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Methods for Risk Assessment of Inorganic Scaling in Crude Oil–Water Transport Trunklines Connected by Multiple Production Flowlines: A Comprehensive Literature Review

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Abstract

Inorganic scale deposition in crude oil–water transport trunklines is a formidable flow assurance challenge, uniquely exacerbated in extensive gathering networks where multiple production flowlines commingle multiphase fluids. As some fields experience progressively higher water cuts, the mixing of incompatible waters, characterized by diverse thermodynamic profiles and varying concentrations of scaling ions (Ca^{2+} , Ba^{2+} , Sr^{2+} , SO_4^{2-} , CO_3^{2-} , etc.) triggers severe precipitation. This comprehensive literature review synthesizes seminal and contemporary studies to critically evaluate the state-of-the-art methodologies for assessing scaling risks in these intricate systems. Progressing chronologically and thematically, the analysis details the transition from static, bulk-fluid thermodynamic equilibrium calculations to dynamic, high-fidelity deterministic and probabilistic approaches. These advanced frameworks include Reactive Transport Modeling (RTM), Computational Fluid Dynamics (CFD), and Machine Learning (ML) architectures. Special emphasis is placed on the mathematical governing equations that dictate trunkline-specific phenomena: multi-stream commingling, non-isothermal gradients, probabilistic kinetic induction, and the profound impact of turbulent transport (turbophoresis) on crystal attachment and wall shear detachment. Finally, an integrated, multi-tier flow assurance workflow is proposed to guide future field-scale risk management and digital twin deployment.

Keywords: inorganic scaling; risk assessment; crude oil–water transport trunklines; multiple flowlines; methodology



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1. Introduction

Flow assurance is a critical discipline in petroleum engineering focused on ensuring the safe, continuous, and economic transport of hydrocarbon fluids from the reservoir to downstream processing facilities. One of the most common and costly threats to this process is the deposition of inorganic mineral scales [1,2]. While scaling phenomena in the near-wellbore region and vertical production tubing have been extensively documented, the specific dynamics of scaling in crude oil–water transport trunklines remain uniquely complex and comparatively under-characterized in traditional models.

A trunkline, serving as the central artery in a field gathering system, operates under vastly different conditions than a single wellbore. Whereas a wellbore typically handles a relatively consistent fluid composition from a specific drainage area, a trunkline receives multiphase fluids, typically crude oil, natural gas, and water, from numerous branch

production flowlines connected at different locations along its route. Each contributing branch flowline introduces a highly specific water chemistry, fundamentally determined by its originating reservoir zone, localized pressure–temperature (P-T) conditions, and historical chemical application in well production procedures (Figure 1). When these chemically distinct aqueous phases converge at a trunkline manifold or T-junction, the established chemical equilibrium is significantly altered. The commingling of “incompatible waters” such as a stream rich in alkaline earth metals (Ca^{2+} , Ba^{2+} , Sr^{2+}) mixing with another rich in sulfates (SO_4^{2-}) frequently triggers severe and immediate supersaturation, leading to the rapid precipitation of sulfate scales [3].

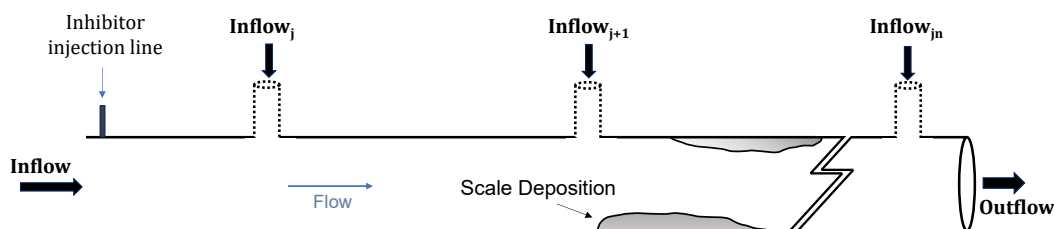


Figure 1. Schematic diagram of a trunkline system with one inhibitor injector line and multiple flowlines exposed to a water oil flow with scaling ions and scale deposition along the lines (not to scale).

Once formed, scale buildup in the trunkline acts as a physical barrier on the inner pipe walls, significantly increasing inner surface roughness and reducing the effective cross-sectional area for flow. Consequently, that would require higher pump pressures to maintain target flow rates, which inherently drives up energy consumption and elevates the risk of pipe failure. In extreme cases, unchecked scaling can completely plug the pipeline, forcing costly, unplanned, and prolonged shutdowns. Furthermore, scale deposits can foster under-deposit corrosion, leading to localized wall thinning, leaks, and potential ruptures that significantly shorten the trunkline’s operational lifespan [4,5]. Mitigating these issues, particularly for resilient deposits like BaSO_4 , often demands frequent mechanical cleaning (e.g., pigging) or continuous, high-dosage chemical inhibitor treatments, both of which carry heavy financial and environmental burdens. Therefore, conducting rigorous scaling risk assessments tailored to specific trunkline operating conditions is essential for the effective planning and design of scale prevention and remediation programs. Table 1 shows the common types of scale seen in oilfields.

A robust risk assessment for trunklines must transcend basic laboratory compatibility tests. The fluid transiting a trunkline undergoes continuous physical, spatial, and thermodynamic evolution over tens to hundreds of kilometers [6]. For example, pressure drops along the pipeline profile induce CO_2 exsolution from the aqueous and oleic phases into the gas phase, fundamentally altering the brine’s pH and heavily driving calcium carbonate (CaCO_3) precipitation [7,8]. Concurrently, temperature gradients dictated by external ambient conditions such as subsea cooling or variations in buried pipeline insulation govern the solubility and phase transformations of sulfate scales, dictating the critical transition from gypsum to hemihydrate and ultimately to anhydrite [9]. Furthermore, the high volumetric flow rates and corresponding high Reynolds numbers associated with trunkline transport introduce severe turbulent boundary layer effects. In this regime, turbophoresis and wall shear stress govern the physical mass transfer, accumulation, and sloughing of scale deposits [10,11]. To address these multifaceted risks, this review systematically examines the mathematical and phenomenological methodologies developed for scale prediction and risk assessment, establishing a rigorous framework for modern flow assurance engineering.

Table 1. Common Oilfield Scales and Their Characteristics.

Scale Type	Primary Drivers	Solubility Profile	Standard Remediation/Prevention
Calcium Carbonate (CaCO ₃)	Pressure drops triggering CO ₂ degassing; localized pH increases.	Highly soluble in weak mineral or organic acids (e.g., HCl, acetic acid).	Acid washes; phosphonate or polycarboxylic acid scale inhibitors.
Barium Sulfate (BaSO ₄)	Mixing incompatible waters (injected seawater + formation brine).	Extremely low solubility; virtually insoluble in standard acids.	Highly difficult to dissolve mechanically/chemically; relies on chelation or proactive threshold inhibitors.
Strontium Sulfate (SrSO ₄)	Co-precipitates with barium sulfate under similar fluid-mixing scenarios.	Sparingly soluble; temperature-dependent behavior.	Kinetic scale inhibitors; chemical removal via specialized chelating agents.
Iron Sulfide (Fe _x S _y)	Sour gas environments (H ₂ S) reacting with corroding steel or formation iron.	Acid-soluble but prone to liberating toxic H ₂ S gas and secondary elemental sulfur precipitation.	Acidizing with effective H ₂ S scavengers and iron sequestrers; continuous chemical inhibition.

2. Mechanistic Foundations and Governing Equations

To accurately evaluate and deploy risk assessment models, it is essential to deeply delineate the fundamental physical, chemical, and mathematical mechanisms that govern inorganic scaling in commingled turbulent pipe flows.

2.1. Thermodynamic Supersaturation and High-Salinity Mixing

The absolute fundamental prerequisite for inorganic scaling is thermodynamic instability, driven primarily by the mixing of incompatible fluids. The driving force for precipitation is mathematically quantified by the Saturation Ratio (SR), which compares the actual ion activity product in the solution to the thermodynamic solubility product (K_{sp}) of the precipitating mineral at a specific temperature and pressure [7,12]:

$$SR = \frac{a_{M^{2+}} a_{A^{2-}}}{K_{sp}(T, P)} \quad (1)$$

where $a_{M^{2+}}$ and $a_{A^{2-}}$ represent the chemical activities of the scaling cations (e.g., Ba²⁺) and anions (e.g., SO₄^{2−}), respectively. The Saturation Index (SI) is the logarithmic expression of this ratio:

$$SI = \log_{10}(SR) \quad (2)$$

A fluid mixture is undersaturated when $SI < 0$, at equilibrium when $SI = 0$, and supersaturated (scaling potential exists) when $SI > 0$. However, in the high-ionic-strength brines typical of mature oilfields (>100,000 mg/L TDS), standard molar concentrations grossly misrepresent true chemical activity due to severe electrostatic shielding between ions.

Lu [13] and Hashemi [14] emphasize the necessity of utilizing the Pitzer ion-interaction model to calculate accurate activity coefficients (γ_i) in these environments. The Pitzer equation is expressed as:

$$\ln \gamma_i = z_i^2 f^\gamma + 2 \sum_j m_j B_{ij} + z_i^2 \sum_j \sum_k m_j m_k C_{ijk} \quad (3)$$

where z_i is the ionic charge of species i , m represents the molality of the interacting species j and k , f^γ is the Debye-Hückel limiting law term (which is highly dependent on total ionic strength and fluid dielectric constant), and B_{ij} and C_{ijk} are the second and third virial coefficients that capture short-range binary and ternary ion interactions.

By applying these equations computationally at every T-junction and commingling node in the trunkline, engineers can generate a localized “Saturation Index Profile” that maps the theoretical maximum precipitable scale mass as different flowlines merge.

2.2. Nucleation Kinetics and Arrhenius Delay Times

Supersaturation represents a thermodynamic end-state; it does not dictate the temporal onset or the rate of scaling. The transition from dissolved aqueous ions to a structured solid phase requires the system to overcome a critical activation energy barrier via nucleation.

In pipeline systems, heterogeneous nucleation (crystal formation directly on the internal pipe wall or suspended particulate matter) overwhelmingly dominates homogeneous nucleation (spontaneous formation in the bulk fluid) due to the substantially lower interfacial free energy requirements [15]. Fahiminia [16] demonstrated that the induction time (t_{ind}), i.e., the critical delay period before macroscopic crystallization begins, follows an Arrhenius-type dependency governed by absolute temperature (T) and the degree of supersaturation:

$$\ln(t_{ind}) = \frac{A}{T^3(\ln SR)^2} + \frac{E_a}{RT} + B \quad (4)$$

where E_a is the activation energy for nucleation, R is the universal gas constant, and A and B are empirically derived kinetic constants specific to the mineral phase (e.g., barite vs. calcite).

An important yet underexplored aspect of nucleation kinetics involves the critical dependence of the activation energy (E_a) and critical nucleus radius (r^*) on initial pipe wall roughness and its temporal evolution due to corrosion. The classical nucleation theory predicts that $r^* = 2\sigma\Omega/(RT \ln SR)$, where σ is interfacial tension and Ω is molar volume. However, for a rough surface with characteristic asperity heights ($\delta_{asperity}$) on the order of micrometers, heterogeneous nucleation preferentially initiates at geometric traps (crevices, scratches, corrosion pits) where the local interfacial energy is substantially reduced [17]. Heterogeneous nucleation models demonstrate that surface defects and localized pitting corrosion act as active geometric traps. By altering the local interfacial free energy, these rough surface topologies significantly lower the activation energy barrier (E_a) for mineral deposition compared to smooth substrates, leading to truncated surface induction times and accelerated scaling onset [15,18].

Nooraiepour [19] proposed an important advancement with a probabilistic nucleation framework. Rather than assuming a uniform onset of scaling across a pipe wall, they demonstrated that the probability of a nucleation event (P_{nuc}) occurring within a specific control volume (V) over time (t) is stochastic:

$$P_{nuc} = 1 - \exp(-J \cdot V \cdot t) \quad (5)$$

where J is the localized nucleation rate. Once stable nuclei are formed, the subsequent rate of mass deposition per unit area (R_g) is modeled empirically as a function of the remaining supersaturation [12]:

$$R_g = K_r(SR - 1)^n \quad (6)$$

where K_r is the surface reaction rate constant (highly dependent on temperature and surface metallurgy) and n is the empirical reaction order (typically $1 \leq n \leq 2$).

Fouling models have been applied to scale deposition following a similar framework as presented in Figure 2.

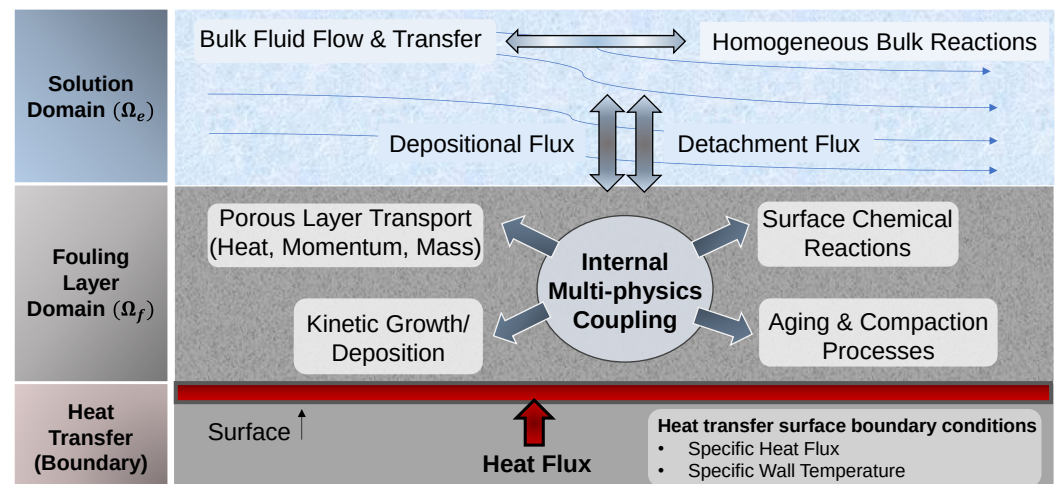


Figure 2. Fouling model framework and simulation domain decomposition. Adapted after [20].

2.3. Hydrodynamic Transport, Turbophoresis, and Detachment

Trunklines operate at high fluid velocities, creating highly turbulent environments where fluid dynamics strictly dictate the transport of reactive ions to the pipe wall and impose immense shear forces that can physically detach formed crystals.

To model this, Mouketou [21] and Silva [22] advocate for the Euler–Lagrange discrete phase model. The multiphase fluid is treated as a continuous Eulerian field governed by the Navier–Stokes equations, while precipitated scale particles are tracked in a Lagrangian reference frame via Newton’s Second Law of Motion [23]:

$$m_p \frac{dv_p}{dt} = F_{drag} + F_{lift} + F_{gravity} + F_{drag_turbophoresis} + F_{virtual_mass} \quad (7)$$

Moriconi [10] showed that in downstream sections of turbulent pipes, scale accumulation is dominated by turbophoresis, the net migration of suspended particles down a turbulence intensity gradient, moving from the highly turbulent bulk core toward the relatively quiescent viscous sublayer at the pipe wall.

A key limitation of many turbophoresis and mass transfer models is their implicit assumption that the Reynolds (Re) and Schmidt (Sc) numbers achieved in laboratory experiments remain consistent with field trunkline conditions. The Reynolds number, $Re = \rho V D / \mu$, quantifies the ratio of inertial to viscous forces; in turbulent pipe flows, Re typically ranges from 10,000 to 100,000 for crude oil systems. The Schmidt number, $Sc = \nu / D_m$, characterizes the relative importance of viscous diffusion to molecular diffusion. For barium sulfate precipitation in water, $Sc \approx 1000$ –10,000. However, the turbophoresis coefficient exhibits strong dependence on both Re and Sc [24]. If laboratory tube tests operate at $Re = 5000$ while field trunklines operate at $Re = 50,000$, the scaling attachment rates measured in the lab will be severely underestimated for field application.

Crucially, scaling is not an infinitely additive process. Løge [25] introduced the rigorous necessity of a detachment term ($R_{detach} = k_d \cdot \tau_w \cdot \delta_s$) driven by localized wall shear stress (τ_w). The net rate of scale accumulation (R_{net}) is therefore a dynamic equilibrium:

$$R_{net} = R_{attach} - k_d \cdot \tau_w \cdot \delta_s \quad (8)$$

where k_d is an empirical detachment coefficient dependent on the crystal morphology and adherence strength, and δ_s is the instantaneous thickness of the scale layer.

This dynamic equilibrium accurately accounts for field observations where scale in high-velocity trunklines often reaches an asymptotic maximum thickness rather than

completely blocking the pipe, provided the shear stress is sufficiently high. However, the detachment coefficient k_d remains poorly characterized and depends critically on crystal morphology, surface adherence strength, and mechanical integrity. Sensitivity analyses show predicted thickness can vary 2–5 times across plausible k_d values, underscoring the necessity for field validation before deployment.

This dynamic equilibrium accurately accounts for field observations where scale in high-velocity trunklines often reaches an asymptotic maximum thickness rather than completely blocking the pipe, consistent with the classical deposition-removal framework of Kern [26]. However, the detachment coefficient k_d remains poorly characterized and depends critically on crystal morphology, surface adherence strength, and substrate-foulant interactions [27,28]. Sensitivity analyses performed by the authors show predicted thickness can vary 2 to 5 times across plausible k_d values, underscoring the necessity for field validation before deployment.

Equation (8) represents the net scale accumulation under steady-state hydrodynamic conditions where the wall shear stress τ_w remains constant in time. However, real trunkline flows exhibit pronounced transience, with the shear stress oscillating at frequencies from 0.01 Hz (slow pressure pulses) to 1 Hz (slug cycles). The detachment coefficient k_d is inherently a function of both local stress magnitude and stress history. If time-averaged shear stress remains below a critical threshold for extended periods, previously adherent crystals can reinforce their bonding through secondary crystallization, rendering them resistant to future detachment. Conversely, rapid oscillations can induce fatigue-like failure, progressively weakening the deposit. Equation (8) should be reformulated to include frequency-dependent mechanical erosion. This enhanced formulation remains an active research frontier not yet available in most commercial RTM codes.

3. Chronological and Thematic Evolution of Scaling Risk Assessment Methodologies

The methodology for predicting inorganic scaling in complex oilfield infrastructure has evolved significantly, shifting from static, single-node approximations to dynamic, fully coupled multiphysics numerical frameworks.

3.1. Empirical Indices and Analytical Screening

In the late 20th century, risk assessment protocols relied heavily on simplified empirical indices originally developed for municipal water treatment, such as the Langelier Saturation Index (LSI), Ryznar Stability Index (RSI), and the Stiff-Davis Index [29]. These indices provided a binary “scaling” or “corrosive” output based solely on bulk fluid pH, temperature, and alkalinity, largely applied by creating static “mixing matrices.” Engineers calculated the SI at 10% incremental mixing ratios (e.g., 10% Flowline A/90% Flowline B, 20%/80%, 30%/70%) to identify the theoretical peak scaling potential [3]. While computationally trivial and useful for preliminary, single-well screening, these analytical methods proved wholly inadequate for multiphase flow in trunklines. They fundamentally failed to account for high temperatures, extreme salinities, multi-phase gas partitioning (critical for CO₂ driven carbonate scaling), and the complex co-precipitation interactions of diverse alkaline earth metals present in produced oilfield brines [1]. Chen [30] calculated SR to evaluate risk of CaSO₄ scale for long production flow lines and showed that CaSO₄ scale could form, especially when introducing incompatible produced waters from different formations/reservoirs.

3.2. Advanced Thermodynamic Modeling

Recognizing the severe constraints of empirical indices, the petroleum industry pivoted to robust geochemical simulators (e.g., PHREEQC, ScaleChem, OLI Systems, Multi-Scale). These software packages utilize comprehensive thermodynamic databases and equations of state to model specific brine compositions under high-pressure, high-temperature (HPHT) conditions. Lu [13] systematically evaluated various thermodynamic data files for PHREEQC, emphasizing that the accuracy of BaSO_4 and CaCO_3 scaling risk prediction is inextricably linked to the internal thermodynamic consistency of the chosen database when extrapolated to extreme reservoir and trunkline boundaries. However, thermodynamic models, inherently assuming infinite time for chemical reactions to reach absolute equilibrium, possess a critical flaw for dynamic systems. They calculate the maximum theoretical mass of scale that could form, but provide zero insight into how fast it will form or where it will deposit geographically along the trunkline.

3.3. Integration of Kinetics and Meso-Scale Validations

To bridge the massive gap between theoretical thermodynamics and actual field deposition rates, researchers systematically pursued kinetic modeling.

The industry standard for kinetic assessment became the Dynamic Tube Blocking Test (TBT). Khormali [31] utilized Response Surface Methodology (RSM) to statistically optimize the prediction of barium sulfate precipitation in TBTs. By systematically varying fluid injection rates, mixing ratios, and temperatures, they developed empirical correlations linking the differential pressure drop across the capillary tube to specific commingling scenarios. However, recognizing that laminar capillary tube tests often fail to scale accurately to massive, highly turbulent trunklines, Contreras [32] pioneered the development of meso-scale flow loop facilities. These large-scale loops accurately replicate the turbulent shear stresses, multiphase flow regimes (slug, stratified, annular), and exact metallurgy of actual trunklines, allowing for the empirical derivation of attachment rate constants that are directly translatable to field-scale engineering algorithms.

Contreras [32] demonstrated that laminar capillary tube results systematically under-predict barite attachment rates by factors of 2–5 compared to turbulent loop results, validating the necessity of high-Reynolds-number meso-scale validation before field deployment.

3.4. Reactive Transport Modeling (RTM)

The most transformative and rigorous advancement in trunkline flow assurance risk assessment is the maturation of Reactive Transport Modeling (RTM). RTM fundamentally alters the computational paradigm by coupling multi-component geochemical reaction engines directly with fluid transport and flow equations. RTM algorithms solve the Advection–Diffusion–Reaction (ADR) equation for every single chemical species i continuously across the spatial domain [33,34]:

$$\frac{\partial(\phi C_i)}{\partial t} + \nabla \cdot (\mathbf{U} C_i - \mathbf{D}_{disp} \nabla C_i) = \sum_{j=1}^{N_r} \nu_{ij} R_j \quad (9)$$

where ϕ is the trunkline volumetric open fraction (equivalent to porosity in rock media), C_i is the concentration of species i , $\mathbf{U}$ is the multiphase fluid velocity vector, $\mathbf{D}_{disp}$ is the hydrodynamic dispersion tensor, ν_{ij} is the stoichiometric coefficient of species i in reaction j , and R_j is the kinetic reaction rate of precipitating mineral j .

The integration of the ADR equation solves the “spatial ion depletion” problem. In a multi-inlet trunkline, as scale precipitates heavily at an upstream T-junction, the bulk fluid transiting downstream becomes physically depleted of scaling ions (Ba^{2+} , SO_4^{2-}). Shabani [35] and Shojaee [36] demonstrated that RTM accurately captures this longitudinal

depletion, thereby preventing the severe overestimation of scaling risks at downstream manifolds, a common and expensive flaw in uncoupled, static thermodynamic models.

Historically, RTMs utilized a Sequential Iterative Approach (SIA), coupling flow and chemistry sequentially, which frequently suffered from mass balance errors in high-velocity systems. To rectify this, Seigneur [34] introduced a Compositional Global Implicit Approach, solving the fluid flow, mass transport, and chemical reaction equations strictly simultaneously in a single large-scale Jacobian matrix, ensuring perfect mass conservation over long-distance transport.

Critical Limitations of Current RTM Implementations: While RTM represents a significant advancement, contemporary implementations (PHREEQC, OLI, ScaleChem) possess several critical limitations. First, thermodynamic databases are optimized for specific ionic strength and temperature ranges (typically 0–200 °C, 0–6 molal); extrapolation to HPHT conditions introduces substantial uncertainty in activity coefficient calculations, with error exceeding ± 0.5 log units in predicted saturation indices. Second, kinetic rate laws assume power-law forms with temperature-dependent constants derived from laboratory experiments often far removed from field operations. Third, most RTM codes cannot simultaneously handle organic-inorganic coprecipitation, forcing engineers to conduct separate calculations that ignore synergistic interactions. Fourth, the numerical solution demands fine spatial discretization ($\Delta x < 1$ mm) and small time steps ($\Delta t < 0.01$ s), rendering full-field simulations of 50+ km trunklines computationally prohibitive ($\sim 10^5$ CPU-hours). As a result, industry practice isolates critical ‘hotspot’ regions for detailed RTM analysis, then applies 1D approximations along reaches, introducing artificial discontinuities. These limitations suggest that current RTM tools are best suited for screening and relative risk ranking rather than absolute quantitative prediction.

3.5. Computational Fluid Dynamics (CFD) and Localized Hotspots

While 1D RTMs are excellent for evaluating the overall longitudinal profile of a trunkline, scaling in the field is overwhelmingly localized at geometric irregularities where fluid streamlines detach and recirculate.

Liu [37] and Rodriguez-Hernandez [38] presented a 2D CFD-based mass-transport model that simulated the concurrent transport of scaling ions and a scale inhibitor in oil–water two-phase turbulent flow in the trunkline fed by multiple flowlines. This CFD model couples the continuity equation, momentum equation, and phase transport equation with the standard turbulence model, and incorporates the chemical species transport equation to describe convection, diffusion, and turbulent mixing, thereby characterizing distribution of velocity, pressure, phase distribution, the scale inhibitor, and all scale-forming ions. Moreover, the study quantified how flow rate, the number and placement, and water chemistries of flowlines control the concentration field of scaling ions. Results show that scaling tends to occur in regions where turbulence creates low-velocity profiles, allowing for higher ion concentration, as presented in Figure 3.

Zhang [20] have utilized numerical simulations, including 3D dynamic mesh technology, to predict the scale layer’s growth on heat transfer surfaces, showing that deposition is often heavier at the rear of pipes, and that high flow velocities can reduce the asymptotic scaling resistance by increasing the shear stress and the removal rate of the foulant.

Bentzon [39] utilized 3D Computational Fluid Dynamics (CFD) to explicitly model scale formation behind sudden expansions, valves, and weld roots. The CFD models successfully predicted the formation of hydrodynamic “shadow zones”—areas of boundary layer separation and flow recirculation where wall shear stress approaches zero, allowing nucleated crystals extended residence time to adhere to the steel surface and grow exponentially.

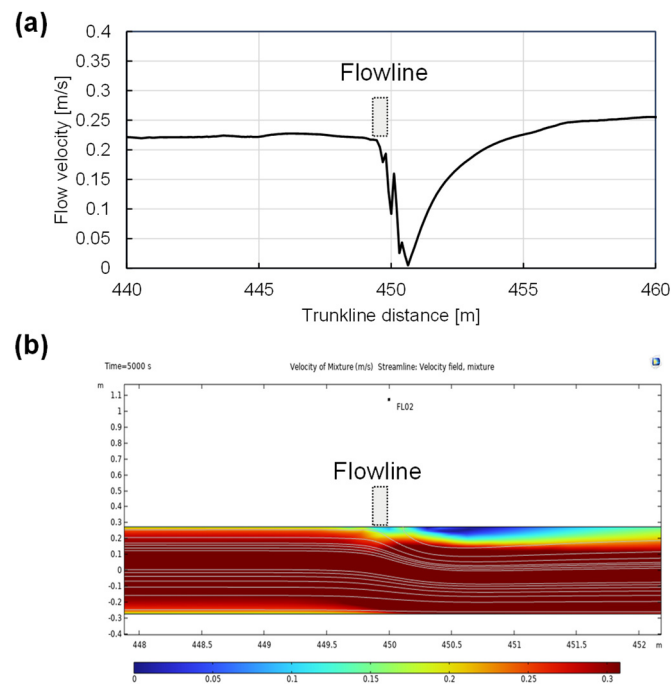


Figure 3. Flow velocity profiles near an injection flowline. (a) Flow velocity as a function of distance. Measurement at the top of the trunkline ($y = 0.27$ m). (b) 2D velocity fields near the flowline.

The most comprehensive deterministic physical modeling approach is the direct integration of RTM into CFD. Pavuluri [40] and Anabaraonye [41] benchmarked the open-source porousMedia4Foam platform, which seamlessly links OpenFOAM (for high-resolution Navier–Stokes fluid dynamics) with PHREEQC (for high-salinity geochemical reactions). For scaling risk assessment in trunkline, this allows for high-fidelity 3D modeling of commingling fluids at complex T-junction manifolds, mapping the exact millimeter-scale wall regions where thermodynamic supersaturation and hydrodynamic turbophoresis synergistically peak.

3.6. Probabilistic and Stochastic Approach

The inherent and unavoidable limitation of all deterministic models (RTM and CFD) is their strict reliance on absolute, deterministic input parameters. In reality, oilfield trunkline conditions are highly transient; branch flowlines experience violent daily fluctuations in flow rate, water cut, temperature, gas–oil ratio (GOR), and ion composition due to dynamics of reservoir and wells, or pump failures.

To account for this, Shoeibi [42] developed a variance-based sensitivity approach utilizing massive Monte Carlo simulations to assess scale risk. Applied to gathering networks, this stochastic methodology allows operators to quantify exactly how uncertainties in daily well test data dynamically translate into probability distribution functions for scale deposition rates, rather than relying on a single, fragile deterministic output.

The accuracy of all methodologies reviewed above depends critically on the fidelity of temperature profiles along the trunkline. Temperature fluctuations arising from ambient cooling, Joule–Thomson expansion at chokes, and transient flow regimes can shift saturation indices, potentially reversing risk predictions. Modeling of automatic temperature control systems embedded in pipeline infrastructure (heating tapes, trace lines, or subsea insulation with active thermal regulation) requires integration of process control algorithms into the RTM-CFD framework [43]. Ilyushin [44] demonstrated that rigorous modeling of automatic temperature control systems significantly improves the predictive accuracy of reactive transport simulations by accounting for feedback control loops and system response delays;

their findings on control system optimization for process thermodynamics are directly applicable to subsea and deepwater trunkline systems where temperature excursions pose acute scaling risk.

3.7. Machine Learning Frameworks

Recently, the deployment of Machine Learning (ML) and Artificial Intelligence represents the newest operational frontier where prediction of properties from trained experimental data showed great accuracy [45–47]. Askar [48] developed highly accurate Artificial Neural Network (ANN) and Ensemble ML models (Random Forest, XGBoost) using historical field data from hundreds of producing wells. Their models accurately predicted the deposition of complex mixed scales (carbonate and sulfide) purely through pattern recognition, entirely bypassing the computational expense of solving the ADR or Navier–Stokes equations.

To bridge the gap between “black box” ML and engineering physics, Tayyebi [49] advanced ML utilization by applying SHAP (SHapley Additive exPlanations) analysis. SHAP analysis forces the ML model to explicitly rank the predictive importance of every input feature. For a trunkline operator, SHAP can instantly identify that the pH fluctuation in a specific branch flowline is the single dominant driver of scale risk for the entire downstream 50 km trunkline, allowing for highly targeted, localized chemical inhibition rather than expensive blanket treatments. The evolution of machine learning is presented in Figure 4.

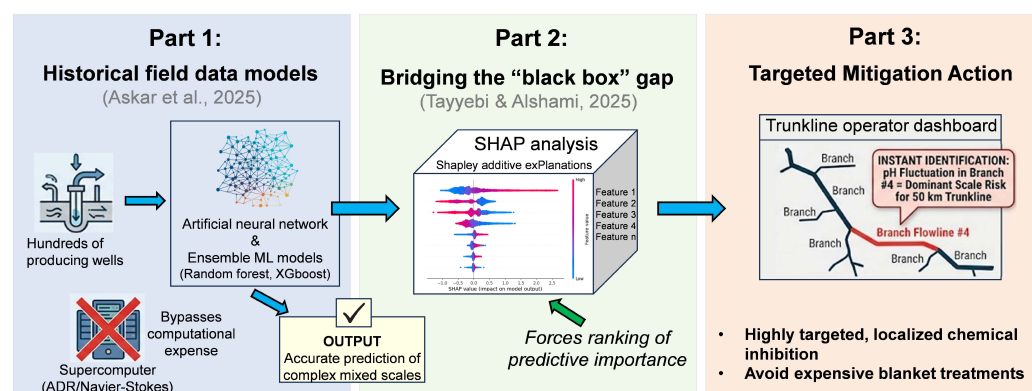


Figure 4. Machine learning frameworks for scale prediction [48,49].

3.8. Cross-Methodology Synthesis and Comparative Evaluation

The evolution of scaling risk assessment methodologies spanning traditional empirical indices, advanced thermodynamics, deterministic numerical frameworks (RTM and CFD), and modern machine learning demonstrates a clear trade-off between predictive resolution, computational overhead, and data dependency. To achieve a true “critical evaluation” of the state of the art, these methodologies must be weighed against each other across three foundational axes: accuracy, computational cost, and data requirements.

Historically, analytical screening via empirical indices like the Langelier Saturation Index (LSI) or Stiff-Davis Index provided a computationally trivial, binary indicator of scaling potential. While advantageous for quick, single-well field screenings requiring minimal bulk water parameters, these indices fail catastrophically in multi-inlet trunklines. They are fundamentally incapable of accounting for high-salinity ion shielding, multiphase CO₂ gas partitioning, and the complex co-precipitation kinetics inherent to commingled production streams. Advanced geochemical thermodynamic models (e.g., PHREEQC, ScaleChem) resolve the salinity and multi-ion limitations by employing Pitzer ion-interaction activity equations. However, their accuracy remains strictly constrained

to thermodynamic end-states. By assuming infinite reaction time to reach equilibrium, pure thermodynamic modeling overpredicts risk by failing to capture where scale will physically deposit or how fast it will grow along a multi-kilometer pipeline profile.

Deterministic frameworks like Reactive Transport Modeling (RTM) and Computational Fluid Dynamics (CFD) bridge this gap by introducing transport physics and physical boundary layers, but they do so at vastly divergent spatial scales. RTM operates primarily on a macro/longitudinal scale, utilizing coupled Advection–Diffusion–Reaction (ADR) equations to track spatial ion depletion as fluids transit downstream. This eliminates the expensive overestimation of downstream scaling risks common to static models. However, RTM’s 1D/2D reach-averaged approximations fail to capture localized structural vulnerabilities.

Conversely, CFD isolates these exact local “hotspots” (such as T-junction manifolds, valves, and weld roots) where fluid streamlines detach and form low-velocity “shadow zones”. By resolving local turbophoresis and wall shear stress detachment, CFD models scale accumulation as a dynamic equilibrium. The critical bottleneck of both RTM and CFD is their immense computational cost. Full-field simulations of long-distance (~50+ km) trunklines using fine spatial grids ($\Delta x < 1$ mm) are computationally prohibitive, often demanding up to 10^5 CPU-hours and requiring highly sensitive, difficult-to-calibrate kinetic parameters like the detachment coefficient (k_d).

Machine Learning (ML) architectures represent a radical departure from these physics-bound constraints. By processing historical data via pattern recognition, ensemble models (e.g., XGBoost, ANN) entirely bypass the computational burden of solving Navier–Stokes or ADR equations, delivering near-instantaneous risk predictions. When paired with interpretability tools like SHAP analysis, ML can unmask non-linear feature interactions, identifying a specific upstream well’s pH fluctuation as the dominant driver for an entire downstream network. Nevertheless, ML remains an ungrounded “black box” completely dependent on massive, high-frequency historical datasets. Unlike RTM or CFD, an uncoupled ML model cannot inherently simulate physical or geometric modifications to the system, making it fragile when extrapolated outside its training boundaries.

To guide engineering deployment, Table 2 synthesizes the comparative performance, resource allocation, and operational bounds of each methodology.

Table 2. Comparative Analysis of Scaling Risk Assessment Methodologies.

Methodology	Representative References	Predictability & Spatial Resolution	Primary Accuracy Limits	Computational Cost & Overhead	Input Data Requirements	Ideal Operational Use-Case
Empirical/ Analytical Indices	[3,29,30]	Very Low	High Error in Trunklines	Minimal	Very Low	Preliminary macro-level screening and generating basic mixing matrix baselines.
		•Static, single-node binary screening. •Cannot map longitudinal profiles.	Completely ignores kinetics, extreme ionic strengths, and multi-stream mixing chemistry.	Near-instantaneous spreadsheet or analytical calculations.	Basic bulk parameters (pH, temperature, alkalinity, total TDS).	
Advanced Thermodynamic Modeling	[13,14]	Low	Overpredicts Real Field Risk	Low to Moderate	Moderate to High	Level 1 screening to determine maximum theoretical precipitation limits at commingling manifolds.
		Maps full longitudinal Saturation Index (SI) profiles along nodes.	Assumes infinite reaction time (absolute equilibrium); fails to predict scaling rates or mass distribution.	Fast convergence using standalone geochemical batch software.	Complete water chemistry ionic profiles (Ca^{2+} , Ba^{2+} , Sr^{2+} , SO_4^{2-} , etc.) and system P-T profiles.	

Table 2. Cont.

Methodology	Representative References	Predictability & Spatial Resolution	Primary Accuracy Limits	Computational Cost & Overhead	Input Data Requirements	Ideal Operational Use-Case
Reactive Transport Modeling (RTM)	[33–36]	<i>High (Macro-scale)</i>	<i>Kinetic Extrapolation Gaps</i>	<i>High</i>	<i>Very High</i>	Longitudinal mass deposition tracking and capturing upstream-to-downstream ion depletion profiles.
		Simulates continuous advection, dispersion, and kinetic reactions along the pipeline network.	Extrapolating laboratory power-law kinetics to extreme field limits introduces uncertainty (± 0.5 log units in SI).	Long-distance networks (50+ km) require fine spatial grids ($\Delta x < 1$ mm), making full-field RTM computationally heavy ($\sim 10^5$ CPU-hours).	Coupled transport parameters, multi-component kinetic constants, and accurate hydraulic velocity fields.	
Computational Fluid Dynamics (CFD)	[20,37–41]	<i>Very High (Micro-scale)</i>	<i>High Shear Parameter Sensitivity</i>	<i>Very High</i>	<i>High</i>	High-fidelity evaluation of localized structural geometric hotspots (valves, T-junctions, choke points).
		Resolves millimeter-scale wall boundary layers, local turbophoresis, and particle tracking.	Heavily dependent on poorly characterized detachment coefficients (k_d), driving 2–5x variances in scale thickness.	Demands massive CPU allocation, complex mesh optimization, and transient multiphase flow calculations.	High-resolution 2D/3D component geometries, surface roughness profiles, and detailed multiphase fluid regimes.	
Machine Learning (ML) & Data-Driven Frameworks	[42,48,49]	<i>High (Temporal/Operational)</i>	<i>Black-Box Boundaries</i>	<i>Low (Deployment Phase)</i>	<i>Massive</i>	Real-time field operations, dynamic blockage probability monitoring, and automated smart-dosing optimization.
		Excellent pattern recognition for highly transient, multi-variable systems.	Incapable of physics-bound extrapolation outside of historical training ranges; lacks intrinsic physical laws.	Avoids complex ADR or Navier-Stokes solvers, providing near-instantaneous real-time predictions.	Extremely dependent on high-frequency SCADA telemetry, long-term well tests, and historic field records.	

4. Proposed Integrated Risk Assessment Workflow for Multi-Inlet Trunklines

This section presents an original synthesis by the authors, integrating the diverse methodologies reviewed in Sections 2 and 3. A comprehensive, multi-tiered workflow is proposed for rigorously assessing scaling risk in complex crude oil–water trunklines receiving disparate fluids from multiple flowlines. Workflow of risk assessment is as follows:

Note: The numerical thresholds embedded in this workflow follow directly from the uncertainty and kinetic analyses presented in Sections 2 and 3, rather than from field validation. The screening criterion of $SI < 0.5$ reflects the documented uncertainty of thermodynamic database extrapolation to HPHT brine conditions, where activity coefficient errors propagate into saturation index deviations that exceed ± 0.5 log units ([13], Section 3.4). A predicted SI below this margin therefore falls within model noise and does not justify escalation to higher tier analysis. The kinetic gate at Level 2 applies the induction time formalism of Fahiminia [16] presented in Equation (4): when the calculated fluid residence time within a supersaturated zone is shorter than the Arrhenius induction time t_{ind} , nucleation lacks sufficient time to proceed before the fluid exits the zone, and the workflow downgrades the risk accordingly. Both criteria serve as conservative screening defaults derived from the reviewed literature. Because database uncertainty varies with brine composition and because induction time constants are mineral and surface specific,

each operator must recalibrate these thresholds against site specific water chemistries, tube blocking tests, or meso-scale flow loop data before deployment [32].

Step 1: Trunkline system data collection, high-frequency production data acquisition, and geochemical characterization

The scaling risk assessment needs to collect parameters of the whole targeted trunkline system to build a physical model. The parameters include trunkline topology (elevation, length), i.e., layout configuration, internal diameter, inner surface roughness, specific metallurgy, and location along the trunkline of all branch production flowlines. The scaling risk assessment requires dynamic production and geochemical data of the system. Therefore, in this phase, it is critical to conduct continuous, high-frequency sampling and SCADA monitoring. Based on all sampling test data and monitoring data, including real-time multiphase flow rates, and water cuts of all inlet branch production flowlines, the dynamic flow, complete ionic profiles (Ca^{2+} , Ba^{2+} , Sr^{2+} , SO_4^{2-} , HCO_3^- , Fe^{2+} , etc.), and precise pH are analyzed and characterized, laying the foundation for the scaling risk assessment.

Step 2: Multiphase hydraulic & thermal profiling

Conduct transient multiphase flow simulations using simulators to generate high-resolution spatial and temporal maps of pressure, temperature, flow regime, flow velocity, and water volume fraction across the entire length of the trunkline.

Step 3: Thermodynamic Mixing Analysis (Level 1 Screening)

Utilize Pitzer-based thermodynamic engines (e.g., SPsim, PHREEQC) to execute massive commingling simulation or calculations at every single T-junction and tie-in point, generating a static “Saturation Index (SI)” profile indicating the absolute theoretical maximum scale mass that could precipitate at specific operation conditions.

Step 4: Kinetic & Hydrodynamic Filtering (Level 2 Modeling)

Apply Arrhenius induction time (t_{ind}) correlations to the SI profile to identify true “Active Scaling Zones” where all thermodynamic and kinetic barriers are defeated. If the calculated fluid residence time within a supersaturated zone is mathematically shorter than the kinetic induction time, the theoretical scaling risk is aggressively downgraded.

Step 5: Reactive transport & geometry evolution (Level 3 Simulation)

Deploy RTM in the Active Scaling Zones or whole trunkline system to simulate advection, reaction, and crucial longitudinal ion depletion. Utilize a coupled CFD-PHREEQC to assess highly localized turbophoresis and wall shear stress detachment, and then perform deterministic, physical prediction of scale thickness growth rate and dynamic calculation of the shrinking internal pipe diameter.

Step 6: Probabilistic uncertainty & ML optimization (Level 4 Operations)

Continuously integrate mechanistic models with stochastic frameworks (Monte Carlo) and ML algorithms that actively ingest live field data to assess a dynamic “Probability of Blockage” caused by the formed scale depositions, and autonomously optimize the exact volume, location, and timing for targeted chemical scale inhibitor injection.

The proposed methodology has been summarized in Table 3.

Table 3. Proposed multi-tier integrated risk assessment workflow.

Tier	Tier Designation	Core Methodologies & Parameters	Primary Objectives & Outputs
Tier 1	Data Acquisition & Geochemical Characterization	High-frequency telemetry (daily SCADA monitoring); aqueous geochemistry (Ca^{2+} , Ba^{2+} , Sr^{2+} , SO_4^{2-} , HCO_3^- , pH, Eh); multiphase hydrodynamics (flow rates, water cuts, fluid P - T profiles).	Establishes baseline inlet boundary conditions for each branch flowline.
Tier 2	Thermodynamic & Kinetic Screening	Pitzer ion-interaction activity models (implemented via PHREEQC/SP _{sim}); Arrhenius-based induction time equations (t_{ind}).	Maps Saturation Index (SI) at critical nodes; identifies “Active Scaling Zones”; executes optimization gating based on the criteria: Skip Tier 3 if: $SI < 0.5$ or $t_{\text{ind}} > t_{\text{residence}}$
Tier 3	Deterministic Physics & Multiphase Hydrodynamics	1D Reactive Transport Modeling (RTM) using Advection-Diffusion-Reaction (ADR) equations; 3D Computational Fluid Dynamics (CFD) with coupled turbophoresis and shear detachment mechanics.	Quantifies millimeter-scale wall deposition profiles via coupled OpenFOAM-PHREEQC dynamic mesh tracking; outputs spatial scale thickness maps, kinetic growth trajectories, and pipe diameter degradation profiles.
Tier 4	Probabilistic Risk & Operational Optimization	Monte Carlo uncertainty quantification (UQ); ensemble and deep learning architectures (XGBoost, ANN); SHAP (SHapley Additive exPlanations) feature ranking.	Computes real-time blockage probability $P(\text{blockage} > \text{threshold})$ via SCADA integration; provides autonomous chemical inhibitor dosing optimization (spatial allocation, volumetric rate, and injection scheduling).

5. Discussion and Future Perspectives

The trajectory of flow assurance research unequivocally points toward the absolute necessity of dynamic, fully coupled multi-physics modeling. Treating a multi-inlet trunkline as a static, well-mixed batch vessel is a fundamental engineering error that leads to either severe under-protection (resulting in catastrophic pipeline blockages and lost production) or gross over-protection (resulting in millions of dollars wasted on unnecessary chemical inhibitors).

A critical practical limitation of current methodologies is their reliance on the assumption of purely inorganic scaling, ignoring the reality that produced crude oil trunklines virtually always co-transport organic compounds alongside aqueous ions. As demonstrated by Hagar [50] in fields with high API crude oils, aqueous inorganic phases (CaCO_3 , BaSO_4) regularly co-deposit with oleic compounds including asphaltenes, naphthenic acids, and wax crystals to form hybrid organic-inorganic structures. These hybrid deposits exhibit profoundly different physicochemical and mechanical properties than dense, pure minerals: they possess drastically higher porosities (40–60% vs. <5% for pure barite), lower densities (1.2–1.4 g/cm³ vs. 2.3–4.5 g/cm³), and reduced surface energy due to their oleic coating. Furthermore, their shear-detachment occurs at significantly lower stresses (~0.1 Pa vs. >10 Pa for pure barite), and their overall growth kinetics are governed by a complex interplay of competing crystal nucleation, polymer precipitation, and complex coacervation. Because current reactive transport modeling (RTM) codes strictly segregate aqueous from oleic chemistry, future frameworks must bridge this gap by integrating equation-of-state modeling (such as Peng-Robinson or SRK) to predict organic phase stability, interfacial tension calculations that account for the surfactant-like behavior of naphthenic acids, asphaltene precipitation kinetics, and hybrid scale mechanical property functions derived from atomic force microscopy (AFM) characterization. Ultimately, because virtually all pro-

duced crude oils carry these organic components, hybrid scaling represents an immediate, present-day operational reality not a distant research area that must be explicitly factored into every field deployment decision.

Several key frontier areas require extensive future investigation to perfect trunkline risk assessment:

- (1) Co-precipitation of Organic and Inorganic Scales (Hybrid Scaling): As Hagar [50] recently highlighted, complex geochemical controls govern the simultaneous deposition of aqueous inorganic scales and oleic organic compounds (asphaltenes, waxes, and naphthenates). These “hybrid scales” exhibit vastly different kinetic growth rates, porosities, and shear-detachment properties compared to pure inorganic crystals. Current RTM architecture strictly handles aqueous inorganic chemistry and must be drastically expanded to co-simulate organic thermodynamic phase envelopes.
- (2) Transient Flow Regimes and Slug Dynamics: The vast majority of current CFD and RTM studies assume steady-state flow conditions. However, crude oil trunklines frequently experience severe hydrodynamic slugging. This phenomenon subjects the pipe wall to irregular shear stress oscillations and alternating water- and oil-wetting cycles. Incorporating transient slug dynamics into scale attachment/detachment models remains a massive, computationally expensive necessity [25].
- (3) Autonomous Digital Twin Implementation: The ultimate paradigm for flow assurance is the creation of fully autonomous Digital Twins. By utilizing generic software interfaces like Alquimia [51] to deeply link diverse biogeochemical codes, future gathering systems will seamlessly ingest real-time sensor data, autonomously execute coupled RTM and ML predictions in the cloud, and actively command chemical injection skids to adjust dosing rates without human intervention.

6. Conclusions

Risk assessment of inorganic scaling in crude oil–water transport trunklines is an extremely complex engineering challenge involving multiple disciplines. When inflowing fluids from different branch production flowlines mix with the mainstream of the trunkline, the changes in the chemical composition of the water make the scaling process more complex, creating a highly dynamic environment in which the thermodynamic supersaturation changes constantly in space and time.

This comprehensive literature review, synthesizing extensive academic and industrial studies, reveals a distinct and successful paradigm shift in flow assurance methodology. The petroleum industry has decisively transitioned from relying on simplistic, static thermodynamic indices to developing and deploying highly robust, high-fidelity mathematical frameworks. By intricately integrating Pitzer activity models for high-salinity mixing, Arrhenius-driven probabilistic kinetic delay times, Euler–Lagrange particle tracking algorithms for turbulent wall attachment, and Global Implicit Advection–Diffusion–Reaction (ADR) solvers for tracking longitudinal ion depletion, operators can now generate exceptionally accurate predictive scale profiles.

Furthermore, the recent integration of probabilistic Monte Carlo frameworks and advanced Machine Learning models provides a critical, final layer of operational security, establishing a vital mechanism for handling the inherent uncertainties of fluctuating field data. Ultimately, this multi-tiered, computationally intensive approach empowers operators to pinpoint the exact location of maximum scaling risk in real-time, thereby significantly optimizing chemical inhibitor deployment and safeguarding the structural and economic integrity of vital oilfield transport trunklines.

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