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Methodology

Optimizing Production Allocation Using Well Test Data and Nodal Analysis to Maximize Total Field Production

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Abstract: Production allocation is a central operational decision in mature oil and gas assets because it determines how limited drawdown, lift-gas, surface-handling, and facility capacities are distributed among producing wells. This article develops a comprehensive publication-oriented framework for optimizing production allocation using well test data and nodal analysis. The paper argues that field production can be increased when short-duration well tests, pressure-transient interpretation, production surveillance, pressure-volume-temperature data, and integrated production models are combined into a calibrated optimization loop. The proposed workflow validates well test data, converts them into well deliverability models, calibrates inflow performance relationship and vertical lift performance curves, integrates individual wells into a surface-network model, and applies constrained optimization to select rate, choke, lift-gas, and routing decisions that maximize total field production while respecting reservoir, wellbore, flowline, separator, water-handling, gas-handling, sand, corrosion, and drawdown limits. Recent literature shows that nodal analysis can identify bottlenecks across the reservoir-to-separator system, while back allocation and data-driven surveillance can reduce the uncertainty of individual well rates when only commingled field production is measured. The article contributes a practical decision framework, an optimization formulation, implementation checklist, and discussion of uncertainty management for production engineers. It concludes that the most reliable allocation strategy is not the highest instantaneous rate from every well, but the field-wide operating point that maximizes stable production under physical, economic, and integrity constraints

Keywords: production allocation; well test data; nodal analysis; integrated production modelling; production optimization

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1. Introduction

Production allocation is the process of assigning measured or forecasted field, platform, or manifold production back to individual wells, zones, strings, reservoirs, or ownership entities. In technical field management, allocation is more than an accounting exercise (Shah et al., 2020). It controls the daily operating philosophy of the asset because it determines which wells receive drawdown, which wells should be choked back, which wells should receive scarce lift gas, and which flow paths should be prioritized when surface constraints become active. Poor allocation can make a field appear optimized at the facility meter while individual wells are producing below potential, operating above safe drawdown, creating unnecessary water or gas, or masking wellbore damage. Conversely, optimized allocation provides a rational basis for maximizing total field production rather than maximizing isolated well rates (Yadua & Lawal, 2023).

Modern petroleum fields commonly operate under multiple interacting constraints. A well with a high individual test rate may not be the best candidate for additional drawdown if it has high water cut, rising gas-oil ratio, unstable sand production, or severe backpressure from a congested flowline (Yadua & Lawal, 2023). A well with a modest test rate may deserve more allocation if it has lower water handling burden, stronger inflow, lower lifting cost, and better deliverability under reduced wellhead pressure. Therefore, production allocation should be treated as a constrained field-wide optimization problem, not as a proportional distribution based only on the latest well-test percentage (Shah et al., 2020).

Well test data and nodal analysis provide the technical bridge between measurement and optimization. Well tests supply direct observations of rate, pressure, fluid composition, and operating conditions. Nodal analysis uses these observations to model the entire production system from the reservoir, through the completion and tubing, to the flowline, manifold, separator, and export constraints. The intersection of the inflow and outflow curves defines the operating point for each well; when wells are connected to a shared surface system, changes in one well alter the pressure environment and deliverability of other wells. Field optimization therefore requires calibrated individual well models as well as a network representation of shared constraints (Shah et al., 2020; Yadua & Lawal, 2023).

Recent studies emphasize this integrated logic. Shah et al. (2020) demonstrated the use of nodal analysis to optimize a gas well by treating each component from reservoir to separator outlet as a resistance in the production system. Salaudeen et al. (2022) applied a nodal analysis program to a Niger Delta petroleum system and selected tubing and flowline combinations based on the maximum operating flow rate. Chaves and Ferreira Filho (2024) highlighted the practical importance of back allocation when only total platform production is measured in real time, proposing a methodology that combines simulations, algorithms, and mathematical programming for well-rate estimation and well-test scheduling. These studies point to a common conclusion: production allocation improves when measurement, physics-based modelling, and optimization are treated as one workflow rather than separate engineering tasks.

The objective of this article is to present a comprehensive framework for optimizing production allocation using well test data and nodal analysis in order to maximize total field production. The article is written for publication and for practical use by production technologists, reservoir engineers, production engineers, and field-development planners. It reviews recent literature from 2020 to 2026, describes the technical concepts underlying the workflow, proposes an optimization formulation, and discusses implementation issues including data quality, model calibration, uncertainty, surveillance frequency, and operational constraints (Shah et al., 2020; Yadua & Lawal, 2023).

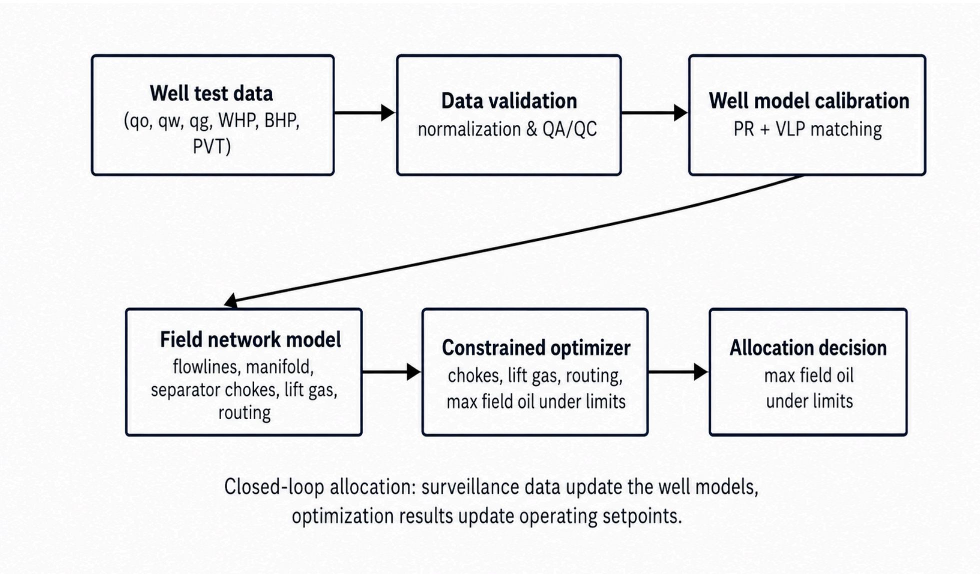

Figure 1. Integrated workflow for production allocation using well test data and nodal analysis (Chaves & Ferreira Filho, 2024; Yadua & Lawal, 2023).

1.1 Conceptual Basis of Production Allocation

Production allocation can be understood at three levels: measurement allocation, engineering allocation, and optimization allocation. Measurement allocation reconciles individual well estimates with the fiscal or facility meter (Yadua & Lawal, 2023).

Engineering allocation interprets the well rates in the context of reservoir pressure, productivity index, water cut, gas-oil ratio, tubing performance, artificial lift, and surface pressure. Optimization allocation uses the calibrated engineering model to select operating decisions that increase total field production while honoring constraints. The third level is the focus of this article (Salaudeen et al., 2022).

Traditional allocation often relies on the latest well test and assumes that a well's contribution remains fixed until the next test. This method is simple but weak when wells decline rapidly, flow intermittently, experience changing water cut, or operate in a surface network where pressure interactions are significant (Salaudeen et al., 2022). In a commingled production system, a well can lose rate because of surface backpressure even if reservoir deliverability remains strong. Another well can show a high-test rate during favorable test conditions but underperform during normal network operation. The allocation framework must therefore distinguish between test performance and sustainable network performance (Yadua & Lawal, 2023).

A robust allocation workflow uses the well test as a calibration event rather than as the final answer. The test provides observed flow and pressure data. Nodal analysis converts the observations into a deliverability model. Back allocation reconciles the model results with total measured field production. Optimization then searches for a better allocation of controllable variables: choke settings, lift-gas rates, pump speed, well routing, tubing configuration, and separator pressure. The result is a field operating plan that recognizes that each well competes for shared pressure and processing capacity (Salaudeen et al., 2022; Yadua & Lawal, 2023).

The key optimization insight is that total field production is usually not maximized by fully opening all wells. Full opening may increase pressure losses in flowlines, overload separators, accelerate water or gas breakthrough, reduce lift efficiency, create unstable multiphase flow, or violate integrity constraints. The optimum operating point is found by comparing the marginal production gain from relaxing each well or constraint. A well should receive additional drawdown or lift gas only when the incremental field oil benefit exceeds the incremental penalty imposed on other wells and on facility capacities (Salaudeen et al., 2022; Yadua & Lawal, 2023).

2. Literature Review

2.1 Well Test Data as the Foundation for Allocation

Well test data are central to production allocation because they provide the most direct evidence of individual well deliverability. Typical test variables include oil rate, gas rate, water rate, wellhead pressure, flowing bottomhole pressure, choke size, tubing-head temperature, separator pressure, fluid properties, and test duration. For diagnostic purposes, buildup, drawdown, pressure-transient, interference, and deliverability tests can also estimate reservoir pressure, permeability, skin, boundaries, and productivity changes. Zhao et al. (2022) emphasized that well test interpretation can be combined with production dynamic analysis to diagnose controlling factors and production characteristics in complex reservoirs. This is important because allocation decisions require not only a rate number, but an explanation of why the rate exists and whether it can be increased safely.

Well tests must be quality controlled before they are used for optimization. Common problems include unstable rates, short test duration, separator carry-over, multiphase metering bias, unrepresentative choke settings, unrecorded downtime, changing wellhead pressure during the test, and commingled production from multiple zones. If such data are used without correction, the nodal model may be calibrated to a false operating point. A practical allocation workflow should therefore include validation rules: remove tests during unstable flowing conditions, normalize rates to standard conditions, reconcile test rates with facility meters, compare liquid and gas trends against historical behavior, and flag results that deviate beyond expected uncertainty (Zhao et al., 2022; Society of Petroleum Engineers, 2025).

The growing use of digital surveillance does not remove the need for well tests; instead, it changes their role. Continuous pressure and rate data improve the frequency of model updates, while periodic well tests still provide anchor points for calibration and regulatory or commercial allocation. Chaves and Ferreira Filho (2024) noted that production rates are crucial for operational decisions, field monitoring, optimization, and fiscal allocation, but that real-time measurement is often available only at total field or platform level. This makes estimation and reconciliation methods essential for reliable well-level allocation.

2.2 Nodal Analysis and System Bottleneck Identification

Nodal analysis is a production-system modelling method that divides the flow path into connected components and evaluates pressure losses and deliverability across each component. The central principle is that production is governed by the balance between reservoir inflow and system outflow. The inflow performance relationship describes how much fluid the reservoir can deliver at a given bottomhole flowing pressure. The vertical lift performance relationship describes the pressure required to lift and transport that fluid through the completion, tubing, flowline, and separator system. The intersection of these curves defines the operating rate under a specific set of conditions (Shah et al., 2020; Salaudeen et al., 2022).

Recent field applications show the practical value of the method. Shah et al. (2020) applied nodal analysis to Well-6 in the Habiganj gas field and evaluated the resistance of components from reservoir to separator outlet, reporting improved production estimates under reduced wellhead pressure scenarios. Salaudeen et al. (2022) used nodal analysis for a Niger Delta well and selected the most economical production string by testing tubing and flowline combinations. Njeudjang et al. (2022) used completion, pressure-volume-temperature, and reservoir data in PIPESIM to evaluate an eruptive well and reported significant production improvement after reducing wellhead pressure and increasing flowline diameter. These examples demonstrate that nodal analysis is not merely a theoretical curve-matching exercise; it is a decision tool for selecting operating and equipment changes.

For allocation optimization, nodal analysis is especially useful because it identifies whether a well is reservoir-limited, tubing-limited, choke-limited, lift-limited, flowline-limited, or facility-limited. A reservoir-limited well may not respond materially to wider choke settings. A tubing-limited well may require artificial lift adjustment, tubing redesign, or scale removal. A flowline-limited well may need rerouting or pressure reduction at the manifold. A facility-limited well may produce less oil if additional liquids overload water-handling capacity. By identifying the active bottleneck, nodal analysis prevents the engineer from allocating scarce drawdown or lift resources to the wrong well (Shah et al., 2020; Salaudeen et al., 2022).

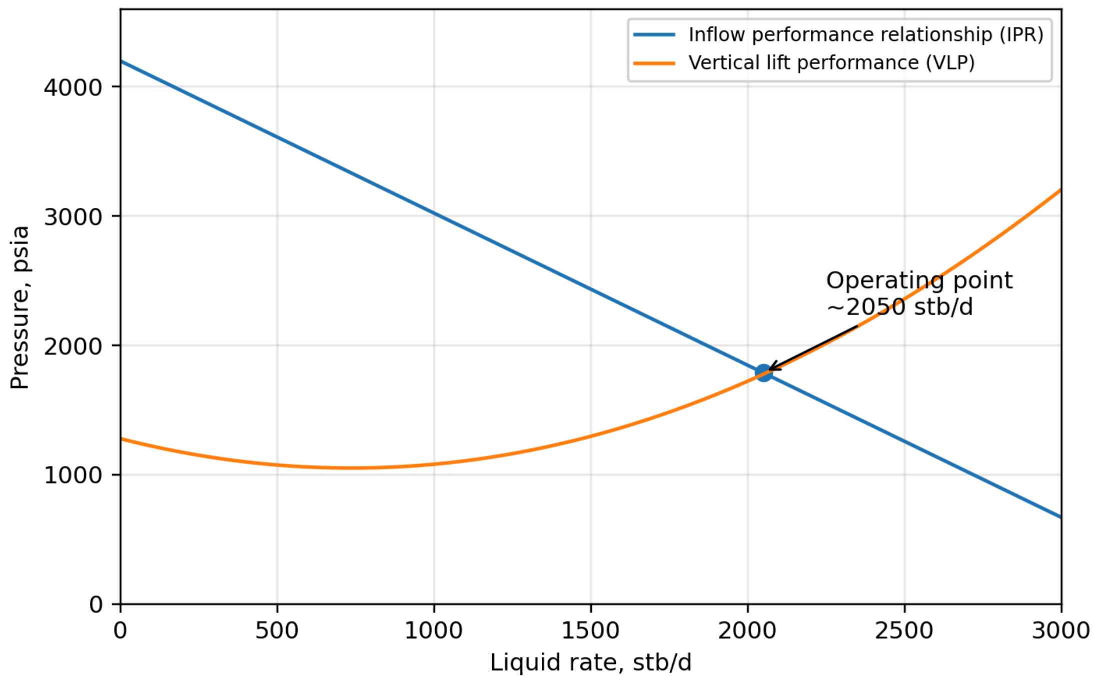

Figure 2. Typical IPR-VLP intersection showing the operating point obtained through nodal analysis (Shah et al., 2020; Salaudeen et al., 2022).

2.3 Integrated Production Modelling and Network Effects

Single-well nodal analysis is necessary but insufficient for field optimization because wells rarely operate independently. Wells share flowlines, manifolds, risers, compressors, separators, water-treatment systems, gas-handling capacity, and export constraints. When one well is opened further, it can increase pressure losses in the common network and reduce the deliverability of connected wells. Yadua and Lawal (2023) showed that controllable variables such as well count, choke size, and separator pressure can alter integrated production-system performance and that increasing well count may raise bulk network flow while also increasing manifold pressure and reducing single-well production. This finding supports field-wide optimization rather than isolated well optimization.

Integrated production modelling links reservoir tanks, well models, and surface-network models into a single system. The model can be used to test scenarios such as lowering separator pressure, changing manifold routing, adding lift gas, modifying choke schedules, shutting in high-water wells, debottlenecking a flowline, or allocating production between parallel separators. The best allocation is the scenario that improves total field oil or economic objective while staying within technical limits (Yadua & Lawal, 2023; Rahmanifard & Gates, 2024).

The difference between well optimization and field optimization is critical. A well may be optimized locally at a higher rate, yet the field may lose production because the well raises backpressure, uses lift gas inefficiently, produces excessive water, or occupies separator capacity that could produce more oil if assigned to another well. Therefore, the objective function should represent total field value, not isolated well potential. This field-level perspective also supports production deferment analysis because it reveals which constraint is truly limiting the asset (Yadua & Lawal, 2023; Rahmanifard & Gates, 2024).

2.4 Back Allocation and Production Reconciliation

Back allocation estimates individual well production from commingled measurements and well-level indicators. It is particularly important in offshore platforms, clustered land assets, and mature fields where continuous multiphase metering may not be installed on every well. Chaves and Ferreira Filho (2024) proposed a back allocation methodology using real-time instrumentation, simulation, classification, error calculation, and optimization modules. Their method estimates well rates while honoring total platform production and assists well-test scheduling by identifying wells that deviate from recent test behavior.

Back allocation should not be treated as a replacement for engineering judgement. Its value depends on the quality of the prior well tests, the validity of the well models, the frequency of surveillance data, and the reconciliation procedure. If a well's allocation factor is based only on a stale test, it may overstate production for a declining well or understate production after stimulation. If the model ignores network backpressure, it may allocate too much production to a well that performs well on test but poorly in commingled operation. Therefore, the allocation engine should include physics-based nodal constraints and periodic recalibration (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

Modern allocation can combine three evidence sources: measured well-test rates, model-predicted well rates, and facility-measured total production. The reconciliation problem is to choose individual well rates that are close to model predictions and test-based expectations while exactly or approximately matching the measured facility totals. When uncertainty is quantified, more reliable tests and measurements receive higher weights, while uncertain or stale data receive lower weights. This creates an auditable allocation process that can support both operational optimization and commercial reporting (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

2.5 Data-Driven Optimization and Machine Learning Support

Recent research increasingly combines physics-based models with data-driven optimization. Feng et al. (2022) proposed a streamline-feature-based objective function and Bayesian adaptive direct search algorithm for well production optimization, showing that a reduced simulation burden can improve optimization efficiency. Rahmanifard et al. (2024) developed an integrated workflow using machine-learning and optimization methods to forecast and optimize gas production in a large horizontal-well dataset. Zhang et al. (2025) described dynamic production optimization through rolling updates of production data for stable wells.

For production allocation, machine learning is useful when it supports rather than replaces engineering models. It can detect abnormal tests, forecast short-term rates, estimate missing variables, classify wells by operating condition, and screen optimization scenarios quickly before detailed nodal simulation. However, purely data-driven models may extrapolate poorly outside historical operating ranges. A field allocation decision can change choke size, separator pressure, routing, or lift-gas distribution, creating conditions that have not occurred in the historical data. Therefore, hybrid workflows are preferable: nodal analysis enforces physics, while data-driven tools accelerate surveillance, anomaly detection, and scenario ranking (Feng et al., 2022; Zhang et al., 2025).

The strongest workflow is a closed-loop system. Well tests calibrate the physics model. Real-time data update the allocation estimate. Optimization recommends new setpoints. The field response is monitored, and the next test schedule is prioritized based on model uncertainty and production value. This loop is consistent with the movement toward surveillance-by-exception and real-time production optimization in contemporary production engineering (Feng et al., 2022; Zhang et al., 2025).

Additional recent evidence strengthens this hybrid position. Production step-up studies using nodal analysis show that changes in tubing size, flowline size, wellhead pressure, and skin can materially alter well deliverability, while intelligent pressure-control strategies for shale gas wells demonstrate that wellbore-surface integration can stabilize production under mixed-pressure operating conditions (Kamga Ngankam et al., 2022; Zhou et al., 2025). Likewise, machine-learning studies for tight sandstone and shale gas wells show that data-driven prediction can improve production-parameter screening, but the results remain most useful when interpreted within physical operating envelopes and facility constraints (Zhu et al., 2022; Sun et al., 2025).

3. Methodology

3.1 Data Requirements

A reliable allocation optimization requires reservoir, wellbore, fluid, surface, and operations data. Reservoir data include static pressure, permeability, thickness, skin, drainage area, relative permeability, completion interval, pressure support, and reservoir boundaries. Wellbore data include tubing size, deviation survey, completion type, artificial-lift design, choke characteristics, restrictions, sand-control equipment, scale history, and intervention records. Fluid data include oil density, gas-oil ratio, formation volume factor, viscosity, water cut, gas specific gravity, and compositional or black-oil PVT description. Surface data include flowline diameters, lengths, roughness, manifold pressures, separator pressure, compressor capacity, water-handling limits, gas-handling limits, and export capacity. Operations data include uptime, choke settings, lift-gas rates, pump speed, well routing, chemical treatment, and facility constraints (Salehian et al., 2021; Yadua & Lawal, 2023).

The dataset should be time-stamped and aligned. A well test is useful for model calibration only when the corresponding choke size, wellhead pressure, separator pressure, and flowline routing are known. A rate without its pressure context is incomplete because nodal analysis needs both the amount of produced fluid and the pressure energy available to move it. Data governance is therefore an engineering requirement, not an administrative preference (Salehian et al., 2021; Yadua & Lawal, 2023).

3.2 Well Test Validation and Normalization

Before model calibration, test data should pass technical validation. The engineer should confirm that the well reached stable flow or that transient effects are accounted for; compare test separator readings with total production meters; check that water cut, gas-oil ratio, and pressure values are plausible relative to trend; identify whether the well was cleaned up, beaned up, or flowing under abnormal facility conditions; and remove periods affected by shut-ins, slugging, separator carry-over, or meter malfunction. Normalization should adjust rates to standard conditions and document any correction factors (Salehian et al., 2021; Yadua & Lawal, 2023).

A useful validation score can be assigned to each test. High-confidence tests have stable rates, adequate duration, consistent pressure, reliable metering, and representative operating conditions. Medium-confidence tests may be used with lower weight. Low-confidence tests should trigger retesting or be used only for qualitative diagnosis. This scoring becomes important in the optimization stage because allocation factors derived from high-quality tests should influence the result more strongly than stale or uncertain tests (Salehian et al., 2021; Yadua & Lawal, 2023).

3.3 Nodal Model Calibration

Model calibration converts validated well-test data into a production-system representation. The inflow model is calibrated by matching productivity index, reservoir pressure, skin, and inflow correlation to observed pressure-rate behavior. The outflow model is calibrated by matching tubing pressure losses, multiphase-flow correlation, roughness, fluid properties, and surface pressure to observed flowing conditions. For artificially lifted wells, pump performance curves, gas-lift valve behavior, injection pressure, and lift-gas rate must also be matched (Salehian et al., 2021; Yadua & Lawal, 2023).

Calibration should avoid the common mistake of forcing one unknown parameter to absorb all model error. For example, increasing skin may match a low rate, but the true cause may be scale in tubing, a partially closed downhole valve, high backpressure, or an inaccurate PVT description. Sensitivity analysis should be run on parameters that have physical uncertainty. The calibrated model should reproduce both the latest well test and the historical trend within acceptable error (Salehian et al., 2021; Yadua & Lawal, 2023).

3.4 Field Network Integration

After each well is calibrated, the wells are connected to the surface network model. This step converts the analysis from individual well deliverability to field deliverability. The model should represent common flowlines, manifolds, separators, compressors, pump stations, and export constraints. The network model calculates how pressure interactions change the operating point of each well. This is essential because a well's optimized single-well rate may not be achievable when all wells flow simultaneously through shared facilities (Salehian et al., 2021; Yadua & Lawal, 2023).

The integrated model must be reconciled with measured field production. If the sum of model-predicted individual rates differs from total facility measurement, the model should be adjusted through a documented reconciliation procedure. The goal is not to hide measurement error, but to create a consistent basis for optimization. Persistent mismatch is a diagnostic signal and may indicate metering problems, unmodelled restrictions, reservoir changes, or inaccurate fluid properties (Salehian et al., 2021; Yadua & Lawal, 2023).

3.5 Optimization Formulation

The optimization problem can be expressed as maximizing total field oil rate or economic value subject to reservoir, well, and facility constraints. Let qoi be the oil rate from well i, qwi the water rate, qgi the gas rate, xi the controllable settings for well i, and y the shared facility settings. A simplified objective is: (Salehian et al., 2021; Yadua & Lawal, 2023).

Maximize: Qoil = Σ qoi(xi, y) for i = 1, 2, ..., n (Salehian et al., 2021; Yadua & Lawal, 2023).

Subject to: Σ qwi ≤ water-handling capacity; Σ qgi ≤ gas-handling capacity; manifold pressure ≤ allowable pressure; separator liquid rate ≤ separator capacity; drawdown per well ≤ safe drawdown; sand, erosion, corrosion, and hydrate constraints are not violated; lift-gas allocation ≤ available lift gas; and each choke, pump, or routing variable remains within operating limits (Salehian et al., 2021; Yadua & Lawal, 2023).

In economic optimization, the objective can be changed from maximum oil rate to maximum net value: oil revenue minus water handling cost, gas compression cost, lift-gas opportunity cost, chemical cost, intervention risk, and deferred production penalties. This is often superior in high-water-cut mature fields because a high gross liquid rate may not create high economic value (Salehian et al., 2021; Yadua & Lawal, 2023).

3.6 Proposed Practical Workflow

3.6.1 Define the allocation objective

The objective may be maximum oil rate, maximum gas rate, maximum condensate recovery, minimum deferment, maximum net present value, or maximum stable production under integrity limits. The chosen objective should be explicit because it affects which wells are favored (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.2 Build the surveillance dataset

Compile recent well tests, pressure data, choke histories, lift-gas rates, pump settings, fluid properties, separator measurements, downtime records, and intervention history. Convert all data into a consistent time basis (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.3 Validate and rank well-test quality

Assign a confidence level to each test based on stability, duration, pressure consistency, metering reliability, and representativeness. Retest wells with high production value and high uncertainty (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.4 Calibrate individual well nodal models

Match IPR and VLP models to validated tests and historical behavior. Conduct sensitivity analysis on reservoir pressure, productivity index, skin, tubing roughness, water cut, gas-oil ratio, artificial lift, and wellhead pressure (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.5 Integrate wells into a field network

Connect well models to flowlines, manifolds, separators, compressors, and export systems. Confirm that network pressures and total production match field data within acceptable error (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.6 Run base-case allocation

Calculate the current operating allocation and compare it with actual field production. Identify bottlenecks and wells with the largest mismatch between potential and actual contribution (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.7 Perform constrained optimization

Vary choke settings, lift-gas rates, pump speeds, routing, and separator pressure within safe limits. Optimize for the field objective, not isolated well rates (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.8 Test operational robustness

Check whether the recommended allocation remains valid under uncertainty in pressure, water cut, gas-oil ratio, meter error, and facility capacity. Reject solutions that are fragile or unsafe (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.9 Implement in stages

Apply changes incrementally, monitor field response, and compare actual response with model prediction. Use deviations to update the model (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

3.6.10 Close the loop

Schedule the next well tests based on uncertainty, production value, and model mismatch. Repeat the allocation cycle at a frequency appropriate to field volatility (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

4. Result

Consider a six-well field producing to a common manifold and separator. The latest tests suggest that all wells could increase rate if chokes are opened, but the facility is constrained by water-handling and gas-handling capacities. A proportional allocation based on test rates would assign more production to the highest gross-rate wells. However, nodal analysis shows that Well W-05 has high water cut and contributes strongly to the water constraint, while Well W-03 has a rising gas-oil ratio and causes separator gas limitation. Well W-02 and W-06 have lower gross rates but stronger oil efficiency per unit of water and gas handled. The field-wide optimum therefore increases W-01, W-02, W-04, and W-06, while slightly reducing W-03 and W-05 (Shah et al., 2020; Yadua & Lawal, 2023).

This example illustrates why allocation must be optimized against total field objective. The field does not gain from maximizing gross liquid if the additional liquid is mostly water, consumes separator capacity, and increases backpressure. It gains from shifting operating capacity toward wells that deliver more saleable hydrocarbons per unit of facility constraint. Figure 3 illustrates a typical allocation change after constrained optimization (Shah et al., 2020; Yadua & Lawal, 2023).

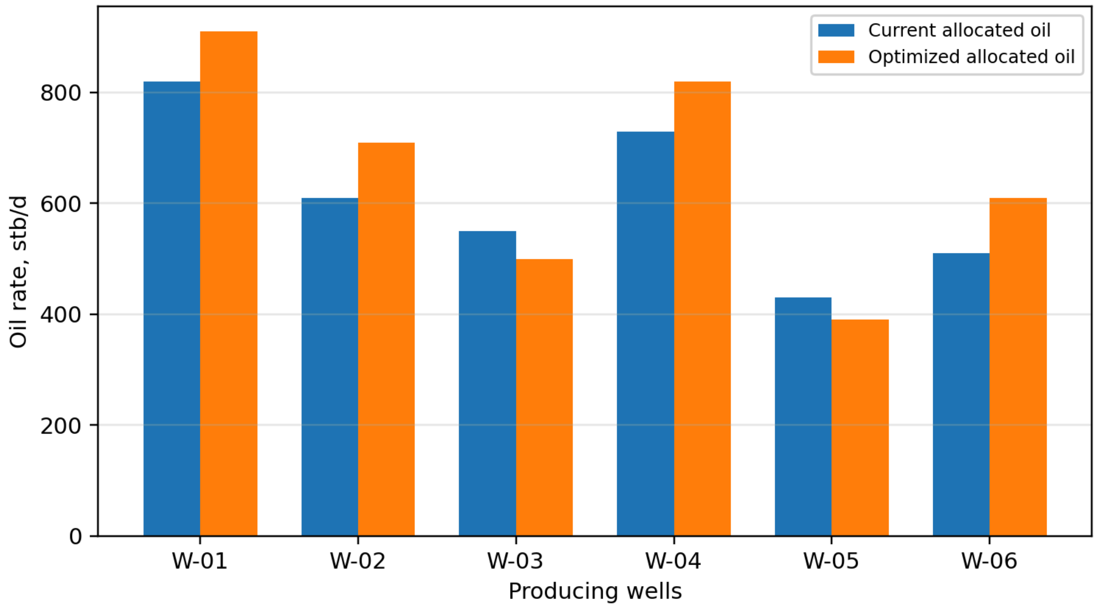

Figure 3. Illustrative current versus optimized well-level oil allocation in a constrained field network (Feng et al., 2022; Zhang et al., 2025).

4.1 Sensitivity Analysis for Allocation Decisions

Sensitivity analysis determines which variables most influence field production. Common variables include choke size, wellhead pressure, separator pressure, tubing diameter, flowline diameter, lift-gas rate, pump speed, water cut, gas-oil ratio, reservoir pressure, productivity index, and skin. Shah et al. (2020) and Njeudjang et al. (2022) both show the importance of pressure and flowline variables in nodal optimization, while

Salaudeen et al. (2022) demonstrates the role of tubing and flowline configuration in selecting an optimal production system.

The engineer should interpret sensitivity results in field context. A choke-opening sensitivity may show higher single-well oil rate, but if the same change raises water cut or causes slugging, the field optimum may require a smaller opening. A separator-pressure sensitivity may show that lower separator pressure increases well deliverability, but compressor constraints or vapor-handling limits may prevent implementation. A lift-gas sensitivity may show diminishing returns, indicating that lift gas should be reallocated to wells with higher marginal oil gain (Salehian et al., 2021; Feng et al., 2022).

Sensitivity analysis is also a communication tool. It helps operations teams understand why a recommendation is made. Instead of saying that a well should be choked back, the engineer can show that the well consumes disproportionate water capacity or causes manifold pressure rise that suppresses neighboring wells. This improves acceptance of optimization decisions (Salehian et al., 2021; Feng et al., 2022).

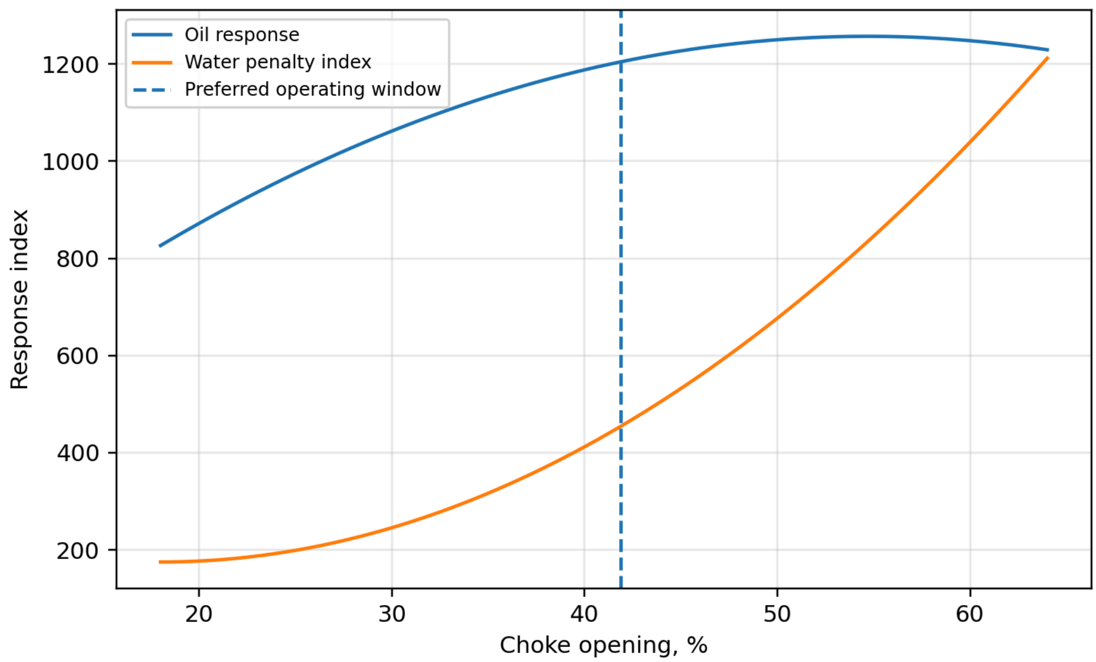

Figure 4. Illustrative choke sensitivity showing the trade-off between oil response and production penalty (Salehian et al., 2021; Feng et al., 2022).

4.2 Uncertainty and Risk Management

Production allocation is uncertain because measurements are uncertain, reservoir conditions change, and models simplify real multiphase flow. The framework should explicitly manage uncertainty rather than conceal it. Key uncertainty sources include multiphase meter accuracy, separator test error, test duration, pressure gauge drift, PVT correlation error, flow-correlation selection, reservoir pressure uncertainty, skin changes, water-cut instability, gas-lift valve performance, and unmeasured restrictions (Salehian et al., 2021; Yadua & Lawal, 2023).

A practical uncertainty approach is to run low, base, and high cases for critical parameters. If an allocation recommendation remains superior across the range, it is robust. If the recommendation changes depending on a single uncertain parameter, the field team should obtain better data before major implementation. For example, if two wells compete for lift gas and the decision depends strongly on uncertain productivity index, a short retest or pressure survey may be more valuable than immediate setpoint change (Salehian et al., 2021; Yadua & Lawal, 2023).

Optimization should also account for operational and integrity risk. Excessive drawdown can cause sand production, water or gas coning, completion damage, fines migration, or accelerated reservoir pressure decline. High velocities can increase erosion and corrosion risk. Low temperatures and pressure changes can increase hydrate or wax risk. Therefore, the optimum allocation must be safe, stable, and sustainable, not merely mathematically maximum (Salehian et al., 2021; Yadua & Lawal, 2023).

4.3 Implementation Challenges

4.3.1 Data Quality and Test Frequency

The most common implementation challenge is poor data quality. Many fields have infrequent tests, inconsistent separator conditions, incomplete pressure records, and undocumented operating changes. Without reliable time-stamped data, optimization becomes speculative. The solution is to create a test-quality protocol and prioritize tests by value of information. Wells with high rate, high uncertainty, high mismatch, or large facility impact should be tested more frequently than stable low-impact wells (Salehian et al., 2021; Yadua & Lawal, 2023).

4.3.2 Model Maintenance

A nodal model is not a one-time study. It must be updated after workovers, stimulation, scale treatment, artificial-lift changes, water breakthrough, pressure depletion, facility changes, and new tests. A stale model can be more dangerous than no model because it creates false confidence. The field team should assign ownership for model maintenance and define a maximum acceptable period between calibration reviews (Salehian et al., 2021; Yadua & Lawal, 2023).

4.3.3 Operations Acceptance

Optimization recommendations may conflict with operator intuition, especially when the model recommends choking back a visibly strong well. Acceptance improves when the decision is explained in field terms: manifold backpressure, water-handling burden, gas constraint, lift-gas efficiency, or integrity limit. A staged implementation plan also reduces risk because operators can observe the field response before full deployment (Salehian et al., 2021; Yadua & Lawal, 2023).

4.3.4 Commercial and Regulatory Constraints

In unitized or multi-owner fields, allocation has commercial implications. Any optimization system must be auditable, transparent, and consistent with allocation agreements and regulatory requirements. Engineering allocation for optimization may differ from fiscal allocation, but the relationship between the two must be documented. The allocation method should preserve traceability from raw test data to final well-level rates (Salehian et al., 2021; Yadua & Lawal, 2023).

4.4 Discussion

The reviewed literature and proposed framework indicate that production allocation optimization is most effective when three principles are followed. First, well test data should be interpreted dynamically rather than used as fixed percentages. A test is an observation of a well under specific conditions; it must be converted into a deliverability model before it can support allocation decisions under different conditions. Second, nodal analysis should be applied from reservoir to separator and extended into a field network. The well operating point depends on both inflow and outflow, and the field operating point depends on pressure interactions among wells and facilities. Third, optimization should maximize field value under constraints, not individual well potential (Rahmanifard & Gates, 2024; Zhang et al., 2025).

The practical advantage of the framework is that it converts production allocation into a repeatable engineering cycle. Field teams can begin with available tests and a simple nodal model, then improve the workflow through better surveillance, back allocation, automated data validation, and optimization algorithms. The approach is scalable: a small onshore field may use spreadsheet-supported nodal calculations and monthly tests; a large offshore field may use integrated production modelling software, real-time data, back allocation algorithms, and daily optimization routines (Rahmanifard & Gates, 2024; Zhang et al., 2025).

The framework also clarifies the relationship between production optimization and reservoir management. Maximizing today's field rate without reservoir constraints can reduce long-term recovery through coning, pressure depletion, or inefficient sweep. Therefore, the field objective should be aligned with reservoir strategy. In waterflood or gas-injection assets, production allocation should be integrated with injection allocation so that voidage replacement, sweep, and pressure support are maintained. In depletion-drive assets, safe drawdown and pressure management may be more important than short-term rate maximization (Rahmanifard & Gates, 2024; Zhang et al., 2025).

Recent digital methods create opportunities but also require discipline. Machine learning can improve forecasting, anomaly detection, and fast screening of scenarios, but physics-based nodal analysis remains essential because allocation decisions often move the system outside historical operating conditions. The best practice is hybrid optimization: use well tests and nodal models to preserve physical consistency, use back allocation to reconcile commingled measurements, and use data-driven tools to update and prioritize decisions quickly (Rahmanifard & Gates, 2024; Zhang et al., 2025).

4.5 Practical Application Matrix for Field Engineers

A publication-level allocation framework should be convertible into field action. The practical matrix below links the most common production-allocation symptoms to the well-test evidence, nodal-analysis diagnosis, optimization response, and expected field benefit. The matrix is useful because production allocation problems are often first noticed as operational symptoms rather than as mathematical optimization problems. For example, a field may show declining total oil although individual well tests appear acceptable. The integrated diagnosis may reveal that the surface network is the limiting node and that opening one high-gas well suppresses several moderate-oil wells connected to the same manifold (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

The matrix also supports surveillance-by-exception. Instead of retesting every well at the same fixed interval, the team can focus on wells whose allocation uncertainty has the greatest production consequence. High-rate wells with unstable gas-oil ratio, high-water wells near facility limits, wells with large model mismatch, and wells whose operating changes strongly affect manifold pressure should receive priority in the test schedule. This aligns well-test frequency with value of information and reduces unnecessary deferment from routine testing (Chaves & Ferreira Filho, 2024; Salaudeen et al., 2022).

Observed symptom	Likely evidence from well test	Nodal-analysis diagnosis	Optimization response	Expected benefit
High gross liquid but low oil gain	High water cut during test; stable pressure	Facility water-handling constraint active	Reduce choke or defer high-water interval; reallocate capacity to oil-efficient wells	Higher saleable oil per unit of liquid handled
Strong well underperforms online	Good test rate but high manifold pressure in normal operation	Surface-network backpressure or flowline bottleneck	Reroute well, lower separator pressure, or debottleneck flowline	Recovery of suppressed deliverability
Lift-gas demand exceeds available supply	Oil response declines at high lift-gas rate	Diminishing gas-lift efficiency	Reallocate lift gas to wells with higher marginal oil response	More oil per unit of lift gas
Rising GOR suppresses field oil	High gas rate and unstable flowing pressure	Gas-handling or compressor constraint active	Choke high-GOR well or optimize separator/compressor settings	Reduced gas constraint and improved total oil
Large mismatch between test and allocation	Recent test does not reconcile with platform total	Stale test, metering bias, or unmodelled restriction	Schedule priority retest and recalibrate the model	Improved confidence and auditable allocation

4.6 Data Governance, Reporting, and Auditability

Production allocation affects field operations, reserves surveillance, deferment accounting, partner reporting, and sometimes fiscal or regulatory reporting. For that reason, the optimization workflow must be auditable. Every allocation result should show the source well test, test date, test confidence score, model version, PVT version, flow-correlation choice, facility meter used for reconciliation, constraints active during optimization, and final operating recommendation. This documentation allows a reviewer to understand how the final well-level rates were derived (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

A strong governance structure separates raw data, validated data, model assumptions, optimization outputs, and approved field instructions. Raw data should remain unchanged. Validated data should contain corrections and flags. Model assumptions should be version-controlled so that past allocation decisions can be reproduced. Optimization outputs should include both the recommended setpoints and the rejected alternatives. Approved field instructions should include implementation date, responsible person, risk controls, and monitoring requirements. This separation prevents the common problem where field decisions are made from a spreadsheet that cannot later be audited (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

Reporting should include both production gain and constraint movement. A recommendation that increases oil by 300 stb/d but raises water handling to 98% of capacity may be less robust than a recommendation that increases oil by 240 stb/d while keeping water handling at 85%. Publication-quality reporting should therefore present field production, well-level allocation, facility utilization, uncertainty range, and operational risk. The report should also state whether the gain is instantaneous, stabilized, or forecasted over a defined period (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

The recommended minimum dashboard contains: total oil, gas, water, and liquid rates; allocated rate by well; model-predicted rate by well; test date and confidence score; actual versus predicted manifold pressure; water-handling and gas-handling utilization; lift-gas allocation and marginal oil response; active constraints; and recommended next tests. This dashboard keeps the allocation workflow connected to day-to-day production management rather than confined to periodic engineering studies (Chaves & Ferreira Filho, 2024; Guluzada & Jabrail, 2026).

4.7 Economic Evaluation of Allocation Options

Although the title of this article emphasizes maximizing total field production, many field decisions should be tested economically. A field may increase oil rate through aggressive drawdown, but the additional production may require higher water handling, gas compression, chemical treatment, workover risk, or earlier facility debottlenecking. The engineering optimum and the economic optimum are therefore not always identical. A publication-ready allocation study should clearly define whether it optimizes physical production, net oil, cash flow, or net present value (Salehian et al., 2021; Yadua & Lawal, 2023).

A simple economic objective can be written as net value equals oil revenue plus gas revenue minus water disposal cost, gas compression cost, lift-gas opportunity cost, chemical cost, power cost, and expected intervention cost. For mature fields, including water and gas penalties is especially important because high gross liquid wells can occupy scarce capacity while contributing little oil. For gas-lifted fields, lift gas should be priced as an opportunity cost because gas used inefficiently in one well cannot be used in another well or sold/exported (Salehian et al., 2021; Yadua & Lawal, 2023).

Economic ranking should be performed after technical screening. Unsafe options, hydrate-prone options, sand-risk options, and reservoir-management violations should be removed before economic optimization. The remaining options can then be ranked by incremental oil, incremental net value, payback period, and robustness. This prevents a superficially profitable operating point from being selected when it violates integrity or long-term recovery objectives (Salehian et al., 2021; Yadua & Lawal, 2023).

For reporting purposes, the production engineer should distinguish between three benefits: recovered deferred production, accelerated production, and incremental recovery. Recovered deferred production occurs when bottlenecks or poor allocation suppress current rates. Accelerated production occurs when the field produces faster, but ultimate recovery is unchanged. Incremental recovery occurs when the allocation improves sweep, pressure management, or reservoir contact in a way that increases recoverable reserves. These categories have different economic meanings and should not be combined without explanation (Salehian et al., 2021; Yadua & Lawal, 2023).

5. Conclusion

Optimizing production allocation using well test data and nodal analysis is a practical route to maximizing total field production under real operating constraints. The central contribution of the method is that it shifts decision-making from static test-based percentages to dynamic field-wide optimization. Well tests provide the measured evidence, nodal analysis provides the physics-based interpretation, field-network modelling captures well interactions, and constrained optimization identifies the best allocation of drawdown, lift energy, choke settings, routing, and facility capacity (Rahmanifard & Gates, 2024; Zhang et al., 2025).

The article concludes that the best-producing field is not necessarily the field in which every well is fully opened. It is the field in which each well is operated at the point where its marginal contribution to total field value is positive after accounting for pressure interactions, fluid-handling burden, artificial-lift efficiency, reservoir management, and integrity limits. Recent studies from 2020 to 2026 support this integrated perspective by demonstrating the value of nodal analysis, back allocation, well-test interpretation, integrated production systems, and optimization algorithms in production management (Rahmanifard & Gates, 2024; Zhang et al., 2025).

For implementation, operators should build a closed-loop allocation process: validate well tests, calibrate nodal models, reconcile well rates with facility totals, optimize under constraints, implement recommendations in stages, and update the model with new surveillance data. This workflow improves production, reduces deferment, supports transparent allocation, and strengthens the technical basis for field operations (Rahmanifard & Gates, 2024; Zhang et al., 2025).

5.1 Recommendations

Operators should establish a formal well-test quality ranking system so that allocation and model calibration are weighted according to data reliability (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

Production teams should maintain calibrated nodal models for all material wells and update them after major operating changes, interventions, or abnormal surveillance trends (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

Field allocation should be optimized using total field oil or economic value under water, gas, pressure, lift, routing, integrity, and reservoir-management constraints (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

Back allocation should be used to reconcile individual well estimates with facility production where continuous well metering is unavailable, but the procedure should remain auditable and tied to validated well tests (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

Sensitivity and uncertainty analysis should accompany every major allocation recommendation, especially where changes affect high-rate wells or shared surface constraints (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

Machine-learning tools should be used to support anomaly detection, forecasting, and scenario screening, while physics-based nodal analysis remains the governing model for operational setpoint decisions (Chaves & Ferreira Filho, 2024; Society of Petroleum Engineers, 2025).

5.2 Future Research Directions

Future work should focus on tighter integration between well-test scheduling and production allocation optimization. Instead of testing wells on a calendar basis, the next test should be selected by value of information: the well whose uncertainty most affects the current optimization decision should be tested first. This approach can reduce testing cost and deferment while improving allocation reliability (Rahmanifard & Gates, 2024; Zhang et al., 2025).

Another research direction is the development of hybrid models that combine nodal analysis, real-time production data, and machine-learning uncertainty estimates. Hybrid models are valuable because they preserve physical consistency while using data-driven tools to detect anomalies and accelerate scenario screening. The main challenge is ensuring that the model does not recommend setpoints outside safe or physically meaningful operating envelopes (Rahmanifard & Gates, 2024; Zhang et al., 2025).

There is also a need for better treatment of multiphase-flow uncertainty in allocation optimization. Flow correlations can give different pressure-loss estimates, especially in deviated wells, high-gas systems, and slugging-prone flowlines. Future allocation workflows should quantify this uncertainty and present recommendations that are robust across plausible correlation choices rather than dependent on one model assumption (Rahmanifard & Gates, 2024; Zhang et al., 2025).

Finally, more published case studies are needed from mature African fields, including Niger Delta assets, where production allocation is strongly affected by aging facilities, commingled production, water-handling limitations, gas constraints, and data-quality challenges. Such studies would improve the practical transferability of allocation frameworks to fields where full real-time metering and high-frequency pressure surveillance may not be available (Rahmanifard & Gates, 2024; Zhang et al., 2025).

5.3 Limitations of the Proposed Framework

The framework presented in this article is deliberately comprehensive, but it has limitations. First, its effectiveness depends on the availability and quality of well test, pressure, PVT, and facility data. In fields where tests are infrequent, pressure gauges are unreliable, or operating histories are poorly documented, the calibrated model may not distinguish between true reservoir decline and measurement error. Under such conditions, the framework should be implemented in phases, beginning with data clean-up and prioritized retesting before advanced optimization is attempted (Zhao et al., 2022; Salehian et al., 2021).

Second, nodal analysis simplifies complex multiphase flow. Different correlations may predict different pressure gradients in wells with high deviation, high gas fraction, unstable flow, severe slugging, wax deposition, scale, or hydrate risk. The model should therefore be treated as a decision-support tool rather than an exact representation of the field. Engineering judgement remains necessary, especially where integrity risks or unusual operating regimes exist (Zhao et al., 2022; Salehian et al., 2021).

Third, optimization can produce mathematically attractive solutions that are operationally difficult. A recommendation may require frequent choke changes, routing changes, compressor adjustments, or field actions that exceed the capacity of the operations team. The final allocation should therefore include an implementability screen. A slightly lower-rate solution that is stable, simple, and safe may be preferable to a higher-rate solution that depends on tight control and frequent manual intervention (Zhao et al., 2022; Salehian et al., 2021).

Fourth, the objective of maximizing total field production may conflict with long-term reservoir-management objectives. Higher short-term drawdown can accelerate water or gas coning, worsen sweep, or reduce pressure support. For this reason, production allocation should be aligned with reservoir strategy and should include limits on drawdown, voidage imbalance, water cut, gas-oil ratio, and reservoir pressure decline. The proposed workflow is strongest when reservoir engineers, production engineers, and operations personnel use the same model and agree on the optimization objective (Zhao et al., 2022; Salehian et al., 2021).

5.4 Final Integrated Model for Publication and Field Use

The final integrated model proposed by this article is a closed-loop field optimization system. It begins with validated well tests, uses nodal analysis to translate tests into deliverability curves, integrates the curves into a surface-network model, reconciles model rates with facility measurements through back allocation, and applies constrained optimization to recommend field setpoints. The model is then updated using the actual field response. This cycle converts production allocation from a static reporting routine into an active production-maximization tool (Yadua & Lawal, 2023; Chaves & Ferreira Filho, 2024).

For publication purposes, the model can be summarized as follows: well tests define the evidence base; nodal analysis defines the physics; integrated production modelling defines the interaction among wells; optimization defines the best feasible operating point; and surveillance defines the feedback mechanism. Each part is necessary. Well tests without models cannot predict new operating conditions. Models without tests may be uncalibrated. Optimization without constraints may be unsafe. Surveillance without decision rules may produce data but not production gain (Yadua & Lawal, 2023; Chaves & Ferreira Filho, 2024).

In practical terms, the framework offers a disciplined answer to a recurring field question: where should the next unit of drawdown, lift energy, or facility capacity be assigned? The answer should go to the well or group of wells that provides the highest marginal contribution to stable total field production after accounting for water, gas, pressure, lift, routing, reservoir, and integrity constraints. This is the essential logic of optimized production allocation using well test data and nodal analysis (Yadua & Lawal, 2023; Chaves & Ferreira Filho, 2024).

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