AI-driven autonomy cuts energy use, emissions, and operator burden

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As refiners contend with increasing complexity, ageing control systems, and growing sustainability pressures, AI-driven autonomy is shifting from ambition to reality. Reinforcement learning (RL) – a branch of artificial intelligence (AI) that learns through interaction – offers a way to navigate this complexity without relying on predefined models or manual tuning. Think of it as a skilled operator who learns by doing, adapting to what works and adjusting decisions in real-time without a rulebook.

Unlike traditional proportional-integral-derivative (PID) or advanced process control (APC) systems, which require extensive engineering and struggle in non-linear environments, RL adapts in real time. According to Energies Media, the oil and gas sector faces challenges such as defect detection, cybersecurity, and logistics network optimisation. However, AI offers a powerful advantage that converts raw data into actionable insights, enhancing operations while reducing costs. The World Economic Forum adds that digital technologies could lower global industrial emissions by at least 4% by 2030, positioning RL as a high-impact tool for efficiency and decarbonisation.

RL learns via real-time interaction, making it well-suited for dynamic, multivariable environments like refineries. This article explores the real-world application of Factorial Kernel Dynamic Policy Programming (FKDPP), an RL developed by Yokogawa and the Nara Institute of Science and Technology. Tested and deployed in live plant operations, FKDPP acts like an experienced process engineer who never sleeps, constantly learning, adjusting, and ensuring the system stays in balance even when conditions change.

Inefficiencies in Traditional Control Methods

Traditional control strategies, including PID control and APC, are well-established but exhibit limitations when applied to highly nonlinear and dynamic industrial environments. Tuning PID loops for non-linear valve behaviour remains difficult and often leads to suboptimal performance under disturbances or feed variations. Furthermore, APC implementation cycles are lengthy, typically requiring seven to eight months, and necessitate extensive step testing for model identification. These factors limit the responsiveness of traditional controls to real-time changes.

Reinforcement learning has been explored as a solution; however, conventional RL algorithms (such as Deep Q-Networks) demand a large number of trials and are highly sensitive to the training dataset. Such characteristics make them unsuitable for real-world process control, where each trial carries operational risk, safety implications, and cost. The industry requires an RL algorithm that is both sample-efficient and robust across variable process conditions.

To overcome these limitations, FKDPP was developed as a data-driven, self-adaptive control model requiring significantly fewer learning trials compared to conventional RL

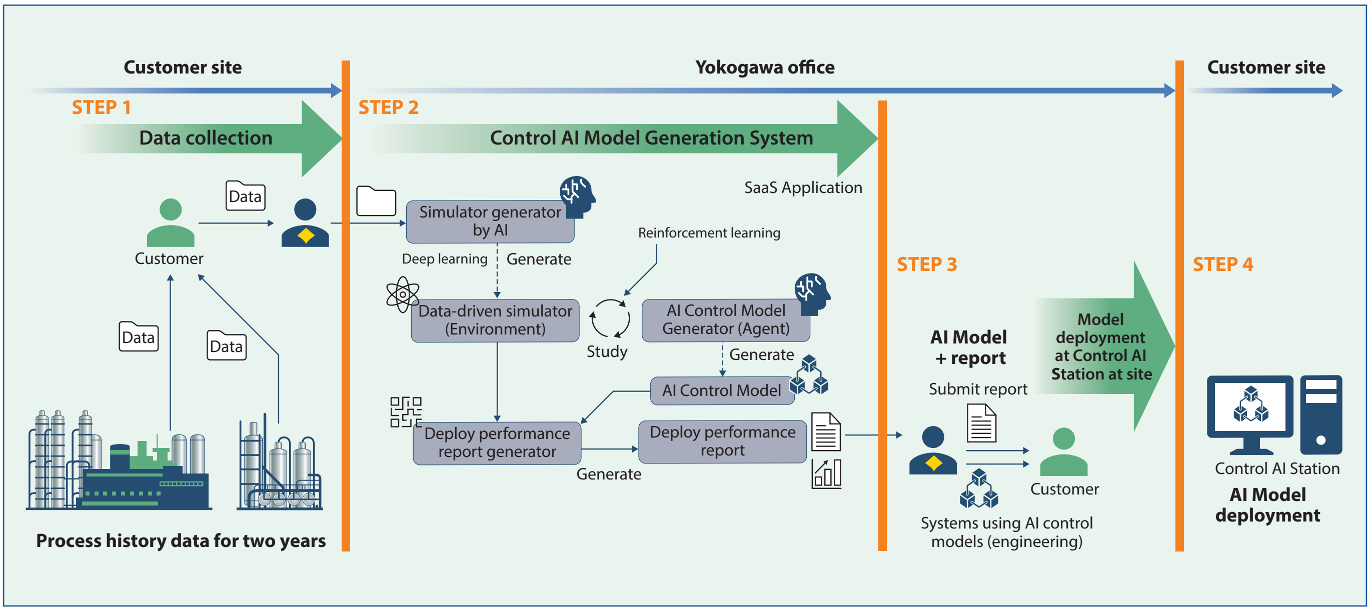
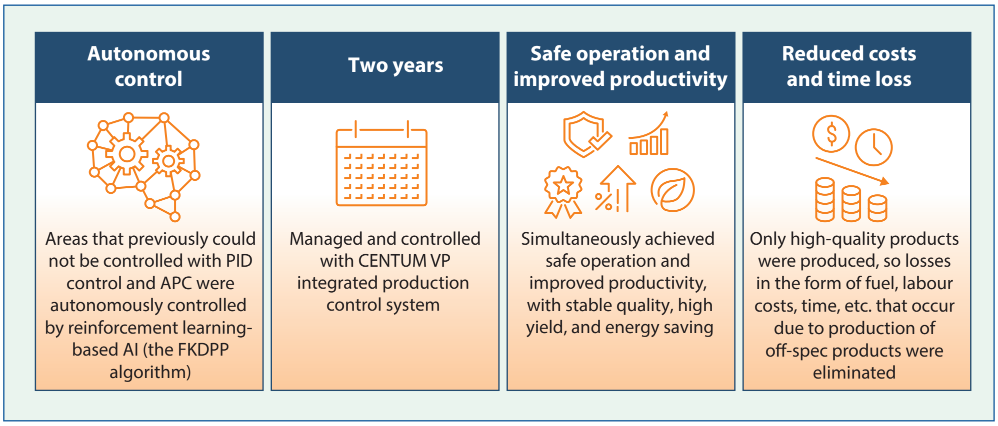


Figure 1 FKDPP AI model lifecycle, from data collection to field deployment via Control AI Station



Autonomous control

Areas that previously could not be controlled with PID control and APC were autonomously controlled by reinforcement learning-based AI (the FKDPP algorithm)

Two years

Managed and controlled with CENTUM VP integrated production control system

Safe operation and improved productivity

Simultaneously achieved safe operation and improved productivity, with stable quality, high yield, and energy saving

Reduced costs and time loss

Only high-quality products were produced, so losses in the form of fuel, labour costs, time, etc. that occur due to production of off-spec products were eliminated

Figure 2 Summary of operational benefits observed from FKDPP deployment at ENEOS, including yield, safety, and automation gains

techniques. In simulation environments, it achieved stable control of complex processes such as distillation and decantation within about 30 learning iterations, demonstrating its rapid convergence capability.

Unlike data-sensitive deep learning models, FKDPP is designed for resilience against process variability, enabling deployment in real-world industrial systems without retraining for every operational change. **Figure 1** illustrates this four-step process.

FKDPP's architecture is optimised to reduce sample complexity and maintain control objectives under disturbances. Integration into existing control systems is achieved through a dedicated Control AI Station operating at Level 2.5/3 of the automation architecture, interfacing with the distributed control system (DCS) via Open Platform Communications (OPC) protocols.

Case Study: Autonomous Operation of a Distillation Column

A chemical production unit operated by ENEOS in Japan served as the testbed for FKDPP deployment. The unit includes a distillation column previously managed via manual intervention, especially under varying ambient conditions and feed disturbances. The objective was to assess whether the AI controller could maintain product quality, reduce energy use, and stabilise operations under these dynamic inputs.

Following training and validation, the FKDPP model was implemented in the plant's CENTUM™ VP control environment. During a controlled trial, the AI system operated the column autonomously for 35 consecutive days. While **Figure 2** highlights overall achievements, the FKDPP system also delivered highly specific improvements in level control, heat recovery, and disturbance rejection, as outlined below:

- Precise maintenance of liquid levels within the distillation column.
- Optimised use of waste heat, reducing reboiler energy consumption.
- Elimination of off-spec product batches.
- Real-time response to weather-induced process disturbances.

The AI controller achieved these results without operator intervention, demonstrating autonomous handling of setpoint adjustments and disturbance rejection. Importantly, when the plant underwent routine shutdown and subsequent restart, the AI model resumed operation without requiring retraining, underscoring its robustness.

Results

Quantitative results from the ENEOS case study highlight the value of FKDPP in refinery and chemical operations:

Energy savings: Steam consumption for the controlled column was reduced by approximately 40%.

Emissions reduction: A corresponding reduction in CO_2 emissions was achieved through optimised heat recovery.

Operational stability: Variability in key process variables was minimised despite fluctuations in feed composition and external temperature.

Product quality: 100% of batches met required specifications, eliminating losses associated with reprocessing or disposal.

Operator workload: Autonomous operation reduced the burden on control room personnel, enabling a shift towards higher-level supervisory tasks.

The algorithm's ability to maintain control without re-tuning further reduces maintenance overhead, making it a sustainable solution with long-term benefits.

Conclusion

The successful deployment of FKDPP demonstrates the viability of reinforcement learning as a control strategy in operational refinery environments. By addressing key limitations of traditional and earlier AI approaches – namely, sample inefficiency and sensitivity to process variation – FKDPP offers a path forward for AI-enabled automation.

Beyond technical performance, the AI system delivers measurable improvements in ROI, sustainability, and process resilience. Energy efficiency gains directly impact operating costs and carbon intensity, aligning with broader industry goals for decarbonisation. Additionally, the system enables consistent quality and throughput, positioning it as a tool for maintaining competitiveness in volatile markets.

The integration of FKDPP into refinery operations represents a significant step toward autonomous process control. As further applications are explored, ranging from three-phase separators to upstream and midstream assets, this technology is poised to play a key role in the next generation of smart manufacturing systems.

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