

Process Simulation Framework for Optimizing Performance in Large-Scale Natural Gas Processing Facilities

Eromosele Asibor¹, Nwakamma Ninduwezuor-Ehiobu²,

¹Shafnet Exploration and Production Ltd,
Lagos State, Nigeria; EromsAsibor@gmail.com

²FieldCore Canada, A GE Vernova Company
Corresponding Author: EromsAsibor@gmail.com
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Abstract

This paper develops a governed simulation lifecycle that connects model credibility, operating envelopes, process safety, reliability, and economic optimization. The study responds to the problem that gas plants face changing feed composition, pressure, temperature, contaminants, throughput, equipment condition, utility limits, and product specifications. It uses an integrative conceptual review of scholarly and professional literature published to date, drawing on process simulation, process systems engineering, natural-gas processing, and process safety sources. The framework organizes eight decision functions: model-purpose definition, thermodynamic method selection, data reconciliation, calibration and validation, sensitivity analysis, optimization, dynamic scenario testing, model governance. It applies those functions across inlet separation, acid-gas removal, dehydration, hydrocarbon dew-point control, compression, fractionation and utilities. The analysis treats uncertainty, process safety, reliability, environmental performance, resource efficiency, economics, and organizational control as connected requirements. The proposed architecture links a system definition, evidence register, model assumptions, intervention portfolio, verification plan, and learning cycle. Its central proposition is that validated steady-state and dynamic models support design, debottlenecking, control, energy efficiency, reliability, and safe operating decisions only when those decisions preserve traceability from measured conditions to selected actions and verified outcomes. The paper offers testable propositions, an implementation roadmap, asset-specific application protocols, and a research agenda. The framework supports case-study testing and quantitative extension without claiming universal performance before field validation.

Keywords: *process simulation; process engineering; reliability; process safety; risk management; asset integrity; environmental performance; decision framework*

Introduction

Reliable process simulation links feed variability, equipment limits, control behavior, utility constraints, and product specifications within a governed model lifecycle. Gas processing plants face continually changing feed composition, pressure, temperature, contaminant loading, throughput, equipment condition, utility availability, and product specifications, and local actions taken to manage one of these variables affect adjacent equipment, utilities, product quality, emissions, workforce exposure, and supply continuity. A defensible framework must therefore define both the physical process and the decision system through which evidence becomes action.

For hydrocarbon dew-point control, the decision model must represent compressor surge explicitly, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because dew-point control sits immediately downstream of compression and inherits its disturbances. Calibration and validation supply part of the evidence for this representation, but no single dataset establishes technical adequacy on its own; the reviewer should record source date, operating mode, measurement uncertainty, model version, and accountable owner so that an apparently precise result cannot conceal a weak underlying assumption, and so that later operating experience can update the decision rather than sit in a separate record. Emerging digital twin and predictive analytics practice extends this evidentiary logic by keeping a live software representation of the asset synchronized with plant data, which increases the premium on the same traceability this framework requires (Kritzinger, Karner, Traar, Henjes, & Sihn, 2018; Rasheed, San, & Kvamsdal, 2020; Cameron, Waaler, & Komulainen, 2018) (Adeyelu, 2018; Ogunwole & Okeke, 2021; Ike & Akokodaripon, 2022) (Ogunwole et al., 2021; Adeyelu, 2018; Ogbuefi et al., 2022). (Qin & Badgwell, 2003; Ilodigwe & Adesemoye, 2021; Okoruwa et al., 2020)=This paper's aim is to develop and justify a governed simulation lifecycle for natural-gas processing facilities that links thermodynamic and unit-operation modeling choices to operating, safety, and economic decisions. The scope covers inlet separation, acid-gas removal, dehydration, hydrocarbon dew-point control, compression, and fractionation and utilities, with attention to how a steady-state or dynamic model of hydrocarbon dew-point control must represent compressor surge, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, before the model can be trusted for debottlenecking or control decisions. The paper's contribution is threefold: it organizes eight simulation-lifecycle functions into a single decision architecture, it ties each function to a verifiable evidence requirement rather than a completed deliverable, and it produces testable propositions that later empirical work can confirm or refute (Cameron & Hangos, 2001). This contribution also responds to a broader shift toward predictive analytics and data driven decision systems across capital intensive industries, in which forecasting and optimization models are expected to support, rather than replace, accountable engineering judgment (Aifuwa et al., 2020; Anene & Clement, 2022; Unamma, Ashore-Onisemo, Iwuanyanwu, & Okwesa, 2018) (Tonoyan & Ayivi-Donkor, 2021b; Aifuwa & Olatunde-Thorpe, 2020; Atakpa, 2021) (Tonoyan et al., 2021; Tonoyan et al., 2021). A recurring difficulty in natural-gas process simulation is that fractionation and utilities systems are validated in isolation from the upstream trains that set their feed conditions, so a model that predicts off-specification export gas at the sales meter may still fail because the calibration evidence for compression or dehydration was never reconciled with it. The analysis therefore treats calibration, uncertainty review, and model-change control as connected requirements that must be demonstrated jointly rather than section by section. This scoping choice follows established guidance that a process model's credibility depends on the full chain of assumptions from raw measurement to final decision, not on any single validation exercise (Seider, Seader, Lewin, & Widagdo, 2009). The wider promise, and limits, of artificial intelligence and machine learning in chemical engineering practice reinforce why such reconciliation cannot be assumed automatically from an algorithm's output (Venkatasubramanian, 2019; Lee, Shin, & Realff, 2018) (Filani & Wedraogo, 2022; Mbonu & Uzoka, 2021b) (Mbonu et al., 2021; Ogeawuchi et al., 2022).

Theoretical Framework

Gas-plant simulation needs defined upset scenarios, credible input data, tested safeguards, and accountable model decisions (Kaplan & Garrick, 1981; Reason, 1997; Center for Chemical Process Safety, 2007; International Organization for Standardization, 2018) (Arumosoye & Obriki, 2021; International Organization for Standardization, 2015; Edivri & Oteri, 2022; Unamma et al., 2018) (Arumosoye & Obriki, 2021; Arumosoye & Obriki, 2020; Obogo et al., 2021). System boundary definition fixes the physical, informational, utility, and market interfaces that a natural-gas process simulation must represent before any downstream calculation is credible. For hydrocarbon dew-point control, the boundary must include the interface with upstream compression, because a model that excludes compressor surge, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, will understate the disturbances the dew-point control train actually experiences. Thermodynamic method selection is one piece of the evidence, but boundary completeness across process, utility, and organizational interfaces is what a model-purpose statement must certify before that evidence is trusted (Seider, Seader, Lewin, & Widagdo, 2009). Process systems engineering scholarship frames this boundary setting task as a core research challenge for the field, and recent work on surrogate modeling shows how a well scoped boundary also determines which reduced order representations remain valid substitutes for a full simulation (Grossmann & Westerberg, 2000; McBride & Sundmacher, 2019) (Mbonu & Oluoha, 2018; Sunday & Oluokun, 2019; Sunday & Omoegun, 2022) (Mbonu et al., 2018; Mbonu et al., 2019; Mbonu et al., 2019).

Functional requirements for compression must state which operating modes the model is expected to reproduce, including startup, turndown, and the relief-overload condition, together with its initiating conditions, detection limits, safeguards, recovery time, and downstream effects. Data reconciliation supplies part of the evidence that a stated functional requirement is actually met, but the requirement itself should be fixed by the design basis and the plant's safe operating limits, not adjusted after the fact to match whatever the model happens to predict. This sequencing, in which functional requirements precede evidence collection, mirrors standard chemical-process design practice (Towler & Sinnott, 2013). Representing the compressor's own surge dynamics inside that functional requirement draws on established nonlinear models of surge and rotating stall, and on multivariable feedback control theory for keeping the compressor within its stable operating region (Gravdahl & Egeland, 1999; Skogestad & Postlethwaite, 2005) (Dogbatsey & Oyeleye, 2019) (Eyetsemitan et al., 2022).

For fractionation and utilities, the functional requirement is that the simulation represent off-specification export gas as a plant-wide event rather than a column-level event, since export quality depends on utility availability, upstream composition, and control-loop interaction as much as on tray or packing performance. Calibration and validation supplies part of the evidence for this requirement, but the requirement should be written into the model-purpose statement so that a model that is accurate in the column but wrong at the export meter is flagged rather than accepted. This whole-plant framing is consistent with process design and integration guidance that treats utility and product-quality constraints as first-class design variables (Smith, 2016). Digital control theory supplies the implementation layer for these constraints once they are defined, since a continuous model-purpose statement must ultimately be executed through sampled, discretized control logic (Ogata, 2010; Franklin, Powell, & Workman, 1998) (Akomolafe & Agu, 2018). These theoretical foundations anchor the eight-function decision architecture developed in the sections that follow. Verification and validation theory establishes that model credibility must be tested against independent evidence rather than assumed from convergence alone (Sargent, 2013),

classical process-modeling theory establishes that a deterministic model requires an explicit, testable structure rather than an implicit best fit to available data (Himmelblau & Bischoff, 1968), and established thermodynamic theory, including cubic equations of state validated against measured phase behavior, supplies the property methods on which every downstream unit-operation model depends (Peng & Robinson, 1976; Soave, 1972). Together, this theoretical base support treating model-purpose definition, thermodynamic method selection, data reconciliation, calibration and validation, sensitivity analysis, optimization, dynamic scenario testing, and model governance as a single, evidence-linked decision architecture rather than as eight independent technical exercises. Statistical treatments of model calibration and uncertainty propagation extend this same logic by formalizing how measured plant data should update, rather than simply confirm, a simulation's parameters and its credible range of prediction (Kennedy & O'Hagan, 2001; Trucano, Swiler, Igusa, Oberkampf, & Pilch, 2006; Oberkampf & Roy, 2010). Generalized corresponding states correlations and standard compilations of pure component and mixture properties extend this property method foundation to the vapor pressure, density and transport property estimates that a natural gas process simulation consumes at every stage (Lee & Kesler, 1975; Poling, Prausnitz, & O'Connell, 2001). Classical transport phenomena theory, in turn, underlies the gravity and momentum-based separation mechanisms that inlet separation depends on before any hydrate risk calculation is meaningful (Bird, Stewart, & Lightfoot, 2002) (Mbonu & Uzoka, 2021a; Adegbite & Ahmed, 2022) (Mbonu et al., 2021).

Methodology

This review follows an integrative conceptual method rather than a statistical meta-analysis, because the framework synthesizes design textbooks, process-safety standards, and applied simulation studies that use incompatible reporting formats. Sources were selected for direct relevance to natural-gas process simulation and were screened against a hard cutoff of December 2022; no source published after that date is included. Coding proceeded unit operation by unit operation, so that evidence on inlet separation and its principal failure mode, hydrate formation, could be compared against the same evidence categories used for every other train in the plant, including initiating conditions, detection limits, safeguards, recovery time, and downstream effects. This approach follows the logic of process modeling texts that treat model scope and assumption inventories as the first synthesis task (Franks, 1972). Coding also drew on the growing literature on soft sensors and data visualization platforms for continuous plant performance monitoring, since these tools increasingly define what counts as usable operating data for a natural gas process simulation (Kadlec, Gabrys, & Strandt, 2009; Ogbale, Okoruwa, Babatope, & Oyewole, 2021) (Ogbale & Akeju, 2021; Okonkwo & Okeke, 2021; Orise & Niniola, 2020) (Okonkwo et al., 2021).

Thematic coding distinguished four evidence types that recur across the reviewed literature: thermodynamic and physical-property evidence, operating and measurement data, safety and reliability evidence, and economic evidence. For acid-gas removal, this coding surfaced a specific gap in how liquid carryover is represented across sources, since some studies treat it as a control problem and others as a mechanical-design problem, with initiating conditions, detection limits, safeguards, recovery time, and downstream effects reported inconsistently. Synthesis logic resolved this by mapping each source's findings onto the paper's eight-function decision architecture rather than onto the source's own vocabulary, which is the approach recommended for cross-disciplinary process-safety synthesis (Center for Chemical Process Safety, 2007). Safety and reliability evidence was further benchmarked against the process fault detection and diagnosis

literature, which offers an independent classification of quantitative model based methods for distinguishing a genuine process fault from a measurement artifact (Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003; Isermann, 2005) (Center for Chemical Process Safety, 2016). The final synthesis step cross-checked each thematic claim against at least one independent source before it was admitted into the framework. For dehydration, for example, claims about solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, were retained only where design guidance and applied case studies agreed. This cross-checking step reduces the risk that a single well-cited but narrow study drives a framework-level conclusion, consistent with recommended practice for verifying simulation-relevant evidence before it is used in a decision model (Sargent, 2013). Economic evidence was screened against established process cost estimation practice and against recent reviews of simulation based cost optimization, so that a claimed economic benefit could be traced to a specific costing method rather than to an unstated assumption (Ulrich & Vasudevan, 2004; Tonoyan, Dada, & Ayivi-Donkor, 2022a) (Tonoyan & Ayivi-Donkor, 2022a; Tonoyan & Ayivi-Donkor, 2021a) (Tonoyan et al., 2022).

Findings and Discussion

Framework Architecture and Technical Basis

Inlet separation removes free liquids and solids from the wellstream before the gas enters downstream conditioning, and its governing mechanisms, gravity and mist-elimination settling, momentum-based separation, and level control, must be represented explicitly if the simulation is to predict hydrate formation risk correctly. Hydrate formation occurs when free water, low temperature, and elevated pressure combine in the presence of light hydrocarbons, and a credible model must capture its initiating conditions, detection limits, safeguards, recovery time, and downstream effects rather than treating hydrate risk as a fixed design margin, following established hydrate-formation prediction methods for natural-gas systems (Campbell, 2004; Sloan & Koh, 2008). Equipment-integrity evidence, including corrosion-inhibitor performance in the separator internals, should be reconciled with the same model rather than tracked in a separate maintenance record. Reference data on natural gas engineering and on the practical design of gas processing facilities provide the equipment level detail, such as separator internals and mist eliminator configuration, that a hydrate risk representation must reflect if it is to remain plant specific rather than generic (Katz & Lee, 1990; Bahadori, 2014) (International Organization for Standardization, 2016; Agbabiaka & Okeke, 2019; Dada & Oluwo, 2021a) (Agbabiaka et al., 2019; Okonkwo et al., 2020; Adeyelu, 2021).

Acid-gas removal by amine absorption is constrained by solvent circulation rate, lean-amine loading, and contactor hydraulics, and its principal simulation-relevant failure mode, liquid carryover into the downstream sweet-gas or acid-gas piping, must be represented with its initiating conditions, detection limits, safeguards, recovery time, and downstream effects rather than assumed away by an idealized separation efficiency. Field experience compiled from natural-gas processing facilities documents the equipment and instrumentation limits that govern this failure mode (Manning & Thompson, 1991). Optimization supplies part of the evidence for an acceptable operating envelope, but that envelope should also reflect non-destructive-testing and integrity findings from the contactor and reboiler circuits, since corrosion-driven wall loss changes the hydraulic and thermal boundary conditions the model assumes. Established gas purification references and natural gas transmission and processing handbooks document the contactor and

reboiler configurations against which a liquid carryover representation should be benchmarked (Kohl & Nielsen, 1997; Mokhatab, Poe, & Speight, 2006) (Ogeawuchi et al., 2022).

Dehydration by triethylene glycol absorption is constrained by contactor temperature, glycol purity, and regenerator reboiler duty, and its principal failure mode, solvent degradation from thermal breakdown, oxygen ingress, or contamination, must be represented with its initiating conditions, detection limits, safeguards, recovery time, and downstream effects rather than assumed constant across a simulation run. Surface-facility design references document the equipment configurations and control philosophies used to manage this failure mode (Arnold & Stewart, 2008). Dynamic scenario testing supplies part of the evidence, but the model should also draw on weld and pressure-boundary integrity evidence from the regenerator and reboiler, since degraded metal condition changes the credible upset scenarios the simulation must reproduce. Comparative studies of alternative dehydration technologies and general natural gas handbooks provide independent benchmarks for the solvent degradation and regeneration performance a dehydration model must reproduce (Netusil & Ditl, 2011; Speight, 2019).

A natural-gas process simulation is only as reliable as the measurements that feed it, so the data architecture for inlet separation must define which variables, composition, pressure, temperature, level, and differential pressure across mist eliminators, carry quality flags and uncertainty bounds before they are used to test for hydrate formation, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects. Systematic data reconciliation methods correct for instrument bias and random error so that reconciled values, not raw readings, drive the hydrate-risk calculation (Narasimhan & Jordache, 2000). Lifecycle risk evidence from produced water management illustrates how the same reconciled measurement stream can be reused to support a safety case and an availability case simultaneously (Falegan & Aniebonam, 2022) (Atakpa & Abolaji, 2022) (Akpe et al., 2021; Aneke et al., 2022).

For acid-gas removal, the data architecture must reconcile solvent circulation rate, lean and rich loading, and contactor temperature profile against a mass and energy balance before liquid carryover, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, can be attributed to a specific operating cause rather than to instrument noise. Calibration and validation supplies part of the evidence, but gross-error detection should be applied first, since an uncorrected bad measurement can masquerade as a genuine process upset (Romagnoli & Sanchez, 2000) (Oyeleye & Fadayomi, 2022) (Oyeleye et al., 2022).

For dehydration, the data architecture must track glycol purity, circulation rate, and regenerator temperature with enough resolution to distinguish gradual solvent degradation, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, from short-term measurement noise. Sensitivity analysis supplies part of the evidence for which variables matter most, but the underlying data-quality rules should be fixed independently of that analysis so that a variable is not excluded merely because early data made it look unimportant (Cameron & Hangos, 2001). Model development for inlet separation should separate three categories of assumption: fixed physical properties, calibrated equipment parameters, and scenario-dependent operating inputs, so that a reviewer can tell which assumptions require re-validation when conditions change. Acceptance criteria for hydrate-formation representation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, should be set before the model is exercised against plant data, following recommended verification and validation practice for simulation models generally (Sargent, 2013).

For acid-gas removal, validation evidence should compare simulated and measured lean and rich amine loading, contactor temperature profile, and treated-gas acid-gas content across more than

one operating point, since a single-point match does not establish that the model correctly represents liquid carryover, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, at other conditions. Thermodynamic method selection supplies part of the evidence, but structured model-analysis methods help separate a poor thermodynamic fit from a poor hydraulic or kinetic assumption (Cameron & Hangos, 2001). Classical separation process theory supplies the vapor liquid equilibrium and mass transfer relationships against which such multi point validation should be checked (Seader, Henley, & Roper, 2011).

For dehydration, validation should test the model's water dew-point prediction against field dew-point measurements across a range of glycol circulation rates, since agreement at design conditions does not guarantee agreement once solvent degradation, its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, begins to shift regenerator performance. Early process-simulation methodology already established that deterministic process models require an explicit, testable structure rather than an implicit best fit to whatever data are available (Himmelblau & Bischoff, 1968). Equipment selection and process design references remain a useful cross check on whether a mismatch between predicted and measured dew point reflects a genuine solvent degradation problem or an unmodeled equipment limitation (Walas, 1990).

Screening, Risk, and Economic Evaluation

Screening criteria for hydrocarbon dew-point control interventions should rank options by their effect on compressor surge margin, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, alongside their capital cost and effect on hydrocarbon dew point, rather than by capital cost alone. Conceptual process design methods provide a structured way to generate and screen such alternatives before detailed simulation work begins, so that the framework is not applied to options that a first-pass economic or hydraulic check would already reject (Douglas, 1988) (Okonkwo & Mayo, 2019) (Okonkwo et al., 2019).

For compression, screening should prioritize interventions that address the root cause of relief overload, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, ahead of interventions that only add relief capacity, since capacity addition treats a symptom rather than the underlying disturbance. Structured retrofitting methods for existing process plant provide criteria for this kind of root-cause prioritization when the unit cannot be redesigned from scratch (Rangaiah, 2016). The Tennessee Eastman plant wide control problem and classical reviews of nonlinear process control remain useful reference cases for testing whether a proposed root cause fix actually removes the disturbance rather than only compensating for it (Downs & Vogel, 1993; Bequette, 1991).

For fractionation and utilities, screening should weigh interventions against their effect on off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, using a documented decision rule rather than engineering judgment applied inconsistently across cases. Table 1 summarizes the eight decision stages used throughout this framework, the primary evidence question each stage answers, and the accept, revise, study, defer, or reject output each stage produces; formal optimization methods provide the underlying basis for ranking competing interventions once that evidence is assembled, and risk-based inspection findings on export-line integrity should inform which interventions are screened out on integrity grounds alone (Edgar, Himmelblau, & Lasdon, 2001; American Petroleum Institute, 2016). Established distillation design practice and structured pinch based energy integration methods give the screening rule its technical content for fractionation and utilities, since a competing intervention's effect on tray performance and on overall utility demand must be assessed

together (Kister, 1992; Kemp, 2007) (Efobi & Fasawe, 2022b; Badmus & Ozowara, 2019a; Okonkwo & Okeke, 2018b) (Okonkwo et al., 2018).

Figure 1 presents a conceptual histogram for diagnosing model residuals during calibration. Table 1 instead provides model-quality measures for constraint accuracy, uncertainty, energy performance, and revalidation.

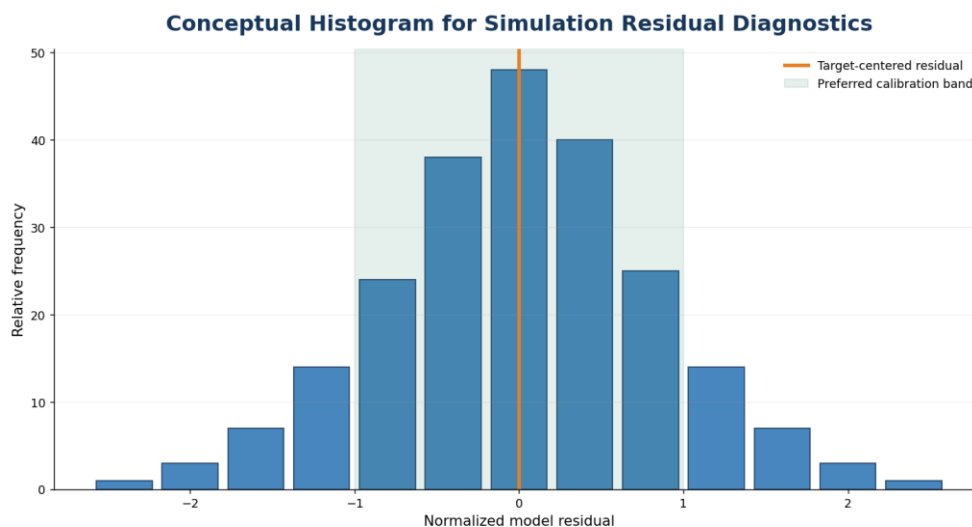


Figure 1. Conceptual normalized-residual histogram for process-simulation calibration.

Table 1. Model-Quality Metrics for Governing Natural-Gas Process Simulation

Quality dimension	Measure	Acceptance signal	Decision supported
Mass balance	Component closure error	Error stays within the approved tolerance	Accept model reconciliation
Thermodynamics	Property prediction deviation	Method reproduces reference behavior	Approve property package
Calibration	Prediction error by unit	Bias is small and explainable	Release calibrated model
Constraints	Limit representation accuracy	Trips and bottlenecks match plant evidence	Use for debottlenecking
Control response	Dynamic response error	Timing and direction match tests	Use for control studies
Energy performance	Specific energy error	Utilities reconcile with measured demand	Evaluate energy options
Uncertainty	Output range confidence	Decision holds across credible inputs	Authorize optimization

Quality dimension	Measure	Acceptance signal	Decision supported
Model currency	Age since validated update	Model reflects current configuration	Schedule revalidation

For hydrocarbon dew-point control, the hazard and reliability dimension centers on compressor surge, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because a surge event can damage rotating equipment within seconds and simultaneously create a process safety and reliability event. Structured hazard evaluation procedures, applied at the model-purpose stage rather than after a design is fixed, help ensure that surge scenarios are represented rather than assumed to be adequately covered by a generic surge margin (Center for Chemical Process Safety, 1992). Established loss-prevention references document how compressor and rotating-equipment failure modes interact with the wider process safety envelope (Mannan, 2012) (Center for Chemical Process Safety, 2007) (Obogo et al., 2021). For compression, quantitative risk analysis should evaluate relief overload, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, against consequence models for overpressure and loss of containment, not only against a qualitative likelihood ranking (Center for Chemical Process Safety, 2000). The same quantitative framing applies to pipeline and interconnecting piping risk, where quantitative risk analysis of pipeline systems laid in a shared corridor shows how failure frequency and consequence estimates can be combined into a single risk metric that supports comparable decisions across assets (Zhang, Qin, & Wang, 2019) (Amayo, 2017).

For fractionation and utilities, environmental and reliability performance both depend on how the model represents off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, since an export excursion can trigger flaring, emissions events, and customer contractual consequences simultaneously. Hazard and operability review of the fractionation and utility train should be repeated whenever the model-purpose statement changes, following established HAZOP practice, so that a revised model does not silently drop a hazard scenario that an earlier review had captured (Kletz, 1999).

Operating-envelope integration for hydrocarbon dew-point control translates the model's compressor surge margin, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, into a daily operating limit that operators can act on without re-running the simulation. This translation follows standard process-control practice for defining safe operating envelopes around a controlled variable's constraint boundary rather than around its set point alone (Seborg, Edgar, Mellichamp, & Doyle, 2016).

For compression, the operating envelope should state the excursion-response actions required when relief overload, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, approaches its limit, and should specify who is authorized to approve a temporary limit change. Process-control design practice treats this kind of constraint-

handling logic as part of the control system design itself, not as a separate operating procedure layered on afterward (Marlin, 2000). Model predictive control practice formalizes this kind of constraint handling directly inside the controller, which is why several operating facilities implement the compression operating envelope as an explicit constraint set rather than as a separate procedure (Camacho & Bordons, 2007).

For fractionation and utilities, the operating envelope must connect off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, to the utility and upstream conditions that most often precede it, so that operators receive an early warning rather than only a post-event alarm. Process dynamics and control theory for multivariable systems supports this kind of anticipatory envelope design when the export specification depends on several coupled process variables (Ogunnaike & Ray, 1994).

Barrier assurance for inlet separation should evaluate each layer, level control, high-level trip, and downstream slug catcher, against hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, using a documented layer-of-protection method rather than a qualitative statement that adequate safeguards exist (Center for Chemical Process Safety, 2001). Barrier definitions should also state each layer's intended performance standard explicitly, following the classification of safety barriers into prevention, detection, control, and mitigation functions (Sklet, 2006).

For acid-gas removal, barrier testing should confirm that instrumentation intended to detect liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, is included in the plant's hazard and operability review and its safety instrumented function assignment, following the structured HAZOP application guidance used across the process industries (International Electrotechnical Commission, 2001). Where a safety instrumented system is the assigned barrier, its safety integrity level should be established and periodically tested according to the applicable functional-safety standard (International Electrotechnical Commission, 2016) (Amayo & Popoola, 2017a) (Obriki & Arumosoye, 2021).

For dehydration, barrier impairment tracking should flag when solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, has degraded a safeguard's assumed performance, such as a relief valve sized against a solvent composition that no longer holds. Pressure-relieving and depressuring system design guidance provides the basis for re-checking relief-valve sizing when process conditions drift from the original design case (American Petroleum Institute, 2014), and pipeline and facility safety management system requirements provide the organizational mechanism for ensuring that such a re-check is actually triggered and closed out (American Petroleum Institute, 2015) (Adeyelu, 2019; American Petroleum Institute, 2016) (Mgbame et al., 2022; Adeyelu, 2019; Akpe et al., 2022).

Techno-economic evaluation of hydrocarbon dew-point control interventions should express compressor surge margin, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, in the same economic terms as capital cost and downtime, using established plant-cost estimation methods so that a safety-motivated intervention and a purely economic one are compared on the same basis (Peters, Timmerhaus, & West, 2003).

For compression, economic evaluation should quantify the cost of relief overload, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, in terms of lost production, equipment damage risk, and flare or emissions cost, following standard chemical-process economic evaluation methods that link process simulation outputs directly to equipment sizing and cost correlations (Turton, Bailie, Whiting, & Shaeiwitz, 2012). Broader process engineering economics treats this kind of energy and equipment costing as a single

accounting exercise, and recent reviews of simulation driven cost optimization confirm that the same steady state model used for design can also support the economic case for a relief system upgrade (Skogestad, 2008; Tonoyan, Dada, & Ayivi-Donkor, 2022b) (Tonoyan & Ayivi-Donkor, 2022c; Tonoyan & Ayivi-Donkor, 2022b; Atta & Adenuga, 2020) (Tonoyan et al., 2022).

For fractionation and utilities, resource evaluation should connect off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, to energy intensity and reprocessing cost, using thermophysical property and unit-cost data appropriate to the specific gas composition (Green & Southard, 2019). This evaluation should be organized within an asset-management framework that treats the simulation model itself as a value-bearing asset requiring its own lifecycle plan (International Organization for Standardization, 2014). Standard thermodynamic property compilations remain the underlying data source for the energy intensity calculations this resource evaluation depends on, since an error in estimated heat capacity or latent heat propagates directly into the reported reprocessing cost (Sandler, 2006) (Ogbete & Ambali, 2020; Annan, 2022; Ahiaeke Patrick & Okeke, 2021) (Patrick et al., 2021; Ogbete et al., 2020; Okonkwo et al., 2021).

Application Across Process Units

Model-purpose and boundary definition for inlet separation begins with an explicit decision statement: what design, debottlenecking, control, or safety decision will the model support, and under which operating modes. The team must specify what evidence will support that decision, which operating modes are included, and which assumptions require later confirmation. Because inlet separation is the plant's first line of defense against liquids and solids carried in the wellstream, the model-purpose statement must state whether hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, is in scope, since a purpose statement that omits this failure mode will produce a model that looks complete but cannot support a safety-relevant decision (Seider, Seader, Lewin, & Widagdo, 2009). Input records should identify source, timestamp, units, uncertainty, configuration, and accountable owner, and a decision threshold should be approved before the final ranking of design options is viewed, so that a favorable economic result cannot override a mandatory safety or legal constraint after the fact (Adewoyin, Ogunnowo, & Ezeugwa, 2020). A short case study of Aspen HYSYS based simulation of an operating natural gas processing plant illustrates how this kind of model purpose statement translates into an actual flowsheet, since the published case documents which streams and equipment items were included and why (Roy & Amin, 2011).

Validation of the model-purpose statement should draw on independent evidence from dehydration wherever the two trains share a common feed or utility, since acceptance should depend on observable performance rather than on completion of a report or work order. Suitable measures include separator availability, mist-eliminator differential pressure trend, detection coverage for hydrate precursor conditions, and verified risk reduction following any safeguard upgrade. The team should test sensitivity to uncertain feed composition, equipment condition, and utility availability, and a credible adverse case should combine hydrate formation with the loss of one important safeguard, such as a fouled or bypassed heater. Differences between predicted and observed performance should trigger a model review rather than an informal adjustment of the acceptance limit, and management of change should capture revised drawings, procedures, training, spares, software versions, alarm settings, and inspection requirements, converting the model-purpose exercise from a one-time study into a controlled operating capability (Komi & Adamolekun, 2021) (Obogo & Obriki, 2020b) (Obogo et al., 2020; Obriki et al., 2022).

Thermodynamic method selection for acid-gas removal begins with a decision statement that specifies which property method the simulation will use to represent vapor-liquid equilibrium between the amine solvent, water, and the acid gases, and why that method is appropriate for the pressure, temperature, and composition range the plant actually operates in. Cubic equations of state such as the Peng-Robinson formulation are well suited to the hydrocarbon-rich, low-polarity streams found elsewhere in the plant (Peng & Robinson, 1976), but acid-gas absorption in aqueous amine solutions is governed by chemical, not purely physical, equilibrium, so an activity-coefficient or electrolyte-specific package, rather than a cubic equation of state alone, is usually required to represent liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, with acceptable accuracy. Design and operating guidance for gas treating and conditioning documents which property methods are appropriate for which acid-gas removal chemistries and operating ranges (Kidnay, Parrish, & McCartney, 2019). Classical activity coefficient models developed for polar and associating liquid mixtures, including the Wilson, NRTL, and UNIQUAC formulations, provide the specific mathematical basis for the electrolyte and activity coefficient packages this selection favors over a cubic equation of state alone (Wilson, 1964; Renon & Prausnitz, 1968; Abrams & Prausnitz, 1975). Validation of the selected thermodynamic method should use independent evidence from hydrocarbon dew-point control wherever feasible, since both trains draw on the same feed characterization and the same underlying property data. Acceptance should depend on the method's ability to reproduce measured dew points, bubble points, and phase envelopes across the plant's actual operating range, not merely on convergence at a single design point. The team should test sensitivity of key outputs, such as treated-gas acid-gas content and hydrocarbon dew point, to alternative property-method choices, including the Soave-Redlich-Kwong formulation where it is the incumbent method (Soave, 1972), and a credible adverse case should include compressor surge occurring while the thermodynamic method is already operating near the edge of its validated composition range. Reference property data compiled for natural-gas processing provide an independent check on simulated phase behavior (Gas Processors Suppliers Association, 2017). Volume translation methods developed for cubic equations of state further improve the liquid density and dew point predictions this validation step checks, without requiring a change to the underlying equation of state itself (Peneloux, Rauzy, & Freze, 1982) (Ilodigwe & Adesemoye, 2019b). Data reconciliation for dehydration begins with a decision statement identifying which measured variables, glycol circulation rate, contactor and regenerator temperatures, and inlet and outlet water content, will be reconciled against a mass and energy balance before they are used to judge model performance. The team must specify what evidence will support the reconciliation, which operating modes are included, and which assumptions require later confirmation. Particular attention should be given to solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because degraded glycol changes both the measured and the true regeneration performance simultaneously, a distinction that systematic gross-error detection methods are specifically designed to make (Narasimhan & Jordache, 2000). Validation of the data-reconciliation procedure should use independent evidence from compression wherever feasible, since compressor suction and discharge measurements provide an energy-balance check that is largely independent of the dehydration measurements themselves. Acceptance should depend on the reconciled balance closing within a stated tolerance across several operating points, not merely at design conditions, and a credible adverse case should include relief overload occurring while the reconciliation procedure is already flagging an unresolved measurement discrepancy. Structured data-processing and reconciliation methods for

chemical process operations provide the statistical basis for setting and defending that tolerance (Romagnoli & Sanchez, 2000).

Steady-state calibration for hydrocarbon dew-point control begins with a decision statement specifying which calibrated parameters, such as tray or packing efficiency and heat-exchanger fouling factors, will be adjusted to match plant data, and over what range of throughput and feed composition that calibration is expected to remain valid. Particular attention should be given to compressor surge, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because a steady-state calibration performed only at normal throughput will not by itself demonstrate that the model behaves correctly as the compressor approaches its surge line. Verification and validation guidance for simulation models recommends stating the calibration's intended range of validity explicitly, rather than allowing it to be assumed from the calibration data alone (Sargent, 2013). Established models of compressor surge dynamics describe precisely this approach to the surge line as a function of speed and flow, which is why the calibration's range of validity should be stated relative to the surge margin rather than only to throughput (Gravdahl & Egeland, 1999).

Validation of the steady-state calibration should use independent evidence from fractionation and utilities wherever feasible, since both trains draw on the same compressed and conditioned gas stream. Acceptance should depend on the calibrated model reproducing plant data at more than one throughput and ambient-temperature condition, and a credible adverse case should include hydrate formation occurring upstream while the calibration is being exercised at an untested operating point. Model-analysis methods that separate structural, parametric, and measurement uncertainty help identify whether a calibration mismatch stems from the wrong model structure or simply the wrong parameter value (Cameron & Hangos, 2001).

Sensitivity and uncertainty analysis for compression begins with a decision statement identifying which input uncertainties, feed composition, ambient temperature, and fouling condition, are to be propagated through the model, and which output variables, such as discharge temperature and surge margin, that propagation is meant to inform. Particular attention should be given to relief overload, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because a sensitivity analysis that ignores the relief system will understate the consequence of an underestimated feed-composition uncertainty. Documented sensitivity-analysis practice warns that a poorly specified sensitivity study can produce a confident-looking but misleading ranking of important variables, which is why the analysis plan should be fixed before the results are seen (Saltelli, Aleksankina, Becker, Fennell, Ferretti, Holst, Li, & Wu, 2019). Formal Latin hypercube based uncertainty propagation methods give this sensitivity plan a defensible statistical basis for combining several uncertain inputs at once, rather than varying them one at a time (Helton & Davis, 2003).

Validation of the sensitivity and uncertainty analysis should use independent evidence from inlet separation wherever feasible, since feed-composition uncertainty originates upstream of compression and its true variability can be characterized from separator and wellstream sampling records. Acceptance should depend on the analysis correctly identifying variables already known, from plant experience, to matter for relief-system loading, and a credible adverse case should include liquid carryover from inlet separation coinciding with the uncertain feed condition the analysis is meant to bound. Deterministic simulation methods established for process analysis provide the modeling basis against which such an uncertainty propagation is checked (Franks, 1972).

Optimization and constraint handling for fractionation and utilities begins with a decision statement specifying the objective, typically maximizing recovery or minimizing energy use, and the hard constraints, including product specifications and utility limits, that any optimized operating point must satisfy. Particular attention should be given to off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because an optimization that treats the export specification as a soft rather than a hard constraint can recommend an operating point that is economically attractive but operationally infeasible. Nonlinear-programming formulations developed for constrained chemical-process optimization provide the mathematical basis for enforcing this distinction (Biegler, 2010; Edgar, Himmelblau, & Lasdon, 2001).

Validation of the optimization result should use independent evidence from acid-gas removal wherever feasible, since acid-gas content is itself a hard constraint on the export specification and any optimization that adjusts fractionation conditions without checking upstream treating performance risks recommending an infeasible point. Acceptance should depend on the optimized operating point being independently confirmed against a full steady-state simulation, not only against the optimizer's internal linearization, and a credible adverse case should include solvent degradation reducing the acid-gas removal margin at the same time the optimizer is recommending a tighter operating point. Real-time optimization practice in industrial processes documents how this kind of cross-checking is built into a production optimization cycle (Darby, Nikolaou, Jones, & Nicholson, 2011). Adaptation strategies developed for real time optimization address the same gap between an optimizer's internal model and full plant behavior by updating the model itself as new plant data arrive, rather than only re solving the optimization problem (Chachuat, Srinivasan, & Bonvin, 2009) (Ike & Akokodari, 2021).

Dynamic scenario testing for inlet separation begins with a decision statement specifying which transient scenarios, startup, shutdown, turndown, and credible upset, the dynamic model must reproduce, and what response is considered acceptable in each case. Particular attention should be given to hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because a steady-state model cannot show whether a transient cooldown during a turndown event creates a temporary hydrate-formation window that a steady-state case would miss. Dynamic process simulation and control methods provide the modeling basis for representing this kind of transient, time-dependent risk (Luyben, 1990; Seborg, Edgar, Mellichamp, & Doyle, 2016; Bequette, 1998).

Validation of the dynamic scenario testing should use independent evidence from dehydration wherever feasible, since both trains typically share the same startup and shutdown sequence and the same utility ramp-up profile. Acceptance should depend on the dynamic model reproducing the timing, not only the final steady value, of a recorded plant transient, and a credible adverse case should include compressor surge occurring during the same transient window the dynamic dehydration test is meant to validate. Classical treatments of chemical process control emphasize that a control scheme validated only at steady state provides no assurance about its transient performance (Stephanopoulos, 1984), a point also emphasized in nonlinear process-control treatments that distinguish steady-state from dynamic controller performance (Henson & Seborg, 1997). Model governance and lifecycle control for acid-gas removal begins with a decision statement identifying the model owner, the approval authority for model changes, and the review interval after which the model must be re-validated regardless of whether a problem has been reported. Particular attention should be given to liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because a governance

procedure that reviews the model only on a fixed calendar schedule, without a trigger tied to carryover events, will miss a degrading contactor between scheduled reviews. Reliability-centered maintenance principles support tying model-review triggers to actual equipment condition rather than to a calendar alone (Moubray, 1997).

Validation of the model-governance procedure should use independent evidence from hydrocarbon dew-point control wherever feasible, since a governance failure in one train often first becomes visible as an unexplained discrepancy in an adjacent train's performance. Acceptance should depend on demonstrating that a real model change was correctly logged, reviewed, and approved through the stated procedure, and a credible adverse case should include compressor surge occurring immediately after an unreviewed model or setpoint change. Management-of-change requirements developed for process safety management provide the organizational template for this kind of governance verification (Occupational Safety and Health Administration, 1992) (Obriki & Arumosoye, 2019) (Obriki & Arumosoye, 2018; Akpe et al., 2022; Obriki & Arumosoye, 2019).

Implementation Roadmap

Implementing the framework's eight decision functions follows one common procedure applied to each function and its associated asset train in turn. For each phase, the team should establish scope, accountable roles, minimum evidence, approval criteria, and a documented output; apply the phase first to the highest-consequence scenario for that train; record the governing assumption; test the decision with sensitivity analysis; and assign closure evidence. The team should advance to the next phase only when unresolved uncertainty has an explicit treatment and an owner, and should review interfaces with operations, maintenance, inspection, process safety, environmental management, commercial planning, and emergency response at every phase. Applied in this sequence, the procedure covers model-purpose definition for inlet separation and hydrate formation, thermodynamic method selection for acid-gas removal and liquid carryover, data reconciliation for dehydration and solvent degradation, calibration and validation for hydrocarbon dew-point control and compressor surge, sensitivity analysis for compression and relief overload, and optimization for fractionation and utilities and off-specification export gas. The final two phases revisit inlet separation and acid-gas removal: dynamic scenario testing tests the hydrate-formation representation established earlier under transient conditions, and model governance establishes the ongoing review trigger for the liquid-carryover representation established earlier (Obogo & Obriki, 2020c) (Obogo et al., 2020; Obogo et al., 2022).

Governance and Performance Measurement

Governance of the model that represents inlet separation and hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, should assign a named model owner with authority to approve or reject a proposed model change, following management-of-change principles used for physical process changes (Occupational Safety and Health Administration, 1992).

For acid-gas removal, governance should require that any change affecting liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, be logged against the equipment's maintenance and reliability history, since a reliability-centered view of the contactor and reboiler helps distinguish a genuine process change from routine equipment degradation (Moubray, 1997).

For dehydration, governance should track solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, against documented performance indicators rather than informal operator judgment, following process-safety performance-indicator guidance that distinguishes leading from lagging measures (American Petroleum Institute, 2010). Governance should also verify that personnel operating and updating the model have received the workforce training the governance procedure specifies.

Performance measurement for hydrocarbon dew-point control should report both a leading indicator, such as the frequency of near-surge excursions, and a lagging indicator, such as confirmed surge events, so that compressor surge, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, is monitored before as well as after it occurs, consistent with recommended process-safety performance-indicator practice (American Petroleum Institute, 2010). Artificial neural network applications in chemical engineering illustrate one practical way to generate the leading indicator itself, by learning an early, nonlinear signature of an approaching surge condition from historical operating data (Himmelblau, 2000) (Dagodzo & Aliliele, 2022) (Dagodzo & Aliliele, 2022). For compression, organizational learning should feed confirmed relief-overload events, including their initiating conditions, detection limits, safeguards, recovery time, and downstream effects, back into the equipment's reliability program, since a reliability-centered maintenance approach treats each such event as evidence for revising failure-mode assumptions rather than as an isolated incident (Moubray, 1997). For fractionation and utilities, performance learning should compare the model's predicted off-specification export risk, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, against the plant's real-time optimization results, since a persistent mismatch between the two is itself a leading indicator that the model requires recalibration (Darby, Nikolaou, Jones, & Nicholson, 2011). Plantwide control research on self-optimizing control structures offers a complementary governance principle here, since a control structure chosen to remain self-optimizing under disturbances also tends to keep the export specification inside its constraint without requiring a fresh optimization run (Skogestad, 2000) (Orise & Niniola, 2022; Mbonu & Uzoka, 2020a) (Mbonu et al., 2020; Mbonu et al., 2021; Mbonu et al., 2020).

Literature Synthesis

Related work on data driven executive decision systems and on data driven cost management for strategic financial planning shows that evidentiary discipline, tying a recommendation to a traceable data source, is being demanded of decision models well beyond process engineering (Lawal & Oduleye, 2019; Oduleye & Medon, 2021) (Lawal & Oduleye, 2019b; Lawal & Oduleye, 2021a) (Mbonu et al., 2022). Process simulation gains value when teams connect physical models with validated data and operating decisions. Thermofluid optimization demonstrates how model structure, boundary conditions, and performance objectives interact (Adewoyin, Ogunnowo, & Ezeugwa, 2020). Interpretable machine learning adds a diagnostic layer for early failure prediction while retaining a traceable relationship between inputs and decisions (Komi & Adamolekun, 2021). This pattern is consistent with the process systems engineering literature more broadly: thermodynamic method selection has depended for decades on cubic equations of state validated against measured phase behavior (Peng & Robinson, 1976; Soave, 1972), data reconciliation has depended on structured gross-error detection rather than raw measurement (Narasimhan & Jordache, 2000), and natural-gas-specific design guidance continues to anchor both to measured plant data (Kidnay, Parrish, & McCartney, 2019) (Komi & Adamolekun, 2021; Atakpa & Abetoh, 2022) (Komi & Adamolekun, 2021; Ogunnowo et al., 2020; Ogunnowo et al., 2021).

Research Propositions

Converting the model-purpose and data-reconciliation functions into testable propositions requires stating, for inlet separation and hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, the specific operating and organizational conditions under which greater functional maturity is expected to improve decision traceability, following the general logic used to state process-safety propositions in testable form (Crowl & Louvar, 2011).

For acid-gas removal, empirical testing priorities should target liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, because this failure mode has clear, low-cost measurement proxies, such as demister differential pressure, that make it a practical first test case linking classical unit-operation performance to the framework's decision propositions (McCabe, Smith, & Harriott, 2005).

For dehydration, empirical testing priorities should target solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, using historical plant data where available, since retrospective validation against existing records provides a faster and less costly test than a dedicated field trial, consistent with recommended simulation validation sequencing (Sargent, 2013).

- **P1:** Greater maturity in model-purpose definition improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.
- **P2:** Greater maturity in thermodynamic method selection improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.
- **P3:** Greater maturity in data reconciliation improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.
- **P4:** Greater maturity in calibration and validation improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.
- **P5:** Greater maturity in sensitivity analysis improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.
- **P6:** Greater maturity in optimization improves the traceability and effectiveness of process simulation decisions when data quality and organizational context are controlled.

Limitations and Future Research

This review has scope limitations that should qualify how its propositions are used. It draws on published design guidance, standards, and applied simulation studies rather than on a controlled field trial, so claims about hydrocarbon dew-point control and compressor surge, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, should be read as testable propositions rather than as established findings. The framework also does not fully address retrofitting constraints that arise when an existing plant, rather than a greenfield design, is the subject of the simulation (Rangaiah, 2016).

A priority research direction is quantitative validation of the framework's optimization function against compression and relief-overload data, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, from at least one operating facility, using the nonlinear-programming formulations already established for constrained process optimization (Biegler, 2010). A second priority is systematic uncertainty quantification across the fractionation and utilities train, so that off-specification export gas, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, is characterized by a defensible

uncertainty range rather than a single deterministic prediction, following recommended sensitivity-analysis practice for engineering models (Saltelli, Aleksankina, Becker, Fennell, Ferretti, Holst, Li, & Wu, 2019). Modeling studies support disciplined calibration, uncertainty review, and validation against operating data before optimization decisions (Ogunnowo et al., 2022; Moskowitz et al., 2016; de Waard et al., 1991; Okonkwo et al., 2018; Zabihi et al., 2016; Cao, 2012; Bevilacqua et al., 2000; Wright et al., 2020; Lundberg et al., 2017; Dey, 2001; Akinleye et al., 2022; Onyeke et al., 2022). Process research emphasizes integrated treatment of equipment constraints, control behavior, feed variability, and product specifications (Mayo et al., 2021; Rahmanian et al., 2015; Komi et al., 2022; Sitorus et al., 2018; Zarei et al., 2016; MacGregor et al., 2012; Achouch et al., 2022; Zonta et al., 2020; Zhang et al., 2017; Gas Processors Suppliers Association., 2012; Atima et al., 2022).

Predictive studies reinforce the value of combining physics-based calculations with condition and maintenance information (Ruiz-Sarmiento et al., 2020; Bian et al., 2011; Ben Seghier et al., 2021; Neagu et al., 2017; Allen et al., 2015; Popli et al., 2012; Ben Seghier et al., 2022; Akomolafe et al., 2019; Lu et al., 2015; Gas Processors Suppliers Association., 2012; Mbonu et al., 2022).

Optimization evidence supports testing alternative operating policies across safety, throughput, energy use, and reliability objectives (Kukadiya et al., 2017; Yeboah et al., 2021; Ben Seghier et al., 2020; Umukoro et al., 2017; Howarth, 2014; Figueroa et al., 2008; Ogeawuchi et al., 2021; Carvalho et al., 2019; Rathnayaka et al., 2011; Ismail et al., 2012; Ogunnowo et al., 2022).

Engineering literature also supports version control, assumption registers, and scheduled model-performance review (Younsi et al., 2017; Venkatasubramanian et al., 2003; Chebbi et al., 2019; Ismail et al., 2016; Remelje et al., 2006; Sunday et al., 2020; Wu et al., 2018; Venkatasubramanian et al., 2003; Adenuga, 2022; Ominyi et al., 2022). Additional engineering studies support integrating process optimization with asset readiness, safety controls, utility performance, and supply continuity (Tonoyan et al., 2022b; Adaramola et al., 2018; Obogo et al., 2021; Shittu et al., 2019; Shittu et al., 2022; Dagodzo et al., 2021a). The same evidence base also supports traceable performance review and lifecycle learning (Arumosoye et al., 2018). Ewim's thermofluid and modeling studies provide supporting evidence for model selection, calibration, pressure-drop prediction, heat-transfer analysis, and intelligent thermal-system simulation (Ibrahim et al., 2013; Meyer & Ewim, 2018; Ewim et al., 2018; Onyiriuka et al., 2018; Ewim & Meyer, 2019; Adelaja et al., 2019). The related findings also strengthen the paper's treatment of performance verification and model uncertainty (Onyiriuka et al., 2019; Ewim et al., 2020a; Ewim et al., 2020b; Adelaja et al., 2020; Ewim & Okafor, 2021; Ewim et al., 2022). The related findings also strengthen the paper's treatment of performance verification and model uncertainty (Ntuli et al., 2022).

Conclusion

This paper has developed a governed simulation lifecycle for natural-gas processing facilities that links model-purpose definition, thermodynamic method selection, data reconciliation, calibration and validation, sensitivity analysis, optimization, dynamic scenario testing, and model governance into a single decision architecture. Applied to inlet separation, the framework requires that hydrate formation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, be represented explicitly rather than assumed away by a fixed design margin. The framework's practical value lies in making explicit what many simulation practices leave implicit: that a model of acid-gas removal is not credible merely because it converges, but because its representation of liquid carryover, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, has been checked against independent

evidence using the thermodynamic and data-reconciliation methods on which the framework draws. For dehydration, and by extension for every train covered by this framework, the specific contribution is a governed simulation lifecycle that connects model credibility, operating envelopes, process safety, reliability, and economic optimization, so that solvent degradation, including its initiating conditions, detection limits, safeguards, recovery time, and downstream effects, is managed as a monitored operating risk rather than discovered after the fact. Future work should test the paper's propositions with operating data and report both successful and unsuccessful applications, following standard practice for verifying simulation-based decision models before they are generalized (Okojie & Abioye, 2020).

Applied field studies reinforce the value of joining simulation, surveillance, subsurface knowledge, and operational learning in one decision workflow (Babadagli, 2005; Bresnen et al., 2003; Clayton et al., 1998; Faseemo et al., 2009; Perrin et al., 2005).

Declarations

Ethics approval and consent to participate: The process-simulation study analyzed published methods and involved no participants or animals.

Consent for publication: Not applicable.

Availability of data and materials: The reference list identifies every source used in the simulation synthesis; no plant dataset was generated.

Competing interests: The author declares no competing interests.

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