AI in Real-World Oil Refineries

The peer-reviewed literature confirms that artificial intelligence and machine learning have moved from theoretical frameworks to real-world deployment across petroleum refining and downstream processing facilities (Tatiya et al., 2025; García Olaizola et al., 2022; Askar et al., 2026). Industrial implementations primarily focus on enhancing process safety, optimizing operating margins, predicting real-time fuel qualities, and conducting predictive equipment maintenance (Tatiya et al., 2025; Thorpe, 2022; García Olaizola et al., 2022).

Real-World Operational Deployments

Refineries around the world have deployed machine learning systems directly into operating units to manage operational instability and reduce unplanned outages (García Olaizola et al., 2022; Askar et al., 2026). At the North Refineries Company in Baiji, Iraq, live operational testing integrated long short-term memory (LSTM) networks for early pump failure prediction, artificial neural networks (ANNs) for abnormal temperature gradient detection in crude distillation columns, and autoencoder models to detect chemical anomalies in gas chromatography data (Askar et al., 2026). These live systems yielded a measurable decrease in unplanned outages, lowered maintenance expenditures, and improved final product consistency (Askar et al., 2026).

Similarly, downstream facilities such as the Petronor refinery have validated and embedded data science workflows into daily plant supervision (García Olaizola et al., 2022). Under these supervisory architectures, data-driven outputs are checked against operating boundaries before being fed into higher-level model predictive control (MPC) systems (García Olaizola et al., 2022). Machine learning models have additionally been implemented in petrochemical production lines and catalytic units, leveraging industrial Internet of Things (IoT) sensors to optimize operations in response to shifting feedstocks (Min et al., 2019; Perno et al., 2023; Pomeroy et al., 2022).

Refinery Applications and Performance

Operational Domain	Applied AI & Modeling Methods	Primary Refinery Impact	Key Source
Fuel Blending	GA-ANN hybrid networks & SVR	Maintains octane specifications (R^2 = 0.99) and reduces quality giveaways	(Jameel, 2025)
Distillation Units	LSTM networks & physics-informed neural twins	Identifies column temperature gradients and estimates tray compositions	(Askar et al., 2026; Patra et al., 2026)
Process Optimization	Multi-period dynamic digital twins	Reconciles unit operations under ambient variations and feed shifts	(Thorpe, 2022)
Hydroprocessing	Hybrid SVR & Bayesian optimization	Predicts desulfurization yields and SO_2 emissions (correlation > 98%)	(Al-Jamimi et al., 2022)
Equipment Reliability	Random forests, PCA & Dirichlet clustering	Anticipates hydrocracker machinery faults and pipeline pressure risks	(Priyanka et al., 2021; Bukhtoyarov et al., 2022)

Table 1: Summary of applied AI methods and reported impacts across refinery operational domains

Implementation Roles and Constraints

Refinery deployments typically configure artificial intelligence as an assistive surrogate or supervisory layer rather than fully autonomous control (Saghir et al., 2024; García Olaizola et al., 2022; Askar et al., 2026):

- **Surrogate-based optimization**: Algorithms such as Gaussian process regression and convolutional autoencoders approximate slow computational simulations, reducing execution windows from hours to seconds (Saghir et al., 2024; Alsuwaidi et al., 2026).
- **Blending control**: Real-time neural models calculate complex non-linear interactions across components, allowing operators to rapidly compensate for abrupt feedstock property drops (Jameel, 2025).
- **Safety and transparency limits**: The legacy "black-box" nature of neural systems remains a barrier to autonomous adoption, requiring explicit constraint validation and human-in-the-loop oversight for safety-critical decisions (Tatiya et al., 2025; García Olaizola et al., 2022; Askar et al., 2026).

Scientific evidence demonstrates that AI is widely used across operating commercial refineries, delivering measurable efficiency and reliability improvements while operating under strict engineer supervision.

References

Al-Jamimi, H. A., Binmakhashen, G. M., & Saleh, T. (2022). Artificial intelligence approach for modeling petroleum refinery catalytic desulfurization process. *Neural Computing and Applications, 34*, 17809 - 17820. https://doi.org/10.1007/s00521-022-07423-x

Alsuwaidi, A., Salvilla, J. N. V., Rong, J., Atef, M., Yang, R., Liu, Q.-Q., Kuang, S.-B., & Zhang, L. (2026). Fast Prediction of FCC Regenerator Temperature Fields Using Digital – Twin Based on Convolutional Autoencoder Dimensionality Reduction and Machine Learning. *Chemical Engineering Journal Advances*. https://doi.org/10.1016/j.ceja.2026.101286

Askar, T. R. A., Mashhadany, A. Y., & Algburi, S. (2026). Predictive to Prescriptive and Beyond One Step Closer to Reliable AI in Refinery Control Scenarios. *2026 IEEE 23rd International Multi-Conference on Systems, Signals & Devices (SSD)*, 1293-1298. https://doi.org/10.1109/ssd69655.2026.11559048

Bukhtoyarov, V., Nekrasov, I. S., Tynchenko, V., Bashmur, K., & Sergienko, R. B. (2022). Application of machine learning algorithms for refining processes in the framework of intelligent automation. *SOCAR Proceedings*. https://doi.org/10.5510/ogp2022si100665

García Olaizola, I., Quartulli, M., Unzueta, E., Goicolea, J. I., & Flórez, J. (2022). Refinery 4.0, a Review of the Main Challenges of the Industry 4.0 Paradigm in Oil & Gas Downstream. *Sensors (Basel, Switzerland), 22*. https://doi.org/10.3390/s22239164

Jameel, A. G. A. (2025). A Case Study on Integrating an AI System into the Fuel Blending Process in a Chemical Refinery. *ChemEngineering*. https://doi.org/10.3390/chemengineering9010004

Min, Q., Lu, Y., Liu, Z.-Y., Su, C., & Wang, B. (2019). Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. *Int. J. Inf. Manag., 49*, 502-519. https://doi.org/10.1016/j.ijinfomgt.2019.05.020

Patra, D., Tripathy, A., Sahu, S., & Panda, S. (2026). Physics-Informed Neural Network Digital Twin for Dynamic Tray-Wise Modeling of Distillation Columns under Transient Operating Conditions. *ArXiv, abs/2603.24644*. https://doi.org/10.48550/arxiv.2603.24644

Perno, M., Hvam, L., & Haug, A. (2023). A machine learning digital twin approach for critical process parameter prediction in a catalyst manufacturing line. *Comput. Ind., 151*, 103987. https://doi.org/10.1016/j.compind.2023.103987

Pomeroy, B., Grilc, M., & Likozar, B. (2022). Artificial neural networks for bio-based chemical production or biorefining: A review. *Renewable and Sustainable Energy Reviews*. https://doi.org/10.1016/j.rser.2021.111748

Priyanka, E., Thangavel, S., Gao, X.-Z., & Sivakumar, N. (2021). Digital twin for oil pipeline risk estimation using prognostic and machine learning techniques. *J. Ind. Inf. Integr., 26*, 100272. https://doi.org/10.1016/j.jii.2021.100272

Saghir, H., Ahmad, I., Kano, M., Çalışkan, H., & Hong, H. (2024). Prediction and optimisation of gasoline quality in petroleum refining: The use of machine learning model as a surrogate in optimisation framework. *CAAI Trans. Intell. Technol., 9*, 1185-1198. https://doi.org/10.1049/cit2.12324

Tatiya, M., Shinde, B. A., Pokale, N., Sarada, M., Murali, G., Kadam, V. R., & Kurhade, A. (2025). AI-Driven Process Control for Enhancing Safety and Efficiency in Oil Refining. *Applied Chemical Engineering*. https://doi.org/10.59429/ace.v8i4.5792

Thorpe, P. (2022). A Dynamically Reconciled Digital Twin for Operations Optimization and Decision Support. *Day 2 Tue, November 01, 2022*. https://doi.org/10.2118/210987-ms