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Application of digital technologies for optimization of oil refining processes

The modern oil refining industry faces increasing demands for energy efficiency, product quality, and environmental compliance. Conventional process control strategies, often based on linear models and periodic optimization, are insufficient to handle the complexity and dynamics of contemporary refining units. This article explores the application of digital technologies–including industrial internet of things (IIoT), machine learning, digital twins, and advanced process control (APC) – for real-time optimization of oil refining processes. A multi-layer architecture is proposed, integrating data acquisition from sensors, predictive analytics for key performance indicators, and closed-loop control. The digital twin framework enables simultaneous simulation of process units (e.g., atmospheric distillation, catalytic cracking, hydrocracking) with continuous parameter calibration using real-time data. Machine learning models predict product yields, energy consumption, and equipment degradation, supporting proactive maintenance and operational adjustments. A comparative analysis of conventional and digital-based approaches is presented, demonstrating potential improvements in throughput, energy efficiency, and reliability. Field case studies illustrate successful implementations in crude distillation units and fluid catalytic cracking units. Challenges related to data integration, model interpretability, and cybersecurity are discussed. The results affirm that the convergence of digital technologies with refining engineering provides a powerful pathway toward sustainable and profitable refinery operations.

Keywords: *oil refining; digital twin; machine learning; advanced process control; real-time optimization; predictive maintenance; energy efficiency; process simulation.*

Introduction. The global oil refining sector is undergoing a profound structural transformation driven by a confluence of economic, technological, and regulatory factors [1, 2]. Among the most significant of these are the persistent volatility of crude oil prices, the ongoing shift in product demand–particularly the growing importance of petrochemical feedstocks over traditional transportation fuels – the tightening of environmental regulations, and the increasing urgency of reducing greenhouse gas emissions and overall carbon footprints [3, 4]. These forces collectively reshape the operational and strategic priorities of modern refineries, compelling them to evolve from conventional production facilities into highly adaptive, data-driven industrial systems [5, 6].

Refineries themselves represent complex, highly integrated process networks composed of numerous interdependent units, including distillation columns, catalytic crackers, hydrotreaters, and blending systems [7, 8]. The economic performance of such systems is highly sensitive to fluctuations in feedstock quality, product specifications, and market conditions [9, 10]. Consequently, refining margins depend critically on the ability to respond rapidly and effectively to both internal process variations and external market signals, all while ensuring safe, reliable, and environmentally compliant operations [11, 12]. However, traditional control and optimization approaches–typically based on steady-state assumptions, simplified first-principles models, and periodic manual adjustments–are increasingly inadequate in capturing the nonlinear, time-varying, and multiscale dynamics inherent in modern refining processes.

In response to these limitations, the industry has witnessed an accelerated adoption of advanced digital technologies [13, 14]. Recent progress in sensor technologies, including high-frequency and high-precision measurement systems, has significantly enhanced the availability and granularity of operational data [15, 16]. At the same time, advances in computational power and data storage capabilities have enabled the processing of large-scale, heterogeneous datasets in near real time [17]. Within this technological landscape, the concept of the digital twin has emerged as a particularly promising paradigm [18]. A digital twin can be defined as a dynamic, virtual representation of a physical asset or process that continuously integrates real-time data to simulate, predict, and optimize system behavior under varying conditions [19, 20].

When coupled with machine learning (ML) and artificial intelligence (AI) methodologies, digital twins extend beyond static modeling frameworks to enable adaptive, data-driven decision-making [21]. These technologies facilitate predictive maintenance, anomaly detection, process optimization, and scenario analysis, thereby improving both operational efficiency and system resilience [22]. Furthermore, the deployment of the industrial internet of things (IIoT) establishes a comprehensive digital infrastructure that ensures seamless connectivity across different layers of refinery operations [23]. This integration allows for the aggregation and harmonization of data from diverse sources, including distributed control systems (DCS), supervisory control and data acquisition (SCADA) systems, laboratory information management systems (LIMS), and enterprise resource planning (ERP) platforms [24].

In parallel, increasingly stringent environmental and regulatory requirements impose additional constraints on refinery operations [25]. Regulatory frameworks aimed at reducing emissions of carbon dioxide, sulfur oxides, nitrogen oxides, and other pollutants necessitate the implementation of advanced monitoring, reporting, and control mechanisms. In this context, digital technologies play a dual role: they not only enhance economic performance through improved efficiency and reduced downtime but also enable compliance with environmental standards through continuous emissions monitoring, energy optimization, and transparent reporting.

Therefore, the integration of digital technologies into refinery operations should be viewed not merely as an optional pathway to competitive advantage but as a strategic imperative. It represents a fundamental shift toward intelligent, autonomous, and sustainable refining systems capable of operating effectively in an increasingly complex and constrained global environment [26].

Thus, the relevance of this research lies in providing a structured framework for adopting digital technologies in oil refining, demonstrating their potential to enhance operational performance, and identifying key implementation challenges.

Objective. The purpose of this article is to propose an integrated digital framework for the optimization of oil refining processes. The research aims to demonstrate how the combination of real-time data, machine learning models, and digital twin simulations can significantly improve process efficiency, product yield, energy consumption, and equipment reliability. This framework is particularly relevant in the context of increasing operational complexity and the industry's digital transformation.

Methods, results and discussion. The proposed digital framework for refining optimization is structured around three hierarchical layers: data acquisition and integration, analytics and modeling, and optimization and control [27]. This layered architecture ensures a continuous flow of information from the physical assets to actionable decisions, as illustrated in figure 1.

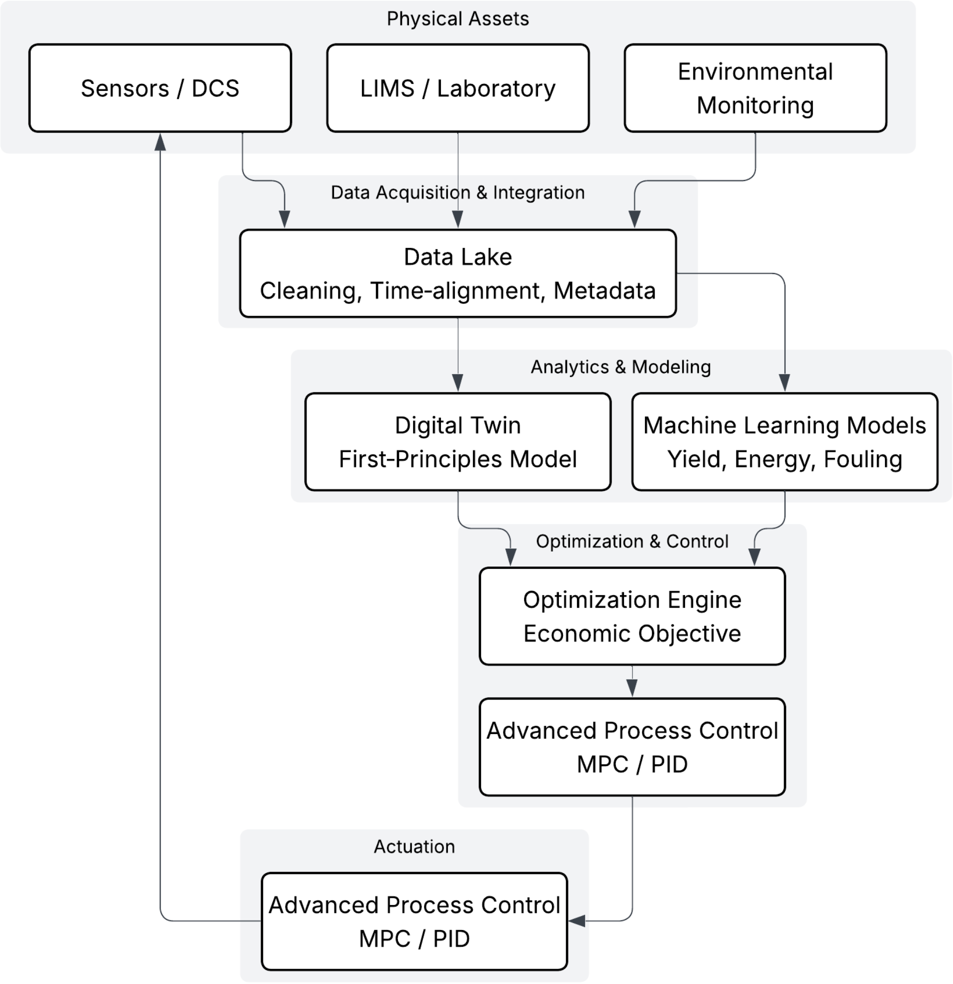

Fig. 1. Architecture of digital framework for refining optimization

Figure 1 depicts the overall architecture, beginning with sensors and control systems that generate real-time measurements. These data streams are aggregated into a unified data lake, where they undergo cleaning and synchronization. From there, the data feeds into the analytics layer, which houses both machine learning models and a dynamic digital twin of the process units. The outputs of the analytics layer are consumed by an optimization engine that computes optimal setpoints; these are then transmitted to the advanced process control (APC) system, which in turn actuates the physical equipment. The closed-loop nature of the architecture enables continuous adaptation to changing conditions.

The foundation of the framework is a comprehensive data infrastructure that aggregates real-time measurements from distributed control systems (DCS), laboratory information management systems (LIMS), and environmental monitoring systems. Key variables include process temperatures, pressures, flow rates, compositions (obtained from online analyzers or laboratory analyses), and equipment condition indicators such as vibration, temperature, and corrosion rates. These heterogeneous data are cleaned to remove outliers and sensor faults, time-aligned to a common sampling grid, and stored in a unified data lake. Metadata tagging and systematic data quality assessment are essential for downstream modeling, as the reliability of any predictive or optimization model depends directly on the quality of the input data.

The analytics layer encompasses both first-principles models and machine learning models, working in concert to provide a faithful representation of the process. A core component is the digital twin of the refinery units – a dynamic simulation that continuously assimilates real-time data and updates its parameters to reflect current conditions. For a crude distillation unit, the digital twin solves material and energy balances, thermodynamic equilibrium, and column hydraulic constraints. The twin can be formulated as a set of differential-algebraic equations (DAEs) that are calibrated using measured data:

$$F\left(x, \dot{x}, u, \theta\right) = 0\ , \tag{1}$$

where x is the state vector (e.g., temperatures, compositions), u is the vector of manipulated variables (feed rate, reflux ratio, steam flow), and θ represents uncertain parameters (e.g., heat transfer coefficients, tray efficiency). The residual between simulated outputs and actual measurements is minimized using an optimization algorithm, resulting in a self-consistent model that reflects current equipment performance. This calibration is performed repeatedly, typically every few minutes, ensuring that the digital twin remains accurate even as feedstocks change or equipment degrades.

Parallel to the digital twin, machine learning models are developed for specific tasks that complement the first-principles simulations. For yield prediction, neural networks estimate the yields of key products – naphtha, kerosene, diesel, gas oil, and residue – as functions of feed properties (density, sulfur content, distillation curve) and operating conditions (temperatures, pressures, flow ratios). Energy consumption forecasting employs gradient boosting or long short-term memory (LSTM) networks to predict fired heater duty, pump power, and overall energy intensity based on historical data and current operating parameters. Fouling and degradation forecasting models, trained on historical equipment data, predict the rate of fouling in heat exchangers or catalyst deactivation in reactors, enabling proactive maintenance scheduling before unplanned shutdowns occur.

The optimization layer uses the digital twin and machine learning models to compute optimal setpoints for process variables. The objective is typically economic: maximize net margin, defined as product revenue minus energy and feedstock costs. The optimization problem can be formulated as:

$$\max_{u}\left(\sum_{i} p_i y_i(u,d) - c_{energy}E(u,d) - c_{feed}Q_{feed}\right), \tag{2}$$

subject to constraints on product qualities, equipment limits, and safety margins. Here, p_i are product prices, y_i are yields predicted by the digital twin, E is energy consumption, c_{energy} is energy cost, c_{feed} is feedstock cost, Q_{feed} is the feed rate, and d represents disturbance variables such as feed composition and ambient conditions. The optimization is solved repeatedly (e.g., every 15–30 minutes) using nonlinear programming algorithms. Because the digital twin is continuously calibrated, the optimizer always works with an up-to-date representation of the process, allowing it to adapt to disturbances and equipment changes.

The optimal setpoints are sent to the advanced process control (APC) layer, which implements them through regulatory controllers (e.g., PID loops). In a more integrated approach, the optimization engine directly provides targets to a model predictive controller (MPC) that handles multivariable interactions and constraints, ensuring smooth transitions and maintaining process stability.

Figure 2 illustrates the closed-loop optimization cycle that underpins this digital framework. Real-time data from the physical plant is used to calibrate the digital twin and update the machine learning models. These calibrated models then drive the optimizer, which generates new setpoints. The setpoints are implemented by the control system, and the cycle repeats. The figure emphasizes the continuous feedback and adaptation that differentiate digital-based optimization from traditional periodic manual adjustments, where decisions are based on outdated information or infrequent laboratory analyses.

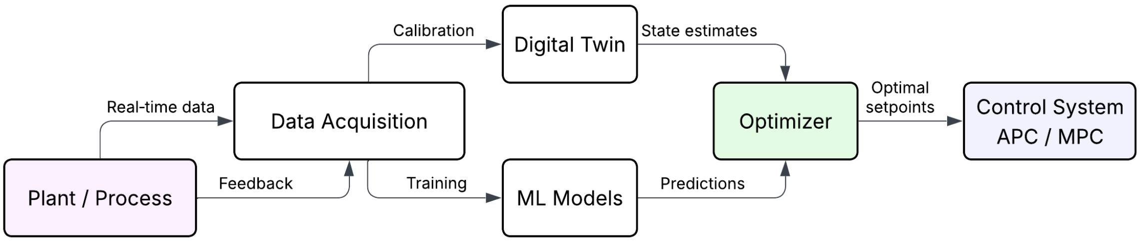

Fig. 2. Closed-loop optimization cycle

Implementation of such digital frameworks has demonstrated tangible benefits in commercial refineries. In a crude distillation unit (CDU) at a European refinery, deployment of a digital twin coupled with real-time optimization yielded a 2.5 % increase in valuable distillate yield and a 4 % reduction in energy consumption. The digital twin continuously reconciled tower balances, allowing operators to maintain optimal reflux and pumparound rates despite varying crude slates. In a fluid catalytic cracking unit (FCCU), machine learning models predicting catalyst activity and coke formation enabled proactive adjustments of regenerator air and catalyst circulation rates, resulting in a 3 % increase in propylene yield and reduced coke burning, thereby extending catalyst life.

Figure 3 compares key performance indicators (KPIs) before and after digital implementation across several units. The bar chart shows consistent improvements in yield (expressed as percentage increase), energy efficiency (percentage reduction in energy intensity), and equipment availability (percentage reduction in unplanned downtime). These results confirm that the integrated digital approach delivers measurable operational and economic gains.

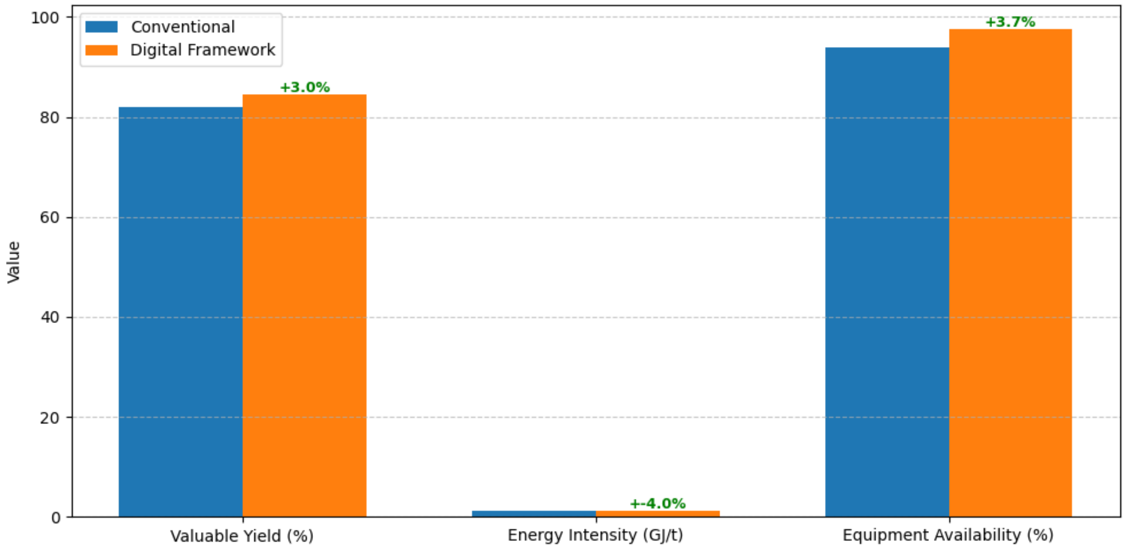

Fig. 3. Performance improvements with digital framework

Despite these successes, several challenges hinder widespread adoption. Data silos, inconsistent data formats, and a lack of interoperability between DCS, LIMS, and third-party software create integration hurdles that require significant engineering effort to overcome. Model interpretability remains a concern – operators are reluctant to act on recommendations from «black-box» models without understanding the underlying reasoning. Explainable AI (XAI) methods that provide transparent justifications for predictions and recommendations are therefore critical. Cybersecurity risks increase with connectivity; a digital twin connected to the control system could become a target for malicious attacks, necessitating robust security measures. Moreover, the transition requires significant investment in infrastructure and training, as well as a cultural shift toward data-driven decision making across the organization.

Future research should focus on developing explainable AI methods tailored to process industries, improving data standards (e.g., OPC UA, MIMOSA) to facilitate interoperability, and creating hybrid models that combine physics-based first principles with data-driven components to enhance robustness and extrapolation capabilities. The integration of reinforcement learning for autonomous process control is another promising direction, as it could enable the system to learn optimal policies directly from interaction with the environment.

Finally, regulatory frameworks should evolve to certify digital twins as reliable decision-support tools, ensuring that their use in safety-critical applications meets rigorous standards of validation and verification.

Conclusions and prospects for further research. The rapid evolution of digital technologies is reshaping the landscape of oil refining, offering unprecedented opportunities to enhance efficiency, reliability, and profitability. This article has presented a comprehensive digital framework that integrates data acquisition, analytics, and optimization into a closed-loop architecture. The framework leverages industrial internet of things (IIoT) connectivity, a unified data lake, machine learning models for predictive tasks, and a dynamic digital twin of refinery units, all orchestrated by an economic optimization engine that continuously recomputes optimal setpoints in response to changing feedstocks, market conditions, and equipment states.

The analysis confirms that such a digital approach yields measurable and consistent benefits. Field implementations in crude distillation units have demonstrated increases in valuable distillate yield of up to 2,5 % and reductions in energy consumption of 4 %. In fluid catalytic cracking units, machine learning-driven predictions of catalyst activity and coke formation enabled proactive adjustments that increased propylene yield by 3 % while extending catalyst life. These gains translate directly into improved margins, reduced emissions, and enhanced operational resilience. More broadly, the closed-loop nature of the framework – where the digital twin and ML models are continuously calibrated with real-time data – ensures that the optimization remains relevant even as disturbances occur, overcoming the limitations of traditional periodic manual adjustments.

Beyond the immediate performance improvements, the framework supports a strategic shift toward predictive and prescriptive operations. The ability to forecast fouling and degradation enables condition-based maintenance, reducing unplanned downtime and extending equipment life. The integration of product yield models with real-time optimization allows refineries to respond swiftly to shifts in market prices, maximizing the production of high-value fractions. Furthermore, the detailed process knowledge encapsulated in the digital twin provides a powerful tool for operator training, what-if analysis, and capital investment planning.

Nevertheless, the path to widespread adoption is not without challenges. Data silos, heterogeneous systems, and the lack of standardized interfaces (e.g., OPC UA, MIMOSA) remain significant integration barriers. The «black-box» nature of many machine learning models creates skepticism among operators and engineers, highlighting the need for explainable AI methods that can provide transparent justifications for recommendations. Cybersecurity concerns escalate as more assets become connected; a digital twin that directly interfaces with the control system must be protected against unauthorized access and malicious manipulation. Additionally, successful implementation requires substantial investment in infrastructure, data governance, and upskilling of the workforce – a cultural shift toward embracing data-driven decision making.

Future research should focus on several interconnected directions. First, the development of robust hybrid models that combine first-principles knowledge with machine learning will improve extrapolation capabilities and reduce the need for large training datasets. Second, explainable AI techniques tailored to process engineering must be advanced to make recommendations interpretable and actionable. Third, the integration of reinforcement learning could enable autonomous process control, where the system learns optimal policies through interaction with the environment, further reducing the need for manual intervention. Fourth, industry-wide data standards and security protocols should be established to facilitate seamless integration and protect critical infrastructure. Finally, as digital twins become more pervasive, regulatory frameworks need to evolve to certify them as reliable decision-support tools, ensuring that their use in safety - critical applications meets rigorous validation and verification requirements.

In conclusion, the convergence of digital technologies – IIoT, machine learning, and digital twins – with refining engineering represents a fundamental shift toward more agile, efficient, and sustainable operations. The framework described in this article provides a practical blueprint for refineries seeking to embark on this transformation. As the industry continues to face pressures to reduce carbon intensity, improve margins, and adapt to changing energy landscapes, the adoption of such digital frameworks will likely become not just a competitive advantage, but a prerequisite for survival. Continued research and collaboration between academia, technology providers, and industry will be essential to realize the full potential of digitalization in oil refining.

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Застосування цифрових технологій для оптимізації процесів нафтопереробки

Сучасна нафтопереробна промисловість стикається зі зростаючими вимогами до енергоефективності, якості продукції та екологічної безпеки. Традиційні стратегії керування процесами, що базуються на лінійних моделях та періодичній оптимізації, є недостатньо ефективними для врахування складності та динаміки сучасних установок. У статті досліджено застосування цифрових технологій – промислового інтернету речей (IIoT), машинного навчання, цифрових двійників та сучасного керування процесами (APC) – для оптимізації процесів нафтопереробки в реальному часі. Запропоновано багаторівневу архітектуру, що поєднує збір даних із датчиків, прогнозну аналітику ключових показників та замкнене керування. Структура цифрового двійника дозволяє одночасно моделювати роботу технологічних установок (атмосферна перегонка, каталітичний крекінг, гідрокрекінг) із безперервним калібруванням параметрів за реальними даними. Моделі машинного навчання прогнозують виходи продуктів, енергоспоживання та знос обладнання, забезпечуючи проактивне технічне обслуговування та оперативне коригування режимів. Проведено порівняльний аналіз традиційного та цифрового підходів, що демонструє потенційне підвищення продуктивності, енергоефективності та надійності. Приклади впровадження на установках первинної перегонки нафти та каталітичного крекінгу підтверджують практичну ефективність. Розглянуто виклики, пов’язані з інтеграцією даних, інтерпретованістю моделей та кібербезпекою. Результати підтверджують, що поєднання цифрових технологій з інженерією нафтопереробки є потужним інструментом для досягнення сталого та рентабельного виробництва.

Ключові слова: нафтопереробка; цифровий двійник; машинне навчання; сучасне керування процесами; оптимізація в реальному часі; прогнозне обслуговування; енергоефективність; моделювання процесів.

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