UDK 665.6:681.5 doi: 10.20998/2078-5364.2026.2.01

Yevhenii Koroviaka, candidate of technical sciences, associate professor,
Volodymyr Khomenko, candidate of technical sciences, associate professor,
Andrii Ihnatov, candidate of technical sciences, associate professor

# APPLICATION OF ADVANCED PROCESS CONTROL AND REAL-TIME OPTIMIZATION FOR ENERGY EFFICIENCY IN OIL REFINING

*Dnipro University of Technology, Dnipro, Ukraine*

**Keywords**: advanced process control, model predictive control, real-time optimization, energy efficiency, oil refining, crude distillation unit, fired heaters, digital twin.

**Introduction**. The global refining industry is currently undergoing a profound transformation driven by the dual imperative of enhancing economic performance while significantly reducing environmental impact [1, 2]. Increasing volatility in energy markets, coupled with stringent environmental regulations and global decarbonization goals, has intensified the need for refineries to optimize their energy usage. Energy expenditures constitute a substantial proportion–typically ranging from 30 % to 50 %–of total operating costs in refining processes [3, 4]. Major energy consumers include fired heaters, compressors, and pumping systems, which are integral to maintaining process continuity but often operate below optimal efficiency due to legacy control strategies [5, 6].

In many conventional refinery setups, process control is predominantly based on decentralized regulatory control loops supplemented by intermittent manual interventions [7, 8]. While such approaches may ensure basic operational stability, they are inherently limited in their ability to handle multivariable interactions, process nonlinearities, and dynamic disturbances [9, 10]. As a result, these systems frequently operate under conservative setpoints, leading to increased energy consumption, reduced throughput efficiency, and elevated greenhouse gas emissions [11, 12]. The growing complexity of modern refining units–characterized by tightly coupled process variables, nonlinear kinetics, and fluctuating feedstock properties–renders traditional control methodologies increasingly inadequate [13].

In response to these challenges, advanced process control (APC), particularly model predictive control (MPC), has emerged as a robust and widely adopted solution. MPC leverages dynamic mathematical models of the process to forecast future system behavior over a defined prediction horizon [14]. By solving a constrained optimization problem in real time, MPC determines optimal adjustments to manipulated variables, ensuring adherence to operational constraints while maximizing performance objectives [15]. This predictive capability enables more precise control of key process parameters, reduces variability, and enhances energy efficiency [16].

The integration of MPC with real-time optimization (RTO) further extends these benefits by aligning operational control with economic objectives. RTO systems periodically compute optimal operating targets based on current process conditions, feedstock characteristics, and prevailing market prices [17, 18]. By continuously updating these targets and feeding them to the MPC layer, the combined APC–RTO framework ensures that refinery operations are not only stable and safe but also economically optimal [19]. This hierarchical control architecture facilitates coordinated decision-making across multiple process units, thereby unlocking additional efficiency gains [20].

Furthermore, regulatory frameworks such as the EU Emissions Trading System and various national energy efficiency directives provide strong incentives for refineries to adopt advanced optimization technologies [21]. Compliance with these regulations often necessitates measurable reductions in carbon intensity and energy consumption, which can be effectively achieved through APC and RTO implementation [22, 23]. At the same time, technological advancements–including the proliferation of online analyzers, improvements in process simulation accuracy, and the development of robust industrial data infrastructures–have significantly lowered the barriers to deploying such systems at scale [24, 25].

Consequently, the relevance of this research is underscored by its focus on the systematic application of APC and RTO methodologies to key refining units [26]. By demonstrating how these advanced control strategies can be effectively implemented to enhance energy efficiency, reduce emissions, and improve economic performance, the study contributes to the broader objective of sustainable refinery operation in an increasingly constrained energy and environmental landscape [27].

Collectively, the literature indicates that APC and RTO are mature technologies with proven benefits, yet their adoption requires a systematic framework that accounts for process dynamics, model accuracy, and economic objectives. This article aims to provide such a framework with a focus on energy efficiency.

**The main part**. The purpose of this article is to propose a structured approach for implementing advanced process control and real-time optimization to improve energy efficiency in oil refining. The study describes the architecture, key components, and practical benefits of APC/RTO systems, supported by case studies in crude distillation, fluid catalytic cracking, and fired heaters [28, 29]. The research also identifies critical success factors and future directions for further enhancing energy performance.

The proposed APC/RTO framework is built upon a hierarchical structure that separates control actions by time scale and scope. Figure 1 illustrates the typical architecture, consisting of three layers: the regulatory control layer (basic PID loops), the multivariable predictive control layer (MPC), and the real-time optimization layer. Each layer operates at a different frequency, with the RTO typically updating economic targets every 1-4 hours, the MPC executing every 1-5 minutes, and the regulatory loops acting at sub-second to second intervals. This separation ensures that fast disturbances are handled by the lowest layer, while economic optimization is performed at a slower pace that aligns with the time constants of feed changes and market price updates.

Figure 1 shows the flow of information: plant measurements are passed to the regulatory layer, then to the MPC, which sends setpoints to the regulatory controllers. The RTO uses reconciled plant data, a rigorous process model, and economic prices to compute optimal operating points, which are then passed to the MPC as targets. The figure also highlights the role of online analyzers and the data reconciliation block that ensures consistent material and energy balances. Online analyzers (e.g., gas chromatographs, near-infrared spectrometers) provide frequent measurements of product qualities, enabling the control system to respond to composition changes without relying on delayed laboratory results.

Data reconciliation and gross error detection form the foundation of accurate real-time optimization. Raw field measurements inevitably contain random noise, biases, and occasional gross errors from sensor malfunction or process leaks. Data reconciliation uses a steady-state process model – typically a set of mass and energy balance equations – to adjust the measurements minimally so that they satisfy the balances.

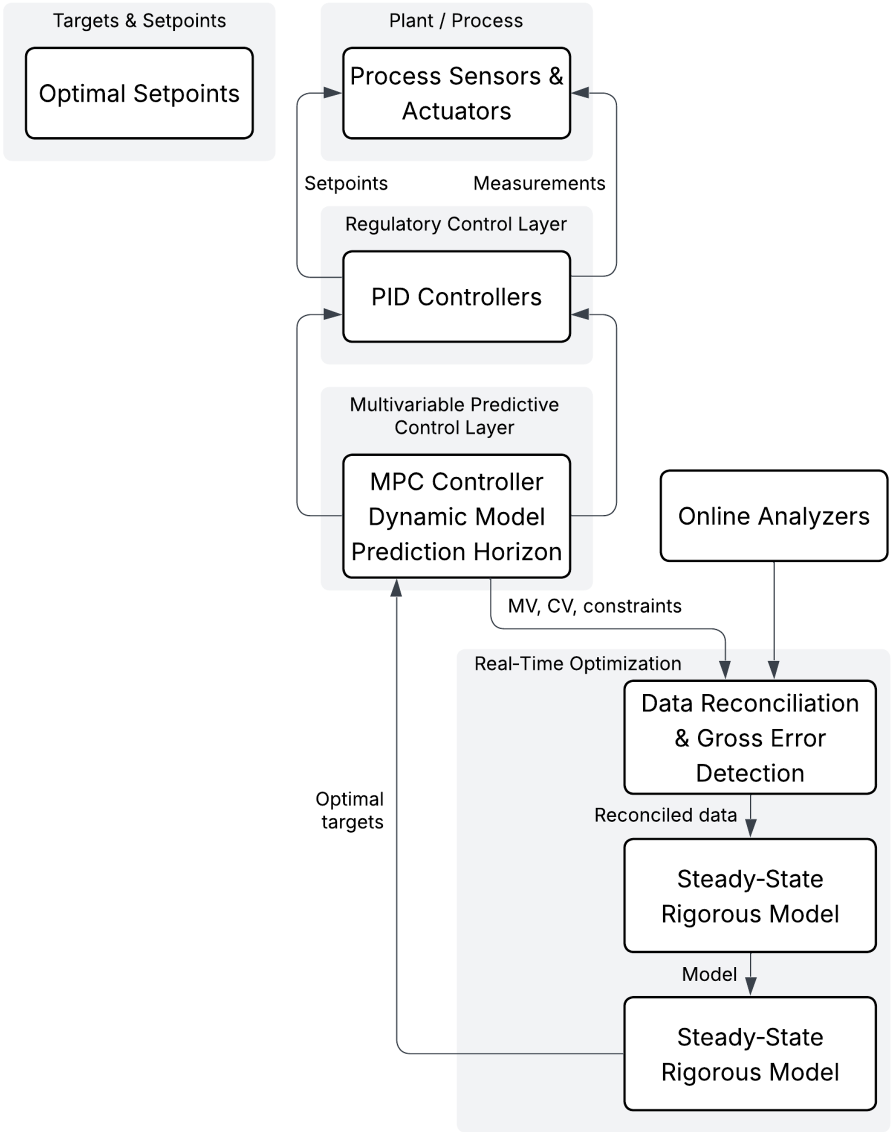


Figure 1 – Hierarchical Architecture of APC and RTO

The reconciled values are statistically optimal estimates that remove inconsistencies and provide a reliable snapshot of the process state. Gross error detection identifies faulty sensors or process leaks by analyzing the residuals between measured and reconciled values. For a crude distillation unit, reconciliation ensures that the yields of products, the heat duties of furnaces and exchangers, and the product qualities are correctly estimated before the optimization is performed. Without this step, the RTO would base its decisions on inconsistent data, potentially leading to suboptimal or even infeasible targets.

Model predictive control (MPC) is the core of the multivariable predictive control layer. The MPC uses a dynamic linear or nonlinear model of the process to predict future outputs over a prediction horizon (typically 30-120 minutes) and computes manipulated variable moves that minimize a quadratic objective while respecting constraints. For energy efficiency, the objective may include minimizing fuel gas consumption, steam usage, or electricity. Common controlled variables include product qualities (e.g., 95 % point of naphtha, flash point of diesel) and energy-related variables such as furnace outlet temperature, reflux ratios, and pumparound duties. The manipulated variables are typically feed rate, setpoints of flow controllers, and air/fuel ratio in furnaces. By explicitly handling interactions – for example, the effect of reflux ratio on both product purity and reboiler duty – and by respecting constraints (e.g., maximum column pressure drop, minimum furnace stack temperature), the MPC can push the process closer to its operational limits without violating safety or quality boundaries. The controller is executed every minute or faster, allowing it to correct disturbances such as feed rate variations or ambient temperature changes before they affect product quality.

Real-time optimization operates at a slower frequency, typically every 1-4 hours. It solves a steady-state optimization problem using a rigorous nonlinear process model, often built from first-principles thermodynamics and equipment performance equations. The objective is to maximize an economic function, which for energy efficiency is often expressed as:

$$\max_u \left( \sum_j p_j y_j(u,d) - c_{fuel} F_{fuel}(u,d) - c_{steam} S(u,d) - c_{elec}(u,d) \right), \tag{1}$$

where $p_j$ are product prices, $y_j$ are yields predicted by the model, $F_{fuel}$ is fuel consumption, $S$ is steam consumption, E is electricity consumption, and d are disturbances (feedstock properties, ambient temperature). Constraints include product specifications (e.g., maximum sulfur content, minimum flash point), equipment limits (e.g., maximum furnace firing, column pressure drop, compressor surge limits), and safety margins. The optimization is repeated periodically, and the optimal setpoints (e.g., furnace outlet temperature, reflux ratio) are sent to the MPC as targets. This closed-loop arrangement ensures that the plant is continuously driven toward the true economic optimum, even as feedstocks and prices change.

**Case study 1**: Crude distillation unit. A European refinery implemented APC and RTO on its 150,000 bbl/day crude unit. The project involved upgrading the DCS, installing online analyzers for key product qualities (naphtha 95 % point, diesel flash point), and deploying a rigorous CDU model for RTO. The MPC controlled the preheat train, furnace, and column with 12 manipulated variables and 18 controlled variables. The RTO updated targets every 4 hours based on real-time crude assay and energy prices. Over a 12-month period, the system reduced fuel gas consumption by 4.2 % and increased valuable distillate yield by 1.8 %, resulting in annual savings of over $2 million. The improved control also reduced temperature variability in the furnace, extending tube life and reducing maintenance costs. This case illustrates how the combination of MPC and RTO can simultaneously improve both energy efficiency and yield.

**Case study 2**: Fluid catalytic cracking unit. A FCCU in the Middle East faced frequent upsets due to changes in catalyst activity and feed composition. The installation of an MPC that manipulated regenerator air, slide valve positions, and riser temperature, coupled with an RTO that adjusted catalyst circulation and regenerator temperature targets, stabilized the unit. Energy consumption in the air blower – a major power consumer – was reduced by 6%. Optimizing coke burning led to lower regenerator temperatures, which reduced catalyst deactivation and extended catalyst life. Moreover, the system enabled the unit to process heavier feeds without exceeding environmental limits on SOx and NOx emissions. The case demonstrates how MPC/RTO can improve the flexibility of processing lower-cost feeds while maintaining energy efficiency and environmental compliance.

**Case study 3**: Fired heaters. Fired heaters account for a large share of refinery energy use, often 30-40 % of total site energy consumption. A dedicated MPC for a furnace with multiple passes and air preheating was implemented. The controller minimized fuel gas consumption by maintaining optimum excess oxygen (typically 2-3 %) and controlling pass outlet temperatures to within ±2 °C. The system also included a model to predict tube skin temperatures, preventing coking and tube failures by avoiding localized overheating. Energy savings of 7 % were reported, with a payback period of less than 18 months. Figure 2 presents a schematic of this typical fired heater control configuration, showing the manipulated variables (fuel flow, air flow, pass dampers) and controlled variables (outlet temperature, excess $O_2$, stack temperature). The figure illustrates how the MPC handles interactions – for example, increasing air flow reduces outlet temperature and also reduces excess $O_2$ if fuel is not adjusted simultaneously – and respects constraints such as maximum fuel flow and minimum air flow for safe combustion.

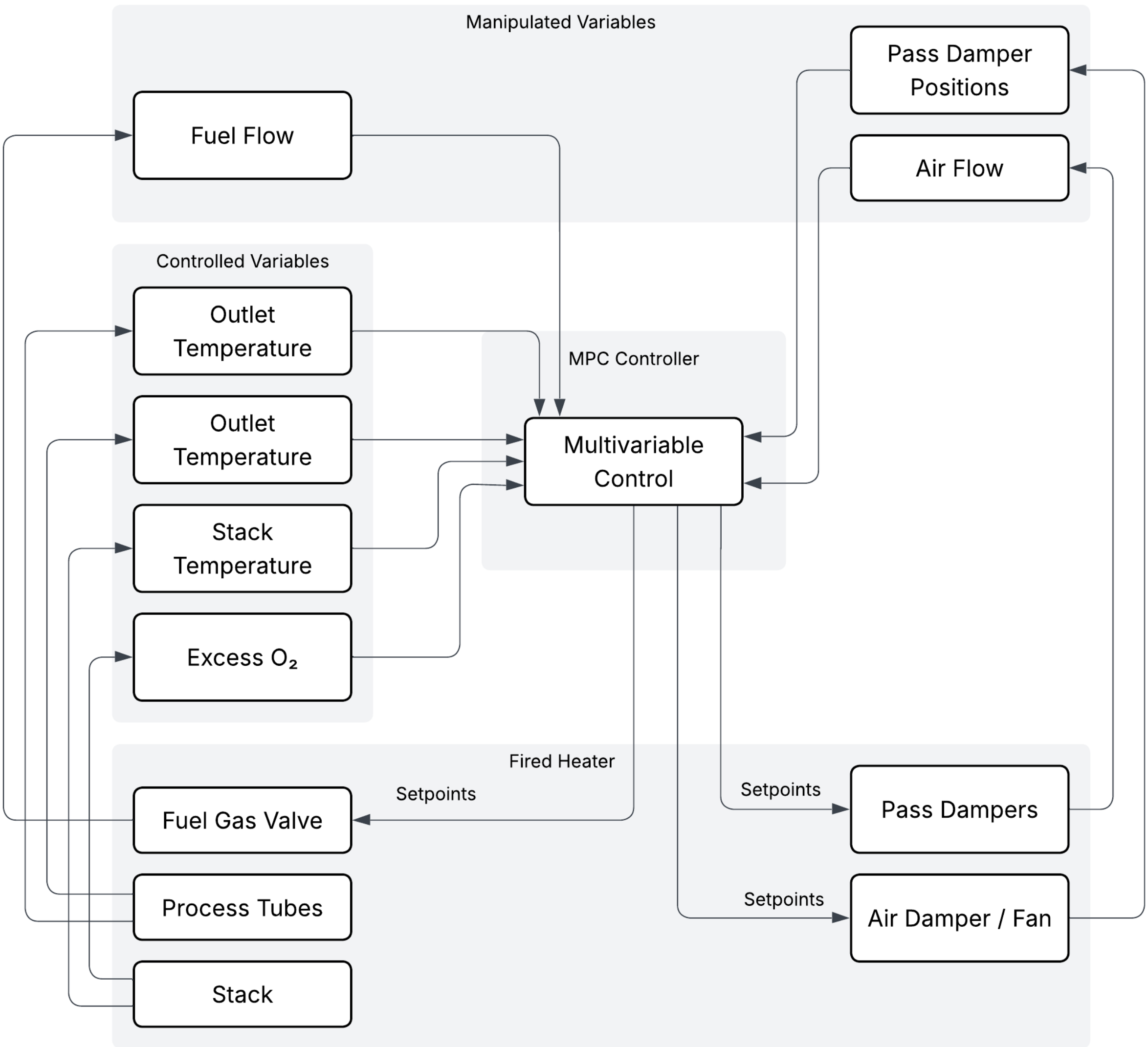


Figure 2 – Fired Heater Control Configuration with MPC

Figure 3 compares key energy indicators before and after APC/RTO implementation across the three case studies, expressed as energy intensity (gigajoules per ton of feed). The bar chart demonstrates reductions ranging from 3 % to 8 %, with the largest gains in fired heaters, which typically have the highest energy intensity and the greatest potential for improvement through tighter control. The results confirm that the hierarchical APC/RTO framework delivers consistent, quantifiable energy savings across diverse refining units.

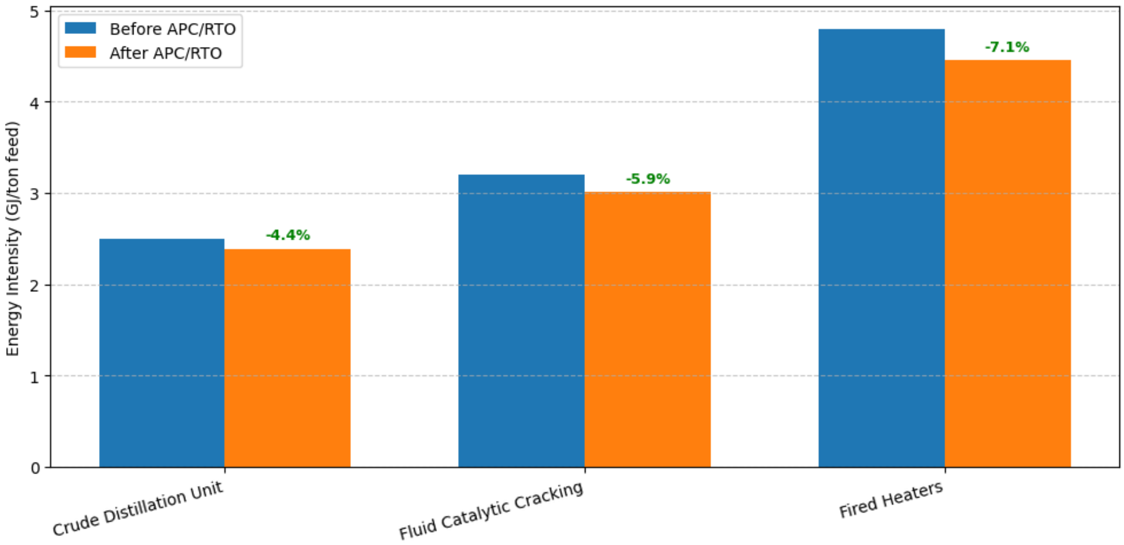


Figure 3 – Energy Efficiency Improvement with APC/RTO

Despite the proven benefits, several challenges must be addressed to ensure successful deployment and sustained performance. Model maintenance is critical; process changes such as revamps, catalyst changes, or equipment degradation degrade model accuracy over time, necessitating periodic re-identification of model parameters. Operator training is essential to build trust and ensure proper handling of control system overrides; operators must understand when to let the system run automatically and when to intervene. Integration with existing DCS and safety systems must be carefully engineered to avoid conflicts – for instance, the MPC should not violate safety interlocks. Furthermore, the economic benefit must be clearly demonstrated to justify the capital investment, which can be substantial for analyzers, controller hardware, and engineering services. Successful projects typically involve a multidisciplinary team of process engineers, control engineers, and operations personnel, and they rely on high-quality instrumentation and analyzers that are properly maintained.

The integration of machine learning with APC and RTO offers promising avenues to further enhance energy efficiency. Machine learning can be used to automatically update model parameters based on operating data, thereby reducing the maintenance burden. It can also predict feed properties from online analyzers or historical data, allowing the RTO to anticipate composition changes. Anomaly detection using machine learning can identify abnormal equipment behavior (e.g., fouling, catalyst deactivation) before it impacts performance. Digital twins – dynamic, high-fidelity simulations – can be used in place of traditional RTO models to enable more frequent updates (every few minutes instead of hours) and to simulate what-if scenarios for operational planning. Reinforcement learning is also being explored for autonomous control of energy-intensive units, where the controller learns optimal policies through interaction with the process. Additionally, the coupling of APC/RTO with carbon capture systems will become increasingly important as refineries aim to achieve net-zero emissions. Real-time optimization of energy consumption and $CO_2$ capture rates, balancing fuel savings against carbon credit prices, will be a key capability of future integrated systems. The continued evolution of these technologies promises to further close the gap between actual plant performance and theoretical economic optimum, driving the refining industry toward greater sustainability.

Figure 3 compares key energy indicators before and after APC/RTO implementation across the three case studies, expressed as energy intensity (GJ per ton of feed). The bar chart demonstrates reductions ranging from 3 % to 8 %, with the largest gains in fired heaters.

Despite the proven benefits, several challenges must be addressed. Model maintenance is critical; process changes (e.g., revamps, catalyst changes) degrade model accuracy over time, necessitating periodic re-identification. Operator training is essential to build trust and ensure proper handling of control system overrides. Integration with existing DCS and safety systems must be carefully engineered to avoid conflicts. Furthermore, the economic benefit must be clearly demonstrated to justify the capital investment. Successful projects typically involve a multidisciplinary team of process engineers, control engineers, and operations personnel, and they rely on high-quality instrumentation and analyzers.

The integration of machine learning with APC and RTO offers promising avenues. Machine learning can be used to automatically update model parameters based on operating data, to predict feed properties, and to detect abnormal events. Digital twins – dynamic, high-fidelity simulations – can be used in place of traditional RTO models to enable more frequent updates and to simulate what-if scenarios. Reinforcement learning is also being explored for autonomous control of energy-intensive units. Additionally, the coupling of APC/RTO with carbon capture systems will become increasingly important as refineries aim to achieve net-zero emissions.

**Conclusions and prospects for further research**. The application of advanced process control and real-time optimization represents a mature, proven strategy for enhancing energy efficiency in oil refining operations. The hierarchical architecture that underpins this approach–comprising a regulatory control layer of basic PID loops, a multivariable predictive control layer using model predictive control, and a steady-state real-time optimization layer–provides a structured framework that aligns control actions with the characteristic time scales of process dynamics. This separation of responsibilities ensures that fast disturbances are handled locally while economic optimization is performed at a frequency consistent with changes in feedstock properties and market prices, allowing the plant to be continuously operated near its true economic optimum.

The case studies presented in this article confirm the tangible benefits of this integrated approach. In a crude distillation unit, the combination of MPC and RTO reduced fuel gas consumption by 4.2 % while simultaneously increasing valuable distillate yield by 1.8 %, demonstrating that energy efficiency and yield improvement are not mutually exclusive objectives. In a fluid catalytic cracking unit, the implementation of APC/RTO stabilized operation against feed and catalyst variations, reducing air blower energy consumption by 6 % and enabling the processing of heavier, lower-cost feeds without exceeding environmental limits. For fired heaters, which represent the single largest energy consumers in most refineries, dedicated MPC achieved energy savings of 7 % by maintaining optimum excess oxygen and tight control of pass outlet temperatures, while also protecting against tube overheating and coking. These results collectively illustrate that the hierarchical framework delivers consistent, quantifiable improvements across diverse process units.

Beyond the direct energy savings, the implementation of such systems yields additional benefits that are critical for modern refining operations. Improved control reduces variability, which in turn allows operation closer to constraints without compromising safety or product quality. Reduced temperature cycling extends equipment life and lowers maintenance costs. Enhanced stability enables operators to confidently process a wider range of feedstocks, improving refinery flexibility in response to changing crude markets. Moreover, the rigorous process models and data reconciliation infrastructure built for APC and RTO provide a foundation for other digital initiatives, including predictive maintenance and advanced analytics.

However, the successful deployment and sustained performance of these systems depend on several critical factors. The accuracy of the process models must be maintained over time through periodic re-identification or adaptive updating, as equipment degradation, catalyst changes, and process revamps inevitably introduce deviations. High-quality instrumentation and online analyzers are essential; unreliable measurements lead to suboptimal control and erode operator trust. Equally important is the human element: operators must be thoroughly trained to understand the system's behavior, to recognize when automatic control is functioning correctly, and to intervene appropriately during abnormal situations. Successful projects consistently involve close collaboration between process engineers, control engineers, and operations personnel, supported by management commitment to the long-term value of advanced control.

Looking forward, several promising research directions will further enhance the capabilities of APC and RTO. One key area is the reduction of model maintenance effort through adaptive and self-learning modeling techniques. Machine learning algorithms that continuously update model parameters using operational data can significantly reduce the engineering burden associated with periodic re-identification. Hybrid models that combine first-principles knowledge with data-driven components offer particular promise, as they can extrapolate beyond the range of historical data while still learning from new operating points.

The integration of machine learning for predictive capabilities will also expand the scope of optimization. Advanced prediction of feed properties using near-infrared spectroscopy combined with neural networks can enable the RTO to anticipate composition changes rather than react to them. Similarly, models that forecast fouling rates in heat exchangers, catalyst deactivation in FCC units, or coking in fired heaters can inform proactive maintenance scheduling and incorporate these degradation effects directly into the optimization objective, balancing immediate energy savings against long-term equipment life.

Digital twin platforms represent a natural evolution of the current RTO infrastructure. Unlike traditional steady-state RTO models, digital twins are dynamic, high-fidelity simulations that run continuously in parallel with the physical plant. They can be used to perform what-if scenario analysis, to test the impact of operational changes before implementation, and to enable more frequent (e.g., every few minutes) optimization updates. When coupled with machine learning for parameter estimation, digital twins can maintain accuracy even under rapidly changing conditions.

As the refining industry faces increasing pressure to reduce carbon emissions, the role of advanced control will expand beyond traditional energy efficiency to encompass optimization of the energy-carbon trade-off. Real-time optimization that balances fuel consumption against carbon credit prices, or that minimizes emissions subject to fuel cost constraints, will become standard. Integration with carbon capture and storage (CCS) units will require coordinated control of the capture process alongside the core refining units. Furthermore, as refineries begin to incorporate renewable energy sources such as solar or wind power for electrical loads, APC systems will need to manage the variability of these sources while maintaining stable operation.

Finally, the convergence of process control, artificial intelligence, and digitalization is laying the groundwork for the next generation of autonomous refineries. Reinforcement learning–where controllers learn optimal policies through direct interaction with the process–offers the potential for systems that continuously improve their performance without explicit model identification. While such approaches are still in early stages of development, they represent a long-term vision of truly self-optimizing plants that adapt autonomously to changing conditions. The continued advancement of these technologies, combined with sustained commitment to implementation best practices, will ensure that APC and RTO remain essential tools for achieving safe, efficient, and sustainable refining operations in the decades ahead.

Література

1. Seijo-Bestilleiro E., Arias-Fernández I., Carro-López D., Naveiro M. Opportunities for Emission Reduction in the Transformation of Petroleum Refining. *Fuels*. 2025. Vol. 6, Iss. 3. P. 66. DOI: https://doi.org/10.3390/fuels6030066.

2. Griffiths S., Sovacool B., Kim J. [et al.]. Decarbonizing the oil refining industry: A systematic review of sociotechnical systems, technological innovations, and policy options. *Energy Research & Social Science*. 2022. Vol. 89. Art. 102542. DOI: https://doi.org/10.1016/j.erss.2022.102542.

3. Rissman J., Bataille C., Masanet E. [et al.]. Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied Energy*. 2020. Vol. 266. Art. 114848. DOI: https://doi.org/10.1016/j.apenergy.2020.114848.

4. Yılbaşı Z. Biofuels, E-Fuels, and Waste-Derived Fuels: Advances, Challenges, and Future Directions. *Sustainability*. 2025. Vol. 17, Iss. 13. Art. 6145. DOI: https://doi.org/10.3390/su17136145.

5. Salomone D. Advanced strategies for the efficient optimization and control of industrial compressed air systems. *Results in Engineering*. 2025. Vol. 26. Art. 105429. DOI: https://doi.org/10.1016/j.rineng.2025.105429.

6. Jørgensen B. N., Ma Z. G. Energy Efficiency and Decarbonization Strategies in Buildings: A Review of Technologies, Policies, and Future Directions. *Applied Sciences*. 2025. Vol. 15, Iss. 21. Art. 11660. DOI: https://doi.org/10.3390/app152111660.

7. Fahsyar P., Ismail Z. Decentralized Energy Management Using Multi-Agent Systems for Remote Hybrid Power Systems. *IntechOpen*. 2026. DOI: https://doi.org/10.5772/intechopen.1014778.

8. Ranaboldo M., Aragüés-Peñalba M., Arica E. [et al.]. A comprehensive overview of industrial demand response status in Europe. *Renewable and Sustainable Energy Reviews*. 2024. Vol. 203. Art. 114797. DOI: https://doi.org/10.1016/j.rser.2024.114797.

9. Zhang F., Li Z., Ma C. [et al.]. Hybrid model predictive and active disturbance rejection control for robust and efficient control of extractive distillation process. *Chemical Engineering Science*. 2026. Vol. 320. Art. 122676. DOI: https://doi.org/10.1016/j.ces.2025.122676.

10. Rojas L., Yepes V., Garcia J. Complex Dynamics and Intelligent Control: Advances, Challenges, and Applications in Mining and Industrial Processes. *Mathematics*. 2025. Vol. 13, Iss. 6. Art. 961. DOI: https://doi.org/10.3390/math13060961.

11. Lin T.-Y., Chiu Y.-H., Chen C.-H., Ji L. Renewable energy consumption efficiency, greenhouse gas emission efficiency, and climate change in Europe. *Geoenergy Science and Engineering*. 2025. Vol. 247. Art. 213665. DOI: https://doi.org/10.1016/j.geoen.2025.213665.

12. Oltulular S. Energy Efficiency and Environmental Technologies in Carbon Emissions Reduction Strategies for a Sustainable Future: Estimation Through Simultaneous Equation Systems. *Energies*. 2025. Vol. 18, Iss. 14. Art. 3596. DOI: https://doi.org/10.3390/en18143596.

13. Song M.-K., Kim D.-W., Mohanty S. [et al.]. Energy-efficient machine learning approaches for enhanced biofuel (Biodiesel) production: A review. *Energy and AI*. 2026. Vol. 24. Art. 100696. DOI: https://doi.org/10.1016/j.egyai.2026.100696.

14. Yu Z., Long J. Review on Advanced Model Predictive Control Technologies for High-Power Converters and Industrial Drives. *Electronics*. 2024. Vol. 13, Iss. 24. Art. 4969. DOI: https://doi.org/10.3390/electronics13244969.

15. Wei Z., Tien P. W., Calautit J. [et al.]. Investigation of a model predictive control (MPC) strategy for seasonal thermochemical energy storage systems in district heating networks. *Applied Energy*. 2024. Vol. 376. Art. 124164. DOI: https://doi.org/10.1016/j.apenergy.2024.124164.

16. Tomažič S., Škrjanc I. Advanced model predictive control strategies for energy-efficient HVAC systems in pharmaceutical facilities. *Energy and Buildings*. 2025. Vol. 347. Art. 116348. DOI: https://doi.org/10.1016/j.enbuild.2025.116348.

17. Zanin A., Gouvêa M., Odloak D. Integrating real-time optimization into the model predictive controller of the FCC system. *Control Engineering Practice*. 2002. Vol. 10. P. 819–831. DOI: https://doi.org/10.1016/S0967-0661(02)00033-3.

18. De Prada C., Sarabia D., Gutierrez G. [et al.]. Integration of RTO and MPC in the Hydrogen Network of a Petrol Refinery. *Processes*. 2017. Vol. 5, Iss. 1. Art. 3. DOI: https://doi.org/10.3390/pr5010003.

19. Pontes K., Wolf I., Embiruçu M., Marquardt W. Dynamic Real-Time Optimization of Industrial Polymerization Processes with Fast Dynamics. *Industrial & Engineering Chemistry Research*. 2015. Vol. 54. DOI: https://doi.org/10.1021/acs.iecr.5b00909.

20. Abdelhadi H., Mahmoud A. M., Saied E. M. M., Mohamed M. A. E. Innovative hierarchical control of multiple microgrids: Cheetah meets PSO. *Energy Reports*. 2024. Vol. 11. P. 4967–4981. DOI: https://doi.org/10.1016/j.egyr.2024.04.055.

21. Mańkowski K., Bajan B., Mrówczyńska-Kamińska A. Renewable energy in EU agribusiness: Review of progress in meeting 2030 renewable energy directive III targets. *Energy Reports*. 2026. Vol. 15. Art. 109031. DOI: https://doi.org/10.1016/j.egyr.2025.109031.

22. Wang J., Li H., Wang C., Ren W. The Impact of Dual Environmental Regulations on Carbon Intensity: A Global Perspective. *Sustainability*. 2025. Vol. 17, Iss. 4. Art. 1446. DOI: https://doi.org/10.3390/su17041446.

23. Shen Y. The power of market regulation: analyzing the impact of energy use rights trading policies on low-carbon transformation. *Sustainable Energy Research*. 2026. Vol. 13. DOI: https://doi.org/10.1186/s40807-025-00235-2.

24. Khan M. I., Yasmeen T., Khan M. [et al.]. Integrating industry 4.0 for enhanced sustainability: Pathways and prospects. *Sustainable Production and Consumption*. 2025. Vol. 54. P. 149–189. DOI: https://doi.org/10.1016/j.spc.2024.12.012.

25. Cavus M. Advancing Power Systems with Renewable Energy and Intelligent Technologies: A Comprehensive Review on Grid Transformation and Integration. *Electronics*. 2025. Vol. 14, Iss. 6. Art. 1159. DOI: https://doi.org/10.3390/electronics14061159.

26. Bauer M., Craig I. Economic Assessment of Advanced Process Control–A Survey and Framework. *Journal of Process Control*. 2008. Vol. 18. P. 2–18. DOI: https://doi.org/10.1016/j.jprocont.2007.05.007.

27. Ramírez-Márquez C., Ponce-Ortega J. M., Segovia-Hernández J. G., Hernández S. Process intensification control: Advancing efficiency and sustainability, a review. *Chemical Engineering and Processing – Process Intensification*. 2025. Vol. 216. Art. 110388. DOI: https://doi.org/10.1016/j.cep.2025.110388.

28. Li H., Zhao Q., Wang R. [et al.]. Integrated Hybrid Modelling and Surrogate Model-Based Operation Optimization of Fluid Catalytic Cracking Process. *Processes*. 2024. Vol. 12, Iss. 11. Art. 2474. DOI: https://doi.org/10.3390/pr12112474.
29. Sánchez R., Palencia-Díaz A., Fábregas-Villegas J., Velilla-Díaz W. Fired Heaters Optimization by Estimating Real-Time Combustion Products Using Numerical Methods. *Energies*. 2024. Vol. 17, Iss. 23. Art. 6190. DOI: https://doi.org/10.3390/en17236190.

Bibliography (transliterated)

1. Seijo-Bestilleiro E., Arias-Fernández I., Carro-López D., Naveiro M. Opportunities for Emission Reduction in the Transformation of Petroleum Refining. *Fuels*. 2025. Vol. 6, Iss. 3. P. 66. DOI: https://doi.org/10.3390/fuels6030066.
2. Griffiths S., Sovacool B., Kim J. [et al.]. Decarbonizing the oil refining industry: A systematic review of sociotechnical systems, technological innovations, and policy options. *Energy Research & Social Science*. 2022. Vol. 89. Art. 102542. DOI: https://doi.org/10.1016/j.erss.2022.102542.
3. Rissman J., Bataille C., Masanet E. [et al.]. Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied Energy*. 2020. Vol. 266. Art. 114848. DOI: https://doi.org/10.1016/j.apenergy.2020.114848.
4. Yılbaşı Z. Biofuels, E-Fuels, and Waste-Derived Fuels: Advances, Challenges, and Future Directions. *Sustainability*. 2025. Vol. 17, Iss. 13. Art. 6145. DOI: https://doi.org/10.3390/su17136145.
5. Salomone D. Advanced strategies for the efficient optimization and control of industrial compressed air systems. *Results in Engineering*. 2025. Vol. 26. Art. 105429. DOI: https://doi.org/10.1016/j.rineng.2025.105429.
6. Jørgensen B. N., Ma Z. G. Energy Efficiency and Decarbonization Strategies in Buildings: A Review of Technologies, Policies, and Future Directions. *Applied Sciences*. 2025. Vol. 15, Iss. 21. Art. 11660. DOI: https://doi.org/10.3390/app152111660.
7. Fahsyar P., Ismail Z. Decentralized Energy Management Using Multi-Agent Systems for Remote Hybrid Power Systems. *IntechOpen*. 2026. DOI: https://doi.org/10.5772/intechopen.1014778.
8. Ranaboldo M., Aragüés-Peñalba M., Arica E. [et al.]. A comprehensive overview of industrial demand response status in Europe. *Renewable and Sustainable Energy Reviews*. 2024. Vol. 203. Art. 114797. DOI: https://doi.org/10.1016/j.rser.2024.114797.
9. Zhang F., Li Z., Ma C. [et al.]. Hybrid model predictive and active disturbance rejection control for robust and efficient control of extractive distillation process. *Chemical Engineering Science*. 2026. Vol. 320. Art. 122676. DOI: https://doi.org/10.1016/j.ces.2025.122676.
10. Rojas L., Yepes V., Garcia J. Complex Dynamics and Intelligent Control: Advances, Challenges, and Applications in Mining and Industrial Processes. *Mathematics*. 2025. Vol. 13, Iss. 6. Art. 961. DOI: https://doi.org/10.3390/math13060961.
11. Lin T.-Y., Chiu Y.-H., Chen C.-H., Ji L. Renewable energy consumption efficiency, greenhouse gas emission efficiency, and climate change in Europe. *Geoenergy Science and Engineering*. 2025. Vol. 247. Art. 213665. DOI: https://doi.org/10.1016/j.geoen.2025.213665.
12. Oltulular S. Energy Efficiency and Environmental Technologies in Carbon Emissions Reduction Strategies for a Sustainable Future: Estimation Through Simultaneous Equa-

tion Systems. *Energies*. 2025. Vol. 18, Iss. 14. Art. 3596. DOI: https://doi.org/10.3390/en18143596.

13. Song M.-K., Kim D.-W., Mohanty S. [et al.]. Energy-efficient machine learning approaches for enhanced biofuel (Biodiesel) production: A review. *Energy and AI*. 2026. Vol. 24. Art. 100696. DOI: https://doi.org/10.1016/j.egyai.2026.100696.

14. Yu Z., Long J. Review on Advanced Model Predictive Control Technologies for High-Power Converters and Industrial Drives. *Electronics*. 2024. Vol. 13, Iss. 24. Art. 4969. DOI: https://doi.org/10.3390/electronics13244969.

15. Wei Z., Tien P. W., Calautit J. [et al.]. Investigation of a model predictive control (MPC) strategy for seasonal thermochemical energy storage systems in district heating networks. *Applied Energy*. 2024. Vol. 376. Art. 124164. DOI: https://doi.org/10.1016/j.apenergy.2024.124164.

16. Tomažič S., Škrjanc I. Advanced model predictive control strategies for energy-efficient HVAC systems in pharmaceutical facilities. *Energy and Buildings*. 2025. Vol. 347. Art. 116348. DOI: https://doi.org/10.1016/j.enbuild.2025.116348.

17. Zanin A., Gouvêa M., Odloak D. Integrating real-time optimization into the model predictive controller of the FCC system. *Control Engineering Practice*. 2002. Vol. 10. P. 819–831. DOI: https://doi.org/10.1016/S0967-0661(02)00033-3.

18. De Prada C., Sarabia D., Gutierrez G. [et al.]. Integration of RTO and MPC in the Hydrogen Network of a Petrol Refinery. *Processes*. 2017. Vol. 5, Iss. 1. Art. 3. DOI: https://doi.org/10.3390/pr5010003.

19. Pontes K., Wolf I., Embiruçu M., Marquardt W. Dynamic Real-Time Optimization of Industrial Polymerization Processes with Fast Dynamics. *Industrial & Engineering Chemistry Research*. 2015. Vol. 54. DOI: https://doi.org/10.1021/acs.iecr.5b00909.

20. Abdelhadi H., Mahmoud A. M., Saied E. M. M., Mohamed M. A. E. Innovative hierarchical control of multiple microgrids: Cheetah meets PSO. *Energy Reports*. 2024. Vol. 11. P. 4967–4981. DOI: https://doi.org/10.1016/j.egyr.2024.04.055.

21. Mańkowski K., Bajan B., Mrówczyńska-Kamińska A. Renewable energy in EU agribusiness: Review of progress in meeting 2030 renewable energy directive III targets. *Energy Reports*. 2026. Vol. 15. Art. 109031. DOI: https://doi.org/10.1016/j.egyr.2025.109031.

22. Wang J., Li H., Wang C., Ren W. The Impact of Dual Environmental Regulations on Carbon Intensity: A Global Perspective. *Sustainability*. 2025. Vol. 17, Iss. 4. Art. 1446. DOI: https://doi.org/10.3390/su17041446.

23. Shen Y. The power of market regulation: analyzing the impact of energy use rights trading policies on low-carbon transformation. *Sustainable Energy Research*. 2026. Vol. 13. DOI: https://doi.org/10.1186/s40807-025-00235-2.

24. Khan M. I., Yasmeen T., Khan M. [et al.]. Integrating industry 4.0 for enhanced sustainability: Pathways and prospects. *Sustainable Production and Consumption*. 2025. Vol. 54. P. 149–189. DOI: https://doi.org/10.1016/j.spc.2024.12.012.

25. Cavus M. Advancing Power Systems with Renewable Energy and Intelligent Technologies: A Comprehensive Review on Grid Transformation and Integration. *Electronics*. 2025. Vol. 14, Iss. 6. Art. 1159. DOI: https://doi.org/10.3390/electronics14061159.

26. Bauer M., Craig I. Economic Assessment of Advanced Process Control–A Survey and Framework. *Journal of Process Control*. 2008. Vol. 18. P. 2–18. DOI: https://doi.org/10.1016/j.jprocont.2007.05.007.

27. Ramírez-Márquez C., Ponce-Ortega J. M., Segovia-Hernández J. G., Hernández S. Process intensification control: Advancing efficiency and sustainability, a review. *Chemical*

*Engineering and Processing – Process Intensification*. 2025. Vol. 216. Art. 110388. DOI: https://doi.org/10.1016/j.cep.2025.110388.

28. Li H., Zhao Q., Wang R. [et al.]. Integrated Hybrid Modelling and Surrogate Model-Based Operation Optimization of Fluid Catalytic Cracking Process. *Processes*. 2024. Vol. 12, Iss. 11. Art. 2474. DOI: https://doi.org/10.3390/pr12112474.

29. Sánchez R., Palencia-Díaz A., Fábregas-Villegas J., Velilla-Díaz W. Fired Heaters Optimization by Estimating Real-Time Combustion Products Using Numerical Methods. *Energies*. 2024. Vol. 17, Iss. 23. Art. 6190. DOI: https://doi.org/10.3390/en17236190.

UDK 665.6:681.5

Yevhenii Koroviaka, candidate of technical sciences, associate professor,
Volodymyr Khomenko, candidate of technical sciences, associate professor,
Andrii Ihnatov, candidate of technical sciences, associate professor

## APPLICATION OF ADVANCED PROCESS CONTROL AND REAL-TIME OPTIMIZATION FOR ENERGY EFFICIENCY IN OIL REFINING

Energy consumption constitutes one of the largest operating expenses in oil refining, and its reduction is critical for both economic performance and environmental compliance. Traditional regulatory control systems, however, are unable to maintain process operations at the true optimum under varying feedstocks and market conditions. This article explores the application of advanced process control (APC) and real-time optimization (RTO) technologies to improve energy efficiency in refining units. The integration of model predictive control (MPC) with rigorous process models, online analyzers, and economic optimization is examined. A hierarchical architecture is presented, comprising regulatory control, multivariable predictive control, and steady-state RTO layers. The role of real-time data reconciliation, gross error detection, and model updating is emphasized. Case studies from crude distillation units (CDU), fluid catalytic cracking (FCC) regenerators, and fired heaters demonstrate energy savings of 3-8% and significant reductions in greenhouse gas emissions. The paper also discusses implementation challenges, including model maintenance, operator training, and integration with existing distributed control systems. Future directions, such as the incorporation of machine learning for adaptive model refinement and the use of digital twins for predictive optimization, are outlined. The results confirm that APC and RTO are essential tools for achieving sustainable and energy-efficient refining operations.

**Keywords**: advanced process control, model predictive control, real-time optimization, energy efficiency, oil refining, crude distillation unit, fired heaters, digital twin.

Є. А. Коровяка, В. Л. Хоменко, А. О. Ігнатов

## ЗАСТОСУВАННЯ СУЧАСНОГО КЕРУВАННЯ ПРОЦЕСАМИ ТА ОПТИМІЗАЦІЇ В РЕАЛЬНОМУ ЧАСІ ДЛЯ ПІДВИЩЕННЯ ЕНЕРГОЕФЕКТИВНОСТІ НАФТОПЕРЕРОБКИ

Енергоспоживання є однією з найбільших статей операційних витрат у нафтопереробці, і його скорочення має критичне значення як для економічної ефективності, так і для екологічної відповідності. Традиційні системи регулювання, однак, не здатні підтримувати роботу процесів у дійсному оптимумі за умов змінної сировини та ринкових коливань. У статті досліджено застосування технологій сучасного керування процесами (APC) та оптимізації в реальному часі (RTO) для підвищення енергоефективності нафтопереробних установок. Розглянуто інтеграцію модельного прогнозуючого керування (MPC) з детермінованими моделями процесів, онлайн-аналізаторами та економічною оптимізацією. Представлено ієрархічну архітектуру, що включає рівні регулювання, багатовимірного прогнозуючого керування та стаціонарної оптимізації. Підкреслено роль узгодження даних у реальному часі, виявлення грубих помилок та оновлення моделей. Приклади з установок первинної перегонки нафти (CDU), регенераторів каталітичного крекінгу (FCC) та трубчастих печей демонструють економію енергії на рівні 3-8% і значне скорочення викидів парникових газів. Розглянуто проблеми впровадження, включаючи підтримку моделей, навчання персоналу та інтеграцію з існуючими розподіленими системами керування. Окреслено перспективні напрями, такі як використання машинного навчання для адаптивного уточнення моделей та застосування цифрових двійників для прогнозної оптимізації. Результати підтверджують, що APC та RTO є важливими інструментами для досягнення сталого та енергоефективного нафтопереробного виробництва.

**Ключові слова**: сучасне керування процесами, модельно-прогнозуюче керування, оптимізація в реальному часі, енергоефективність, нафтопереробка, установка первинної перегонки нафти, трубчасті печі, цифровий двійник.

*Отримано редколегією 18.03.2026*

***Коровяка Євгеній Анатолійович (Yevhenii Koroviaka)****, канд. техн. наук, доцент, зав. каф. Національного технічного університету «Дніпровська політехніка», https://orcid.org/0000-0002-2675-6610;*

***Хоменко Володимир Львович (Volodymyr Khomenko)****, канд. техн. наук, доцент, доцент Національного технічного університету «Дніпровська політехніка» https://orcid.org/0000-0002-3607-5106;*

***Ігнатов Андрій Олександрович (Andrii Ihnatov)****, канд. техн. наук, доцент, доцент Національного технічного університету «Дніпровська політехніка» https://orcid.org/0000-0002-7653-125X.*