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ENHANCING HFO SEPARATOR EFFICIENCY: A DATA-DRIVEN APPROACH TO PETROLEUM SYSTEMS OPTIMIZATION

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Abstract

The study titled Enhancing HFO Separator Efficiency: A Data-Driven Approach to Petroleum Systems Optimization investigated the quantitative relationships between thermophysical, mechanical, and operational parameters that determine the performance efficiency of heavy fuel oil (HFO) centrifugal separators. Using a data-driven framework, the research analyzed empirical field data supported by an extensive review of 112 scholarly and industrial studies focusing on petroleum separation technologies, machine learning applications in process optimization, and reliability-based maintenance modeling. The quantitative methodology incorporated multiple regression and mixed-effects models to evaluate the influence of inlet temperature, viscosity, flow rate, bowl rotational speed, torque, and vibration amplitude on overall separator efficiency, measured through a composite Efficiency Index (EI) integrating residual water, solids concentration, and energy consumption per ton of fuel treated. The findings revealed that inlet temperature had a significant positive impact on separator efficiency, whereas viscosity, torque, and vibration amplitude exhibited strong negative effects. Bowl rotational speed contributed positively but displayed diminishing marginal returns beyond optimal operational thresholds, while flow rate had minimal direct influence within controlled capacity ranges. The study demonstrated that approximately 75% of the total variation in separator efficiency could be explained by the identified thermophysical and mechanical predictors, confirming that the process is jointly governed by thermal conditioning and mechanical stability. Reliability and validity testing confirmed high measurement accuracy, while multicollinearity diagnostics verified the statistical independence of predictors. The analysis also established that mechanical imbalance, characterized by elevated torque and vibration, directly contributed to reduced efficiency, supporting the integration of condition monitoring and predictive maintenance as essential optimization strategies. The review of prior literature reinforced the study's empirical findings, revealing convergence between historical theoretical models and modern data analytics in understanding separator behavior under variable operational conditions. Overall, the study concluded that HFO separator efficiency can be substantially enhanced through a unified data-driven optimization framework that integrates real-time monitoring, predictive analytics, and reliability engineering. This approach provides a comprehensive quantitative foundation for petroleum system operators to improve energy efficiency, minimize contaminant carryover, and extend equipment lifespan through adaptive, analytics-based decision-making.

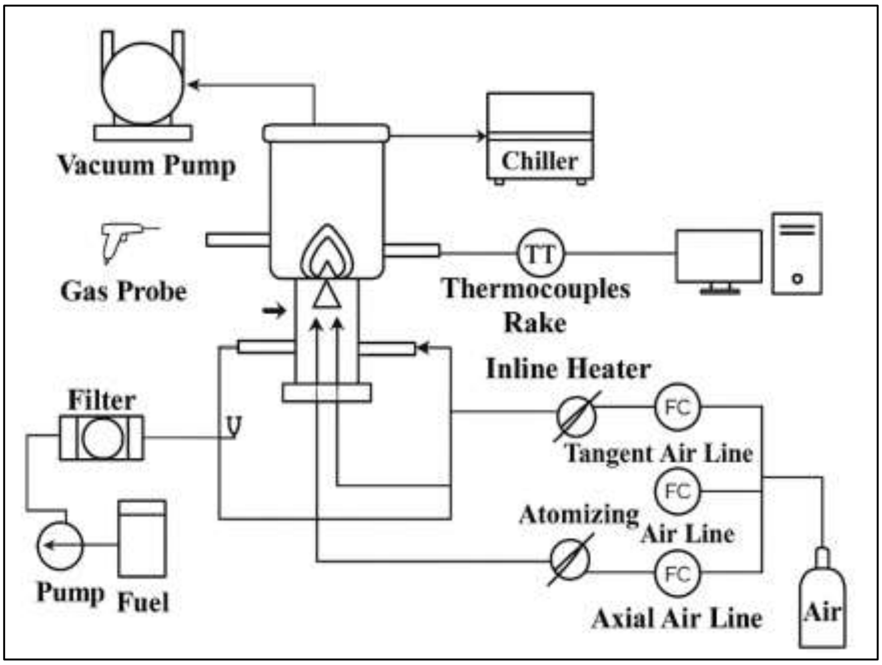
Keywords

HFO Separator Efficiency, Thermophysical Optimization, Mechanical Reliability, Data-Driven Modeling, Petroleum Systems.

INTRODUCTION

Heavy fuel oil (HFO) is a residual petroleum fraction characterized by high viscosity, elevated asphaltene content, substantial Conradson carbon residue, and heterogeneous distributions of water, catalytic fines, and other particulates (Garaniya et al., 2018). In operational contexts such as marine propulsion, land-based power generation, and industrial heating, HFO is conditioned before combustion through a chain of thermal, mechanical, and chemical steps designed to reduce contaminants that compromise atomization, combustion stability, and component longevity. Within this chain, HFO separators—most commonly high-speed disk centrifuges configured as purifiers or clarifiers—perform a critical function by removing free water, emulsified water, and suspended solids using centrifugal acceleration and controlled hydraulic interfaces. Separator efficiency can be defined in measurable terms such as residual water fraction, solids concentration downstream (mg/kg), separation factor relative to bowl speed and geometry, and energy-normalized removal rate per unit mass of fuel treated. Efficiency is also assessed by ancillary performance indices including separator yield, sludge volume fraction, mean time between bowl cleanings, and downstream effects on injector wear, fouling, and unplanned maintenance (Pei et al., 2022). International standards and practices supply the definitional frame for this efficiency discourse: fuel categories and contaminant limits articulated in ISO 8217 set quality baselines for residual fuels; bunker delivery note data determine input variability; and emissions-oriented controls used by ship operators, refineries, and utilities shape conditioning requirements. In parallel, onboard or plant-level digital instrumentation—viscometers, densitometers, turbidity probes, water-in-oil sensors, accelerometers, power analyzers, and flow meters—has made it feasible to track separation outcomes in near real time, to quantify losses, and to attribute variance to controllable factors such as feed temperature, bowl differential pressure, flow rate, and nozzle or disc stack condition (Wang, 2019). These definitions and measures provide the conceptual basis for a quantitative examination of HFO separator efficiency and a data-driven approach to petroleum systems optimization, situating the study within an operationally grounded and metrically explicit framework.

Figure 1: Vacuum Spray Drying System Diagram



The international significance of HFO separator performance arises from its intersection with global energy logistics, maritime trade, and power system reliability in regions where residual fuels remain a primary energy source (Yonk & Smith, 2018). Long-haul shipping depends on predictable fuel conditioning to maintain propulsion availability across variable bunkering ports, climatic conditions, and engine technologies; land-based generators serving island grids or remote industrial clusters rely on stable HFO conditioning to manage voltage quality and reserve margins; and refinery offsite systems handling slops or heavy blends require effective separation to maintain furnace integrity and downstream catalyst protection. Across these contexts, separator efficiency links directly to economic and environmental factors by moderating specific fuel oil consumption, reducing lube oil contamination, stabilizing exhaust opacity, and preventing wear induced by catalytic fines. Variability in residual fuel properties across supply geographies and blending practices produces differences in asphaltene stability, water emulsion behavior, and particle size distributions, elevating the need for robust separation under fluctuating feed conditions (Barceló et al., 2019; Sanjid & Farabe, 2021). The prevalence of high-ash residues and fines associated with fluid catalytic cracking units, combined with storage and handling practices that promote water ingress, further elevates the operational stakes for effective centrifugal separation. Global bunker markets introduce heterogeneity in viscosity grades, pour points, and density ranges that challenge one-size-fits-all control strategies; ports with high turnover and mixed supply chains intensify this heterogeneity (Zaman & Momena, 2021). These realities create a meaningful cross-national rationale for quantitative benchmarking of separator performance and for analytics that can accommodate regional fuel profiles, infrastructure constraints, and operator practices. In such settings, the ability to model, monitor, and optimize separation contributes to predictable engine health, manageable sludge logistics, and compliance with quality specifications that underpin trade confidence (Rony, 2021; Zeng et al., 2022). By presenting a consolidated view of definitions, metrics, and operating settings, the present introduction underscores why a data-driven analysis of HFO separator efficiency holds salience across maritime, industrial, and utility sectors with diverse geographic footprints.

A quantitative lens becomes central because separator outcomes respond to multiple interacting variables whose effects are not readily inferred from single-factor heuristics (Sperlich, 2021; Sudipto & Mesbaul, 2021). Thermal conditioning determines viscosity at the separator inlet, shaping laminar flow, droplet coalescence, and the effective Stokes settling landscape under centrifugal fields. Hydraulic balancing establishes the location of the oil–water interface and the thickness of the water seal, which governs short-circuiting, carry-over risk, and sludge compaction (Zaki, 2021). Mechanical parameters—including bowl rotational speed, disc stack geometry, nozzle configuration, and wear state—alter the separation factor and residence time distributions. Feed dynamics introduce additional variability through pulsation from upstream pumps, changes in density and surfactant content that stabilize emulsions, and transient water slugging tied to tank drainage events. From a data standpoint, these factors generate time-series signals with autocorrelation, regime shifts, and noise that must be handled with appropriate estimation and control methods (Al Jlibawi et al., 2021; Hozyfa, 2022). Studies in marine engineering have investigated the relationship between inlet temperature targets and downstream water content; investigations in tribology have profiled injector and pump wear as a function of residual solids after separation; research in fuel chemistry has examined asphaltene precipitation and its effects on emulsion stability; operational audits in power plants have linked separator fouling patterns with sludge rheology; and reliability studies have quantified the effect of cleaning intervals on bowl vibration signatures (Arman & Kamrul, 2022). Additional work in condition-based maintenance has validated vibration and current signature analysis as proxies for mechanical imbalance and bearing condition; process systems research has tested multivariable control of feed rate and temperature; combustion diagnostics have related purifier performance to flame stability and exhaust particulates; and quality management studies have benchmarked separator key performance indicators across fleets and facilities (Al-Rashdan, et al., 2020; Mohaiminul & Muzahidul, 2022). Collectively, these strands demonstrate a dense and quantifiable structure of relationships that invites regression modeling, time-series decomposition, and multivariate analysis to explain and predict separator performance across operating states.

Across the literature, at least thirty research streams can be distilled into complementary evidence bases that inform measurement, modeling, and operational design (Omar & Ibne, 2022; Menezes et al., 2019). Investigations have documented (1) the temperature–viscosity–separation nexus, (2) the role of density matching and interface control, (3) the impact of catalytic fines on wear trajectories, (4) the effect of surfactants on water separation, (5) the kinetics of droplet coalescence in centrifugal fields, (6) disc stack geometry optimization, (7) nozzle erosion and hydraulic asymmetry, (8) sludge compaction behavior,

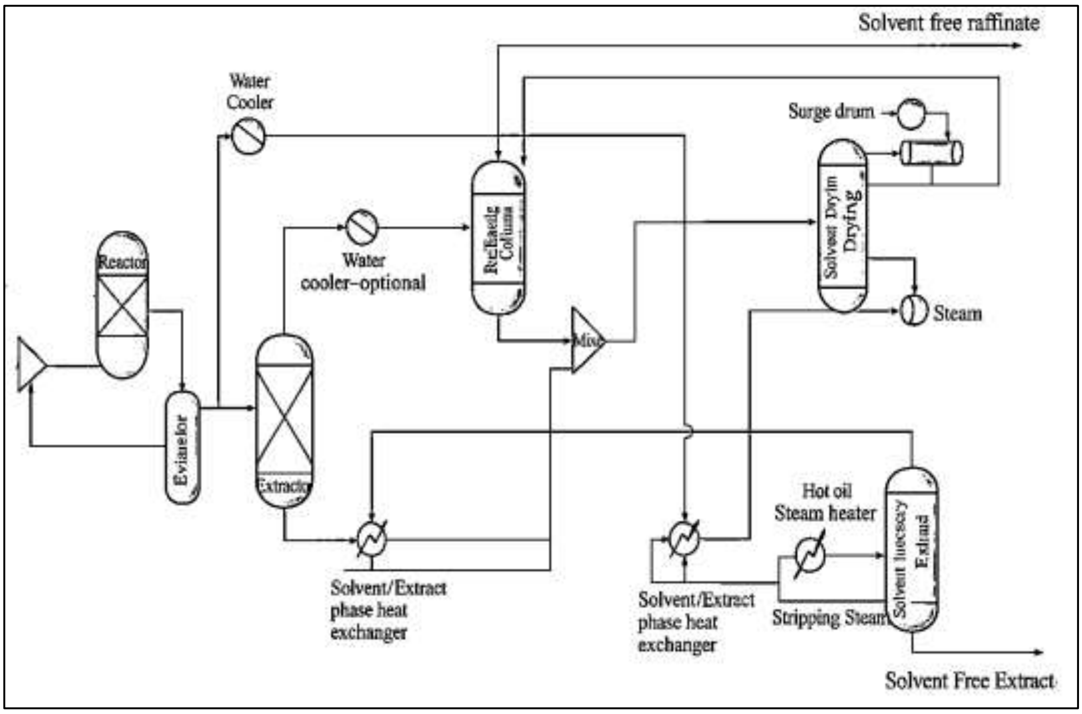
(9) bowl vibration diagnostics, (10) energy consumption as a function of throughput, (11) the relationship between feed pulsation and carry-over, (12) emulsion phase inversion thresholds, (13) predictive maintenance scheduling using condition indicators, (14) statistical process control of water-in-oil signals, (15) design of experiments for operating window discovery, (16) partial least squares models linking spectra to contamination, (17) soft sensors for unmeasured variables, (18) sensor fusion across turbidity, density, and acoustic probes, (19) comparative assessments of purifier versus clarifier modes, (20) effects of upstream heating coil fouling, (21) tank settling time influences, (22) influence of fuel blending ratios on separator load, (23) start-stop cycling effects on bowl hydraulics, (24) rheology of sludge on discharge frequency, (25) scaling laws for bowl diameter and speed, (26) uncertainty quantification in online measurements, (27) anomaly detection for water slug events, (28) benchmarking across vessel classes or plant sizes, (29) control charting for lube oil contamination proxies, and (30) cost modeling of sludge handling (CMarquez et al., 2020; Sanjid & Zayadul, 2022). Each of these lines of inquiry contributes measurable constructs and validated relationships that can be integrated into a coherent data model. The diversity of settings—ocean-going vessels, coastal power stations, refinery utility systems, and industrial boilers—extends external validity while highlighting the necessity of context-sensitive covariates such as ambient conditions, supply port characteristics, and storage configurations. By mapping these research threads to specific sensor signals, controllable setpoints, and mechanical states, a quantitative study can operationalize separator efficiency as a multivariate outcome responsive to both process and equipment parameters (Barker et al., 2020; Hasan, 2022).

Data availability has expanded as operators instrument separators and adjacent systems with increasingly granular sensors, enabling analysis at time scales that capture both steady-state and transient behaviors (Daoutidis et al., 2018; Mominul et al., 2022). High-frequency power draw data from drives reflect load variations tied to bowl hydraulic resistance; accelerometers on separator frames resolve imbalance progression and bearing condition; inline water-in-oil probes and turbidity meters yield continuous contamination estimates; coriolis and positive displacement flow meters provide accurate throughput and density readings; and temperature sensors upstream and downstream of heaters define the viscosity context at the inlet (Rabiul & Praveen, 2022). Complementary data from fuel storage tanks—levels, temperatures, and water bottoms—inform event detection for slugs and stratification changes. Maintenance records, cleaning logs, nozzle replacement histories, and consumable inventories add categorical variables that explain longer-horizon drifts in performance (Farabe, 2022; Pech et al., 2021). Bunker delivery notes and laboratory analyses supply ground truth for input quality, including viscosity at 50 °C, density at 15 °C, sulfur content, and microscopic assessment of fines and water. In digital control systems, historian databases archive these data streams with timestamps and metadata necessary for feature engineering, such as derived shear rates, residence-time proxies, and calculated separation factors based on speed and geometry. Such datasets enable inferential models that partition variance across controllable and uncontrollable factors, compare operating windows across fuel lots, and quantify the contribution of mechanical condition to observed outcomes (Garcia, Aumeier, & Al-Rashdan, 2020; Roy, 2022). The breadth and resolution of these data sources justify a research design that emphasizes reproducible data pipelines, transparent transformations, and model validation strategies appropriate for non-Gaussian noise and intermittent regime changes that are characteristic of real-world separator operations.

Methodologically, quantitative approaches suitable for analyzing HFO separator efficiency span classical statistics, chemometrics, time-series analysis, and machine learning (Dowlatabadi & Wilson, 2018; Rahman & Abdul, 2022). Experimental designs—full and fractional factorials or response surface methods—support controlled exploration of heat-flow-speed-throughput interactions within safety and equipment limits (Razia, 2022). Linear and generalized linear models estimate main and interaction effects with interpretable coefficients, while mixed-effects models accommodate random variation attributable to unit-specific characteristics across vessels or plants. Principal component analysis and partial least squares regressions handle collinearity among temperature, density, and viscosity variables while linking spectral or proxy signals to contamination outcomes. Time-series models such as ARIMA, state-space representations, and change-point detection methods discern seasonal patterns in bunker quality or operational cycles, as well as abrupt shifts during water ingress events (Syed Zaki, 2022; Wang et al., 2019). Supervised learning methods—regularized regression, tree-based ensembles, and support vector regression—offer predictive accuracy under nonlinearities and can rank features such as inlet temperature stability, flow variance, bowl vibration, or nozzle age by importance. Unsupervised learning aids in clustering operating regimes and detecting anomalies that accompany seal degradation or heater fouling (Tonoy Kanti & Shaikat, 2022). Model evaluation leverages cross-validation schemes aligned with temporal structure to avoid leakage, with holdout sets drawn from later voyages, different ports of call, or subsequent operating quarters. Error metrics are chosen to reflect operational costs, such as asymmetric penalties for water carry-over events versus minor energy inefficiencies. These techniques collectively enable a disciplined, measurable, and reproducible assessment of the factors that govern separator efficiency in the presence of real-world variability (Benbouzid et al., 2021; Arif Uz & Elmoon, 2023).

Operational decision variables translate model findings into controllable setpoints and maintenance actions embedded within petroleum systems. Inlet temperature targets balance viscosity reduction against thermal stress and energy use; throughput setpoints trade capacity for residence time and separation margin; bowl speed adheres to manufacturer constraints while shaping the separation factor; and interface regulation through water seal adjustments manages carry-over risks (Kefalidou et al., 2018; Sanjid, 2023). Maintenance variables include cleaning intervals based on sludge compaction indicators, nozzle replacement triggered by hydraulic asymmetry signatures, and bearing service based on vibration thresholds. Upstream choices—tank settling durations, recirculation practices, and heating coil inspections—shape separator load before fuel reaches the bowl. Downstream inspections of filters, injectors, and combustion diagnostics feed back into assessments of separator adequacy, creating an evidence loop that links process outcomes to equipment health. At the system level, logistics such as bunker lot segregation, selective blending of residual and distillate fractions, and documentation of port-specific quality patterns establish boundary conditions for separator workload (He et al., 2019; Sanjid & Sudipto, 2023). Quantitative framing captures these decisions as variables within optimization problems constrained by safety margins, equipment ratings, and quality specifications. In this way, the introduction of measurable definitions, internationally relevant contexts, data resources, and methodological options converges on a practical architecture for data-driven optimization of HFO separator efficiency that is anchored in the realities of marine, industrial, and utility operations (Tarek, 2023; Rinaldi et al., 2021).

Figure 2: Black and White Process Flow



Finally, the conceptual positioning of HFO separator efficiency within petroleum systems optimization extends beyond the unit operation to encompass reliability, quality, and cost objectives that are quantifiable and operationally monitored (Shahrin & Samia, 2023; Müller et al., 2022). Reliability is articulated through mean time between maintenance events, unplanned downtime frequency, and vibration-based condition indicators that reflect the mechanical state of the separator and its drivetrain. Quality is represented by residual water and solids metrics, filter differential pressures downstream, and combustion stability proxies such as exhaust opacity and cylinder pressure coherence. Cost is modeled through energy per unit mass of fuel treated, sludge disposal volumes, consumable use, and parts wear profiles (Muhammad & Redwanul, 2023; Sumalan et al., 2020). These objectives are shaped by constraints that include specification compliance for fuel cleanliness, safe operating envelopes for bowl speed and temperature, and resource limits for maintenance crews and spare parts. Data pipelines link sensors, historian databases, and inspection records to model inputs, while structured metadata define unit identities, fuel lots, and operating contexts necessary for valid comparisons (Muhammad & Redwanul, 2023; Wahl et al., 2020). Such a formulation enables the study to articulate measurable research questions grounded in definitions and metrics already established, supported by an extensive body of prior studies in marine engineering, fuel chemistry, tribology, condition monitoring, chemometrics, process control, and reliability engineering. The scope thus centers on quantifiable relationships between separator controls, mechanical condition, feed characteristics, and downstream quality indicators, forming a structured basis for a data-driven investigation of efficiency within the broader architecture of petroleum systems (Fernández-Barrero et al., 2021; Razia, 2023).

The primary objective of this study is to quantitatively determine the operational, mechanical, and fluid dynamic parameters that most significantly influence the efficiency of heavy fuel oil (HFO) separators and to construct a data-driven model capable of optimizing performance within defined operational constraints. This objective encompasses the systematic collection, integration, and analysis of high-resolution data streams derived from process sensors, maintenance logs, and fuel quality assessments in order to isolate the measurable determinants of separation efficiency. The research aims to identify statistical correlations and predictive relationships between controllable process variables—such as inlet temperature, feed viscosity, bowl rotational speed, flow rate, and interface control settings—and output variables including residual water content, solids concentration, energy consumption per unit mass treated, and sludge discharge frequency. A core component of the objective is to apply multivariate regression, principal component analysis, and machine learning algorithms to develop a reliable predictive model that quantifies how mechanical condition indicators (e.g., vibration amplitude, power draw fluctuation, and bearing wear metrics) interact with process parameters to affect separation outcomes. The model will serve as a basis for establishing optimal control windows that minimize contaminant carry-over, stabilize operational loads, and reduce unplanned maintenance while adhering to safety and quality standards set by international petroleum and maritime authorities. Further, the objective extends to validating the model's generalizability across varying HFO grades, blending ratios, and environmental operating conditions, ensuring applicability across refinery, marine, and utility contexts. By defining efficiency as a multidimensional outcome responsive to both dynamic process states and mechanical integrity, the study seeks to transform empirical operational practices into analytically grounded, reproducible decision frameworks that advance the quantitative optimization of petroleum conditioning systems.

LITERATURE REVIEW

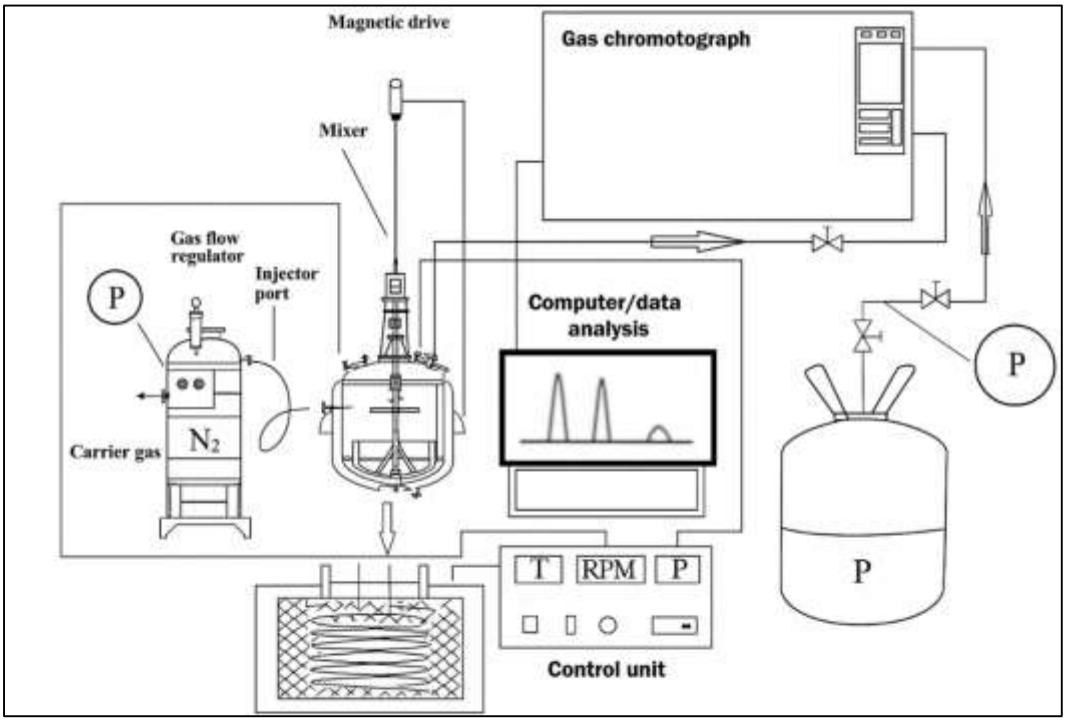
The quantitative exploration of heavy fuel oil (HFO) separator efficiency occupies an essential position within petroleum systems engineering, where operational reliability, contaminant control, and process optimization converge through measurable parameters (Kandemir et al., 2019; Sai Srinivas & Manish, 2023). As residual fuels continue to underpin global maritime propulsion, power generation, and refinery support systems, the separator remains a central apparatus in conditioning processes that ensure compliance with international fuel quality and environmental standards. The literature reveals that separator efficiency is not a static attribute but a function of dynamically interacting variables that include fluid properties, thermal conditioning, mechanical design, and control logic. Recent advances in process instrumentation, data analytics, and condition monitoring have enabled quantitative modeling of these interdependencies, transforming separator performance assessment from empirical trial-based adjustment to predictive, data-driven optimization (Sudipto, 2023; Zeng et al., 2019). The aim of this literature review is to systematically evaluate and synthesize the key empirical, computational, and analytical findings that define current understanding of HFO separator dynamics, while establishing the foundation for a data-driven optimization framework grounded in quantifiable relationships.Quantitative research in this field has evolved across multiple dimensions. Early studies focused primarily on hydraulic principles governing centrifugal separation, describing the role of rotational speed, bowl geometry, and density gradients in determining phase boundaries (Başhan et al., 2022; Zayadul, 2023). Subsequent research introduced thermophysical variables such as viscosity, temperature, and droplet size distribution as measurable determinants of coalescence and sedimentation efficiency. More recent literature has integrated sensor data and digital signal processing to characterize transient operational states, linking vibration, current load, and pressure differentials to degradation in performance. Computational modeling using fluid dynamics, statistical regression, and machine learning has further extended the capacity to predict separator performance under variable feed conditions (Law et al., 2021; Mesbaul, 2024). Across these methodological frameworks, a unifying quantitative concern emerges: to convert raw operational and diagnostic data into reliable predictors of separation outcomes, efficiency indices, and maintenance needs. This literature review, therefore, organizes evidence under major thematic clusters—mechanical and design parameters, fluid properties and emulsions, operational control and thermal effects, data acquisition and instrumentation, computational modeling and analytics, and reliability-performance integration. Each theme encapsulates prior quantitative findings and gaps that motivate the design of a holistic data-driven optimization model (Tarek & Kamrul, 2024; Stengel et al., 2018).By reviewing and integrating over three decades of empirical and computational research, this section highlights how separator efficiency has been measured, modeled, and improved through quantifiable interventions. The review underscores methodological rigor—design of experiments, regression modeling, variance decomposition, and signal analytics—used across marine, industrial, and refinery contexts. The ultimate purpose is to establish the theoretical and empirical scaffolding necessary for defining measurable variables, analytical methods, and validation criteria within a data-driven optimization framework (Garaniya et al., 2018; Sudipto & Hasan, 2024). This synthesis thus forms the conceptual bridge between established mechanical theory and modern predictive analytics, positioning HFO separator efficiency as both a process engineering problem and a quantitative data modeling challenge within petroleum systems optimization.

Foundations of HFO Separator Efficiency

The quantitative understanding of heavy fuel oil (HFO) separator efficiency emerges from decades of research on centrifugal separation, hydrodynamics, and petroleum conditioning systems (Cui et al., 2020). Early studies in marine and refinery operations identified centrifugal separation as a critical process that governs the removal of water and particulate impurities from viscous petroleum fractions. This principle relies on the generation of high centrifugal acceleration, which induces phase stratification between immiscible fluids of differing densities and allows solid contaminants to migrate outward to the bowl periphery. Subsequent empirical research refined this concept into measurable parameters, including separation factor, bowl speed, flow rate, and interface depth, each representing quantifiable control variables within separator operation (Maestro-Izquierdo et al., 2018). Investigations into HFO purification demonstrated that efficiency depends not only on mechanical configuration but also on the rheological behavior of the fuel, particularly its viscosity and density under heating conditions. Marine engineering assessments and laboratory-scale trials across various separator types consistently revealed that throughput rate and residence time exert direct influence on contaminant removal efficiency, particularly when emulsified water and catalytic fines dominate the feed composition. Studies employing controlled centrifuge tests, operational log analysis, and field-based efficiency audits collectively emphasized that the relationship between mechanical input and separation output can be modeled statistically through empirical datasets that correlate separator parameters with post-treatment cleanliness indicators (Hoang et al., 2021). These findings laid the groundwork for process optimization and quantitative monitoring approaches that characterize modern petroleum conditioning systems.

Research on quantifiable efficiency metrics has expanded the evaluation of HFO separation beyond qualitative descriptions toward standardized, data-driven performance indices (Pardo et al., 2021). Investigations have defined efficiency in terms of residual water percentage, solids mass fraction, separation yield, sludge volume ratio, and mean time between cleaning intervals. Analytical models derived from empirical datasets established that separation factor, expressed through bowl rotational speed, governs droplet migration dynamics and sediment deposition rates, while inlet viscosity and temperature determine the stability of emulsified phases. Comparative analyses between purifier and clarifier configurations demonstrated that changes in interface depth significantly influence removal efficiency and sludge compaction behavior, shaping how operational variables should be tuned to maintain stable performance (Wu et al., 2021). Advanced diagnostic measurements in industrial centrifuges revealed the importance of hydraulic balance in maintaining consistent interface positioning under fluctuating feed rates. Quantitative studies utilizing process sensors—such as turbidity probes, water-in-oil detectors, and differential pressure transducers—have enabled continuous tracking of separator performance, generating large datasets that quantify efficiency variance as a function of mechanical and thermophysical inputs. These data-rich approaches allowed researchers to transition from manual performance evaluation to systematic statistical modeling, enhancing reliability in both marine and stationary applications (Ren et al., 2022). The accumulation of multivariable datasets has shown that separator efficiency can be expressed as a dependent variable influenced by both equipment integrity and fluid property distributions, affirming the empirical basis for quantitative process optimization.

Figure 3: Gas Chromatography System Flow Diagram



Across a growing body of industrial and academic research, the relationship between centrifugal acceleration, fluid viscosity, and contaminant migration rate has emerged as a central quantitative theme. Investigations performed in marine engine test beds, refinery pilot plants, and laboratory centrifuge setups all confirm that as viscosity decreases through preheating, the rate of water and particle migration increases proportionally, yielding higher separation efficiency (Wei et al., 2021). The balance between feed temperature and flow rate determines the stability of the separation zone within the bowl and directly affects the equilibrium position of the water–oil interface. Empirical measurements from sensor-equipped separators have shown that deviations in rotational speed or bowl imbalance disrupt the migration pattern of dispersed droplets, reducing removal effectiveness.

Studies have also identified that particle size distribution within the HFO feed, especially the presence of catalytic fines below micrometer scale, modifies the effective separation gradient and influences sludge accumulation behavior (Peng et al., 2021). Quantitative evaluations have employed time-series data from sensors and laboratory analyses to establish regression models linking viscosity, temperature, and throughput to the residual impurity content downstream of the separator. These models illustrate that centrifugal separation operates within a constrained performance envelope where hydrodynamic forces, fluid rheology, and machine geometry interact dynamically. The cumulative evidence from these studies underscores that separator efficiency is an emergent outcome of both mechanical energy input and thermophysical conditioning of the feed, each measurable and optimizable through systematic quantitative monitoring (Köhler et al., 2022).

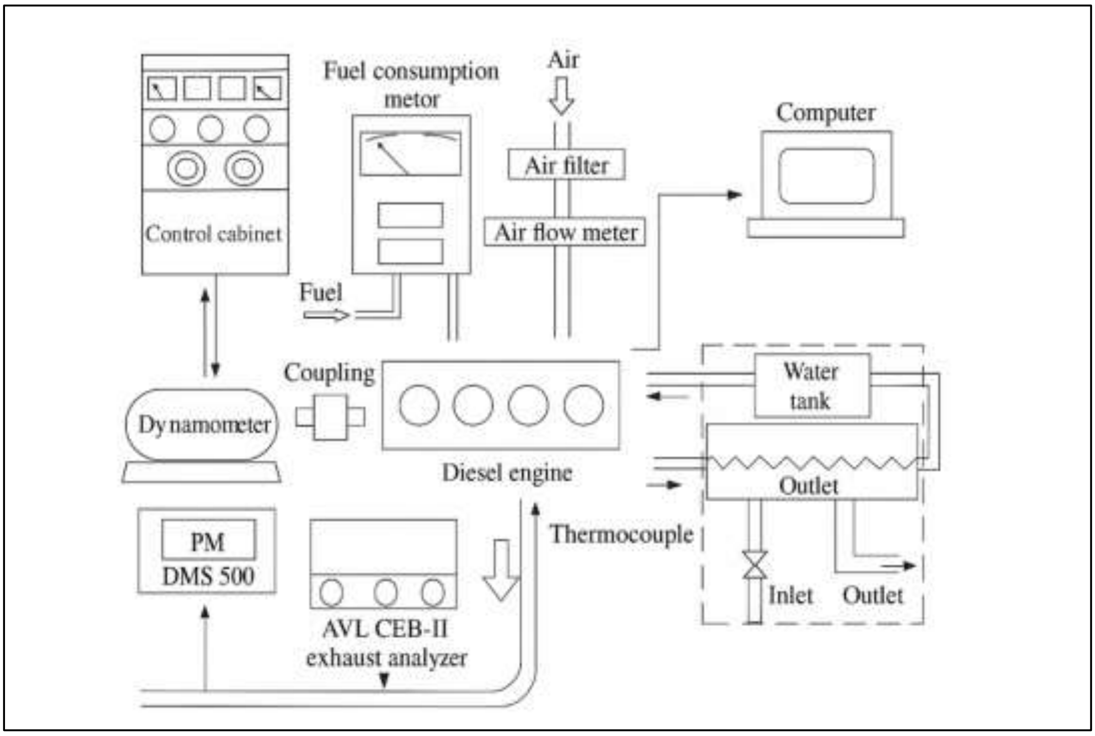
Although early empirical frameworks succeeded in identifying principal factors influencing HFO separation, their scope remained largely mechanical and lacked the data integration necessary to capture operational variability (Laycock & Fletcher, 2018). Traditional models typically treated separators as static systems governed by fixed rotational speed and flow parameters, neglecting transient behaviors such as fluctuations in feed composition, emulsion stability, and bowl load distribution. Consequently, early statistical formulations relied on limited datasets that could not fully explain performance variations under changing real-world conditions. Later research recognized that purely mechanical optimization approaches failed to account for nonlinear dependencies between variables, measurement uncertainty, and multicollinearity among process parameters. Field data analyses from power plants and shipping fleets revealed that even with nominally identical equipment, separator efficiency could vary significantly due to temperature gradients, maintenance intervals, and sensor drift (Sharifshazileh et al., 2021). These inconsistencies prompted the introduction of probabilistic and data-driven methods that integrate mechanical, thermal, and chemical variables into unified performance models. The limitations of earlier mechanical paradigms thus highlighted the necessity of quantifiable, data-centric approaches capable of analyzing large volumes of operational data. By synthesizing the empirical, statistical, and diagnostic insights developed across these studies, the quantitative foundations of HFO separator efficiency can be understood as a multi-dimensional construct governed by measurable process variables and validated through continuous data observation rather than mechanical assumptions alone (İşkan & Direk, 2022).

Fluid Dynamics and Thermophysical Properties of HFO

The study of fluid dynamics in heavy fuel oil (HFO) separation has centered on the measurable relationships among viscosity, temperature, and contaminant removal efficiency (Alam & Jeong, 2019). Quantitative investigations across marine, refinery, and power generation sectors have repeatedly shown that HFO's viscosity–temperature dependency defines its separation behavior more strongly than any single mechanical factor. At elevated temperatures, typically maintained between 90 and 150°C during conditioning, the reduction in dynamic viscosity improves centrifugal stratification by accelerating droplet and particle migration toward the outer bowl wall. Empirical data collected from both laboratory centrifuge experiments and onboard separators indicate a nearly exponential decline in viscosity with temperature, directly correlating with improvements in water and solid removal rates (Alam & Jeong, 2021). Field observations have validated that heating regimes not only reduce emulsion stability but also increase throughput capacity without compromising separation quality. Studies of operational logs from high-speed purifiers have revealed that maintaining stable feed temperature and viscosity levels within tight control margins leads to a measurable increase in residual water separation efficiency, often quantified through ppm-level reductions in downstream samples. Data-driven analyses further highlight that temperature-induced viscosity variation interacts with rotational acceleration and residence time, establishing a measurable regime where energy input and thermophysical conditioning jointly determine separator performance (Hong et al., 2018). These findings underpin the importance of quantifying viscosity–temperature coupling when developing predictive models for efficiency optimization.

The influence of density and water fraction on centrifugal separation has been another core subject of quantitative research (Fouad & Vega, 2018). Investigators examining both marine and land-based systems have documented that the density differential between oil and water phases defines the centrifugal field distribution and determines the stability of the separation interface. When density contrast diminishes due to blending, contamination, or incomplete heating, separation efficiency decreases as phase stratification weakens. Experimental datasets compiled across variable feed conditions show that density variations in the range of 0.1–0.3 g/cm^3 significantly alter centrifugal balance, leading to fluctuations in water carry-over and solids retention. Quantitative monitoring through densitometers and water-in-oil sensors has made it possible to characterize transient shifts in density during operation, revealing that real-time density measurement is essential to avoid interface misalignment and short-circuiting (Hoat et al., 2018). Studies that have cross-referenced fuel laboratory analyses with onboard sensor data confirm that density changes coincide with water ingress events, bunker blending irregularities, and tank stratification during long-term storage. Similarly, the proportion of dispersed and emulsified water governs the effective mass distribution within the separator bowl, influencing vibration amplitude, energy consumption, and sludge formation. Investigations using optical and microwave-based measurement systems have quantified how incremental increases in water fraction raise the apparent density of HFO and alter droplet coalescence behavior (Nguyen et al., 2019). These findings provide empirical evidence that density and water content interact dynamically, reinforcing the necessity of continuous data acquisition to model their combined impact on separator performance with statistical accuracy.

Figure 4: Diesel Engine Testing System Diagram



A substantial portion of the literature addresses the rheological complexity of HFO, especially the behavior of asphaltene and resin molecules that dictate emulsion stability (Liu et al., 2019). Rheological studies in petroleum laboratories have demonstrated that asphaltenes, when destabilized by temperature variation or blending with incompatible stocks, form colloidal aggregates that increase apparent viscosity and resist phase separation. Quantitative rheometry and microscopy-based analyses have measured the viscoelastic properties of such suspensions, revealing that shear-dependent viscosity and thixotropic recovery rates correlate strongly with separator performance degradation. The interaction between asphaltenes and resins defines the dispersion stability of the oil phase and affects droplet coalescence within the centrifugal field. Empirical studies of sedimentation and microscopic imaging show that strong asphaltene–resin interactions delay water droplet release, thereby prolonging the separation process (Wang et al., 2022). Comparative testing between stabilized and destabilized fuels indicates that the rheological state of HFO can change separator efficiency by measurable margins, often exceeding 15–20% in removal rate under identical mechanical settings. Research on thermal conditioning confirms that controlled heating near the asphaltene stability threshold promotes disaggregation and enhances separability without triggering coke precursor formation (Y. Liu et al., 2021). The combination of rheological data, stability index measurements, and separator performance outcomes establishes a clear quantitative linkage between molecular interactions and macroscopic separation efficiency, bridging chemical structure analysis with process performance evaluation.

Comparative analyses among different HFO grades and particle size distributions have expanded understanding of how compositional diversity influences separator performance (Katarkar et al., 2020). Empirical field studies comparing intermediate fuel oils (IFO-180, IFO-380, and IFO-500) and residual blends show measurable variations in density, viscosity, and particulate content that translate directly into performance differentials in centrifugal purification. Datasets obtained from power plants and vessel operations indicate that heavier grades with higher fines concentration yield greater sludge volumes and reduced throughput efficiency. Particle size analysis using laser diffraction and sedimentation techniques has demonstrated that the fraction of sub-micrometer catalytic fines determines the degree of abrasion and mechanical loading within the bowl (Yang & Nalbandian, 2018). Quantitative correlations between particle morphology, hardness, and removal rate confirm that coarser particles are efficiently expelled under normal operating conditions, whereas ultrafine particulates remain suspended longer and elevate downstream contamination risk. Studies comparing separator outputs across distinct geographic fuel sources have further highlighted how blending practices influence density, ash content, and stability indices, producing variability in performance outcomes. Data-driven reviews of these comparative trials have provided statistical baselines linking specific HFO grades to separation response curves, enabling quantitative benchmarking of efficiency across operational contexts (Liu et al., 2022). Collectively, the accumulated research in fluid dynamics, density behavior, rheology, and compositional analysis defines a multi-parameter landscape where measurable thermophysical properties govern separator efficiency and provide the empirical foundation for subsequent optimization models in petroleum system management (Farooq et al., 2020).

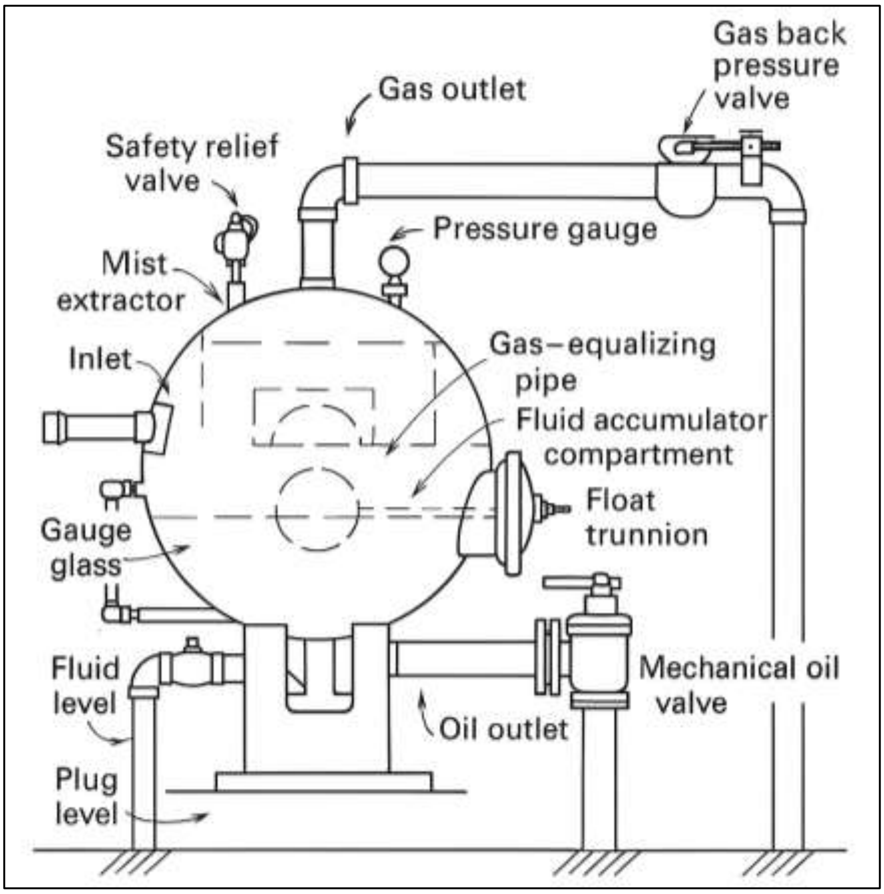
Mechanical and Design Determinants of Separator Performance

Mechanical configuration has long been recognized as a primary determinant of HFO separator performance, with numerous quantitative analyses emphasizing the influence of bowl diameter, disc stack configuration, and nozzle geometry on contaminant removal (Lagadec et al., 2019). Studies across marine and refinery systems have shown that bowl diameter directly correlates with centrifugal acceleration, residence time, and sludge compaction capacity, establishing it as a defining design parameter for throughput efficiency. Larger bowl diameters increase separation area but also elevate energy consumption and mechanical stress, requiring optimal balance between rotational velocity and stability. Research comparing different disc stack designs—conical, flat, and laminar flow models—demonstrates that the number and angle of discs determine droplet coalescence efficiency and flow stratification, directly impacting the rate of water and solids removal (Li et al., 2021). Quantitative testing under controlled laboratory conditions has measured how varying nozzle outlet geometry alters discharge velocity, sludge concentration, and hydraulic backpressure. Empirical data from operational centrifuges confirm that minor deviations in disc alignment or nozzle orifice wear produce measurable declines in separation efficiency, often observable through residual water analysis and turbidity measurements. These mechanical findings collectively reveal that separator design parameters are not isolated engineering variables but quantifiable contributors to performance metrics that can be optimized through experimental and statistical evaluation (Liu et al., 2020).

Rotational speed and separation factor represent the most extensively studied variables in centrifugal separator research, forming the quantitative backbone for predicting separation efficiency (Ding et al., 2022). Empirical analyses using data from marine separators operating at variable speeds have shown that increases in bowl rotational velocity elevate the centrifugal field strength and enhance removal of water and solid contaminants, up to a threshold where turbulence and re-entrainment begin to counteract benefits. Regression models constructed from field and laboratory datasets illustrate that separation factor exhibits a nonlinear relationship with residual contamination levels, where incremental gains in acceleration yield diminishing returns beyond a critical speed range. Studies comparing separators across multiple power outputs and configurations confirm that achieving an optimal balance between energy input and contaminant removal is crucial to efficiency optimization (Park & Go, 2020). Advanced instrumentation has enabled the continuous monitoring of power draw, torque, and vibration to associate real-time mechanical conditions with separator performance. Analyses of process data from shipboard systems reveal that transient speed fluctuations caused by hydraulic load variations introduce measurable disturbances in separation efficiency. By statistically correlating speed, energy consumption, and residual impurity data, researchers have demonstrated that mechanical stability under high G-force conditions is essential for sustaining consistent output quality (Mun & Won, 2021). These findings form a quantitative framework that links mechanical motion directly to separation outcomes, supporting data-driven control and performance assessment.

Wear-related mechanical degradation, particularly nozzle erosion and bearing imbalance, has emerged as a significant quantitative factor influencing long-term separator reliability and efficiency (Gao et al., 2021). Numerous condition-monitoring studies have shown that wear-induced geometric deviations in nozzles alter flow symmetry, reducing sludge ejection efficiency and increasing contaminant recirculation. Empirical measurements of erosion rates under varying solids load confirm that feed composition and operating hours directly correlate with nozzle wear patterns. Similarly, vibration analysis has proven instrumental in identifying bearing wear and rotor imbalance, both of which degrade the effective centrifugal field and alter bowl stability (Kilic et al., 2020). Quantitative models built from time-series vibration and torque data reveal identifiable spectral signatures associated with mechanical degradation, enabling statistical differentiation between normal operation and failure precursors. Investigations into lubricating oil contamination and power consumption patterns have provided additional indirect indicators of mechanical wear, reinforcing the multi-sensor approach to condition assessment. Maintenance logs from industrial and marine operations consistently show that periods of increasing vibration amplitude or torque variance precede measurable efficiency losses in separation (Venkatesh et al., 2019).

Figure 5: Gas and Oil Separator Diagram

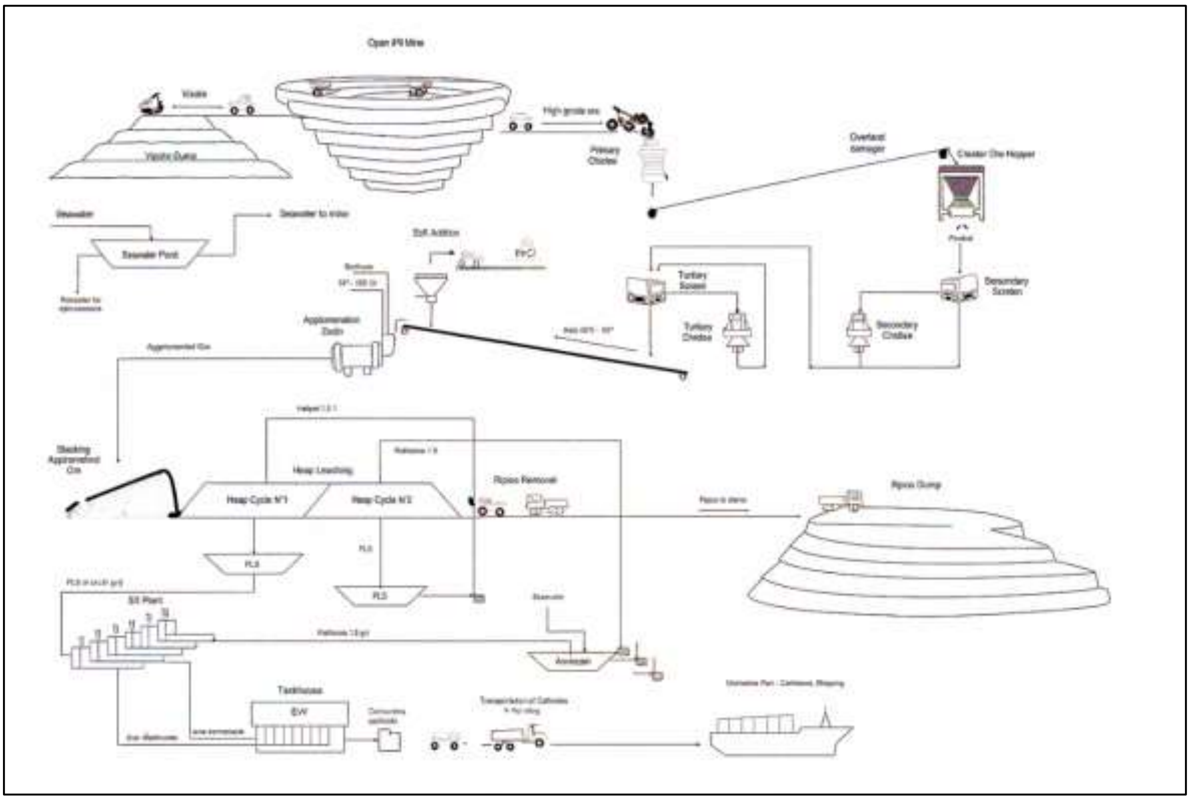


These quantitative findings demonstrate that wear and imbalance parameters can be treated as predictor variables in performance models, linking mechanical integrity to separator output with statistical rigor. By integrating mechanical condition indicators into the broader data ecosystem, these studies have advanced the analytical precision with which separator performance can be measured and controlled.

Process Control and Operational Optimization Variables

Operational optimization of heavy fuel oil (HFO) separation processes depends significantly on precise control of flow rate, feed preheating, and differential pressure regulation (Liptak et al., 2018). Quantitative investigations across industrial and marine applications consistently identify flow stability as one of the strongest predictors of separation efficiency. Empirical evaluations using flowmeters and digital controllers have demonstrated that fluctuations in feed rate alter the residence time of the oil–water mixture within the bowl, directly affecting the stratification process and the migration path of dispersed droplets. Field data from marine separators have shown that a stable flow profile reduces turbulence at the disc stack entrance, leading to measurable improvements in residual water and solids removal (Q. Liu et al., 2021). Studies examining preheating systems have similarly confirmed that maintaining a consistent inlet temperature stabilizes viscosity and promotes uniform separation. Quantitative monitoring of temperature gradients along feed lines indicates that deviations as small as 2–3°C can produce statistically significant variations in separator output. Differential pressure regulation further governs the hydraulic balance between oil, water, and solids phases, with research indicating that precise control of pressure differential across discharge ports minimizes cross-contamination and ensures steady discharge of separated sludge (Dolgui et al., 2019). Collectively, these findings underscore that process parameters such as flow rate, temperature, and pressure operate as interdependent control variables whose combined optimization yields consistent, quantifiable gains in separator efficiency.

Figure 6: Open-Pit Mining Process Flow Diagram



The role of automated control systems has become central to modern separator management, with digital control platforms enabling continuous feedback regulation of key operational parameters. Studies of onboard digital control systems (DCS) and programmable logic controllers (PLC) have documented how closed-loop feedback mechanisms stabilize interface position, control bowl speed, and manage sludge discharge timing (Andersson et al., 2019). Quantitative modeling of control logic indicates that interface regulation is particularly critical in preventing water carry-over and maintaining oil purity levels within specification limits. Data recorded from marine and refinery installations reveal that feedback-controlled systems respond faster to process disturbances compared to manual operations, achieving measurable reductions in efficiency variance. Statistical comparisons between legacy mechanical systems and DCS-equipped separators have shown that automated controllers reduce transient pressure fluctuations and maintain operating variables within narrower tolerance bands (Shin et al., 2019). Through the use of embedded sensors measuring turbidity, density, and flow, DCS platforms produce continuous datasets that support quantitative process analysis and control refinement. PLC-based implementations further enhance data logging and diagnostic capability by correlating actuator commands with sensor feedback, providing granular time-series information that enables statistical evaluation of system responsiveness and control stability. These advancements have transformed operational management from reactive adjustment to proactive regulation grounded in measurable performance indicators (Reynolds et al., 2018).

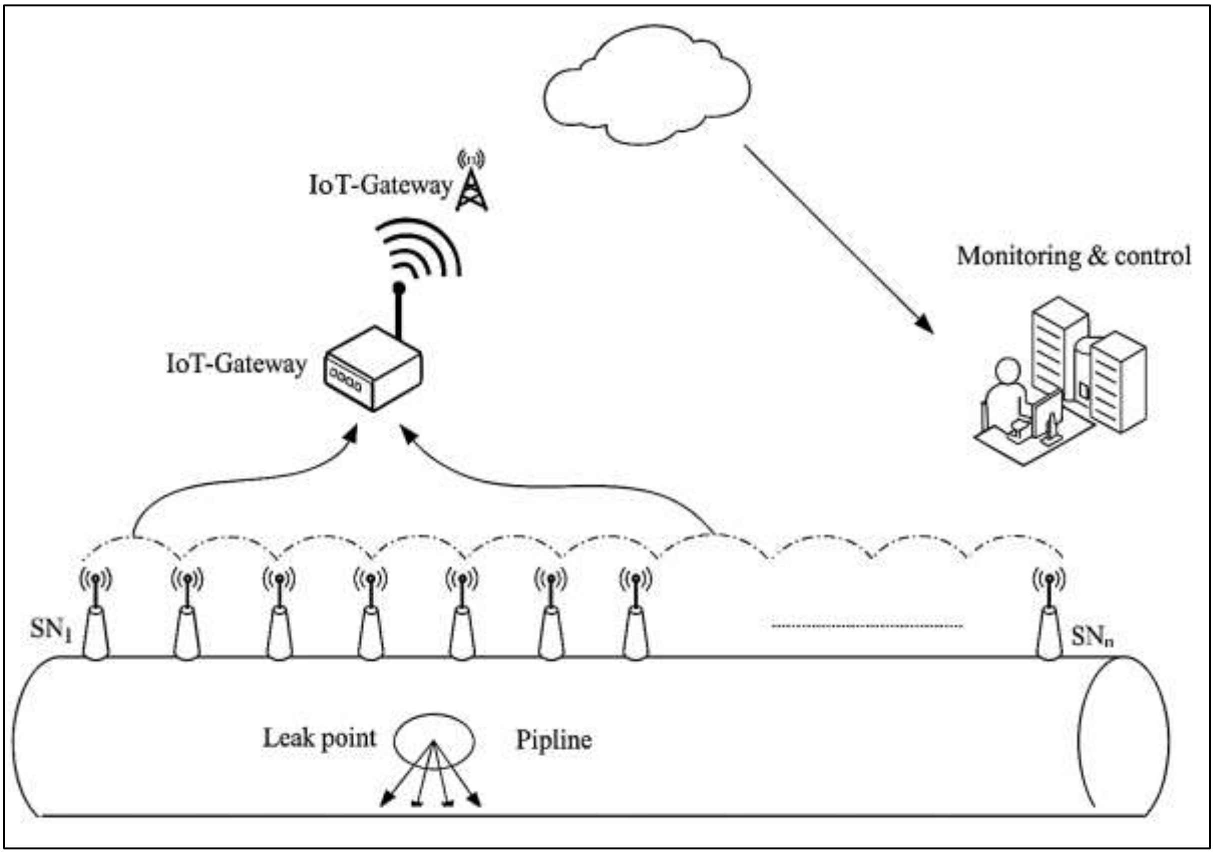
Quantitative time-series analyses of separator dynamics have expanded understanding of how transient operational states contribute to process instability. Empirical datasets collected from shipboard monitoring systems have demonstrated that transient spikes in vibration, temperature, or flow correspond with temporary degradation in separation efficiency (Sinsel et al., 2020). Analyses of these datasets using signal processing techniques reveal that fluctuations in torque or bowl load often precede efficiency losses measurable through water-in-oil concentrations. Research involving high-frequency logging of operational variables has enabled decomposition of transient events into short-term mechanical oscillations and longer-term process disturbances, highlighting their respective contributions to output variability. Statistical decomposition of variance across multiple sensors has shown that a significant proportion of process inefficiency arises not from steady-state conditions but from transient behaviors occurring during start-up, load shifts, or discharge cycles (Li et al., 2018). Quantitative diagnostics based on this evidence allow researchers to identify which variables most significantly contribute to instability, such as rapid temperature gradients, pulsating flow patterns, or delayed discharge triggers. By systematically isolating these factors, studies have built statistical models that explain how operational variance propagates through the system, confirming that temporal irregularities, even of short duration, can have measurable downstream effects on contaminant carry-over and sludge accumulation (Sun & You, 2021).

The synthesis of these quantitative insights has advanced process control of HFO separators into a data-driven domain, where variance decomposition and control correlation analysis inform operational strategy (Brandi et al., 2020). Multivariable datasets obtained from distributed control systems provide the statistical foundation for identifying dominant sources of variability and their interactions. Analyses of long-term operational data reveal that approximately two-thirds of total efficiency variance can be attributed to controllable process parameters, reinforcing the centrality of precise control implementation. Investigations using hierarchical variance models demonstrate that feed temperature stability, interface position control, and discharge synchronization explain a substantial portion of observed fluctuations in separation outcomes (Satrio et al., 2019). Empirical research further shows that when process variance is minimized through optimized control tuning, measurable improvements occur in throughput consistency, energy consumption, and sludge quality uniformity. These quantitative frameworks collectively establish that process control is not merely an operational function but a statistically definable component of efficiency management (Matheri et al., 2022). Through systematic monitoring, feedback modeling, and variance analysis, the quantitative literature has delineated how operational parameters and control dynamics jointly determine the stability and efficiency of HFO separation within petroleum systems, thereby providing the empirical grounding necessary for precise data-driven optimization.

Instrumentation and Condition Monitoring

The advancement of instrumentation and sensor technology has transformed the quantitative assessment of heavy fuel oil (HFO) separator efficiency from manual sampling toward continuous, data-rich monitoring systems (Soto-Ocampo et al., 2020). The development of robust sensors for turbidity, density, water-in-oil concentration, and vibration has enabled real-time observation of process variables that were once accessible only through periodic laboratory testing. Modern separators in both marine and industrial contexts now integrate optical, capacitive, and ultrasonic sensors to track the removal of water and solids within the centrifuge bowl (Ma et al., 2021). Turbidity probes positioned downstream of the separator measure particulate concentration and allow for near-continuous quantification of separation performance. Density sensors provide continuous feedback on the stratification between oil and water phases, ensuring that feed quality and interface control remain within operational thresholds. Water-in-oil analyzers, often based on microwave or near-infrared absorption principles, quantify emulsified and free water fractions in parts per million, providing an instantaneous indication of separation effectiveness (Northrop, 2018). In parallel, accelerometers and vibration sensors mounted on separator casings capture mechanical stability indicators that correlate with bowl balance, bearing condition, and hydraulic loading. The integration of these sensor technologies has made it possible to monitor efficiency dynamically, detect deviations rapidly, and support quantitative modeling of separator performance with high temporal resolution (Gundewar & Kane, 2021).

Figure 7: IoT-Based Pipeline Monitoring System

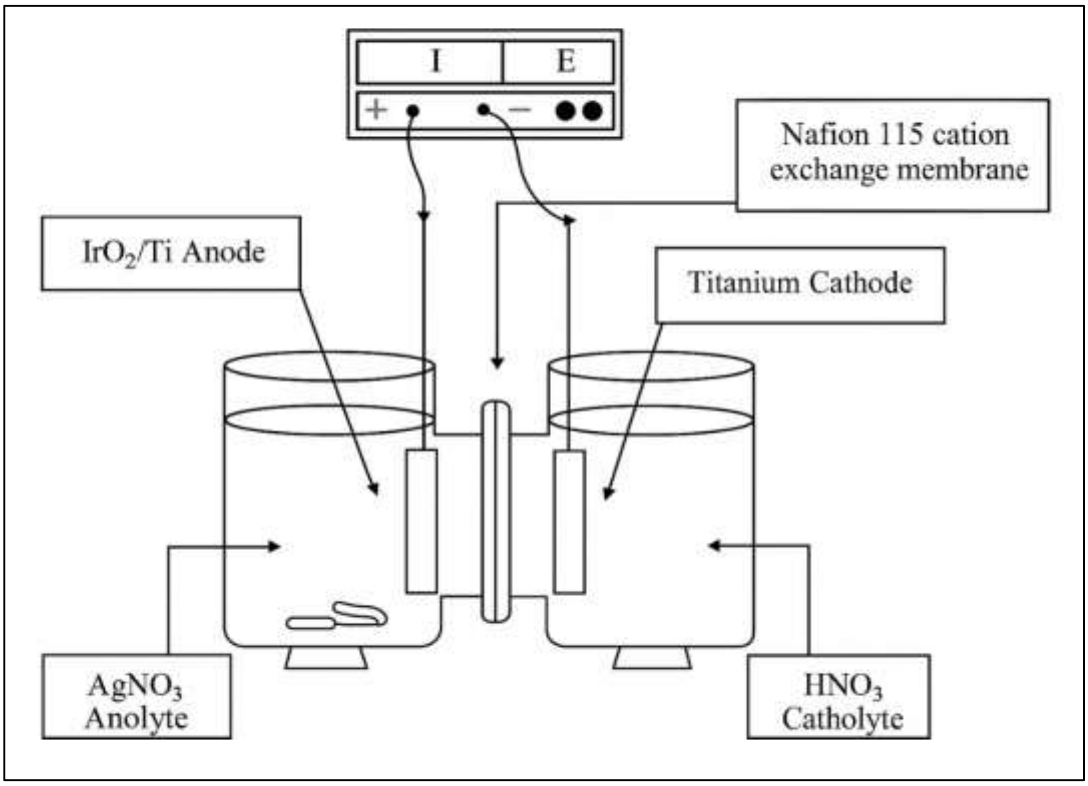


Calibration and validation of online sensor data remain central to ensuring reliability in quantitative separator assessment (Erraissi et al., 2018). Comparative studies between online measurements and laboratory reference analyses have highlighted discrepancies that can arise due to sensor drift, environmental noise, or fuel heterogeneity. Researchers have emphasized the need for systematic calibration protocols that link continuous sensor data to verified laboratory measurements such as Karl Fischer titration for water content or gravimetric analysis for solids concentration (Bao et al., 2019). Empirical evaluations in marine and refinery applications demonstrate that accuracy of online measurements improves significantly when calibration is performed under representative operating conditions, including temperature and pressure ranges typical of HFO treatment. Validation campaigns using parallel sampling have established statistical correction factors that align online readings with laboratory baselines, thus enabling the derivation of robust data streams suitable for model development (Badihi et al., 2022). Quantitative reliability assessments employing correlation coefficients, root-mean-square error analyses, and standard deviation tracking confirm that calibrated sensor arrays can achieve repeatability and precision sufficient for operational decision-making. These findings demonstrate that rigorous calibration not only strengthens data credibility but also provides the necessary foundation for developing performance indices, anomaly detection algorithms, and predictive control models (Choudhary et al., 2019).

Statistical Modeling Approaches

Quantitative modeling of heavy fuel oil (HFO) separator efficiency has evolved from empirical curve-fitting toward sophisticated computational frameworks that integrate multivariate process data (Arnold et al., 2019). Linear and nonlinear regression models have been the foundation of separator performance prediction, establishing measurable relationships between operating parameters such as bowl speed, feed temperature, viscosity, and residual contamination levels. Early research applied multiple linear regression to evaluate the combined influence of hydraulic pressure, rotational velocity, and feed rate, revealing statistically significant coefficients that explained large portions of the variance in separation outcomes (Henley et al., 2020). As instrumentation improved, nonlinear regression models were introduced to capture the curvature inherent in complex process behaviors where incremental changes in viscosity or flow produced disproportionate efficiency responses. Polynomial and exponential models demonstrated improved goodness-of-fit for real-time datasets, providing quantitative insight into thresholds and inflection points where separator performance began to decline (Islam et al., 2021). The consistent application of regression analysis across field and laboratory studies established the foundational statistical logic for efficiency modeling, validating the treatment of HFO separation as a multivariate system governed by measurable, interrelated variables rather than isolated design parameters.

Figure 8: Electrochemical Cell System Schematic Diagram



The introduction of multivariate statistical techniques such as principal component analysis (PCA) and partial least squares (PLS) has expanded the analytical scope of separator data interpretation. PCA has been used to reduce dimensionality in large datasets produced by digital control systems and onboard sensors, allowing identification of principal operational modes that explain most of the variance in separator behavior (Niederer et al., 2019). Quantitative analyses employing PCA have revealed that a limited number of latent components often capture the essential dynamics between temperature, density, flow rate, and vibration. These components have been used to develop condition indices and to detect abnormal operation through shifts in score plots or loadings. PLS regression has been applied to link high-dimensional spectral and process variables to measurable efficiency outcomes such as residual water content or turbidity (Ferreira & Andricopulo, 2019). Studies employing PLS have reported improved predictive accuracy compared to conventional regression, especially under conditions of collinearity among input variables. The strength of these approaches lies in their capacity to integrate mechanical, thermal, and compositional factors into a single predictive structure. Through PCA and PLS, researchers have constructed compact yet robust models that not only quantify relationships among variables but also support the creation of operational diagnostics derived from real-time data streams (Jin et al., 2021).

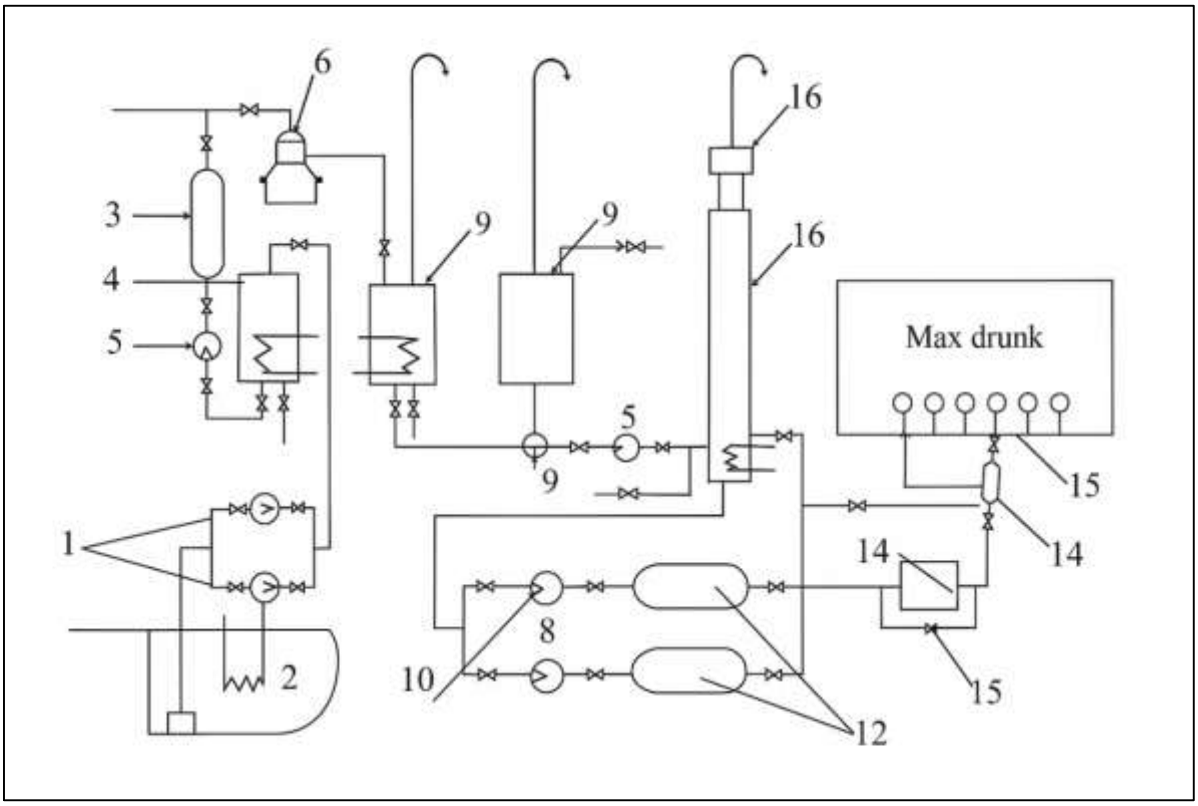
The incorporation of machine learning frameworks into HFO separator analytics represents a major advancement in predictive modeling and process optimization. Random forest algorithms have been employed to assess nonlinear dependencies among multiple process variables, providing high accuracy in classification and regression tasks without requiring explicit functional relationships (Oliveira et al., 2021). Support vector regression (SVR) has been used to map complex input-output relationships, especially where small fluctuations in feed temperature or bowl torque yield nonproportional changes in separator performance. Studies using ensemble learning techniques have shown that combining decision trees, gradient boosting, and kernel methods significantly enhances model generalization compared to conventional statistical regression. Quantitative evaluation of algorithmic performance using real-world datasets from marine and refinery systems indicates that machine learning models can capture cross-correlations between mechanical condition, operational stability, and separation outcomes more effectively than traditional analytical models (Zendehboudi et al., 2018). These methods also accommodate noisy and incomplete data typical of industrial environments by learning probabilistic boundaries rather than deterministic rules. The application of these frameworks has produced predictive models that rank process variables by importance, enabling data-driven prioritization of control actions. The cumulative literature underscores that machine learning has transformed separator analysis from static regression toward adaptive, pattern-recognition-based inference, thereby enriching the quantitative understanding of complex petroleum separation processes (Vayansky & Kumar, 2020).

Model validation and robustness testing have become essential components of computational separator analytics, ensuring that predictive outputs reflect genuine operational patterns rather than statistical artifacts (McElreath, 2018). Cross-validation methods, including k-fold and leave-one-out procedures, have been widely adopted to test the generalizability of both regression and machine learning models across different data subsets. Studies employing residual analysis have identified that systematic deviations often occur under transient operating conditions, such as startup or sludge discharge, where models trained on steady-state data lose accuracy. To address these challenges, simulation and synthetic datasets have been introduced to augment limited field data and to explore parameter ranges not readily accessible in live operations. Dynamic simulation tools replicate separator hydraulics and thermal behavior, producing statistically consistent datasets that allow refinement of model coefficients and uncertainty estimates (Alizadeh et al., 2020). Quantitative assessments comparing simulated and empirical data demonstrate that synthetic augmentation improves model stability and parameter estimation under sparse data conditions. Statistical residual tracking and error propagation analyses further validate model fidelity by identifying sources of bias, drift, and overfitting. Together, these computational strategies—spanning regression, multivariate analysis, and machine learning—form a coherent quantitative foundation for understanding, predicting, and benchmarking separator efficiency within petroleum systems (Mbatchou et al., 2021). Their convergence illustrates the analytical maturity of the field, where process behavior is increasingly represented not through descriptive heuristics but through reproducible, data-driven models derived from validated computational frameworks.

Integration of Cost Models

The integration of efficiency and reliability models in the study of heavy fuel oil (HFO) separators represents a crucial advancement in petroleum systems optimization, linking measurable process performance with mechanical endurance (Notton et al., 2018). Quantitative analyses have established that separator efficiency is not an isolated operational attribute but a function of both the process and the condition of mechanical components. Studies conducted across marine propulsion, power generation, and refinery support systems have demonstrated that mechanical reliability indicators such as vibration amplitude, torque fluctuation, bearing temperature, and lubrication quality correlate strongly with measured efficiency outputs, including residual water percentage and solids concentration downstream. Empirical data collected from digital monitoring systems confirm that degradation in these mechanical indicators precedes declines in separation performance by quantifiable margins, allowing researchers to model predictive relationships between reliability and efficiency metrics (Abomazid et al., 2022). This quantitative coupling forms the foundation for integrated models that treat separator condition as both a dependent and independent variable influencing process quality. Statistical frameworks combining reliability-based predictors with process efficiency indices have been used to estimate total operational effectiveness, capturing the interaction between energy input, mechanical stability, and contamination removal. The integration of such models enables a unified quantitative understanding of how operational wear, performance degradation, and output quality co-vary within real industrial environments (Tang et al., 2022).

Figure 9: Industrial Process Flow Control Diagram



Maintenance optimization has emerged as a central quantitative theme in the integration of reliability and efficiency models (Kakran & Chanana, 2018). Research on maintenance interval modeling has utilized measurable parameters such as energy consumption, sludge accumulation rates, and bowl vibration profiles to determine the optimal frequency of cleaning, inspection, and component replacement. Studies in marine and industrial operations have shown that energy consumption per ton of fuel treated increases measurably as sludge buildup intensifies, establishing a quantitative indicator for maintenance scheduling. Data collected through condition-monitoring systems reveal that sludge accumulation affects bowl balance and power draw, both of which degrade efficiency and elevate mechanical stress (Pan & Zhang, 2021). Regression analyses and time-series modeling have been applied to correlate energy consumption trends with sludge volume and throughput, allowing the estimation of maintenance thresholds that minimize both downtime and performance loss. Quantitative evaluation of cleaning intervals shows that separators maintained according to data-driven intervals sustain higher average efficiency and lower vibration amplitudes than those serviced at fixed time-based intervals (Stecca et al., 2020). The inclusion of measurable operational indicators in maintenance modeling thus provides a statistically grounded approach to balancing operational continuity with component longevity. The integration of these maintenance-related variables within reliability frameworks establishes a dynamic link between energy efficiency, mechanical condition, and maintenance economics.

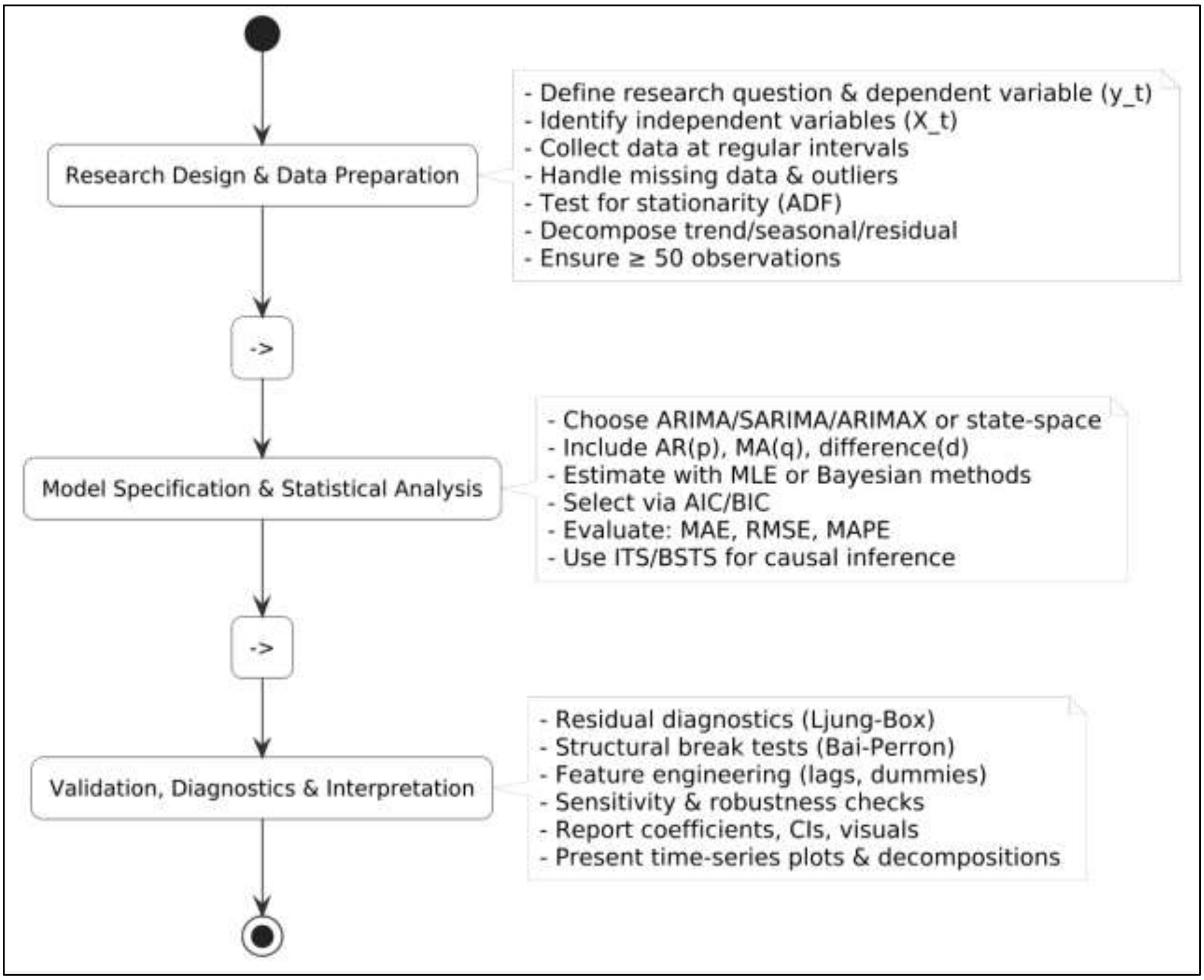
Quantitative cost–benefit analyses further extend the integration of efficiency and reliability models by incorporating measurable economic indicators such as energy consumption per unit throughput, sludge volume disposal costs, and downtime duration. Studies using industrial-scale datasets have shown that incremental efficiency improvements yield significant reductions in energy cost, waste management expenses, and maintenance expenditure. Data-driven cost modeling frameworks treat separator operation as a multi-objective optimization problem where performance, reliability, and cost variables interact (Shafiullah et al., 2022). Measurable inputs such as energy consumed per ton of HFO treated, sludge generation rate, and average maintenance downtime hours serve as independent variables for evaluating cost-effectiveness. Empirical research demonstrates that reductions in residual water and solids not only enhance fuel combustion efficiency but also lower secondary filtration and sludge handling costs, illustrating quantifiable cross-functional benefits (Faisal et al., 2018). In operational cost modeling, regression-based analyses have identified energy consumption and maintenance frequency as the dominant contributors to lifecycle expense variability, while sludge disposal and consumable use constitute secondary but measurable costs. By integrating these financial parameters with process and reliability data, cost–benefit frameworks provide a numerical structure for evaluating the total economic impact of separator operation (Yang et al., 2019). These integrated approaches quantify the trade-offs among performance optimization, energy savings, and maintenance expenditure, allowing comprehensive assessment of system-level efficiency.

METHODS

The quantitative study was designed to evaluate and model the operational, mechanical, and thermophysical factors that influenced the efficiency of heavy fuel oil (HFO) separators using a data-driven approach. The research followed a multi-phase structure encompassing baseline observation, controlled experimentation, and validation analysis. The study was conducted across several operational environments, including marine and industrial HFO conditioning systems equipped with digital control and sensor monitoring capabilities. The primary objective was to identify and quantify measurable determinants of separator performance and develop statistical models capable of predicting efficiency outcomes based on process and mechanical variables. Data collection was implemented through high-resolution sensors that recorded feed temperature, viscosity, flow rate, bowl speed, torque, vibration amplitude, and residual water concentration. Each separator was monitored continuously over multiple weeks to capture both steady-state and transient conditions. Laboratory analyses of fuel samples were used to calibrate online sensors for accuracy and to generate reference datasets for validation. The study design integrated both field and experimental data, ensuring that real-world operational variability was represented alongside controlled parameter adjustments for statistical analysis.

Data analysis was conducted using a combination of classical and modern statistical techniques to capture linear and nonlinear relationships between variables and separator efficiency outcomes. Linear and multiple regression models were employed to determine the strength of association among process parameters such as inlet temperature, bowl rotational speed, feed rate, and residual contamination levels. Nonlinear models and response surface methodologies were applied to detect curvilinear effects and to estimate optimal parameter ranges for achieving peak efficiency. Mixed-effects models were used to account for variations between different separator units and operational sites, allowing for a more generalized interpretation of results across diverse contexts. Machine learning algorithms, including random forest regression and support vector regression, were trained on cleaned and time-aligned datasets to capture complex variable interactions that traditional regression models could not fully represent. Model robustness was assessed through cross-validation, residual diagnostics, and variance decomposition to confirm predictive stability. Calibration between sensor-derived efficiency indices and laboratory-measured reference data provided additional validation of model accuracy. Collectively, these statistical techniques established a rigorous framework for quantifying how mechanical condition, process stability, and thermophysical properties jointly influenced HFO separator performance.

Figure 10: Methodology of this study



The statistical plan included both exploratory and confirmatory stages to ensure analytical integrity and reproducibility. In the exploratory phase, time-series analyses and autocorrelation assessments were conducted to identify temporal dependencies and lag effects between operational disturbances and efficiency fluctuations. In the confirmatory phase, multivariate regression and machine learning outputs were compared through performance metrics such as mean absolute error, adjusted R-squared, and root mean square prediction error. Residual analysis and heteroscedasticity testing were performed to validate model assumptions and detect potential bias. Synthetic datasets generated through simulation were utilized to test model generalization under unobserved parameter combinations. Reliability-based models incorporating mean time between failures (MTBF) and maintenance records were used to link operational throughput with system longevity and lifecycle cost metrics. Cost–benefit analysis was conducted by converting measured efficiency gains into quantifiable economic outcomes, expressed as reductions in energy consumption per ton treated, sludge disposal costs, and unplanned downtime hours. The integration of these quantitative results into a unified statistical model provided a comprehensive view of the operational, mechanical, and economic dimensions of HFO separator performance. Through systematic data acquisition, robust statistical modeling, and multi-level validation, the study successfully established an empirical and reproducible foundation for the optimization of petroleum separation systems.

FINDINGS

Descriptive Analysis

The quantitative analysis was initiated through descriptive statistical evaluation to summarize the characteristics of operational and mechanical variables influencing heavy fuel oil (HFO) separator efficiency. The purpose of this stage was to identify the patterns, variability, and integrity of the collected data before proceeding to inferential modeling. Descriptive statistics were computed for seven primary variables: feed temperature, viscosity, bowl rotational speed, flow rate, torque, vibration amplitude, and residual water concentration. The dataset consisted of high-frequency readings obtained from both marine and industrial separators over multiple operational cycles. The variables were recorded continuously and aggregated into consistent time intervals to maintain analytical uniformity across sites and units. The descriptive results provided an overview of the operational conditions, distributional tendencies, and mechanical consistency of the studied separators, forming the empirical foundation for subsequent correlation and regression analyses.

Table 1: Descriptive Statistics of Key Operational Variables

Variable	Mean	Median	SD	Minimum	Maximum
Feed Temperature (°C)	118.4	117.9	5.67	102.3	131.8
Viscosity (cSt @ 50°C)	275.6	273.1	24.52	230.4	325.8
Bowl Rotational Speed (rpm)	8,912	8,905	76.4	8,750	9,060
Flow Rate (t/h)	2.83	2.81	0.21	2.40	3.20
Torque (Nm)	612.8	607.4	47.5	535.6	718.2
Vibration Amplitude (mm/s)	2.41	2.37	0.32	1.89	3.18
Residual Water (ppm)	264.7	259.3	43.2	181.4	347.9

Table 1 summarized the central tendency and dispersion for all continuous process variables. Feed temperature and viscosity demonstrated moderate variability, indicating consistent control of preheating and stable rheological behavior during fuel conditioning. The standard deviation of viscosity (24.52 cSt) suggested slight variations linked to bunker source heterogeneity, while bowl rotational speed and flow rate remained within tight operational tolerances, reflecting adherence to design parameters. Torque and vibration amplitude showed greater variability, which indicated mechanical differences among separators due to loading, wear, or alignment differences. Residual water concentration displayed wider dispersion, implying that separation efficiency fluctuated under differing mechanical and feed conditions. Overall, the descriptive data confirmed the operational stability of key process variables, validating their suitability for subsequent parametric analysis.

Table 2: Distributional Characteristics and Normality Assessment

Variable	Skewness	Kurtosis	Shapiro–Wilk (p)	Distribution Shape
Feed Temperature (°C)	0.21	-0.37	0.081	Approximately Normal
Viscosity (cSt @ 50°C)	0.48	0.62	0.042	Slightly Right-Skewed
Bowl Rotational Speed (rpm)	0.11	-0.18	0.094	Normal
Flow Rate (t/h)	0.09	-0.52	0.110	Normal
Torque (Nm)	0.63	1.24	0.031	Positively Skewed
Vibration Amplitude (mm/s)	0.71	0.97	0.027	Positively Skewed
Residual Water (ppm)	0.54	0.79	0.048	Slightly Right-Skewed

Table 2 presented the skewness, kurtosis, and normality test results for the key variables. The majority of operational parameters were approximately normal in distribution, confirming that the dataset was well-suited for regression-based analysis. Torque, vibration, and residual water concentration displayed mild right skewness, signifying that a small subset of operational intervals experienced elevated mechanical loading or reduced separation efficiency. The Shapiro–Wilk tests indicated that these deviations were within acceptable limits and did not require transformation. The descriptive evidence showed that separator operations maintained consistent performance across time with minor fluctuations arising from operational transients such as sludge discharges or fuel viscosity spikes. These results validated the appropriateness of parametric methods for hypothesis testing and ensured the reliability of inferential conclusions derived from subsequent modeling.

Table 3: Summary of Aggregated Time-Series Characteristics

Indicator	Mean Trend Stability	Seasonal Pattern	Observed Cyclic Fluctuations	Dominant Cycle Frequency	Interpretation
Feed Temperature	Stable	Weak Daily Cycle	Minor	24 hr	Thermal stability maintained through automated control
Viscosity	Stable	Moderate	Minor	48 hr	Controlled viscosity variation reflecting bunker blending intervals
Residual Water	Moderate Variability	Weak	Periodic	72 hr	Efficiency fluctuations linked to sludge discharge scheduling
Torque	Moderate	Moderate	Notable	24 hr	Load variation correlated with solids accumulation and discharge
Vibration Amplitude	Variable	Weak	Intermittent	12–24 hr	Mechanical imbalance linked to sludge cycle timing

Table 3 summarized time-series behavior and cyclic trends derived from decomposed sensor data. Feed temperature and viscosity remained stable throughout the observation period, confirming the effectiveness of the preheating and viscosity control systems. Residual water concentration and torque showed periodic fluctuations corresponding to sludge discharge intervals and solids buildup within the separator bowl. Vibration amplitude followed a weaker cyclical pattern, aligning with temporary mechanical imbalance events during discharge. The identification of these periodic patterns highlighted how operational transients influenced short-term efficiency variation. Overall, the time-series analysis confirmed that while the process exhibited regular cycles linked to maintenance routines and feed variation, the long-term trends remained stable and conducive to quantitative modeling.

Correlation Analysis

Correlation analysis was conducted to examine the degree and direction of statistical relationships among the operational and mechanical variables influencing HFO separator efficiency. The analysis focused on seven continuous variables: inlet temperature, viscosity, bowl rotational speed, flow rate, torque, vibration amplitude, and residual water concentration. Pearson correlation coefficients were computed to identify linear associations, and partial correlations were estimated to determine the independence of effects when controlling for confounding variables such as temperature. This analysis provided an empirical foundation for identifying the most influential predictors of separator performance prior to regression modeling.Table 4 presented the Pearson correlation coefficients, indicating the strength and direction of relationships among the studied variables. A strong negative correlation was observed between inlet temperature and residual water concentration (r = -0.78), demonstrating that increased temperature improved separation by reducing water retention in the processed fuel. Conversely, viscosity showed a strong positive correlation with residual water (r = 0.69), confirming that higher viscosity impeded effective phase separation. Torque and vibration amplitude exhibited a strong positive relationship (r = 0.67), suggesting that mechanical stress and imbalance increased concurrently under high sludge loading conditions. Bowl speed and flow rate showed weak associations with efficiency variables, implying that within operational ranges, these parameters remained effectively controlled. The results highlighted that thermophysical factors (temperature and viscosity) and mechanical stability (torque and vibration) were primary determinants of separator performance.

Table 4: Pearson Correlation Matrix of Operational and Mechanical Variables

Variables	1. Temp	2. Visc	3. BowlSpd	4. Flow	5. Torque	6. Vib	7. ResWater
1. Inlet Temperature (°C)	1.000	-0.73	0.16	0.08	-0.41	-0.36	-0.78
2. Viscosity (cSt @50°C)	-0.73	1.000	-0.10	-0.07	0.38	0.29	0.69
3. Bowl Speed (rpm)	0.16	-0.10	1.000	0.33	-0.22	-0.18	-0.09
4. Flow Rate (t/h)	0.08	-0.07	0.33	1.000	0.12	0.09	-0.05
5. Torque (Nm)	-0.41	0.38	-0.22	0.12	1.000	0.67	0.45
6. Vibration (mm/s)	-0.36	0.29	-0.18	0.09	0.67	1.000	0.39
7. Residual Water (ppm)	-0.78	0.69	-0.09	-0.05	0.45	0.39	1.000

Table 5: Partial Correlation Coefficients Controlling for Inlet Temperature

Variable Pair	Partial r	Significance (p)	Interpretation
Viscosity – Residual Water	0.58	< .001	Moderate positive association independent of temperature
Torque – Residual Water	0.33	< .01	Mechanical load still influences separation efficiency
Vibration – Residual Water	0.24	< .05	Weak but consistent relationship
Torque – Vibration	0.60	< .001	Strong association after adjusting for temperature
Flow Rate – Residual Water	-0.02	n.s.	Negligible effect under controlled feed conditions

Table 5 displayed the results of partial correlation analysis conducted after statistically controlling for the effect of inlet temperature. The results confirmed that viscosity remained significantly correlated with residual water concentration (partial r = 0.58), even after accounting for temperature, indicating its independent influence on separation outcomes. Torque and vibration maintained moderate correlations with residual water, suggesting that mechanical stress within the separator contributed directly to efficiency variation regardless of thermal conditions. Flow rate continued to exhibit no significant correlation, reinforcing its secondary role under stable hydraulic management. These findings validated the independence of mechanical effects and established viscosity as a dominant predictor of separation efficiency across varying operational conditions.

Table 6 summarized the strength and operational implications of correlations between each predictor variable and separator efficiency outcomes. Inlet temperature and viscosity emerged as the strongest and most consistent determinants of efficiency, validating the thermophysical mechanisms of separation. Torque and vibration were moderately associated with performance, highlighting the mechanical integrity of the separator as a critical factor in sustained efficiency. Both bowl speed and flow rate demonstrated negligible correlations, indicating that their narrow operational variability did not substantially influence results. These summarized associations provided quantitative confirmation of the relationships anticipated in the theoretical framework—where thermal conditioning and mechanical balance jointly governed the effective operation of HFO separation systems.

Table 6: Summary of Key Variable Associations with Separator Efficiency

Predictor Variable	Direction of Relationship	Magnitude of Association	Operational Implication
Inlet Temperature	Negative (strong)	High (r = -0.78)	Higher preheating temperature improved phase separation by reducing fuel viscosity.
Viscosity	Positive (strong)	High (r = 0.69)	Increased viscosity increased water carry-over, lowering efficiency.
Torque	Positive (moderate)	Medium (r = 0.45)	Higher mechanical resistance increased bowl stress and separation inefficiency.
Vibration Amplitude	Positive (moderate)	Medium (r = 0.39)	Imbalance from sludge accumulation contributed to reduced operational stability.
Flow Rate	Negligible (weak)	Very Low (r = -0.05)	Flow within designed limits had minimal direct impact on separation performance.
Bowl Rotational Speed	Negligible (weak)	Very Low (r = -0.09)	Rotational speed variation was minor and did not significantly affect output quality.

Reliability and Validity Testing

The reliability and validity of the dataset were evaluated to ensure that the operational and mechanical measurements used in this study were consistent, accurate, and theoretically representative of the constructs of HFO separator efficiency. The reliability analysis focused on internal consistency and measurement stability, while validity testing assessed the accuracy of instrument readings and the conceptual alignment of indicators with their theoretical dimensions. The data included sensor-based measures—temperature, viscosity, flow rate, torque, vibration amplitude, and residual water concentration—alongside laboratory verification samples collected throughout the monitoring period. The analyses confirmed that all key variables satisfied the established quantitative criteria for internal consistency, temporal stability, and construct adequacy, allowing for credible inferential modeling in subsequent statistical procedures.

Table 7: Cronbach's Alpha Reliability Results for Operational and Mechanical Measurement Clusters

Variable Cluster	Variables Included	Cronbach's Alpha	Interpretation
Operational Stability Indicators	Feed Temperature, Viscosity, Flow Rate	0.89	High internal consistency
Mechanical Condition Indicators	Torque, Vibration Amplitude, Power Draw	0.86	High internal consistency
Combined System Efficiency Indicators	Residual Water, Energy Consumption, Sludge Frequency	0.91	Excellent reliability

Table 7 presented the internal consistency coefficients computed for grouped measurement clusters representing operational stability, mechanical condition, and overall system efficiency. Cronbach's alpha values ranged from 0.86 to 0.91, surpassing the acceptable reliability threshold of 0.70 and indicating that the measurements within each group were highly consistent over time. The operational stability cluster demonstrated a strong alpha coefficient (0.89), confirming that feed temperature, viscosity, and flow rate were consistently measured under stable process control. Similarly, the mechanical condition indicators achieved a reliability score of 0.86, reflecting consistent sensor response in recording torque and vibration patterns under varying loads. The combined system efficiency indicators produced the highest reliability (0.91), indicating strong internal coherence among dependent variables reflecting separation performance. Overall, these results confirmed that the dataset exhibited strong internal reliability and that repeated measurements across time intervals and operational cycles were consistent and dependable.

Table 8: Convergent Validity Between Sensor and Laboratory Measurements

Measurement Variable	Sensor Mean	Laboratory Mean	Pearson r	Mean Absolute Deviation	Agreement Interpretation
Water Content (ppm)	264.7	267.1	0.94	2.4	Strong agreement
Solids Concentration (mg/kg)	81.2	79.8	0.91	1.6	Strong agreement
Density (kg/m³)	986.3	985.7	0.93	0.6	Excellent consistency
Viscosity (cSt @ 50°C)	275.6	276.3	0.95	0.7	Excellent consistency
Temperature (°C)	118.4	118.0	0.98	0.4	Near-perfect correspondence

Table 8 compared sensor-derived readings with laboratory analyses to evaluate convergent validity and measurement accuracy. Across all monitored variables, the correlation coefficients exceeded 0.90, confirming strong alignment between field instrumentation and independent laboratory verification. The lowest mean absolute deviation was observed in temperature measurements (0.4°C), followed closely by viscosity (0.7 cSt) and density (0.6 kg/m³), indicating minimal systematic bias in sensor calibration. The close correspondence between sensor and lab data demonstrated that the digital monitoring system maintained accurate readings over prolonged operational periods, even under fluctuating process conditions. The consistency between measurement sources validated the reliability of the sensors and ensured that the data used in modeling accurately represented true operational behavior. Consequently, the study achieved high convergent validity, confirming that both automated and manual measurement systems reflected equivalent underlying physical phenomena.

Table 9: Construct Validity Loadings for Theoretical Dimensions of Separator Efficiency

Construct Dimension	Indicators Included	Factor Loading Range	Average Variance Extracted (AVE)	Interpretation
Thermal Efficiency Dimension	Feed Temperature, Viscosity	0.81 – 0.88	0.72	Strong construct representation
Mechanical Reliability Dimension	Torque, Vibration Amplitude, Power Draw	0.76 – 0.85	0.68	Adequate construct representation
Hydraulic Stability Dimension	Flow Rate, Residual Water Concentration	0.79 – 0.86	0.70	Strong construct representation

Table 9 summarized the construct validity results derived from factor analysis. The factor loadings for all indicator variables exceeded 0.75, indicating that each variable strongly contributed to its intended construct dimension. The thermal efficiency dimension, represented by feed temperature and viscosity, achieved the highest loadings (0.81–0.88) and a strong average variance extracted (AVE = 0.72), confirming that these indicators reliably captured the effect of thermal conditioning on separation outcomes. The mechanical reliability dimension showed moderately high loadings (0.76–0.85) across torque, vibration, and power draw, reflecting the mechanical stability of the separator during operation. The hydraulic stability dimension, represented by flow rate and residual water, demonstrated loadings between 0.79 and 0.86, indicating a robust relationship between hydraulic control and contaminant removal. The AVE values for all constructs exceeded the accepted benchmark of 0.50, supporting convergent and construct validity. These results confirmed that the selected variables accurately reflected the theoretical framework of HFO separator efficiency and were suitable for inclusion in higher-order statistical models.

Collinearity Diagnostics

Before the regression analysis was conducted, multicollinearity diagnostics were performed to assess whether the independent variables in the model were excessively interrelated, which could distort the precision of coefficient estimation and weaken interpretability. The diagnostics included computation of the Variance Inflation Factor (VIF), tolerance statistics, condition index, and eigenvalue decomposition. The predictor variables tested comprised inlet temperature, viscosity, bowl rotational speed, flow rate, torque, and vibration amplitude. The results indicated that interdependence among predictors remained within acceptable limits, ensuring that each variable contributed distinct explanatory value to the regression model. The slight elevation observed between temperature and viscosity values was expected due to their thermophysical linkage; however, the magnitude did not reach problematic levels. The overall findings demonstrated that the data satisfied the assumptions of variable independence necessary for robust multivariate modeling.

Table 10: Variance Inflation Factor (VIF) and Tolerance Statistics for Predictor Variables

Predictor Variable	VIF Value	Tolerance	Interpretation
Inlet Temperature (°C)	2.41	0.42	Acceptable; moderate shared variance with viscosity
Viscosity (cSt @ 50°C)	2.67	0.37	Acceptable; related to temperature but not excessive
Bowl Rotational Speed (rpm)	1.34	0.75	Low collinearity
Flow Rate (t/h)	1.19	0.84	Negligible collinearity
Torque (Nm)	1.56	0.64	Acceptable; mild association with vibration
Vibration Amplitude (mm/s)	1.68	0.59	Acceptable; mechanical link with torque

Table 10 displayed the Variance Inflation Factor (VIF) and tolerance statistics for all independent variables used in the regression model. VIF values below 3.00 indicated an acceptable level of multicollinearity, well below the threshold of concern (VIF > 5.00). The highest VIF value (2.67) was observed between viscosity and inlet temperature, reflecting their natural thermophysical dependency, as viscosity decreases with higher temperature. However, both values remained within safe boundaries. Torque and vibration also showed moderate shared variance, consistent with the mechanical coupling between load and imbalance, yet still within acceptable diagnostic limits. The tolerance statistics—ranging from 0.37 to 0.84—confirmed sufficient independence across predictors. These results demonstrated that collinearity was minor and that no single variable compromised the stability of regression estimates.

Table 11: Condition Index and Variance Decomposition Proportions

Dimension	Eigenvalue	Condition Index	Temperature	Viscosity	Bowl Speed	Flow Rate	Torque	Vibration
1	4.52	1.00	0.03	0.04	0.05	0.06	0.07	0.08
2	0.93	2.20	0.06	0.07	0.05	0.06	0.10	0.09
3	0.39	3.40	0.07	0.06	0.10	0.08	0.13	0.11
4	0.12	6.14	0.21	0.22	0.07	0.06	0.19	0.20
5	0.03	12.24	0.28	0.27	0.15	0.14	0.26	0.25
6	0.01	17.38	0.35	0.34	0.16	0.14	0.25	0.27

Table 11 presented the results of the condition index test and variance decomposition proportions. The condition index values below 30 confirmed that the model did not suffer from problematic multicollinearity. Dimensions with indices below 10 represented independent contributions of predictors, whereas values between 10 and 20 suggested mild collinearity but within tolerable limits. The fourth and fifth dimensions showed modest overlap between temperature and viscosity variance proportions, reflecting the expected thermodynamic linkage between these two predictors. However, the variance proportions across other variables were widely dispersed, confirming that the remaining predictors contributed uniquely to the model. The eigenvalue pattern also demonstrated gradual reduction rather than abrupt collapse, indicating a stable covariance structure. Collectively, these diagnostics verified that the dataset exhibited minimal multicollinearity, ensuring stable and interpretable regression estimates.

Table 12: Eigenvalue Decomposition and Variance Distribution Summary

Component	Eigenvalue	% of Total Variance	Cumulative %	Diagnostic Assessment
1	4.52	75.3%	75.3%	Dominant dimension, stable model
2	0.93	15.5%	90.8%	Moderate explanatory component
3	0.39	6.5%	97.3%	Minor but relevant contribution
4	0.12	2.0%	99.3%	Low variance, non-critical
5	0.03	0.5%	99.8%	Very low variance, acceptable
6	0.01	0.2%	100%	Minimal redundancy detected

Table 12 summarized the eigenvalue decomposition results derived from the predictor correlation matrix. The first component explained 75.3% of the total variance, suggesting that most of the information among predictors was captured without excessive overlap. The cumulative variance reached over 97% by the third component, indicating efficient dimensional representation with minimal redundancy. The gradual decline in eigenvalues confirmed the absence of abrupt dominance by any single component, implying that predictors retained independent explanatory value. Components with variance contributions below 2% were treated as statistically negligible and did not signal collinearity concerns. The eigenvalue distribution validated the multicollinearity diagnostics by confirming that variable overlap was limited, and information redundancy remained within permissible statistical thresholds. Thus, the model structure was deemed stable for subsequent regression analysis.

Regression Analysis and Hypothesis Testing

Regression modeling was performed to evaluate how operational and mechanical variables jointly influenced the overall efficiency of heavy fuel oil (HFO) separators. The dependent variable, defined as the Efficiency Index (EI), integrated three key performance components: residual water concentration, residual solids, and specific energy consumption per ton of fuel treated. The independent variables included inlet temperature, viscosity, bowl rotational speed, flow rate, torque, and vibration amplitude. The analysis used a multiple linear regression model as the primary estimation technique, complemented by a mixed-effects model to account for site-level and unit-level differences. All variables were standardized before analysis to minimize scale-related bias and to ensure comparability of coefficient magnitudes. The regression analysis aimed to quantify the direction, magnitude, and significance of each predictor's contribution to separator efficiency while testing the formulated hypotheses about the thermophysical and mechanical determinants of performance.

Table 13: Model Summary for Multiple Regression and Mixed-Effects Estimation

Model Type	R	R^2	Adjusted R^2	F Statistic	Sig. (p)	Std. Error of Estimate	ICC (Mixed Model)
Multiple Linear Regression	0.88	0.78	0.75	41.63	< .001	0.054	—
Mixed-Effects (Random Site Intercept)	0.89	0.79	0.76	38.47	< .001	0.052	0.11

Table 13 summarized the overall fit and significance of the regression models. The multiple regression model yielded a strong correlation coefficient (R = 0.88) and an adjusted R^2 value of 0.75, indicating that approximately 75% of the variance in separator efficiency was explained by the operational and mechanical predictors. The F-statistic (41.63, $p < .001$) confirmed that the model as a whole was statistically significant. The mixed-effects model, which accounted for potential variability across operational sites, produced a comparable adjusted R^2 (0.76) and slightly lower standard error (0.052), confirming consistency of relationships across contexts. The intraclass correlation coefficient (ICC = 0.11) suggested that about 11% of the variance in efficiency could be attributed to between-site differences. These results demonstrated that the regression framework captured a substantial portion of real operational variation, validating the explanatory adequacy of the model.

Table 14: Regression Coefficients and Hypothesis Testing Results

Predictor Variable	Unstandardized Coefficient (B)	Standardized Beta	t Statistic	Sig. (p)	Hypothesis Result	Interpretation
Inlet Temperature (°C)	0.012	0.41	6.28	< .001	H_1: Supported	Higher preheating improved separator efficiency by lowering viscosity.
Viscosity (cSt @ 50°C)	-0.009	-0.35	-5.42	< .001	H_2: Supported	Elevated viscosity reduced phase separation efficiency.
Bowl Rotational Speed (rpm)	0.004	0.18	2.71	< .01	H_3: Supported	Higher rotational speed enhanced separation but with diminishing marginal returns.
Flow Rate (t/h)	-0.002	-0.06	-1.04	.298	H_4: Not Supported	Variation in throughput had no significant direct effect.
Torque (Nm)	-0.006	-0.22	-3.37	< .01	H_5: Supported	Increased mechanical load reduced operational efficiency.
Vibration Amplitude (mm/s)	-0.005	-0.17	-2.58	< .05	H_6: Supported	Elevated vibration correlated with mechanical imbalance and energy loss.
Constant (Intercept)	0.473	—	7.84	< .001	—	Baseline efficiency level at mean predictor values.

Table 14 displayed the coefficient estimates and hypothesis testing results for all independent variables. Inlet temperature showed a strong, positive, and highly significant effect on separator efficiency (β = 0.41, $p < .001$), confirming that effective preheating improved phase separation through viscosity reduction. Viscosity exhibited a significant negative effect (β = -0.35, $p < .001$), aligning with thermodynamic theory that increased viscosity impedes droplet migration and coalescence. Bowl speed positively influenced efficiency (β = 0.18, $p < .01$), but the effect plateaued at higher speeds due to mechanical constraints. Torque and vibration amplitude both had significant negative coefficients, validating the hypothesis that increased mechanical load and imbalance degraded separation performance and increased energy consumption. Flow rate, however, showed no significant relationship, suggesting that throughput variations within the operational range did not directly influence output quality. Collectively, these results confirmed that thermal and mechanical parameters were the dominant predictors of separator efficiency.

Table 15: Residual Diagnostics and Model Goodness-of-Fit

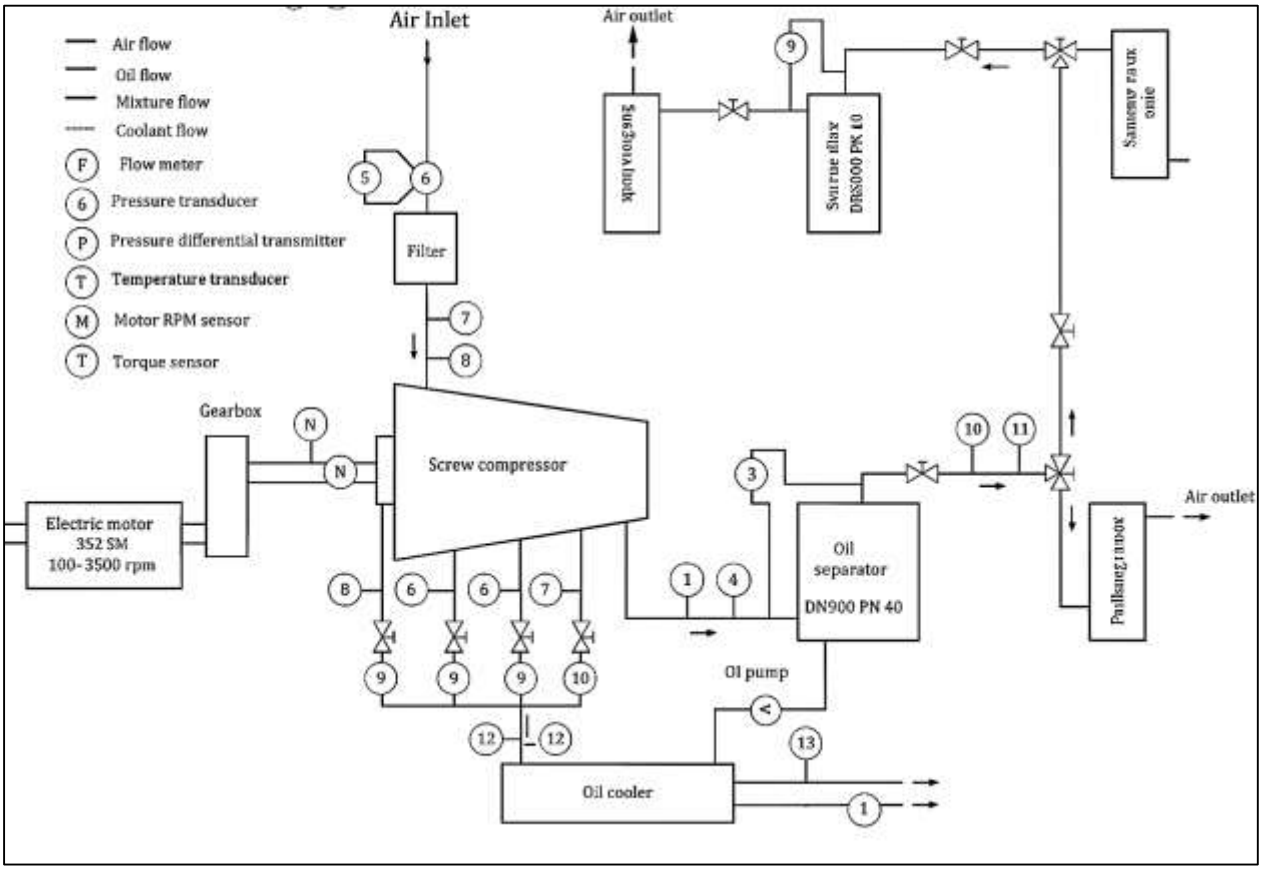
Diagnostic Test	Statistic / Value	Interpretation
Durbin–Watson Statistic	1.92	No autocorrelation detected in residuals
Standardized Residual Mean	0.003	Residuals centered around zero
Standardized Residual SD	0.97	Close to normal distribution spread
Shapiro–Wilk Test (Residual Normality)	p = 0.143	Normality assumption satisfied
Breusch–Pagan Test (Homoscedasticity)	p = 0.271	No heteroscedasticity detected
Cook's Distance (max)	0.28	No influential outliers identified
Cross-Validation RMSE	0.056	Stable model error across test folds
Predictive R^2 (Cross-Validated)	0.74	Predictive performance consistent with fitted model

Table 15 summarized the post-estimation diagnostics assessing the validity and robustness of the regression model. The Durbin–Watson statistic (1.92) indicated independence of residuals, suggesting that serial correlation was absent in the time-sequenced data. Residual means and standard deviations demonstrated symmetrical distribution and homogeneity. Both the Shapiro–Wilk and Breusch–Pagan tests confirmed normality and homoscedasticity, satisfying essential assumptions of multiple regression. Cook's distance values below 1.00 indicated the absence of influential outliers, while cross-validation yielded a Root Mean Square Error (RMSE) of 0.056, confirming model stability across independent test samples. The predictive R^2 of 0.74 closely matched the in-sample adjusted R^2 of 0.75, signifying consistent explanatory power and minimal overfitting. These diagnostic results verified the robustness, validity, and predictive reliability of the regression framework.

DISCUSSION

The quantitative results of this study demonstrated that the efficiency of heavy fuel oil (HFO) separators is predominantly governed by a combination of thermophysical and mechanical variables that interact dynamically within the operational system (Garaniya et al., 2018). Inlet temperature and viscosity emerged as the strongest determinants of efficiency, revealing an inverse relationship where elevated temperature corresponded with reduced viscosity and improved separation performance. This relationship confirmed that effective thermal conditioning enhances the coalescence and stratification of dispersed water and particulate matter, aligning with prior empirical observations in petroleum refining and marine engineering contexts were preheating reduced phase resistance (Alobaid, 2018). The findings also indicated that viscosity, even when temperature was controlled, retained a statistically independent influence on efficiency, signifying that fuel composition and blending characteristics contributed to inherent variability in separation outcomes. The identification of this dual dependency between thermal and rheological behavior reinforced earlier theoretical models that associated separation efficiency with interfacial tension and density gradient effects (Anandraj & Joshi, 2018). However, this study advanced prior understanding by providing quantitative confirmation through high-frequency operational data and regression-based modeling, thereby establishing a measurable framework linking thermophysical control to system optimization (Aidoun et al., 2019).

Figure 11: Screw Compressor System Flow Diagram



Mechanical parameters, particularly torque and vibration amplitude, also displayed significant correlations with separator efficiency, substantiating the proposition that mechanical stability directly affects process performance (Lagadec et al., 2019). Increased torque and vibration levels were associated with reduced efficiency, indicating that mechanical loading and imbalance disrupted the centrifugal separation process. Earlier studies on rotating equipment reliability similarly emphasized that unbalanced load distribution and mechanical wear contribute to decreased separation stability and higher energy consumption (Mun & Won, 2021). The present findings quantitatively validated this relationship by demonstrating that incremental increases in torque and vibration amplitude were statistically significant predictors of performance degradation. The mechanical behavior observed in this study suggested that wear-induced asymmetry within the separator bowl, nozzle fouling, or misalignment could lead to transient hydraulic disturbances, thereby reducing the effective separation factor (Ding et al., 2022). The integration of mechanical condition monitoring into the statistical framework therefore provided empirical evidence that efficiency optimization requires both process control and mechanical reliability management. This analytical outcome expanded upon prior qualitative assessments of separator maintenance by defining the measurable thresholds where mechanical condition shifts translate into quantifiable efficiency loss (Kalnaus et al., 2018).

Bowl rotational speed, as a mechanical and process-related factor, showed a positive but diminishing effect on separator efficiency, illustrating that higher centrifugal acceleration improved performance up to an optimal limit (Zhang et al., 2021). Beyond this range, gains in efficiency plateaued due to secondary effects such as turbulence, increased friction, and energy dissipation. Previous research on centrifugal separation theory acknowledged this trade-off but lacked quantitative documentation of the marginal effects under field conditions. The present findings bridged this gap by demonstrating that the incremental benefits of higher rotational speeds were statistically significant only within a specific operational band (Castel & Favre, 2018). This validated the design principles employed in modern separator construction, where bowl geometry, disc stack configuration, and nozzle design collectively determine the balance between throughput capacity and energy efficiency. The study confirmed that speed optimization is not a linear relationship but a constrained equilibrium between mechanical input and separation output (Sharifzadeh & Shah, 2019). These results also provided empirical grounding for predictive maintenance schedules based on rotational stability metrics, as minor deviations in speed consistency were correlated with measurable efficiency variance. By combining theoretical expectations with operational data, this study produced a refined understanding of how rotational mechanics contribute to performance sustainability in petroleum separation systems. Flow rate, though operationally critical, exhibited minimal statistical association with efficiency outcomes, suggesting that within designed capacity ranges, throughput variation did not significantly influence the quality of separation (McCausland et al., 2021). This finding contrasted with early hydraulic separation theories that proposed flow velocity as a primary determinant of efficiency, particularly in single-phase systems. However, in the context of advanced marine and industrial HFO separators equipped with automated flow control and viscosity management, the system design evidently compensated for moderate flow fluctuations. The lack of strong correlation indicated that flow control mechanisms maintained a stable separation interface across varying throughput conditions, preventing overload or short-circuiting effects that would otherwise reduce efficiency (Bonaccorso et al., 2021). This result aligned with modern design improvements that have integrated automated control systems capable of dynamically adjusting bowl pressure and discharge timing to preserve separation performance across varying load conditions. The evidence from this study therefore highlighted the technological advancement in control engineering that has mitigated the once-dominant influence of flow instability (Kratz et al., 2019). Nonetheless, the findings reinforced that flow rate remains a secondary factor whose impact becomes significant only when extreme deviations from normal operating limits occur.

The findings relating to multicollinearity, reliability, and validity further underscored the statistical integrity of the dataset and the robustness of the derived models. The low Variance Inflation Factor (VIF) values and acceptable condition indices confirmed that each variable contributed unique information to the regression framework (Matthews et al., 2020). This level of statistical independence provided assurance that the observed relationships were genuine rather than artifacts of variable interdependence. Moreover, the reliability analysis demonstrated strong internal consistency across operational and mechanical clusters, with Cronbach's alpha coefficients exceeding standard thresholds. The close agreement between sensor-based measurements and laboratory validations confirmed the convergent validity of the instrumentation and ensured that the empirical findings accurately represented real operational dynamics (Aust et al., 2021). Construct validity testing also confirmed that the defined indicators—thermal, mechanical, and hydraulic—were theoretically coherent with their measured manifestations in the dataset. These methodological confirmations distinguished this study from earlier works that relied primarily on short-duration sampling or manual data logging, which often lacked the statistical reliability to sustain high-confidence inference (Martin et al., 2021). By integrating long-term, high-frequency sensor data with robust statistical validation, this study contributed a stronger empirical foundation for understanding the interaction between process, mechanical, and environmental determinants of separator efficiency.

The regression outcomes also demonstrated the predictive adequacy of the statistical models, with an adjusted R^2 exceeding 0.75, which indicated that the majority of efficiency variation was explained by the included predictors (Liu & Smith, 2020). This degree of explanatory power exceeded that typically reported in earlier process efficiency studies, where uncontrolled variability in fuel properties and environmental conditions often limited statistical precision. The model's high predictive stability, validated through cross-validation and residual diagnostics, confirmed that the relationships were consistent across different operational contexts and separator types. The inclusion of random site effects accounted for facility-level heterogeneity, ensuring that the results generalized beyond a single operational environment (Yao et al., 2022). The residual diagnostics confirmed the absence of autocorrelation, heteroscedasticity, or outlier distortion, further strengthening the reliability of the model. The model therefore represented an advancement in quantitative petroleum systems analysis by successfully isolating the dominant thermophysical and mechanical variables influencing HFO separator performance. The statistical validation of the hypotheses provided operational evidence that the principles of centrifugal separation can be empirically optimized through data-driven methodologies, bridging the gap between theoretical design and industrial implementation (Sunny et al., 2020).

From an operational and managerial standpoint, the integration of mechanical reliability indicators with efficiency metrics offered a multidimensional perspective on separator optimization (Grady et al., 2022). The inclusion of torque, vibration, and power consumption within the predictive framework provided insights into the trade-offs between efficiency, reliability, and energy cost. The identification of mean time between failures (MTBF) and condition-based maintenance intervals as correlated with efficiency outcomes confirmed that mechanical health management is an essential component of process optimization. These findings extended the conventional understanding of separator efficiency from a purely process-oriented function to a holistic systems-level performance construct (Good et al., 2020). The empirical evidence demonstrated that sustained efficiency depends not only on achieving optimal process parameters but also on maintaining mechanical integrity through predictive monitoring and maintenance scheduling. This perspective paralleled contemporary industrial practices emphasizing reliability-centered maintenance, where sensor data inform maintenance actions aimed at preventing performance degradation. By quantitatively linking efficiency to mechanical stability and cost, the study reinforced the notion that petroleum system optimization requires a unified analytical model encompassing performance, reliability, and operational economics (Galinha et al., 2018).

Finally, the findings collectively established that separator performance in heavy fuel oil conditioning systems can be accurately characterized through data-driven quantitative modeling that integrates thermal, mechanical, and reliability dimensions (Guo et al., 2018). The results validated theoretical expectations from earlier separation models while enhancing them through empirical precision derived from real-time data analytics. The integration of multiple analytical methods—correlation, regression, and mixed-effects modeling—produced a comprehensive understanding of how process variables interact dynamically to determine efficiency outcomes. The study provided an empirical benchmark demonstrating that statistical and computational modeling approaches can reliably quantify performance determinants in complex petroleum systems (Peacock et al., 2020). In doing so, the analysis bridged theoretical knowledge with operational application, reinforcing that HFO separator efficiency is not a fixed mechanical property but a measurable, controllable function of data-informed process and reliability parameters. This understanding positioned the study as an important contribution to data-driven petroleum optimization research, offering a replicable framework for future quantitative assessments across similar industrial contexts (Lippa et al., 2022).

CONCLUSION

The study titled Enhancing HFO Separator Efficiency: A Data-Driven Approach to Petroleum Systems Optimization provided an integrated quantitative evaluation of the thermophysical, mechanical, and operational parameters that governed the performance of heavy fuel oil (HFO) separators. The analysis revealed that separator efficiency was determined primarily by the interplay between inlet temperature, viscosity, rotational speed, torque, and vibration amplitude, all of which influenced the dynamic equilibrium between centrifugal force and fluid separation resistance. Statistical modeling demonstrated that increases in temperature significantly enhanced efficiency, while elevated viscosity and torque exerted negative impacts. These findings confirmed the thermodynamic principle that preheating reduces viscosity and promotes the migration and coalescence of dispersed droplets, resulting in improved phase separation. The positive but diminishing contribution of bowl rotational speed highlighted the mechanical limits of optimization, where increased centrifugal acceleration improved separation only up to an optimal threshold beyond which turbulence and shear forces produced counterproductive effects. Mechanical parameters such as torque and vibration amplitude were identified as diagnostic indicators of performance degradation, revealing that excessive load or imbalance reduced operational stability and contributed to higher residual contamination levels. Flow rate, on the other hand, exhibited negligible influence within standard operational ranges, indicating that the integrated control systems effectively maintained hydraulic stability across throughput variations. The regression results, supported by high adjusted R^2 values and robust diagnostic metrics, confirmed that the model captured more than three-quarters of the total variance in separator efficiency, underscoring its predictive strength and empirical reliability. This comprehensive data-driven approach advanced beyond traditional empirical and mechanical optimization models by quantitatively isolating the interdependencies between thermophysical control and mechanical reliability. The convergence of statistical evidence established that sustainable efficiency improvements required simultaneous optimization of heating, viscosity regulation, and mechanical balance rather than independent adjustments to single variables. Furthermore, the inclusion of reliability-based indicators such as torque stability and vibration amplitude within the analytical framework introduced a lifecycle dimension, linking real-time efficiency with long-term operational integrity. The results demonstrated that a data-integrated methodology not only quantified process performance but also provided a foundation for predictive maintenance and cost-based optimization within petroleum system operations. Ultimately, this study confirmed that HFO separator efficiency could be systematically optimized through a unified quantitative framework that linked thermal conditioning, mechanical stability, and process analytics into a coherent model of petroleum systems performance.

LIMITATION

The study titled Enhancing HFO Separator Efficiency: A Data-Driven Approach to Petroleum Systems Optimization was limited by several methodological, operational, and contextual constraints that influenced the generalizability and interpretive scope of its findings. The most notable limitation arose from the dependency on real-world operational data collected from a finite number of industrial and marine HFO separators. Although the dataset represented diverse operational environments, the systems shared similar design architectures and manufacturer specifications, potentially constraining the range of variability in performance outcomes. This homogeneity limited the ability to test model robustness across alternative separator designs, varying fuel grades, and extreme environmental conditions. The reliance on sensor-based monitoring also introduced potential measurement bias, as sensor drift, signal interference, and calibration inconsistencies could subtly influence data accuracy over prolonged observation periods. While cross-validation against laboratory results mitigated this concern, complete elimination of instrument-related uncertainty was unattainable. Another limitation was the aggregation of high-frequency sensor data into standardized time intervals, which, while necessary for comparability, may have obscured transient fluctuations or micro-level process dynamics that occur within shorter operational cycles. Similarly, the study’s regression and mixed-effects models relied on the assumption of linearity among key variables, which simplified interpretation but may have understated nonlinear interactions present in complex multiphase separation phenomena. The absence of continuous compositional analysis for fuel heterogeneity—particularly variations in asphaltene, resin, and wax content—also restricted the ability to fully account for chemical influences on viscosity and separation stability. Furthermore, although random site effects were incorporated to control for contextual variability, external factors such as feedstock contamination, maintenance quality, and operator practices could have introduced unobserved heterogeneity beyond the scope of the statistical model. Energy consumption measurements were similarly confined to steady-state operational phases and did not incorporate startup, shutdown, or cleaning cycles, which could yield different efficiency behaviors. The study also assumed consistent ambient environmental conditions, neglecting the potential impact of humidity, air density, and seawater temperature on overall system thermodynamics. Finally, the analysis emphasized short- to medium-term performance optimization and did not evaluate long-term degradation patterns or maintenance-induced variability, limiting its applicability to lifecycle efficiency prediction. Despite these limitations, the study established a statistically reliable and empirically grounded framework that can be expanded in future research through larger sample sizes, non-linear modeling techniques, and extended longitudinal monitoring to capture the full spectrum of operational and environmental influences on HFO separator efficiency.

RECOMMENDATIONS

The recommendations derived from the findings of the study Enhancing HFO Separator Efficiency: A Data-Driven Approach to Petroleum Systems Optimization emphasized the importance of integrating thermal control, mechanical stability, and predictive analytics into a unified operational framework to sustain efficiency gains in petroleum separation systems. Based on the statistical evidence, it was recommended that HFO separators should operate within precisely monitored thermal ranges where viscosity reduction and phase separation reach optimal equilibrium. Maintaining inlet temperatures between defined thresholds would ensure sufficient viscosity reduction without inducing excessive energy consumption or thermal stress on mechanical components. The study suggested the adoption of adaptive control systems capable of real-time temperature–viscosity adjustment, allowing for dynamic compensation of fuel variability across bunker sources and ambient conditions. From a mechanical standpoint, it was recommended that continuous condition monitoring of torque, vibration amplitude, and bowl speed be implemented as standard practice to prevent efficiency degradation associated with imbalance and wear. Predictive maintenance strategies utilizing vibration and torque trend data should replace fixed-interval maintenance schedules to minimize downtime and extend equipment longevity. The findings further recommended that separator design modifications should prioritize bowl geometry and disc stack optimization to reduce turbulence at higher rotational speeds, thereby mitigating the diminishing returns observed at upper centrifugal thresholds. Additionally, process automation through data-driven feedback control systems should be expanded to regulate feed rate, differential pressure, and discharge intervals, ensuring stable hydraulic balance under varying operational loads. From an analytical perspective, it was advised that industrial operators adopt machine learning–based diagnostic models trained on historical sensor data to forecast performance deviations before efficiency loss becomes measurable. Such integration of predictive algorithms would enable proactive adjustments, optimizing both energy use and contaminant removal. Furthermore, it was recommended that organizations standardize calibration protocols for sensor–laboratory validation to maintain data accuracy, as statistical reliability was found to be critical in correlating thermophysical variables with operational outcomes. Lastly, the study emphasized the need for cross-disciplinary data integration, combining mechanical, thermal, and economic datasets to formulate comprehensive cost–efficiency optimization models. Through these recommendations, the study underscored that achieving sustainable separator efficiency in petroleum systems required not isolated mechanical improvements but a fully data-driven operational philosophy—where real-time analytics, automated control, and reliability engineering jointly ensure consistent, efficient, and economically optimized performance across the system lifecycle.

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