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# Data-Driven Management of Operational Efficiency at Gas Processing Plants: Integrating Process Simulation, Statistical Control, and Economic Optimization

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***Abstract*** *— Operational efficiency at a gas processing plant is shaped by the daily maintenance of the process regime, and the plant's margin depends on how closely that regime runs to its technological limits. Three families of instruments are available at almost every modern facility: rigorous process simulation, statistical analysis of operating data, and economic optimization of the process regime in real time. Each family carries its own software and its own owner within the organization, and each has a limited effect when operating alone. This paper develops an integrated efficiency management loop that binds the 3 families into a single decision cycle. Simulation defines the feasible boundary of the regime, statistical control compresses the dispersion of parameters around the setpoint, and economic optimization determines how far the setpoint may be moved toward the boundary. The conceptual core of the model treats the operating margin as a priced quantity that contracts as variability falls. The methods applied are systems analysis, comparative analysis of English-language publications published between 2021 and 2025, and synthesis with the author's professional experience at gas processing plants in Western Siberia. Generalized indicators from that experience illustrate the loop, covering a decline in process losses from 0.64% to 0.44% of plant throughput, growth in valuable fraction recovery, and a 10% reduction in greenhouse gas emissions. The results are addressed to process engineers, process control specialists, and production managers.*

***Keywords*— gas processing plant, operational efficiency, process simulation, statistical process control, economic optimization of the operating regime, natural gas liquids, process variability, data-driven management.**

## I. INTRODUCTION

Gas processing plants convert associated petroleum gas into dry-stripped gas, liquefied gases, and natural gas liquids (NGL). The commercial result of such a plant is formed in the daily maintenance of the process regime. Capital projects define the outer envelope of what a facility can achieve, and the position of the working point within that envelope is determined each shift. A fractionation column running 3 °C away from its best overhead temperature sends valuable components into the residue gas for as long as the setting holds, and this loss appears in no incident report and triggers no alarm.

Three families of instruments serve the management of the working point at a modern plant. The first family is a rigorous process simulation. Sun et al. (2023) developed a simulation model of natural gas condensate recovery and used it to maximize ethane and propane recovery while keeping energy consumption and product quality within target ranges. The second family is a statistical analysis of operating data. Control charts make the dispersion of a parameter visible over time and separate assignable causes of variation from the process's background noise (Sałaciński et al., 2023). The third family is the economic optimization of the operating regime in real time. Faria et al. (2023) describe the industrial hierarchy in which a steady-state optimization layer computes economically optimal setpoints from a rigorous model and passes them down to supervisory and regulatory control.

Each family arrived at the plant along its own path, with its own software, its own vocabulary, and its own owner inside the organization. Simulation belongs to process engineering, statistical analysis belongs to reliability and quality functions, and economic evaluation of the regime belongs to planning. The 3 groups meet at budget reviews and part again. Pugna et al. (2022) found the barriers to a data-driven organizational model in the energy sector to be managerial and cultural, with the absence of strategy and skills identified as the leading obstacles, and managers unwilling to trust data that runs counter to their prior commitments.

The literature analyzed for this study does not describe a management loop that binds the 3 families at the level of a gas-processing plant. Ji et al. (2025) document a persistent gap between algorithm-centric research in chemical process monitoring and its industrial deployment, in which increasing model complexity leads to poor generalization and limited transparency. El Hakim et al. (2025) apply such a binding to one debutanizer column, combining steady-state simulation, response surface methodology, and predictive control, and report higher LPG recovery along with a decline in reboiler duty. The step from a single column to a plant-wide management loop with an identified organizational carrier remains open, as far as the author is aware.

Two earlier papers by the author addressed adjacent objects. Dovbik (2025) examined the process safety manual as an instrument of industrial safety and proposed the concept of a living manual embedded in digital control loops. Dovbik (2026) examined the management of engineering projects to modernize hydrocarbon transportation infrastructure and proposed a hybrid adaptive control model. The object of the present paper is the operational efficiency of a producing gas processing plant, and the loop developed below acts on the process regime of that plant.

The aim of the study is to develop and substantiate an integrated, data-driven model to manage the operational efficiency of gas processing plants.

Four objectives follow from this aim. First, to systematize contemporary approaches to simulation, statistical control, and economic optimization of the operating regime. Second, to identify the limits of each approach when it operates in isolation. Third, to formulate an integrated management loop and its conceptual core. Fourth, to illustrate the loop with generalized indicators from industrial practice and to state the boundaries within which the illustration holds.

The scientific novelty consists in treating the operating margin between the setpoint and the technological constraint as a priced quantity that contracts as variability falls, and in assigning the closing role in the loop to the process technologist.

The hypothesis is stated as follows. Gains in operational efficiency arise from shortening the loop time between observing a parameter, estimating the economic consequence of its current value, and correcting the setpoint. A single instrument family, applied alone, yields a local effect that decays once organizational attention shifts elsewhere.

## II. MATERIALS AND METHODS

### 2.1. Methodological basis and search protocol

The methodological core of the study is systems analysis, which treats the process regime of a gas processing plant as an element of a sociotechnical system that includes equipment, instrumentation, the laboratory, the control room crew, and the economic planning function. Comparative analysis was applied to the 3 instrument families to determine what each produces and where that output ceases to be useful. Synthesis combined the propositions drawn from the literature with the author's industrial experience.

The information base was formed from English-language publications issued between 2021 and 2025 and retrieved from Google Scholar, Scopus, Web of Science, ScienceDirect, MDPI, and IEEE

Xplore. The search queries covered gas processing plant operational efficiency, NGL recovery optimization, process simulation of natural gas, statistical process control in the chemical industry, real-time optimization, economic model predictive control, process variability reduction, flare gas recovery, and data-driven decision making in the process industry.

Publications were entered into the corpus when they addressed the process industry or the oil and gas sector, reported a method or a case with stated results, and appeared in peer-reviewed venues. Materials of a commercial character were excluded. The resulting corpus covers process simulation, statistical quality control, real-time economic optimization, flare gas recovery, digital twins, and the organizational side of data-driven management, which allowed each layer of the model to rest on published evidence.

**2.2. Empirical basis and its limitations**

The empirical component of the study rests on the author's professional experience as a senior technologist responsible for 2 gas processing plants and 2 compressor stations in Western Siberia. That position covered setting targets for key process indicators, analyzing deviations from process regime norms, reviewing material and energy balances, and supervising digital tools for process efficiency.

The boundaries of this empirical component are stated here and repeated in Section 4.5. Internal reports, data exports, and corporate databases were not used in the preparation of this paper. The indicators cited in Section 4.4 are generalized results of the work described above. No control group was formed, no experimental design was applied, and no claim of reproducibility is made. The commercial name of the real-time economic optimization system operated at the plants is withheld as the operating company's intellectual property, and the system is described by its functions. Aspen Plus and Minitab are third-party commercial products and are named in the text.

## III. RESULTS

**3.1. Process simulation as the model layer**

Rigorous process simulation answers the question of how the process will behave under a given set of conditions. A model of a gas processing train reproduces material and energy balances across compression, cooling, absorption, deethanization, and debutanization, and it returns the composition of every stream for any combination of feed, pressure, temperature, and reflux. Sun et al. (2023) applied this capability to condensate recovery using an ethane-propane refrigerant mixture and combined 3 optimization objectives that a plant faces simultaneously: maximum recovery of ethane and propane, minimum energy consumption, and product quality within contractual limits. Their sensitivity analysis quantified how changes in the cooler outlet temperature and the expander outlet pressure affect compressor shaft power and plant profit.

For a management loop, the valuable output of a simulation model is the constraint envelope. The model indicates how far a parameter can travel before hydrate formation, flooding, freeze-out, or off-specification product occurs, and the shape of the response near that limit.

The limitation of this layer is drift. A model calibrated against design data describes an idealized plant that ceases to exist after the first season of operation. Heat exchanger fouling shifts approach temperatures, feed composition changes as the field matures, and instrument bias accumulates between calibrations. A model that is never reconciled with measured data returns a constraint envelope that deviates from the physical one, and a recommendation built on it either wastes margin or violates a limit. Simulation states where the boundary lies at the moment of calibration and stays silent about what the plant is doing now.

**3.2. Statistical control as the variability layer**

Statistical analysis of operating data describes the second dimension of the working point: the dispersion of a parameter around its target. Sałaciński et al. (2023) analyzed control charts with fixed and variable parameters and showed that charts with variable sample sizes, variable sampling intervals, and variable control limits detect a shift of the process mean earlier than their classical counterparts. For a process engineer, this earlier detection translates into a shorter interval during which the plant runs off target before anyone notices.

A broader toolkit surrounds the control chart. Capability indices relate the spread of a parameter to the width of its tolerance, measurement system analysis establishes what share of the observed variation belongs to the instrument and to the laboratory, and designed experiments identify which of the candidate causes moves the parameter of interest.

The economic weight of this layer is documented. Alarcón et al. (2024) applied a combined Lean and Six Sigma framework at a chemical manufacturer over 2 years, integrating process mapping, root cause analysis, and statistical process control, and they reported a 50% reduction in the variability of several products alongside a 40% reduction in costs associated with product losses and a 54% reduction in costs from raw material losses. Variability and money move together, and a change in the first produces a change in the second.

The limitation of this layer mirrors the limitation of the first one. Statistics characterizes the distribution and identifies the causes behind its width. It says nothing about which setpoint should replace the current one, and it attaches no price to the dispersion it has measured. A plant can hold a parameter under sound statistical control at a value that leaves a fifth of the available margin unused.

### 3.3. Economic optimization as the value layer

The third layer converts the regime into money. Faria et al. (2023) set out the industrial hierarchy in which steady-state real-time optimization computes economically optimal setpoints from a rigorous model updated by parameter adaptation and passes them to model predictive control, which holds the plant against them minute by minute. Their review also identifies practical obstacles, including the requirement that the plant reach a steady state before optimization can run and the need for data reconciliation before any parameter estimate is trusted.

Xu (2024) sharpened the question of how much of the available economic potential is captured by existing strategies. The concepts of optimization margin and optimization efficiency were introduced as measures of the quality of a control strategy, and a nested optimization structure that maximizes the margin online produced 7.11% higher profit than competing strategies on a continuous stirred tank reactor case. The finding relevant here is that real-time optimization, dynamic real-time optimization, and economic model predictive control leave part of the margin unused.

The limitation of this layer is trust. A recommendation to move a setpoint 2 °C closer to a limit is executed by the shift crew when the crew knows how wide the distribution around that setpoint is and how the plant behaves at the boundary. Without that knowledge, the recommendation is discounted, the crew restores the familiar setting, and the economic layer degrades into a report that changes nothing on the panel.

### 3.4. The environmental dimension of the regime

The environmental result of a gas processing plant follows from the same working point. Gas routed to the flare during upsets, off-specification production, and unplanned shutdowns carries hydrocarbons that were destined for sale, and fuel gas burned to maintain reboiler duty carries the same double cost. Elgarahy et al. (2024) reviewed strategies for flare gas recovery across technical, environmental, modeling, and economic dimensions and recommended simpler recovery routes, even when profit is lower, reflecting the reliability requirements of an operating facility.

Two consequences follow for the management loop. The first is that emissions reduction and loss reduction are the same task viewed in different registers, since hydrocarbons that would otherwise exit the plant through the flare stack instead exit through the product manifold. The second is that a stable regime produces fewer excursions and fewer flaring events, placing the environmental result downstream of the variability layer in Section 3.2.

### 3.5. The integration gap

The 3 layers described above are mature, and their integration is not. Ji et al. (2025) reviewed data-driven process monitoring across statistical, probabilistic, and deep learning approaches and documented a persistent gap between algorithm-centric research and industrial deployment, where increasing model complexity leads to poor generalization, limited transparency, and difficulty achieving fault detection and root cause diagnosis simultaneously. The obstacle they describe is not the absence of methods.

Digital twin technology shows the same pattern. Meza et al. (2024) reviewed digital twin development in the oil and gas industry and found the underlying tools and frameworks to be non-standardized, unfamiliar to many practitioners, and applied only in pilot projects.

The closest published approach to an integrated loop appears in El Hakim et al. (2025), where simulation, designed experiments with response surface methodology, and predictive control were assembled for LPG recovery in a debutanizer column. That assembly operates at the scale of 1 column and 1 controller. It leaves open the question of who within the enterprise carries the loop, how the layers exchange information across organizational boundaries, and what happens when a product's price changes overnight.

Table 1 summarizes the comparison of the layers along the dimensions that matter for their integration.

*Table 1. Comparative characteristics of the instrument layers*

| Parameter | Model layer | Variability layer | Value layer |
|---|---|---|---|
| Function | Defines feasible operating limits | Measures dispersion of parameters | Converts the regime into money |
| Tools | Aspen Plus and equivalent simulators | Control charts, capability indices, DOE, Minitab | Real-time economic optimization of the regime |
| Input data | Design basis, feed composition, equipment data | Archived process values, laboratory results | Prices of feed, products and energy |
| Output | Constraint envelope and scenario results | Distribution width and assignable causes | Direction and value of a setpoint change |
| Decision horizon | Weeks to months | Days to weeks | Hours to days |
| Organizational owner | Process engineering | Reliability and quality functions | Planning and economics |
| Limitation in isolated use | Drifts away from the plant without recalibration | Attaches no price to the measured dispersion | Discounted where the true dispersion is unknown |
| Role in the loop | Sets where the constraint lies | Compresses dispersion around the setpoint | Sets how far the setpoint may move |

The row that governs the model's design is the organizational owner. A gap that runs between departments is closed by a management decision and by a working procedure, and additional software leaves it where it was.

## IV. DISCUSSION

### 4.1. Architecture of the integrated efficiency management loop

The proposed model connects the 3 layers into a closed cycle of 6 stages that repeat on a fixed rhythm.

The first stage is data acquisition. Archived process values from the control system are joined with laboratory results for the same period and checked for gaps, frozen sensors, and evident bias.

The second stage is the characterization of variability. Control charts and capability indices are built for parameters that carry economic weight, including column overhead and bottom temperatures, absorber pressure, reflux ratios, and the residual content of target components in the residue gas.

The third stage is calibration of the process model. The simulation model is reconciled against the measured data of the same period, and the reconciled model then yields the constraint envelope under current conditions of fouling, feed composition, and ambient temperature.

The fourth stage is the economic optimum. The objective function combines the value of the recovered fractions, the cost of the energy consumed to recover them, and the penalty attached to off-specification production, and the optimum is computed inside the envelope obtained at the third stage.

The fifth stage is the setpoint and the operating window. The optimum is translated into a value that a panel operator can hold, along with a band around it that reflects the dispersion measured at the second stage. The width of the band carries the statistical result into the control room.

The sixth stage is verification. The realized effect over the following period is compared against the expected effect, and the difference enters the next cycle. A model that promised 0.3% and delivered 0.05% is reporting on its own calibration.

Fig. 1 presents the structure of the loop.

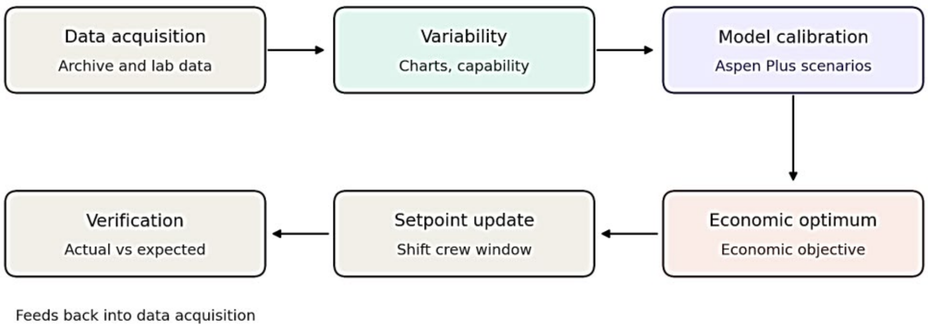


*Fig. 1. Architecture of the integrated efficiency management loop*

The rhythm of the cycle matters as much as its content. A loop that closes once a year reproduces the calendar-based revision of documentation criticized in earlier work on process safety manuals (Dovbik, 2025). A loop that closes every month keeps the model near the plant and keeps the operating window near the current state of the equipment.

**4.2. Pricing the operating margin**

The conceptual core of the model concerns the margin between the setpoint and the technological constraint. A plant holds that margin because the parameter fluctuates, and a setpoint placed at the constraint would put half of the distribution across it. The width of the margin follows the width of the distribution, and the relation can be written as a setpoint equal to the constraint minus k multiplied by the standard deviation of the parameter, where k is chosen from the acceptable probability of crossing the limit and from the consequences of the crossing.

Three conclusions follow from this expression, and each belongs to a different layer of the model. The value of the constraint comes from the calibrated simulation model. The standard deviation value comes from the statistical layer and decreases as assignable causes are removed. The value of k comes from the economic layer, since the acceptable probability of an excursion depends on what an excursion costs and on what the additional recovery is worth.

The practical sequence follows from the same expression. Compression of the distribution comes first, and the shift of the mean toward the constraint comes second. A shift attempted before the compression raises the frequency of excursions, produces off-specification product, and ends with the crew restoring the old setting and losing confidence in the tool that suggested the move. Fig. 2 illustrates the mechanism.

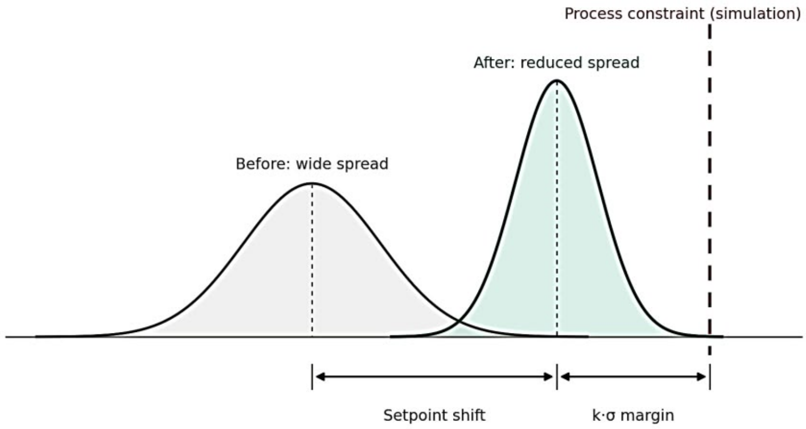


*Fig. 2. Variability reduction as a precondition for shifting the operating setpoint toward the process constraint*

The principle of reducing variation before moving the mean is established in advanced process control practice and in quality engineering, and the results of Alarcón et al. (2024) rest on the same logic. The contribution offered here is the placement of that principle inside a plant-level management loop, with a statement of which organizational function supplies each of the 3 quantities and with a defined carrier for the decision.

That carrier is the process technologist, who holds the constraint envelope through work with the simulation model, receives the variability picture from the analysis of process regime deviations, and takes part in the economic planning of production. No other position at a gas processing plant sees all 3 quantities at once.

### 4.3. Organizational conditions and maturity of integration

The loop runs on organizational conditions that are easier to state than to build, and the maturity of integration can be described through 4 levels.

At level 0, the 3 instrument families are used from time to time by different services, and their outputs are presented together. At level 1, pairwise connections appear, where a simulation study is checked against operating data or a statistical finding is priced by the planning function. At level 2, the full cycle closes, and a person makes the decision on the setpoint with all 3 inputs in hand. At level 3, the cycle closes with feedback, in which the realized effect of the previous decision enters the next decision, and the loop becomes self-correcting.

Movement between levels depends on conditions that lie outside the software. The first condition is a shared data foundation, since a simulation calibrated to one version of the material balance and a control chart built on another version invite debate over the numbers and postpone the decision about the regime. The second condition is a fixed rhythm, since a loop without a schedule closes when someone remembers it. The third condition is the authority to change a setpoint, which must reside with a role that can also be held accountable for the result.

A loop that produces a recommendation contradicting an established practice will be tested against the documented unwillingness to trust data reported by Pugna et al. (2022), and the verification stage exists in part to address that test with realized results.

### 4.4. Illustrative case

The loop described above summarizes the approach applied by the author at 2 gas processing plants in Western Siberia, and Section 4.5 states the limits within which the following indicators should be read.

Work on the variability layer came first. Analysis of deviations from process regime norms, investigation of the root causes behind alarm activations, and correction of the norms themselves reduced the number of process regime violations by more than 30%. This reduction is the entry condition for everything that follows, since a distribution that has stopped drifting can be moved.

Work on the model and value layers was carried out. Aspen Plus was used for evaluating regime scenarios, Minitab for the statistical treatment of operating data arrays, and a real-time system for economic optimization of the process regime, which expressed the current operating point in monetary terms. The combination maximized NGL output, resulting in an economic effect of close to 200 million rubles.

The loss indicator moved in parallel. The level of process losses declined from 0.64% to 0.44% of plant throughput. Losses of this kind are hydrocarbons that entered the plant and left it without becoming product, and their reduction converts into additional saleable volume.

The environmental result appeared over the same period. Greenhouse gas emissions at the Vyngapurovsky gas processing plant declined by 10%, attributable to reduced gas sent to the flare, the search for and elimination of leaks, and steadier plant operation.

More than 10 investment projects were developed to support these outcomes, and 2 of them were implemented with budgets of nearly 100 million rubles each. Such projects remove physical constraints that no adjustment of the regime can remove.

The 3 results are outputs from a single mechanism. Reduced variability permitted a shift of the operating point toward the constraint, which increased the recovery of propane, butane, and NGL, and the same stability reduced flaring and the associated emissions.

**4.5. Limitations and directions for further work**

The illustrative case carries limitations that bound any conclusion drawn from it. The first of them concerns causal attribution. The indicators cited above accompanied the application of the described approach at plants where equipment, personnel, feed composition, and market conditions were changing simultaneously. No control group existed against which the loop's contribution could be isolated.

The second limitation concerns measurement. A distribution measured with a biased sensor yields a margin that protects nothing, making measurement system analysis a precondition for the second stage of the cycle.

The third limitation concerns the stability of the economic layer. Prices of feed, products, and energy move, and an optimum computed under one price ratio ceases to be optimal under another. The economic layer requires the shortest revision cycle of the 3.

The fourth limitation concerns transfer. Plants differ in configuration, feed richness, and equipment condition, and the constraint envelope of one plant says nothing about the envelope of another. Transfer requires recalibration of the model layer and fresh measurement of the variability layer.

Further work can proceed along 3 directions. The first is the formalization of the choice of k for the parameter groups of a gas processing plant. The second is the behavior of the loop under strong variation of feed composition, which is characteristic of associated gas from mature fields. The third is the integration of predictive analytics into the verification stage, where the tools reviewed by Meza et al. (2024) could shorten the interval between a decision and its assessment.

## V. CONCLUSION

The study set out to develop an integrated, data-driven model to manage the operational efficiency of gas processing plants, and the 4 objectives stated in the introduction were addressed sequentially.

Contemporary approaches to process simulation, statistical control, and economic optimization of the operating regime were systematized. Each of the 3 families is mature and available to a modern plant in the form of commercial software.

The limits of each family in isolation were identified. Simulation defines a constraint envelope that drifts away from the plant without regular reconciliation against measured data. Statistical control measures the dispersion of a parameter and its causes, and it attaches no price to what it has measured and proposes no new setpoint. Economic optimization produces a recommendation whose acceptance depends on knowledge of the true dispersion, and in the absence of that knowledge, the recommendation is discounted by the people who would have to execute it.

An integrated management loop was formulated. Six stages connect data acquisition, characterization of variability, calibration of the process model, computation of the economic optimum, translation of the optimum into a setpoint and an operating window, and verification of the realized effect against the expected one. The conceptual core of the loop treats the margin between the setpoint and the technological constraint as a priced quantity that contracts as variability falls, yielding a sequence of compressing the distribution first and moving the mean second.

The loop was illustrated with generalized indicators from industrial practice, where a reduction of process regime violations by more than 30% preceded a decline of losses from 0.64% to 0.44% of throughput, the maximization of NGL output with an economic effect close to 200 million rubles, and a 10% reduction of greenhouse gas emissions at one of the plants. The boundaries of the illustration were stated, and the absence of a control group means that these indicators support the model without proving it.

The hypothesis holds within these boundaries. The 3 results appeared together and followed the same sequence of work, which supports the proposition that they are outputs of a single mechanism operating by shortening the loop time between observation, valuation, and regime correction.

## REFERENCES


[1] Alarcón, F. J., Calero, M., Martín-Lara, M. Á., & Pérez-Huertas, S. (2024). An integrated lean and six sigma framework for improving productivity performance: A case study in a Spanish chemicals manufacturer. Applied Sciences, 14(23), 10894. https://doi.org/10.3390/app142310894

[2] Dovbik, A. (2025). Technological regulations as an instrument for ensuring safety at oil refining facilities. World Journal of Advanced Research and Reviews, 28(3), 1698–1703. https://doi.org/10.30574/wjarr.2025.28.3.4251

[3] Dovbik, A. (2026). Management of engineering projects for the modernization of hydrocarbon transportation infrastructure. International Journal of Scientific Engineering and Science, 10(1), 78–82.

[4] El Hakim, B. A., Abdel-Goad, M. A.-H., Awad, M. E., & Shoaib, A. M. (2025). AI enhanced model predictive control for optimizing LPG recovery through integrated computational modeling, design of experiments and multivariate regression. Scientific Reports, 15, 29249. https://doi.org/10.1038/s41598-025-13899-z

[5] Elgarahy, A. M., Hammad, A., Shehata, M., Ayyad, A., El-Qelish, M., Elwakeel, K. Z., & Maged, A. (2024). Reliable sustainable management strategies for flare gas recovery: Technical, environmental, modeling, and economic assessment: A comprehensive review. Environmental Science and Pollution Research, 31(19), 27566–27608. https://doi.org/10.1007/s11356-024-32864-3

[6] Faria, R. de R., Capron, B. D. O., de Souza Jr., M. B., & Secchi, A. R. (2023). One-layer real-time optimization using reinforcement learning: A review with guidelines. Processes, 11(1), 123. https://doi.org/10.3390/pr11010123

[7] Ji, C., Ma, F., Rao, J., Wang, J., & Sun, W. (2025). Bridging the gap in chemical process monitoring: Beyond algorithm-centric research toward industrial deployment. Processes, 13(12), 3809. https://doi.org/10.3390/pr13123809

[8] Meza, E. B. M., Souza, D. G. B. d., Copetti, A., Sobral, A. P. B., Silva, G. V., Tammela, I., & Cardoso, R. (2024). Tools, technologies and frameworks for digital twins in the oil and gas industry: An in-depth analysis. Sensors, 24(19), 6457. https://doi.org/10.3390/s24196457

[9] Pugna, I. B., Boldeanu, D. M., Gheorghe, M., Cozgarea, G., & Cozgarea, A. N. (2022). Management perspectives towards the data-driven organization in the energy sector. Energies, 15(16), 5775. https://doi.org/10.3390/en15165775

[10] Sałaciński, T., Chrzanowski, J., & Chmielewski, T. (2023). Statistical process control using control charts with variable parameters. Processes, 11(9), 2744. https://doi.org/10.3390/pr11092744

[11] Sun, J., Zhou, R., Wang, L., Zeng, X., Hu, S., Yu, H., & Jiang, L. (2023). Process simulation and integration of natural gas condensate recovery using ethane–propane refrigerant mixture. Processes, 11(8), 2495. https://doi.org/10.3390/pr11082495

[12] Xu, J. (2024). Efficiency-oriented model predictive control: A novel MPC strategy to optimize the global process performance. Sensors, 24(17), 5732. https://doi.org/10.3390/s24175732