

How ENEOS put reinforcement learning in control of a chemical plant

By Rehana Begg

Butadiene is just one building block in a chemical plant, but for ENEOS Materials Corporation it is an essential starting point for synthetic rubber used in products ranging from tires and seals to hoses and other engineered components.

To produce high-purity butadiene, ENEOS employs a distillation process to separate it from other hydrocarbons. The process runs continuously, so changes in temperature, feed composition and heat can affect product quality and energy use.

At ENEOS Materials' Yokkaichi Plant in Japan, much of this process was already highly automated. But in 2022, operators at one purification tower were still repeatedly adjusting valves to maintain a stable tower level while maximizing waste-heat recovery. It was exactly the kind of complex control challenge that conventional PID and APC systems had not fully solved; it created an opportunity for ENEOS Materials and Yokogawa to test whether reinforcement learning-based AI could take over the decision-making.

Presenting the use case at YNOW2026, Yokogawa's Flagship Users Conference & Exhibition, Yoshiro Sakura, Manager, Production Technology Department, ENEOS Materials Corporation, said ENEOS Materials deliberately targeted a control process that still required frequent operator intervention.

"In the selection of the target, we did not want to replace PID or APC where they already work well," Sakura

said. "We looked for a process that still needed frequent operator actions. The target also needed a clear control projection, useful process data, and meaningful impact on stability, quality and energy use. Finally, we found one [distillation column]."

The team selected a purification tower where operators adjusted two valves about every 15 minutes to keep the tower level stable while capturing as much waste heat as possible. Automating those adjustments offered the potential to reduce steam use while maintaining stable operation and product quality.

The engineering challenge became the AI use case: Could an algorithm balance the competing demands of level stability, waste-heat recovery and product quality?

Rather than learn directly on the production plant, the team first built a dynamic simulator using actual plant data.

Testing autonomy in phases

ENEOS Materials and Yokogawa used a progressive deployment process to move from simulation to autonomous operation. First, they built a dynamic model of the actual plant and trained

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—Yoshiro Sakura, Manager,
Production Technology Department,
ENEOS Materials Corporation



the reinforcement-learning model on the simulator. Engineers then evaluated and refined the AI's behavior using plant data and their own process knowledge, checking its control actions, safety and potential energy benefits. If the model's behavior was difficult to explain or its energy benefit was unclear, the team returned to training and refinement.

The project next moved into a human-in-the-loop phase, in which operators reviewed the AI's recommendations and manually entered accepted manipulated-variable settings into the DCS. This provided an opportunity to observe the model's behavior in the real process before giving it direct control. As Sakura explained, "This long review period reduced the risk and helped operators understand and trust the model."

After this period of evaluation, the team moved to closed-loop autonomous control. The AI was constrained by rule-based limits, while existing DCS alarms, interlocks and other safety systems remained active. Operators could stop the AI and return to conventional DCS operation. "The key principle was simple: the AI model was never the only safety barrier," said Sakura.

The structured deployment process gave operators and engineers confidence in the model. The next question was whether the system could deliver sustained performance under real-world operating conditions.

Four years of autonomous operation

The project delivered three important milestones: it worked autonomously, remained reliable under changing conditions and proved durable in production.

Sakura explained that the first major test came from January 17 to February 21, 2022. The model controlled the process continuously for 35 days, or 840 hours, without a manual takeover or off-spec product. "This proved that autonomous control could work continuously in the real plant," explained Sakura, and further pointed out that this was the first reported case of AI directly controlling outputs in a chemical plant.

Over the following year, it handled seasonal temperature changes of about 40°C and daily changes in feedstock composition while keeping the process stable and reducing steam use and related CO₂ emissions by about 40% compared with manual control.

And finally, the technology moved beyond demonstration into routine production, where it has now operated for more than four years through regular shutdowns and maintenance without model-related problems, he said.

Scaling autonomy without compromising safety

Sakura highlighted three lessons for scaling autonomous control: use AI for control problems that remain unresolved rather than replacing effective PID or APC loops; move from simulation to human verification and then autonomous control step by step; and treat AI as one layer within a broader safety system, never as the sole safeguard.

First, use AI where conventional control still falls short. Sakura said ENEOS does not view AI as a replacement for

PID or APC. Instead, his team targeted a control challenge that still required frequent operator intervention and identified a use case where an algorithm could deliver measurable improvements in stability, product quality and energy efficiency.

Second, build confidence through step-by-step validation. In this case, the project progressed from a dynamic simulator to engineering review, followed by a six-month human-in-the-loop period before the model was allowed to control the process directly. This phased approach provided evidence that the model behaved as expected while giving operators time to understand and trust its decisions. "We verify step by step," Sakura stressed.

Finally, treat AI as one component of the control system, not the safety system itself. Once implemented, the model operated within rule-based limits and alongside existing DCS alarms, interlocks and other guardrails. Operators also retained the ability to disable the AI and return to conventional control. The approach deliberately avoided making AI the primary line of defense.

While the project centered on a butadiene-purification tower, Sakura suggested the underlying principles apply broadly to manufacturers evaluating autonomous process control.

"In short," he said, "choose the right problem, proceed step by step, and never depend on AI alone." ∞

