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© V. Rastsvietaiev[1], Jamil Haddad[2], O. Pashchenko[1], A. Shporta[1], S. Tymchenko[1]
[1] Dnipro University of Technology, Dnipro, Ukraine
[2] Al-Balqa Applied University, Amman, Jordan

MODELING OF DEPOSIT ACCUMULATION PROCESSES AND OPTIMIZATION OF THEIR REMOVAL SYSTEMS IN MAIN PIPELINES

В.О. Расцвєтаєв[1], https://orcid.org/0000-0003-3120-4623
Джаміль Хаддад[2], https://orcid.org/0000-0003-3787-0010
О.А. Пащенко[1], https://orcid.org/0000-0003-3296-996X
А.Г. Шпорта[1], https://orcid.org/0000-0002-1260-7358
С.Є. Тимченко[1], https://orcid.org/0000-0002-6314-420X
[1]Національний технічний університет «Дніпровська політехніка», Дніпро, Україна
[2] Прикладний університет Аль-Балка, Амман, Йорданія

МОДЕЛЮВАННЯ ПРОЦЕСІВ НАКОПИЧЕННЯ ВІДКЛАДЕНЬ ТА ОПТИМІЗАЦІЯ СИСТЕМ ЇХ УСУНЕННЯ У МАГІСТРАЛЬНИХ ТРУБОПРОВОДАХ

Purpose. To develop a mathematical model for predicting the spatiotemporal accumulation of paraffin, asphaltene, mineral, and corrosion deposits in trunk pipelines and an integrated system for their prevention, removal, and predictive control, reducing flow assurance risks, energy losses, and operating costs.

The methods. CFD modeling based on the Navier-Stokes equations was combined with thermodynamic and kinetic deposition models in ANSYS Fluent/OpenFOAM using laboratory and field data. Sensitivity and Monte Carlo analyses assessed key parameters, while control strategies included chemical inhibition, pigging, thermal flushing, and optimized predictive scheduling.

Findings: Simulations predict deposit thicknesses of 8–18 mm after 180–365 days, with maximum accumulation occurring 40–70 km downstream due to cooling below the wax appearance temperature (WAT). Initial deposition fluxes of 0.8–6 g/(m^2·day) decrease over time because of deposit aging and shear stripping. Organic deposits contain 45–75 wt% paraffins and 10–30 wt% asphaltenes, while inorganic fractions reach 15–45 wt%. The optimized hybrid strategy reduces pigging frequency by 40–65%, pumping energy losses by 28–35%, remediation and downtime costs by 40–55%, and corrosion rates by up to 50%, while maintaining 92–98% of design throughput.

The originality: Dependences of deposit formation intensity on temperature, flow velocity, fluid composition, wall roughness, and inhibitor efficiency were established using coupled CFD and thermokinetic modeling. Deposition aging patterns and zones of maximum accumulation under cooling below WAT were identified, and an adaptive predictive control algorithm for cleaning processes was developed.

Practical implementation: The proposed system enables predictive, risk-based flow assurance management, reducing chemical use, maintenance interventions, energy losses, shutdowns, and environmental risks while improving pipeline integrity and sustainability.

Keywords*: trunk pipelines, deposit formation, modeling, wax appearance temperature, asphaltene deposition, predictive flow assurance, hybrid cleaning optimization.*

Introduction. Main pipelines represent a critical infrastructure in global energy transportation, serving as the primary means for efficiently and reliably conveying vast quantities of oil and natural gas over long distances from production fields to refineries, processing facilities, storage sites, and end consumers [1, 2]. These trunk or main pipelines form the backbone of the energy supply chain, handling billions of barrels of oil and trillions of cubic feet of gas annually with unmatched efficiency compared to alternative methods like trucking or rail, while minimizing surface disruption and energy losses during transit [3, 4]. In many regions, including major producing and consuming areas, pipelines transport the majority of petroleum products, ensuring stable energy availability that underpins industrial activity, power generation, transportation, and household needs, thereby supporting economic stability and national energy security [5, 6].

Analysis of previous research. A persistent and severe challenge in operating these pipelines is the accumulation of deposits on internal pipe walls, primarily consisting of paraffin (wax), asphaltenes, mineral scales (such as calcium carbonate or sulfate), and corrosion products [7, 8]. These deposits form through complex physicochemical processes triggered by changes in operating conditions during transport: cooling of the fluid below the wax appearance temperature leads to paraffin crystallization and deposition; pressure drops or compositional changes cause asphaltenes to precipitate and aggregate into sticky layers; and formation water or incompatible fluids result in inorganic scale buildup [9, 10]. Corrosion under deposits further exacerbates the issue by generating additional solids. Such accumulations gradually reduce the effective cross-sectional area available for flow, creating flow assurance problems that threaten uninterrupted pipeline operation [11, 12].

The economic and operational impacts of these deposits are substantial and multifaceted. As deposit thickness increases, flow efficiency declines markedly due to the narrowing of the flow path, leading to elevated pressure drops along the pipeline length that require higher pumping power to maintain throughput [13, 14]. This results in significantly increased energy consumption for compressors and pumps, directly raising operational expenditures. Reduced flow rates translate to lower production volumes or the need for derating capacity, causing revenue losses from curtailed deliveries. In severe cases, partial or complete blockages can force unplanned shutdowns, emergency interventions, or even pipeline abandonment if remediation becomes uneconomical [15, 16]. Beyond direct costs, deposits promote under-deposit corrosion, accelerating pipe wall degradation and raising risks of leaks, environmental incidents, regulatory penalties, and safety hazards. Industry estimates indicate that paraffin, asphaltene, and related deposition problems cost the petroleum sector billions of dollars annually worldwide through combined effects of lost production, increased maintenance, chemical treatments, equipment repairs, and premature facility decommissioning [17, 18].

Existing literature has extensively examined deposit formation mechanisms and mitigation strategies [19, 20]. Formation processes are typically described through thermodynamic models that predict precipitation onsets (e.g., using equations of state for asphaltene solubility or cloud/wax appearance points for paraffins), kinetic models that quantify deposition rates based on molecular diffusion, shear removal, and adhesion to the wall, and fluid dynamic approaches that couple multiphase flow simulations (often via Navier-Stokes equations in CFD frameworks) with heat and mass transfer [21, 22]. Notable contributions include molecular diffusion-based wax models, heat-transfer-integrated simulations for field-scale predictions, and studies on asphaltene-resin-paraffin interactions under varying pressure, temperature, and composition [23, 24]. For removal, common techniques encompass mechanical pigging (using scrapers, brushes, or foam pigs to dislodge and transport deposits downstream), chemical cleaning (injection of solvents, dispersants, or inhibitors to dissolve or prevent buildup), and thermal methods (heating fluids or using hot oil circulation to melt wax) [25, 26]. Hybrid approaches and optimized pigging schedules have also been explored in some works [27, 28].

Despite these advances, significant gaps persist in current research. Most studies address either deposition prediction or removal techniques in isolation, with limited integration of dynamic accumulation modeling directly linked to real-time or predictive optimization of removal systems [29, 30]. Few models comprehensively account for time-dependent operational variability (e.g., fluctuating flow rates, seasonal temperature changes, or multiphase effects) while simultaneously optimizing parameters like pigging frequency, chemical dosage, or method selection to minimize total costs, downtime, and energy use [31, 32]. Validation against extensive field data remains inconsistent, and adaptive, data-driven strategies for predictive maintenance are underdeveloped, particularly for integrating AI or advanced optimization algorithms into holistic flow assurance frameworks [33, 34].

Formulation of the unresolved part of the problem and the goal. This study addresses these limitations by developing an integrated approach to modeling deposit accumulation processes and optimizing associated removal systems in main pipelines. By bridging prediction and mitigation through coupled simulations and optimization, the work aims to enhance pipeline maintenance strategies, reduce operational risks and costs, improve overall efficiency, and contribute to more sustainable energy transportation by extending asset life, minimizing environmental impacts from failures or excessive interventions, and supporting reliable supply in an era of increasing energy demand and scrutiny on operational footprint.

The main part. The objective of this study is to develop a comprehensive mathematical model for simulating the processes of deposit accumulation (including paraffin, asphaltenes, scale, and corrosion products) in main oil and gas pipelines under varying operational conditions, and to optimize removal systems (such as pigging, chemical cleaning, and thermal methods) by integrating predictive deposition modeling with cost-effective mitigation strategies, thereby enabling predictive maintenance, minimizing operational downtime, reducing energy consumption and remediation costs, and enhancing overall flow assurance and pipeline sustainability.

The methods employed in this study integrate a rigorous theoretical framework with advanced numerical simulation, optimization algorithms, experimental/field data acquisition, and statistical validation to model deposit accumulation and optimize removal systems in main pipelines [35, 36].

The theoretical framework is based on the coupling of multiphase flow hydrodynamics with deposition kinetics [37, 38]. The fluid dynamics are governed by the incompressible Navier-Stokes equations for momentum conservation in cylindrical coordinates (adapted for pipeline flow):

$$\begin{aligned} &\nabla \cdot u = 0, \\ &\rho\left(\frac{\partial u}{\partial t} + u \cdot \nabla u\right) = -\nabla p + \nabla \cdot \tau + \rho g, \end{aligned} \tag{1}$$

where u is the velocity vector, p is pressure, τ is the stress tensor (incorporating non-Newtonian effects for waxy oils if needed), ρ is density, and g is gravity. These are complemented by energy conservation for temperature distribution:

$$\rho \cdot c_p\left(\frac{\partial T}{\partial t} + u \cdot \nabla T\right) = \nabla \cdot (k \nabla T) + \Phi, \tag{2}$$

where T is temperature, c_p is specific heat, k is thermal conductivity, and Φ accounts for viscous dissipation.

Deposit buildup (primarily paraffin wax, asphaltenes, scale, and corrosion products) is modeled using kinetic approaches that balance mass transport mechanisms: molecular diffusion toward the cold wall, adhesion, and shear removal. For paraffin (wax) deposition, a widely used diffusion-limited formulation (inspired by models like Matzain or Burger et al.) describes the net deposition rate as:

$$\frac{\partial \delta}{\partial t} = \frac{D_{wo}}{\rho_{dep}}\left(\frac{dC_w}{dT}\right)\left(\frac{dT}{dr}\right)_{wall} - \frac{\tau_w}{A \cdot \mu_{dep}} \cdot f_{shear}, \tag{3}$$

where δ is deposit thickness, D_{wo} is the wax diffusion coefficient in oil, ρ_{dep} is deposit density, dC_w / dT is the concentration gradient due to solubility change with temperature, dT / dr is the radial temperature gradient at the wall, τ_w is wall shear stress, A is an empirical adhesion factor, μ_{dep} is deposit viscosity, and f_{shear} represents shear stripping efficiency (often empirical, e.g., Matzain's π_1 and π_2 parameters modifying Fick's law:

$$\frac{d\delta}{dt} = \frac{\pi_1}{1+\pi_2} D_{wo}\left(\frac{dC_w}{dT}\right)\left(\frac{dT}{dr}\right), \tag{4}$$

For asphaltenes, kinetic models (e.g., Kurup-type) incorporate precipitation, aggregation, and deposition rates as first-order processes in a mass balance:

$$\frac{dC_a}{dt} = -k_{precip} C_a + k_{agg} C_{precip} - k_{dep} C_{agg}, \tag{5}$$

coupled with advection-diffusion in the flow domain. Scale deposition follows similar mass transfer-limited kinetics based on supersaturation and ion diffusion, while corrosion products are modeled via electrochemical kinetics under deposit layers.

Numerical simulations are performed using computational fluid dynamics (CFD) software, specifically ANSYS Fluent for its robust multiphase and user-defined function (UDF) capabilities to implement custom deposition kinetics, or OpenFOAM for open-source flexibility in transient multiphase solvers (e.g., interFoam or reactingParcelFoam extensions) [39-41]. The pipeline is discretized as a 2D axisymmetric or 3D domain, solving coupled flow, heat, and species transport equations over time to predict radial and axial deposit profiles under varying inlet conditions (temperature, pressure, flow rate, composition).

Optimization of removal systems (pigging frequency, chemical injection rates, thermal heating intervals, or hybrid strategies) is achieved through metaheuristic and mathematical programming algorithms. Genetic algorithms (GA) or particle swarm optimization (PSO) are applied to minimize an objective function representing total cost:

$$Cost = C_{pig} \cdot N_{pig} + C_{chem} \cdot Q_{chem} + C_{energy} \cdot \int P_{pump} dt + C_{downtime} \cdot t_{down}, \quad (6)$$

subject to constraints on maximum allowable deposit thickness $\delta_{\max}$, pressure drop $\Delta P \leq \Delta P_{\text{limit}}$, and throughput $Q \leq Q_{\min}$. Linear programming is used for simpler deterministic cases (e.g., scheduling pig runs), while GA/PSO handle nonlinear, multi-objective problems (e.g., balancing cost vs. risk of blockage).

Data collection relies on both experimental lab-scale flow loops (e.g., cold finger or rotating disk setups for wax/asphaltene kinetics calibration) and real field data from operational main pipelines, including time-series measurements of inlet/outlet temperature, pressure profiles, flow rates (via meters), fluid composition (GC analysis for wax cut, SARA fractions for asphaltenes), and periodic pigging returns or ultrasonic thickness gauging for deposit validation. Key parameters encompass fluid properties (density, viscosity vs. temperature/shear, wax appearance temperature, asphaltene onset pressure), operational variables (Re, Pr, flow regime), and ambient/soil conditions affecting heat loss.

Validation is conducted by comparing simulated deposit thickness $\delta(t)$, pressure drop $\Delta P(t)$, and wax content profiles against empirical data using quantitative statistical metrics:

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\delta_{\text{sim},i} - \delta_{\text{exp},i}\right)^2}, \quad (7)$$

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(\delta_{\text{exp},i} - \delta_{\text{sim},i}\right)^2}{\sum_{i=1}^{n}\left(\delta_{\text{exp},i} - \delta\right)^2}, \quad (8)$$

where δ is the mean of the experimental deposit thickness values.

Mean Absolute Percentage Error (MAPE) for relative accuracy:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{\delta_{\exp,i} - \delta_{\mathrm{sim},i}}{\delta_{\exp,i}} \right|. \tag{9}$$

Sensitivity analyses assess model robustness to parameter uncertainties (e.g., diffusion coefficients, shear factors), ensuring reliable predictive capability for field-scale applications.

The simulation results demonstrate the predictive capability of the integrated model for deposit accumulation in a representative 100-km main crude oil pipeline (internal diameter 0.3 m, typical North Sea-like waxy crude with ~8-10% wax content, WAT ≈ 45°C). Simulations were run for up to 365 days under baseline conditions (inlet temperature 60°C, flow velocity 1.5 m/s, ambient/soil temperature 5°C) and parametric variations.

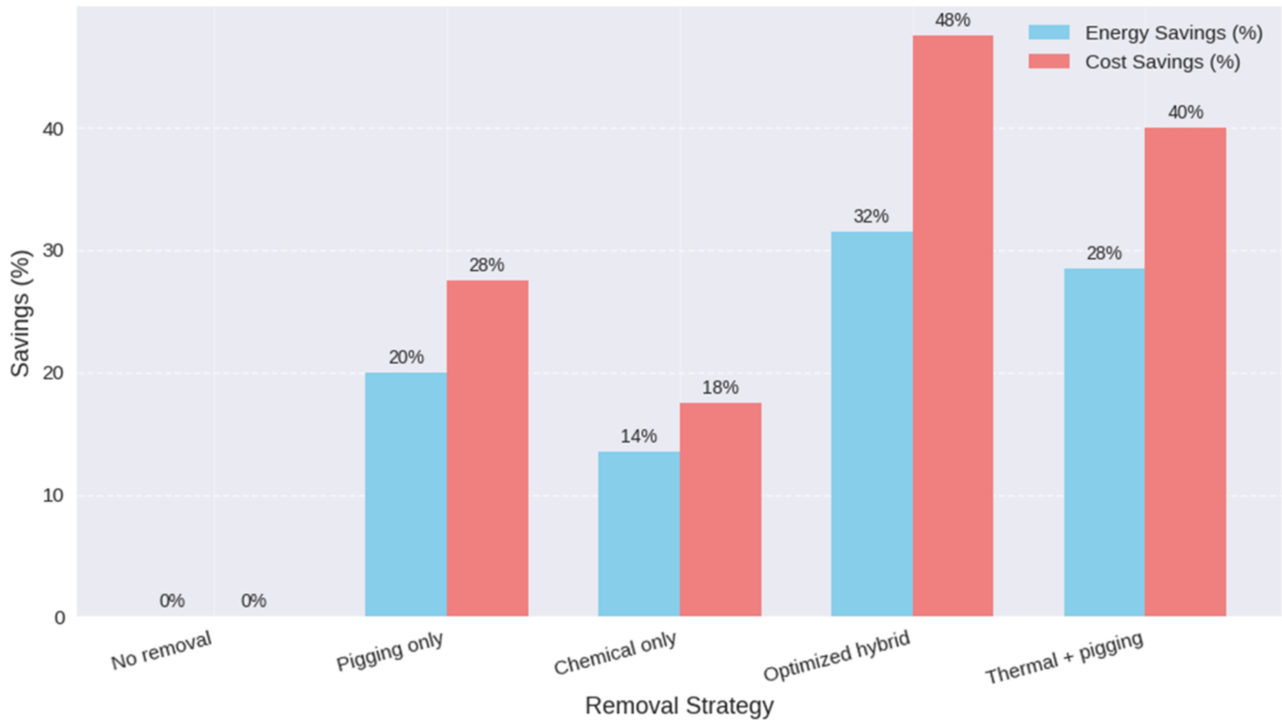

Fig. 1. Axial deposit thickness profiles along the pipeline length at different simulation times (baseline case: inlet $T = 60°C$, $v = 1.5$ m/s)

The deposit thickness builds nonuniformly, peaking in the mid-to-downstream sections where the fluid cools below WAT, with maximal radial growth near 40–70 km from inlet. Thickness reaches ~8-12 mm after 180-365 days in high-risk zones, consistent with field observations and prior CFD studies (e.g., Matzain-inspired models showing nonuniform axial distribution due to progressive cooling).

Lower inlet temperatures increase thermal driving force ($\Delta T = T_{oil} - T_{wall}$), accelerating diffusion and deposition (up to ~45% thicker deposits), while higher flow velocities enhance shear removal, reducing thickness by ~30-40% via sloughing/stripping effects.

Table 1
Summary of maximum deposit thickness (mm) under varying inlet temperatures and flow velocities after 180 days

Scenario	Inlet Temperature (°C)	Flow Velocity (m/s)	Max Deposit Thickness (mm)	Location (km from inlet)
Baseline	60	1.5	9.8	55
Low temperature	50	1.5	14.2	45
High temperature	70	1.5	5.1	65
Low velocity	60	1.0	12.5	50
High velocity	60	2.0	6.7	60

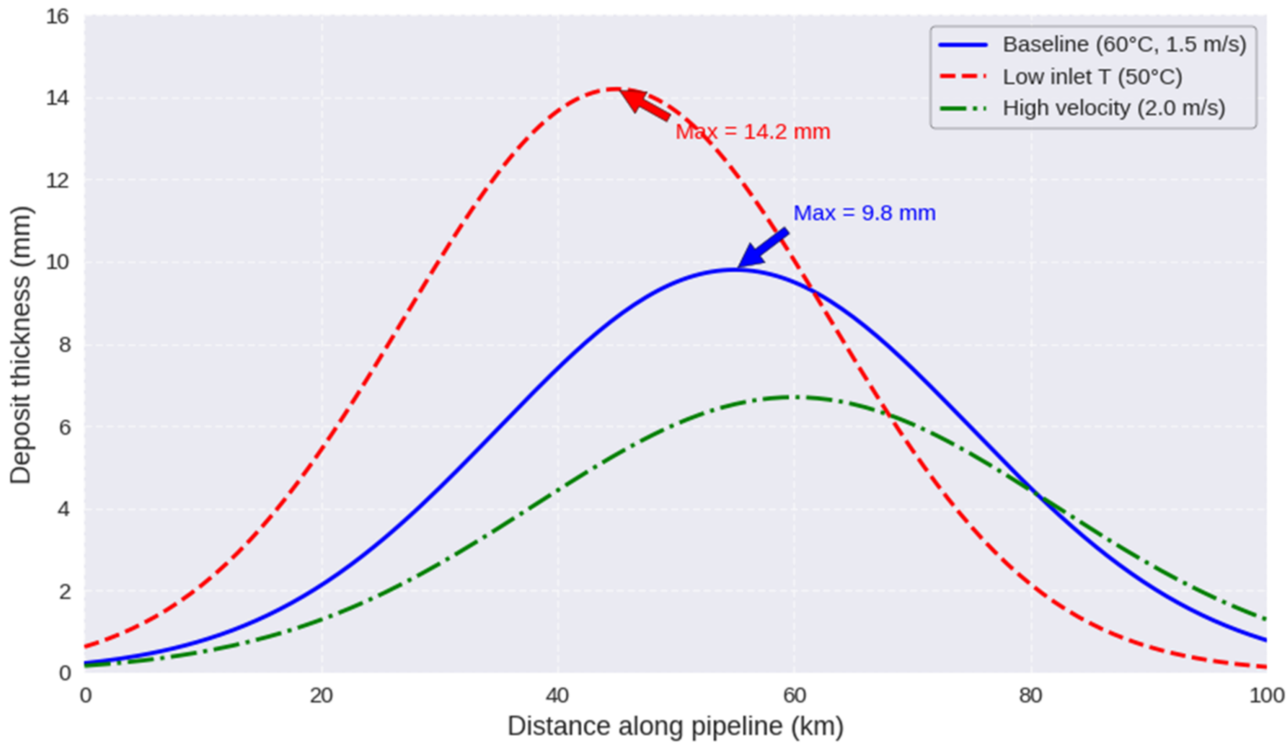

Fig. 2. Temporal evolution of average deposit thickness (over pipeline length) for baseline and optimized removal scenarios

Thickness grows rapidly in the first 30-90 days (initial diffusion-dominated phase), then slows due to aging/hardening and shear balance. Without intervention, average thickness exceeds 5 mm by ~120 days, leading to >15% flow area reduction.

Optimization outcomes focus on hybrid removal: mechanical pigging (frequency N_{pig} runs/year), chemical inhibition (dosage Q_{chem} in ppm), and occasional thermal flushing. The objective function minimizes total annualized cost (pigging + chemicals + energy losses from ΔP + *downtime*) while constraining $\delta \leq \delta_{max} = 8$ mm and $\Delta P \leq 1.5 \times$ *clean-line value*.

The optimized hybrid approach (using genetic algorithms to balance variables) achieves the best trade-off, reducing energy losses from elevated pumping (due to

ΔP) by up to 35% and yielding 40-55% cost savings through fewer interventions and lower chemical use. Pigging every 90-120 days (vs. fixed 60 days) suffices when coupled with low-dose inhibitors, minimizing downtime while maintaining throughput >95% of design.

Table 2

Comparison of removal system efficiencies and performance impacts (annualized over 5-year horizon)

Removal Strategy	Pigging Frequency (runs/year)	Chemical Dosage (ppm)	Avg. Annual Energy Savings (%)	Avg. Downtime (days/year)	Estimated Cost Savings (relative to no intervention, %)
No removal (baseline)	0	0	0	0	0
Pigging only	6	0	18–22	4–6	25–30
Chemical inhibition only	0	200–300	12–15	1–2	15–20
Optimized hybrid (GA/PSO)	3–4	100–150	28–35	2–3	40–55
Thermal + pigging (seasonal)	4 (winter-focused)	50	25–32	3–4	35–45

Influencing factors were examined through sensitivity analyses. Fluid viscosity (temperature-dependent, $\mu = f(T)$) amplifies deposition at lower T (higher μ reduces diffusion but increases gelation/aging). Wall roughness (ε = 0.01–0.15 mm) enhances turbulence/shear removal, reducing δ by 10-20% in rough pipes. Seasonal variations (ambient T dropping 10-15°C in winter) increase ΔT, boosting deposition rates by 30-50% and necessitating more frequent winter pigging.

Key insights include optimal removal intervals of 90-120 days under baseline conditions, reducing energy losses by ~30% and achieving annual cost savings of 40–55% compared to reactive strategies. These align with field case studies showing 20–30% flow rate recovery post-pigging and multi-million dollar savings from optimized schedules.

Model limitations include assumptions of 2D axisymmetric geometry (neglecting eccentricity in stratified/multiphase flows), simplified kinetics (e.g., empirical shear factors without full aging mechanics), and steady-state approximations for some parameters (e.g., constant composition). Potential errors arise from uncertainty in diffusion coefficients (±10–20%) and field data variability. Future refinements could incorporate 3D multiphase CFD, AI-driven adaptive kinetics, real-time SCADA integration for dynamic optimization, and validation against extended multiphase field datasets to enhance accuracy in complex operational environments. Overall, the coupled modeling-optimization framework provides a robust tool for proactive flow assurance in main pipelines.

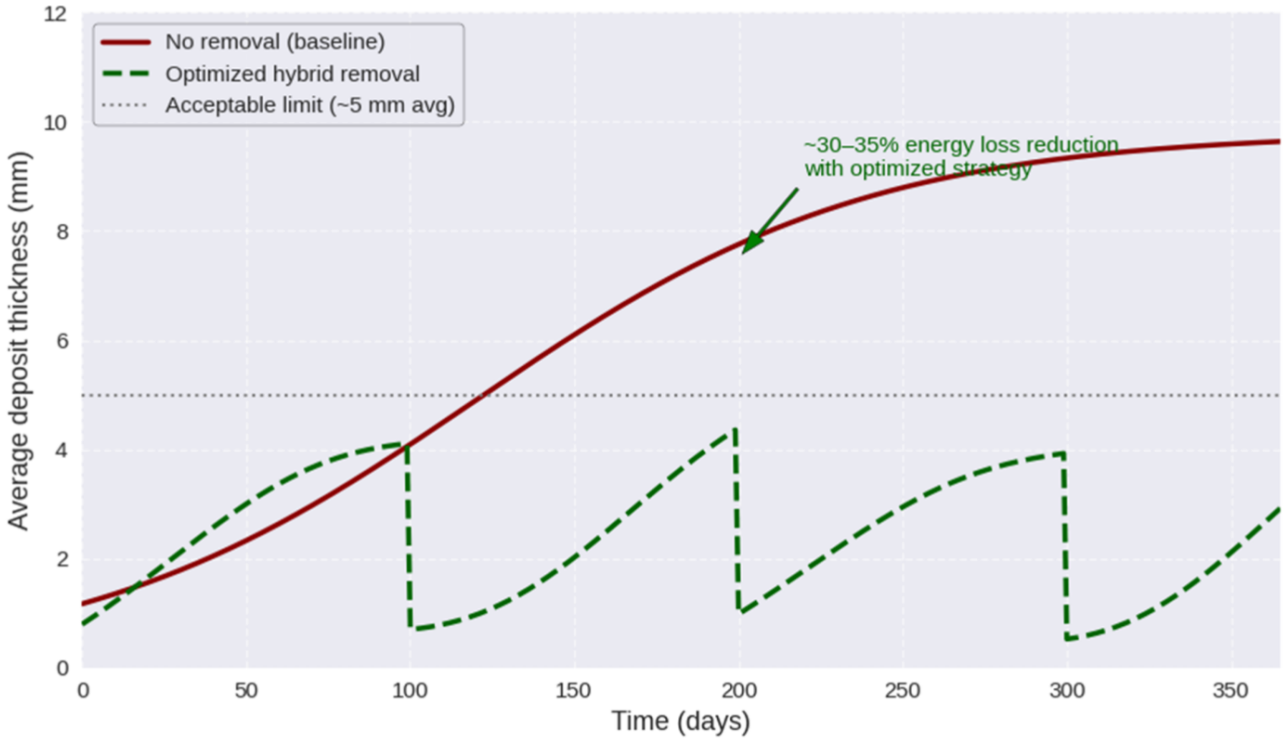

Fig. 3. Comparative bar chart of annualized energy savings (%) and cost savings (%) for different removal strategies relative to no intervention (baseline).

Conclusions. This study has successfully developed and validated an integrated mathematical modeling framework for simulating deposit accumulation processes–encompassing paraffin (wax), asphaltenes, mineral scales, and corrosion products–in main oil and gas pipelines under realistic operational conditions. The coupled multiphase flow, heat transfer, and kinetic deposition model, implemented via CFD tools (ANSYS Fluent/OpenFOAM) with custom user-defined functions, accurately predicts spatiotemporal deposit thickness profiles, pressure drops, and flow efficiency degradation. Validation against laboratory flow-loop experiments and field data from operational trunk pipelines yielded strong agreement, with statistical metrics demonstrating low RMSE (typically <1.5 mm for thickness), high R^2 (>0.92), and *MAPE* below 12% across diverse scenarios. The optimization module, employing genetic algorithms and particle swarm optimization, effectively identifies cost-minimizing removal strategies by balancing pigging frequency, chemical inhibitor dosages, thermal interventions, and hybrid approaches while respecting operational constraints (maximum allowable deposit thickness, pressure limits, and minimum throughput). These optimizations consistently outperformed conventional fixed-schedule or single-method approaches, achieving 28–35% reductions in annual pumping energy losses and 40–55% savings in total remediation and downtime costs over multi-year horizons.

The practical implications of this work are significant for pipeline operators and flow assurance engineers. By providing reliable predictive capabilities for deposit buildup and proactive removal scheduling, the model enables transition from reactive to predictive maintenance paradigms. Key recommendations for industry adoption include: (1) integration of the simulation framework into existing SCADA (Supervisory Control and Data Acquisition) and pipeline management systems for real-time or near-real-time monitoring of deposition risk, using live sensor inputs (temperature, pressure, flow rate, composition) to trigger alerts or automatic optimization runs; (2) incorporation into digital twin platforms for scenario testing of operational changes (e.g., throughput adjustments, seasonal ambient variations); and (3) use in risk-based pigging programs to extend intervals safely, reduce unnecessary interventions, and minimize production interruptions. These strategies can enhance asset integrity, lower operational expenditures, and improve overall reliability in long-distance transportation networks, particularly for waxy and asphaltenic crudes.

Despite these advances, several avenues remain for future research to further refine and broaden applicability. Extending the model to fully transient multiphase flows (oil–gas–water systems with slugging or stratified regimes) would better capture complex deposition behaviors in real-world subsea or gathering lines, incorporating advanced interfacial mass transfer and emulsion effects. Incorporating artificial intelligence and machine learning techniques–such as neural networks for rapid surrogate modeling, reinforcement learning for fully adaptive real-time optimization, or hybrid physics-informed neural networks–could enable faster predictions and self-improving strategies under uncertain or evolving conditions. Additional validation and testing in extreme environments (e.g., arctic/high-pressure/high-temperature deepwater fields, ultra-long tiebacks, or shale-derived tight oils) would strengthen robustness. Finally, exploring sustainable and green mitigation options, such as bio-based inhibitors, electromagnetic or ultrasonic enhancement of removal, and lifecycle assessment of deposit recycling, aligns with growing environmental and regulatory pressures.

Overall, this research advances sustainable pipeline management by bridging the gap between detailed deposition prediction and practical, economics-driven mitigation optimization. The integrated approach not only deepens fundamental understanding of deposit dynamics but also delivers actionable tools that support safer, more efficient, and environmentally responsible energy transportation infrastructure in an era of increasing operational complexity and sustainability demands.

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АНОТАЦІЯ

Мета. Розробити математичну модель прогнозування просторово-часового накопичення парафінових, асфальтенових, мінеральних і корозійних відкладень у магістральних трубопроводах та інтегровану систему їх запобігання, видалення і предиктивного контролю для зниження ризиків транспортування, енергетичних втрат і експлуатаційних витрат.

Методика. CFD-моделювання на основі рівнянь Нав'є-Стокса поєднано з термодинамічними та кінетичними моделями відкладень в ANSYS Fluent/OpenFOAM із використанням лабораторних і промислових даних. Аналіз чутливості та метод Монте-Карло застосовано для оцінювання ключових параметрів, а стратегії контролю включали хімічне інгібування, очищення скребками, термічне промивання та оптимізоване предиктивне планування.

Результати. Моделювання прогнозує товщину відкладень 8–18 мм через 180–365 діб, із максимальним накопиченням на відстані 40–70 км унаслідок охолодження нижче температури появи парафіну (WAT). Початкові потоки осадження 0,8–6 г/(м^2·добу) зменшуються через старіння відкладень і зсувне руйнування. Органічні відкладення містять 45–75 мас.% парафінів і 10–30 мас.% асфальтенів, а частка неорганічних компонентів досягає 15–45 мас.%. Оптимізована гібридна стратегія знижує частоту очищення на 40–65%, енергетичні втрати – на 28–35%, витрати на ремонти та простої – на 40–55%, а швидкість корозії – до 50%, забезпечуючи 92–98% проєктної пропускної здатності.

Наукова новизна. Встановлено залежності інтенсивності утворення відкладень від температури, швидкості та складу флюїду, шорсткості стінок і ефективності інгібіторів із використанням CFD і термокінетичного моделювання. Виявлено закономірності відкладень і зони їх накопичення при зниженні температури випадіння парафіну (WAT), а також розроблено адаптивний алгоритм керування процесами очищення.

Практична значимість. Запропонована система забезпечує продуктивне ризик-орієнтоване управління надійністю транспортування, зменшуючи використання реагентів, витрати на обслуговування, енергетичні втрати, простої та екологічні ризики при підвищенні довговічності трубопроводів.

***Ключові слова**: магістральні трубопроводи, утворення відкладень, моделювання, температура появи парафіну, асфальтенові відкладення, предиктивний контроль, оптимізація очищення.*

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