applications

Real-world application scenario

This study's regression-based EVR model offers a practical decision-support tool for pipeline design and real-time operational adjustments. For example, consider a typical gas-condensate pipeline with these conditions: 1). Operating pressure: 1000 psi; 2). Superficial gas velocity (Vsg): 20 m/s; 3). Superficial liquid velocity (Vsl): 2 m/s; and 4). Pipe diameter: 6 inches.

Using the proposed RSM-predicted model, the EVR is approximately 1.45, indicating a high risk of internal erosion. To lower the EVR below the critical threshold (EVR < 1), operators could increase the diameter to 10 inches, resulting in an EVR of about 0.78 under the same flow conditions. This adjustment would significantly reduce the risk of erosion without decreasing throughput.

Compared to established models such as Salama and DNV correlations, the proposed RSM-based model offers improved computational efficiency and adaptability to multiphase simulation outputs. However, unlike empirical models derived from experimental data, the present model requires further validation to ensure predictive reliability under field conditions.

Design guidelines based on EVR modeling

The guidelines in Table translate the relationship between velocity, diameter, and EVR into clear operational limits. By defining safe velocity ranges for each pipe size, they assist engineers in selecting diameters that maintain EVR < 1 during design and in verifying safe operating conditions during production. These limits also support system upgrades and integrity assessments by indicating when higher flow rates exceed erosion-safe thresholds. Overall, the design limits presented in Table 7 are derived for a gas condensate in a 2000 m straight pipeline configuration and do not account for complex geometrical features such as elbows, tees, valves, or fittings, where localized turbulence and erosion are typically more severe. Therefore, these values should be used only for preliminary assessment and not as definitive design criteria.

CONCLUSION

Based on simulation results, the following conclusions can be drawn: 1). The model predicts EVR, not actual erosion rate, and is valid only for clean-service straight pipeline conditions within the studied range; 2). EVR decreases significantly as diameter increases, a trend that power-law regression models effectively represent; 3). Mass flow demonstrates a clear linear relationship between mass flow rate and EVR. However, the higher slope of the EVR line at the minimum is caused by the most significant effect of the diameter at that point; 4). At a constant diameter of 12", EVR increases significantly with mass flow, decreases slightly with pressure, and is minimally affected by temperature; 5). The regression model's high predictive accuracy (R^2 = 0.9937) was confirmed in forecasting EVR across different pressure, temperature, and flow conditions; 6). Diameter and fluid velocity have a much greater impact on EVR than other parameters.

ACKNOWLEDGEMENT

The corresponding author appreciatively acknowledges the Interdisciplinary Research Centre for Hydrogen Technologies and Carbon Management at King Fahd University of Petroleum

Table 7. Guidelines for pipeline pre-selection.

Pipe diameter (inches)	Safe max Vsg (m/s)	Safe max Vsl (m/s)	Approximate EVR
6"	≈ 5.0	≈ 0.5	1
8"	≈ 19.6	≈ 1.96	0.997
10"	≈ 34.1	≈ 3.41	0.999
12"	≈ 48.3	≈ 4.83	0.999

& Minerals, Dhahran 31261, Saudi Arabia, for supporting this study. The authors express their sincere appreciation to the Centre of Flow Assurance, Universiti Teknologi PETRONAS, for fostering a supportive working environment and financial support that contributed to the successful completion of this work. The authors also gratefully acknowledge the support from the Higher Education Commission (HEC), Pakistan, for providing financial assistance.

DECLARATIONS

Authors' contributions

Bilal Ahmed: conceptualization, data curation, methodology, software, validation, writing – original draft. Syed Mohammad Mahmood: conceptualization, data curation, investigation, methodology, project administration, validation, visualization, writing – original draft. Mysara Eissa Mohyaldinn: conceptualization, supervision, writing – review & editing. Muhammad Jawad Khan: validation, formal analysis, software, writing – original draft. Fahd Saeed Alakbari: data curation, methodology, software, writing – original draft, writing – review & editing.

Funding statement

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

Competing interest

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.

The use of AI or AI-assisted technologies

The author(s) used Deepseek Copilot to assist. After using this tool, the authors review and edit the content as needed and take full responsibility for the publication's content.

GLOSSARY OF TERMS AND SYMBOLS

Terms & Symbols	Definition	Unit
EVR	Erosional Velocity Ratio	Dimensionless
Vsg	Superficial gas velocity	m/s
Vsl	Superficial liquid velocity	m/s
Ve	Erosional velocity (API RP 14E)	m/s (or ft/s)
ρm	Mixture fluid density	kg/m³ (or lb/ft³)
ρg	Gas density	kg/m³
ρl	Liquid density	kg/m³
Usg	Superficial gas velocity used in OLGA/API equation	m/s
Usl	Superficial liquid film velocity	m/s
Usd	Superficial liquid droplet velocity	m/s
C	API RP 14E erosion constant	Dimensionless
D	Pipe diameter	inch
P	Operating pressure	psi
T	Operating temperature	°C
ṁ (Mass flow)	Total mass flow rate	kg/s
RSM	Response Surface Methodology	—
DOE	Design of Experiments	—
BBD	Box–Behnken Design	—
CCD	Central Composite Design	—
OLGA	Dynamic multiphase flow simulation software	—
API RP 14E	American Petroleum Institute Recommended Practice for erosional velocity	—
ANOVA	Analysis of Variance	—
CFD	Computational Fluid Dynamics	—
ANN	Artificial Neural Network	—
OFAT	One-Factor-at-a-Time analysis	—

RMSE	Root Mean Square Error	Same as response (EVR)
MAE	Mean Absolute Error	Same as response (EVR)
R^2	Coefficient of determination	Dimensionless
Adjusted R^2	Adjusted coefficient of determination	Dimensionless
Predicted R^2	Predicted coefficient of determination	Dimensionless
COV	Coefficient of Variation	%
Std. Dev.	Standard deviation	Same as response
η	Response variable in the RSM equation (EVR)	Dimensionless
f(x)	Unknown response function	—
$x_1, x_2, \ldots, x_n$	Predictor (independent) variables	Variable-dependent

REFERENCES

Adalarasan, R., Santhanakumar, M. & Rajmohan, M., (2015), Application of Grey Taguchi-based response surface methodology (GT-RSM) for optimizing the plasma arc cutting parameters of 304L stainless steel. The International Journal of Advanced Manufacturing Technology,78 , .1170-1161https://doi.org/10.1007/s00170-014-6744-.

Al Shalabi, E. W., (2014), Modeling the effect of injecting low salinity water on oil recovery from carbonate reservoirs, Emad W. Al Shalabi.https://doi.org/10.2523/IPTC-17244-M:

Al Wardi, K. H. M. S., (2020), Crude Oil Characterization, Hydraulic Analysis and Process Optimization of Real Case Study in Omani Oil Field, Sultan Qaboos University (Oman).

Alakbari, F. S., Mohyaldinn, M. E., Mahmood, S. M., Hassan, A. M., Ashena, R. & Al-Fakih, A., (2025), A Statistics-Based Correlation for the Assessment of Water-Based Mud Performance: Yield Point Prediction. Arabian Journal for Science and Engineering,50 ,.4942-4927 https://doi.org/10.1007/s13369-024-09415-.

Alim, M., Lee, J.-H., Akoh, C., Choi, M.-S., Jeon, M.-S., Shin, J.-A. & Lee, K.-T., (2008), Enzymatic transesterification of fractionated rice bran oil with conjugated linoleic acid: Optimization by response surface methodology. LWT-Food Science and Technology,41 ,-764 .770https://doi.org/10.1016/j.lwt.2007.06.00.

Asghar, A., Abdul Raman, A. A. & Daud, W. M. a. W., (2014), A comparison of central composite design and Taguchi method for optimizing Fenton process. The scientific world journal, 2014,.869120 https://doi.org/10.1155/2014/86912.

Auni, N. R., Afdhol, M. K., Fikri, M. R. & Erfando, T., (2023), Potensi Polimer Sintetik Sebagai Bahan Chemical Enhaced Oil Recovery Untuk Meningkatkan Sweep Efficiency pada Skala Pengujian Laboratorium. *Lembaran publikasi minyak dan gas bumi,*57 ,21-9 .

Bashir, I., Inam, S., Sana-Ul-Hussnain, M., Shafee, I., Aijaz, M., Ullah, R., Haider, M., Qureshi, H., Khan, M. & Ahmad, H., (2024), Erosion Mitigation During Testing of High Deliverability Gas Well-A Case Study. International Petroleum Technology Conference. IPTC, D031S135R001.https://doi.org/10.2523/IPTC-23511.

Bourgoyne Jr, A., (1989), Experimental study of erosion in diverter systems due to sand production. SPE/IADC Drilling Conference and Exhibition, . SPE, SPE-18716-MS.https://doi.org/10.2118/18716-M.

Ceylan, H., Kubilay, S., Aktas, N. & Sahiner, N. (2008), An approach for prediction of optimum reaction conditions for laccase-catalyzed bio-transformation of 1-naphthol by response surface methodology (RSM). Bioresource technology,99 ,.2031-2025 https://doi.org/10.1016/j.biortech.2007.03.01.

Chang, A., Dong, Q., Zhang, J., Shao, M. & Vafai, K., (2025), Investigation of the erosion wear mechanism of bend pipes for the action of multiphase flow in CO2 flooding industry. International Journal of Numerical Methods for Heat & Fluid Flow,35 ,229-2264 .

Chen, X., Mclaury, B. S. & Shirazi, S. A., (2006), Numerical and experimental investigation of the relative erosion severity between plugged tees and elbows in dilute gas/solid two-phase flow. Wear,261 ,.729-715 https://doi.org/10.1016/j.wear.2006.01.02.

Dawud, E. R. & Shakya, A. K., (2019), HPLC-PDA analysis of ACE-inhibitors, hydrochlorothiazide and indapamide utilizing design of experiments. Arabian Journal of chemistry,12 ,.728-718 https://doi.org/10.1016/j.arabjc.2014.10.05.

Deng, L. & Cai, C., (2010), Bridge model updating using response surface method and genetic algorithm. Journal of Bridge Engineering,15 , .564-553https://doi.org/10.1061/(ASCE)BE.1943-5592.000009.

Deng, Y., Liu, Y., Chen, J. & Zhang, Y. Numerical simulation of the erosion in the 90 elbow. AIP Conference Proceedings, (2013), American Institute of Physics, 671-683.https://doi.org/10.1063/1.481692.

Derdour, F. Z., Kezzar, M. & Khochemane, L., (2018), Optimization of penetration rate in rotary percussive drilling using two techniques: Taguchi analysis and response surface methodology (RMS). Powder technology,339 , .853-846https://doi.org/10.1016/j.powtec.2018.08.03.

George, I. S., Orji, C. U. & Douglas, I. E., (2024), Flow assurance analysis in Front End Engineering Design (FEED) of Subsea Flowline and Riser.https://doi.org/10.30574/wjarr.2024.22.2.150.

Ghomian, Y., (2008), Reservoir simulation studies for coupled carbon dioxide sequestration and enhanced oil recovery, The University of Texas at Austin.

Ghorbani, D., (2008), Development of methodology for optimization and design of chemical flooding, The University of Texas at Austin.

Grant, G. & Tabakoff, W., (1975), Erosion prediction in turbomachinery resulting from environmental solid particles. Journal of Aircraft,12 ,.478-471 https://doi.org/10.2514/3.5982.

Hong, B., Li, Y., Li, X., Ji, S., Yu, Y., Fan, D., Qian, Y., Guo, J. & Gong, J., (2021), Numerical Simulation of Gas-Solid Two-Phase Erosion for Elbow and Tee Pipe in Gas Field. Energies,14 , .6609https://doi.org/10.3390/en14206609https://doi.org/10.3390/en1420660.

Khor, S., Limpasurat, B., Zhang, M. & Graa, I., (2023a), Integrated Pore-to-Process Modelling Approach for Confident Decision-Making in Field Development of a Complex Onshore Gas-Condensate Asset in the Middle East. Abu Dhabi International Petroleum Exhibition and Conference. SPE, D041S130R006.https://doi.org/10.2118/216864-M:

Khor, S. H., Limpasurat, T., Zhang, M. Q. & Graa, I., (2023b), Unlocking Ultimate Values of a Complex Gas-Condensate Light-Oil Asset in the Middle East with Integrated Pore-to-Process Solutions. International Petroleum Technology Conference. IPTC, D012S003R002.https://doi.org/10.2523/IPTC-23062-M.

Liang, C., Xiong, W., Wang, H., Carriveau, R., Ting, D.-K. & Wang, Z., (2023a), Identification of slug flow in underwater compressed gas energy storage pipeline using pressure signals. IET Conference Proceedings CP833. IET, 7-14.https://doi.org/10.1049/icp.2023.154:

Liang, C., Xiong, W., Wang, H. & Wang, Z., (2023b), Experimental and OLGA Modeling Investigation for Slugging in Underwater Compressed Gas Energy Storage Systems. Applied Sciences,13 ,9575 .

Marbun, M., Nijusiho Manik, S. & Karim, A. G., (2025), Analisis Pengaruh Temperatur, pH dan Laju Alir Terhadap Pembentukan Scale. *Lembaran Publikasi Minyak dan Gas Bumi,*59 , 20-11.

Myers, R. H., Montgomery, D. C. & Anderson-Cook, C. M., (2016), Response surface methodology: process and product optimization using designed experiments, John Wiley & Sons

Nadeem, A., Vieira, R. E. & Shirazi, S. 2025. Sand detection using acoustic sand monitors for liquid-dominated multiphase flow production. SPE Journal, 30 ,224-210 .

Obiomah, F., (2025), Pipeline Transportation of Hydrocarbons.

Onyegiri, I. E., Briggs, T. A. & Ekwe, E. B., (2020), Investigation of the effects of flowline sizes, flow rates, insulation material, type and configuration on flow assurance of waxy crude. Innovative Systems Design and Engineering, .11https://doi.org/10.7176/ISDE/11-3-0.

Osman, A., El-Shaib, M., Shehata, A. & Shehadeh, M., (2025), Advancing Pipeline Integrity: An Experimental Investigation into Acoustic Emission Monitoring of Erosion-Corrosion Mechanisms. Results in Engineering,108820 .

Othman, N. T. A., Putra, Z. A., Abidin, S. a. Z. & Ali, F. I. M., (2023), CFD analysis of erosion rate in oil and gas pipeline industry. Jurnal Teknologi (Sciences & Engineering), 85 ,-59 .66https://doi.org/10.11113/ jurnalteknologi.v85.2047.

Othman, N. T. A., Putra, Z. A., Abidin, S. a. Z. & Ali, F. I. M., (2024), Integration of CFD analysis and artificial neural networks for estimation of erosion rate in oil and gas pipelines. Results in Engineering, 24 , .103288https://doi.org/10.1016/ j.rineng.2024.10328.

Parsi, M., Al-Sarkhi, A., Kara, M., Sharma, P., Mclaury, B. S. & Shirazi, S. A., (2017), A new dimensionless number for solid particle erosion in natural gas elbows. Wear, 390 ,.83-80 https:// doi.org/10.1016/j.wear.2017.07.00.

Peters, A. E., Charlesugochukwu, O. & Samson, N. Parametric Analysis of Subsea Multiphase Pipeline.

Peters, A. E., Charlesugochukwu, O. & Samson, N., (2022), Parametric Analysis of Subsea Multiphase Pipeline. 2022.

Pleshkov, D., Corella Moya, C. A., Corella Moya, B. R., Ortiz, A. V. S., Paredes, L., Huaca, A., Chicaiza, F., Marin, G. A., Garcia, J. N., Tapia, R. a. V. & Rajain, A. K., (2022), Pipeline Transportation of Hydrocarbons.

Disruptive Dumpflooding Completion, Case Study Ecuador. Offshore Technology Conference Asia. D041S029R003.https:// doi.org/10.4043/31533-m.

Salama, M. & Venkatesh, E., (1983), Evaluation of API RP 14E erosional velocity limitations for offshore gas wells. Offshore technology conference. OTC, OTC-4485-MS.https:// doi.org/10.4043/4485-M.

Satiyawira, B., Maulani, M., Samura, L., Pramadika, H., Nugrahanti, A., Rosyidan, C., Prima, A., Arkaan, M. D. & Yanti, W., (2025), Drilling Fluid Optimization Using Response Surface Methodology. Scientific Contributions Oil and Gas, 48 ,294-281 .

Shirazi, S. A., Mclaury, B. S., Shadley, J. R., Roberts, K. P., Rybicki, E. F., Rincon, H. E., Hassani, S., Al-Mutahar, F. M. & Al-Aithan, G. H., (2025), Erosion–Corrosion in Oil and Gas Pipelines. Oil and Gas Pipelines: Integrity, Safety, and Security Handbook, 2 ,1102-1078 .

Su, C., Rydahl, A. & Shea, R., (2003), Liquid Inventory Management in Wet Gas Pipelines. SPE Latin America and Caribbean Petroleum Engineering Conference. SPE, SPE-81177-MS.https://doi.org/10.2118/81177-M.

Supmea, (2023), Flow Rate And Pressure: Features, Relationship & Applications [Online]. Available: https://www.supmeaauto.com/ training/flow-rate-and-pressure#content-section- [Accessed 2025].

Svedeman, S. & Arnold, K., (1993), Criteria for sizing multiphase flow lines for erosive/ corrosive services. SPE 26569. 68th Annual Technical Conference of the Society of Petroleum Engineers, Houston, Texas. https:// doi.org/10.2118/26569-P.

Tony, B., Chandra, S., Purba, R. J., Solihan, M. F. & Saputra, E. D., (2025), Transient Simulation to Analyze Wax Deposition and Flow Pattern Behavior Along Tubing Under Esp Installation and Gassy Well Condition. *Scientific Contributions Oil and Gas,* 48 ,112-91 . https://

doi.org/10.29017/scog.v48i3.1731.

Venriza, O. & Wahyuni, C., (2024), Optimization of Crude Oil Transmission Process by Installing Electric Heat Tracing in Off-Plot Piping. *Scientific Contributions Oil and Gas*, LEMIGAS RD Center for Oil and Gas Technology, 47,-167 175. https://doi.org/10.29017/SCOG.47.3.1631.

Veza, I., Spraggon, M., Fattah, I. M. R. & Idris, M., (2023), Response surface methodology (RSM) for optimizing engine performance and emissions fueled with biofuel: Review of RSM for sustainability energy transition. Results in Engineering,18 ,.101213 https://doi.org/10.1016/j.rineng.2023.10121.

Vieira, R. E., (2014), Sand erosion model improvement for elbows in gas production, multiphase annular and low-liquid flow, The University of Tulsa.

Zabeti, M., Daud, W. M. a. W. & Aroua, M. K., (2010), Biodiesel production using alumina-supported calcium oxide: An optimization study. Fuel Processing Technology,91 ,-243 .248https://doi.org/10.1016/j.fuproc.2009.10.00.