DOI: 10.12700/AIS.2025.003

Exploring the Applications of Artificial Intelligence in Sulfur Recovery Units: A Review

Ecem Muge Andoglu Coskun
Chemical Engineering Department
Bilecik Seyh Edebali University
Bilecik, Türkiye
email muge.andoglu@bilecik.edu.tr

***Abstract*—The Sulfur Recovery Units, particularly the Claus process, are critical in the natural gas and petroleum industries for recovering sulfur from hydrogen sulfide (H2S) and other sulfur compounds. Even if traditional methods have been employed for decades, the integration of Artificial Intelligence (AI) is applied to sulfur recovery recently in the aim of improving efficiency, reducing costs, and enhancing environmental compliance. This literature review examines the key applications and contributions of AI in the sulfur recovery process. The results show that from conceptual constructs for adaptive controls, artificial intelligence became an effective driver of process intelligence in sulfur recovery units. This new era of AI is characterized by deep learning, transfer learning, and hybrid modeling that allow for accurate prediction, improved emission control, and robust optimization under uncertain process conditions. The studies examined show consistent progress from neural estimators to autonomous, interpretable SRU systems that can adapt in real time.**

Keywords*—*Claus process, artificial intelligence, machine learning, sulfur recovery

I. Introduction

Sulfur recovery units are essential for treating sour gases and meeting environmental regulations. Their main function is to recover elemental sulfur from H2S via the Claus process and related tail-gas treatment operations. Fig.1 illustrates a typical Sulfur Recovery Unit (SRU), where hydrogen sulfide (H2S) is partially oxidized in the reaction furnace to form sulfur dioxide (SO2) and elemental sulfur [1]. The process gases then pass through condensers and catalytic reactors to convert remaining H2S and SO2 into sulfur, which is collected while the tail gas is treated to reduce emissions.

Monitoring and control of key variables such as conversion efficiency, SO2 concentration, and temperature are crucial yet challenging due to high temperature, process coupling, and sensor limitations. Traditional first-principle models often fail to capture dynamic nonlinearities.

Recent advances in artificial intelligence (AI)—including machine learning (ML), deep learning (DL), and hybrid approaches—have enabled data-driven "soft sensors" capable of estimating unmeasured variables and improving predictive control accuracy.

This review consolidates state-of-the-art research on AI techniques in SRUs and similar chemical process environments, highlighting progress from early neural networks to modern transformer-based and transfer-learning frameworks in the years 1994-2025.

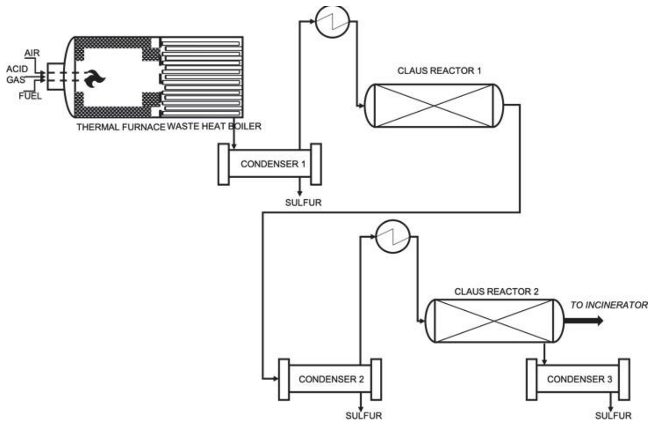

Fig. 1. Basic scheme of a sulfur recovery unit.

II. Literature Review

Table 1 provides the review of the literature investigates the evolution of AI in sulfur recovery units from early adaptive control and basic soft sensors in the 1990s to advanced deep learning, transformer, and graph-based models in 2025. Approaches include neural networks, autoencoders, ensemble methods, transfer learning, and reinforcement learning through which accurate soft sensing, process optimization, and real-time monitoring is possible. Recent findings highlight robustness, interpretability, semi-supervised learning, and hybrid knowledge-data integration approaches as new trends to address complex, dynamic, and multivariate SRU processes.

Progression of predictive performance in AI-based sulfur recovery unit (SRU) models from 1994 to 2025 is given Fig.2. Early adaptive control approaches achieved limited precision but established the foundation for intelligent process control. Over the following decades, accuracy improved steadily with the introduction of neural networks, ensemble learning, and hybrid deep learning architectures. Recent demonstrate predictive accuracies approaching 99% in dynamic SRU environments.

A. Early Developments: Adaptive and Neural Control

The earliest AI-related SRU control effort was by Cunningham [2], who applied adaptive control to stabilize Claus process operations and improve sulfur yield. This study laid the groundwork for data-driven process automation. In the early 2000s, Fortuna et al. [3] proposed neural-network-based soft analyzers for real-time estimation of unmeasured variables, demonstrating the feasibility of intelligent monitoring. These pioneering efforts established the conceptual basis for integrating AI with process control systems.

TABLE I. REPRESENTATIVE STUDIES ON AI-BASED SRU AND PROCESS SOFT SENSING

Ref.	Year	Focus/Objective	Method/Model	Key Findings	Contribution to AI in SRUs
[2]	1994	Improve SRU operation stability and sulfur yield.	Adaptive control algorithm.	Demonstrated robust process regulation via adaptive control.	Laid the foundation for intelligent control in SRUs.
[3]	2003	Develop real-time analyzers for process monitoring.	Neural network-based soft analyzers.	Enabled accurate estimation of unmeasured SRU variables.	Introduced soft sensing to SRU process control.
[4]	2014	Estimate optimal sulfinol concentration in gas treatment.	Stabilized MLP with regularization.	Improved robustness and accuracy of gas treatment modeling.	Demonstrated neural model adaptability applicable to SRUs.
[5]	2015	Enhance chemical process quality prediction.	Selective ensemble of local PLS models.	Improved prediction accuracy under varying conditions.	Provided ensemble modeling strategies for SRU soft sensors.
[6]	2017	Design adaptive soft sensors for time-varying processes.	Gaussian Process Regression with time-delay reconstruction.	Enhanced adaptability to dynamic process changes.	Enabled dynamic modeling approaches for SRUs.
[7]	2018	Monitor SRU quality under changing conditions.	Multi-State-Dependent Parameter model.	Achieved accurate soft sensing for sulfur recovery.	Strengthened adaptive quality monitoring in SRUs.
[8]	2019	Improve refinery quality monitoring with AI.	Regression Neural Network.	Enhanced model accuracy with optimized training.	Advanced data-driven quality estimation relevant to SRUs.
[9]	2019	Optimize SRU operation and reduce energy use.	Multi-objective optimization with reaction kinetics.	Minimized energy consumption while maintaining conversion efficiency.	Showed optimization benefits using AI modeling in SRUs.
[10]	2020	Predict industrial quality variables.	Stacked Enhanced Autoencoder.	Extracted deep nonlinear features for accurate prediction.	Advanced data-driven feature learning for SRU sensors.
[11]	2020	Model SRU soft analyzers with deep learning.	Stacked Isomorphic Autoencoder.	Provided reliable estimation of SRU key process parameters.	Applied deep architectures to SRU soft analyzer design.
[12]	2021	Improve interpretability of soft sensors.	Evolutionary Multi-objective Optimization.	Achieved balanced trade-off between accuracy and transparency.	Enhanced explainable AI frameworks for SRU modeling.
[13]	2021	Develop dynamic soft sensors for SRUs.	Echo-State Network (ESN).	Captured temporal correlations in SRU dynamics.	Introduced reservoir computing for SRU variable prediction.
[14]	2021	Assess soft sensor transferability across processes.	RNN and LSTM architectures.	Validated reusability and adaptability across datasets.	Promoted cross-process generalization for SRUs.
[15]	2023	Simplify H2S thermal conversion kinetics.	Machine-learning reduced kinetic model.	Provided fast and accurate process simulation.	Applied ML-based kinetic modeling to SRU reactors.
[16]	2023	Model multivariate soft sensor relationships.	Balanced Mixture-of-Experts (MoE).	Improved feature learning and correlation handling.	Enhanced SRU soft sensor performance with MoE framework.
[17]	2023	Integrate domain knowledge with ML.	Contextual Mixture-of-Experts.	Increased prediction interpretability and reliability.	Promoted hybrid knowledge-data-driven modeling in SRUs.
[18]	2024	Study adversarial attacks on industrial soft sensors.	Mirror Output Attack & Translation Mirror Output Attack.	Identified vulnerabilities in NN-based sensing systems.	Strengthened AI model security for SRUs.
[19]	2024	Enhance transfer learning for process modeling.	Parallel SAE with transfer-incremental learning.	Improved adaptability to varying SRU conditions.	Advanced continuous learning for SRU optimization.
[20]	2024	Design predictive soft sensors.	Multi-step-ahead Hankel Dynamic Mode Decomposition.	Enhanced SRU prediction accuracy and control readiness.	Enabled proactive process control in SRUs.
[21]	2024	Model composite dynamic systems.	Layer-wise residual-driven learning.	Captured fast and slow process dynamics effectively.	Improved multi-scale SRU process modeling.
[22]	2024	Enhance LSTM reliability for noisy data.	Information Filtering Unit-based LSTM.	Improved robustness in signal processing.	Strengthened time-series learning in SRU soft sensors.
[23]	2024	Handle label scarcity in SRU modeling.	ISSA-VMD-ESN semi-supervised hybrid.	Achieved high accuracy with limited supervision.	Extended AI usability in low-data SRU environments.
[24]	2024	Improve nonlinear modeling for soft sensing.	Distributed Nonlinear Bi-LSTM.	Enhanced representation of nonlinear SRU features.	Advanced deep recurrent modeling for SRU prediction.
[25]	2024	Integrate AI-based reconciliation into SRU control.	State-Dependent Parameter + Regression Filter.	Reduced process control errors.	Improved SRU stability and closed-loop performance.
[26]	2024	Model spatiotemporal causality in industrial systems.	Knowledge-Data Guided Reinforcement Learning.	Captured temporal causal dependencies.	Applied RL for adaptive SRU control and optimization.
[27]	2024	Predict SO2 emissions in SRU incinerators.	AI-based forecasting model.	Accurately predicted emission patterns.	Supported sustainable SRU emission control.
[28]	2024	Model dynamic processes for soft sensing.	TCN-CBAM-LSTM hybrid model.	Improved temporal feature extraction.	Strengthened sequential learning for SRUs.
[29]	2025	Develop transferable soft sensors.	Graph-based Predictable Deep Transfer Network.	Achieved strong cross-domain adaptability.	Advanced knowledge transfer for SRU AI models.
[30]	2025	Extract global dynamic features from industrial data.	Autoencoder with hidden layer enhancement.	Improved dynamic feature representation.	Enhanced data-driven dynamic modeling in SRUs.
[31]	2025	Address nonlinear time-delay processes.	LASSO Transformer Network.	Increased interpretability and forecasting precision.	Applied transformer-based deep learning to SRUs.

[32]	2025	Implement AI-driven control optimization.	AI Surrogate Model.	Improved operational efficiency and control stability.	Introduced direct AI control frameworks for SRUs.
[33]	2025	Improve online sensing accuracy.	Adaptive Multilevel Regression Integration.	Achieved real-time error compensation.	Enhanced SRU process adaptability and monitoring.
[34]	2025	Continuously predict industrial quality indices.	Deep Temporal Feature Extraction with Ensemble Modeling.	Maintained accuracy under dynamic process drift.	Improved adaptive SRU model updating mechanisms.
[35]	2025	Generate virtual sensor data.	Self-Attention Embedded StyleGAN.	Created realistic synthetic data for training.	Expanded SRU datasets for robust AI learning.
[36]	2025	Design robust soft sensors under input collinearity.	Finite-time delay and regressor identification.	Identified optimal input regressors for modeling.	Refined AI-based SRU sensor design strategies.

MLP: multilayer perceptrons; PLS: partial least squares; RNN: Recurrent Neural Network; LSTM: long short-term memory network; SAE: Stacked Autoencoders; ISSA: Improved sparrow search algorithm; VMD: Variational mode composition; TCN: Temporal convolutional network; CBAM: Convolutional block attention module; LASSO: Least absolute shrinkage and selection operator transformer; GAN: Generative adversarial network

B. *Emergence of Soft Sensors and Hybrid Estimation*

The next phase focused on soft sensors—virtual models estimating difficult-to-measure variables using historical data. Garmroodi Asil and Shahsavand [4] and Shao and Tian [5] developed multilayer perceptron and ensemble regression models to improve robustness in chemical process prediction. Bidar et al. [7] extended this concept to sulfur recovery monitoring via multi-state-dependent parameter models, achieving improved adaptability. Deep learning architectures such as Gaussian Process Regression [6] and autoencoders [10], [11] further enhanced nonlinear feature extraction and dynamic modeling.

Simultaneously, optimization-driven AI systems began emerging. Rahman et al. [9] applied multi-objective optimization to minimize SRU energy use without compromising conversion efficiency, while Yuan et al. [11] introduced stacked autoencoders to capture deep correlations between process variables. These studies demonstrated that AI can outperform traditional empirical or first-principles models when addressing data-driven nonlinearities.

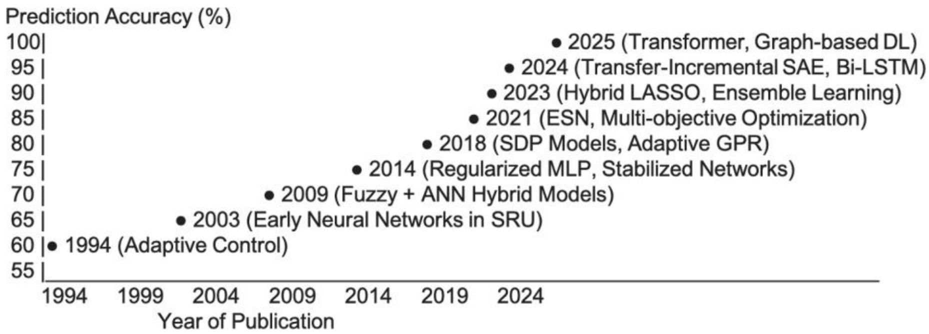

Fig. 2. Progression of predictive performance in AI-based sulfur recovery unit (SRU) models from 1994 to 2025.

C. *Advancements in Dynamic Modeling and Deep Learning*

Between 2021 and 2024, SRU modeling shifted toward recurrent and reservoir computing. Patanè and Xibilia [13] and Curreri et al. [14] adopted echo-state networks (ESN) and long short-term memory (LSTM) architectures to capture dynamic temporal patterns, enabling predictive control. Concurrently, Huang et al. [16] and Souza et al. [17] introduced mixture-of-experts (MoE) frameworks, integrating data-driven and domain-based reasoning for improved interpretability.

In parallel, Dell'Angelo et al. [15] utilized machine learning to simplify kinetic modeling of H2S thermal conversion, allowing faster process simulations. Security and robustness concerns were also addressed—Chen et al. [18] examined adversarial attacks on soft sensors, revealing vulnerabilities in neural monitoring systems, while Talaei et al. [25] proposed regression-based reconciliation filters to mitigate sensor noise and ensure reliable control.

Deep transfer learning was another milestone. Mou et al. [19] and Zhang et al. [21] designed transferable soft sensors capable of learning across different process domains, significantly reducing retraining needs. Wang & Li [23] extended into the problem of label scarcity by using semi-supervised hybrid architectures and enhanced reliability in the scenario of underdeveloped data.

D. *Recent Innovations: Reinforcement Learning and Generative AI*

Recent contributions emphasize reinforcement learning (RL) and generative AI for intelligent SRU operation. Zhang et al. [26] applied RL to model spatiotemporal causality in industrial systems, providing adaptive control strategies for SRUs. Thameem et al. [27] developed AI-based emission forecasting to predict SO2 release from SRU incinerators, supporting regulatory compliance and sustainability.

Emerging generative models, such as the StyleGAN-based framework by Zhang et al. [35], produced realistic virtual sensor data to augment training datasets. Such synthetic data generation enhances model generalization in low-sample environments. Meanwhile, transformer architectures like the LASSO Transformer Network [31] and hybrid TCN-CBAM-LSTM models [28] improved sequential learning and interpretability. Finally, recent contributions by Liu et al. [32], Wu et al. [33], and Zhao et al. [34] demonstrated adaptive multilevel regression and surrogate modeling for online error compensation, marking the newest phase in real-time AI-driven SRU monitoring.

III. Discussion

The literature review shows a clear transition from early static neural models to hybrid deep architectures, where knowledge, optimization, and domain adaptation are merged. The main trends include:

- Improved Model Generalization: With multi-objective optimization and ensemble learning.
- Dynamic Adaptation: Via recurrent and transfer learning networks.
- Interpretability and Trust: Improved using regularization and feature selection frameworks.
- Operational Integration: Surrogate models allow for real-time process control and emission prediction.

However, challenges persist. Most studies are based on limited industrial datasets and lack benchmark comparisons. For black-box architectures, model explainability is limited. Furthermore, deployment in safety-critical SRUs requires robust validation, cybersecurity, and adaptive maintenance strategies.

IV. Conclusion

Artificial intelligence technology has rapidly changed sulfur recovery units' modeling and control, and has increased predictive power, flexibility, and environmental compliance. With AI-driven soft sensors and surrogate models, it is possible to monitor the important process variables in ways that traditional measurements would be challenging to do. Though interpretability and industrial validation are challenging, the integration of hybrid and deep learning architectures marks a significant advancement in SRU technology. Further studies blending AI, process knowledge, and sustainable operation principles will be essential to ensure the next generation of intelligent SRUs.

References

[1] F. Manenti, D. Papasidero, G. Bozzano, and E. Ranzi, “Model-based optimization of sulfur recovery units,” *Comput. Chem. Eng.*, vol. 66, pp. 244–251, 2014.

[2] Cunningham, D. B., “Adaptive control of sulfur recovery units,” *Hydrocarb. Process.*, vol. 73, no. 8, 1994.

[3] L. Fortuna, A. Rizzo, M. Sinatra, and M. G. Xibilia, “Soft analyzers for a sulfur recovery unit,” *Control Eng. Pract.*, vol. 11, no. 12, pp. 1491–1500, 2003.

[4] A. Garmroodi Asil and A. Shahsavand, “Reliable estimation of optimal sulfinol concentration in gas treatment unit via novel stabilized MLP and regularization network,” *J. Nat. Gas Sci. Eng.*, vol. 21, pp. 791–804, 2014.

[5] W. Shao and X. Tian, “Adaptive soft sensor for quality prediction of chemical processes based on selective ensemble of local partial least squares models,” *Chem. Eng. Res. Des.*, vol. 95, pp. 113–132, 2015.

[6] W. Xiong, Y. Li, Y. Zhao, and B. Huang, “Adaptive soft sensor based on time difference Gaussian process regression with local time-delay reconstruction,” *Chem. Eng. Res. Des.*, vol. 117, pp. 670–680, 2017.

[7] B. Bidar, F. Shahraki, J. Sadeghi, and M. M. Khalilipour, “Soft Sensor Modeling Based on Multi-State-Dependent Parameter Models and Application for Quality Monitoring in Industrial Sulfur Recovery Process,” *IEEE Sens. J.*, vol. 18, no. 11, pp. 4583–4591, 2018.

[8] H. Singh, A. K. Pani, and H. K. Mohanta, “Quality monitoring in petroleum refinery with regression neural network: Improving prediction accuracy with appropriate design of training set,” *Measurement*, vol. 134, pp. 698–709, 2019.

[9] R. K. Rahman, S. Ibrahim, and A. Raj, “Multi-objective optimization of sulfur recovery units using a detailed reaction mechanism to reduce energy consumption and destruct feed contaminants,” *Comput. Chem. Eng.*, vol. 128, pp. 21–34, 2019.

[10] X. Yuan, S. Qi, and Y. Wang, “Stacked Enhanced Auto-Encoder for Data-Driven Soft Sensing of Quality Variable,” *IEEE Trans. Instrum. Meas.*, vol. 69, no. 10, pp. 7953–7961, 2020.

[11] X. Yuan, Y. Wang, C. Yang, and W. Gui, “Stacked isomorphic autoencoder based soft analyzer and its application to sulfur recovery unit,” *Inf. Sci.*, vol. 534, pp. 72–84, 2020.

[12] V. H. Alves Ribeiro and G. Reynoso-Meza, “Feature selection and regularization of interpretable soft sensors using evolutionary multi-objective optimization design procedures,” *Chemom. Intell. Lab. Syst.*, vol. 212, p. 104278, 2021.

[13] L. Patanè and M. G. Xibilia, “Echo-state networks for soft sensor design in an SRU process,” *Inf. Sci.*, vol. 566, pp. 195–214, 2021.

[14] F. Curreri, L. Patanè, and M. G. Xibilia, “RNN- and LSTM-Based Soft Sensors Transferability for an Industrial Process,” *Sensors*, vol. 21, no. 3, p. 823, 2021.

[15] A. Dell'Angelo, E. M. Andoglu, S. Kaytakoglu, and F. Manenti, “A machine-learning reduced kinetic model for H_2S thermal conversion process,” *Chem. Prod. Process Model.*, vol. 18, no. 1, pp. 117–133, 2023.

[16] Y. Huang, E. H. Wang, Z. Liu, L. Pan, H. Li, and X. Liu, “Modeling Task Relationships in Multivariate Soft Sensor With Balanced Mixture-of-Experts,” *IEEE Trans. Ind. Inform.*, vol. 19, no. 5, pp. 6556–6564, 2023.

[17] F. Souza, T. Offermans, R. Barendse, G. Postma, and J. Jansen, “Contextual Mixture of Experts: Integrating Knowledge into Predictive Modeling,” *IEEE Trans. Ind. Inform.*, vol. 19, no. 8, pp. 9048–9059, 2023.

[18] L. Chen, Q.-X. Zhu, and Y.-L. He, “Adversarial Attacks for Neural Network-Based Industrial Soft Sensors: Mirror Output Attack and Translation Mirror Output Attack,” *IEEE Trans. Ind. Inform.*, vol. 20, no. 2, pp. 2378–2386, 2024.

[19] T. Mou, J. Liu, Y. Zou, S. Li, and M. G. Xibilia, “Enhanced industrial process modeling with transfer-incremental-learning: A parallel SAE approach and its application to a sulfur recovery unit,” *Control Eng. Pract.*, vol. 148, p. 105955, 2024.

[20] L. Patanè, F. Sapuppo, and M. G. Xibilia, “Soft Sensors for Industrial Processes Using Multi-Step-Ahead Hankel Dynamic Mode Decomposition with Control,” *Electronics*, vol. 13, no. 15, p. 3047, 2024.

[21] Z. Zhang, X. Yang, J. Huang, and Y. A. W. Shardt, “Layer-wise-residual-driven approach for soft sensing in composite dynamic system based on slow and fast time-varying latent variables,” *Chemom. Intell. Lab. Syst.*, vol. 254, p. 105245, 2024.

[22] X. Zheng *et al.*, “A temporal convolution network-based just-in-time learning method for industrial quality variable prediction,” *Chem. Eng. Res. Des.*, vol. 212, pp. 168–184, 2024.

[23] Q. Wang and L. Li, “Research on semi-supervised soft sensor modeling method for sulfur recovery unit based on ISSA-VMD-ESN,” *Chem. Eng. Sci.*, vol. 298, p. 120397, 2024.

[24] Y.-L. He, P.-F. Wang, and Q.-X. Zhu, “Improved Bi-LSTM With Distributed Nonlinear Extensions and Parallel Inputs for Soft Sensing,” *IEEE Trans. Ind. Inform.*, vol. 20, no. 3, pp. 3748–3755, 2024.

[25] B. K. Talaei, F. Shahraki, J. Sadeghi, and M. M. Khalilipour, “Enhancing Soft Sensor Performance in Control Loops: Integrating State-Dependent Parameter Method With Regression-Based Dynamic Data Reconciliation Filter,” *IEEE Sens. J.*, vol. 24, no. 5, pp. 7018–7029, 2024.

[26] X. Zhang, C. Song, J. Zhao, Z. Xu, and X. Deng, “Spatial-Temporal Causality Modeling for Industrial Processes With a Knowledge-Data Guided Reinforcement Learning,” *IEEE Trans. Ind. Inform.*, vol. 20, no. 4, pp. 5634–5646, 2024.

[27] M. Thameem, A. Raj, A. Berrouk, M. A. Jaoude, and A. A. AlHammadi, “Artificial intelligence-based forecasting model for incinerator in sulfur recovery units to predict SO2 emissions,” *Environ. Res.*, vol. 249, p. 118329, 2024.

[28] J. Li and Y. Hao, “Dynamic Soft Sensor Modeling and Its Application Using TCN-CBAM-LSTM Method,” *J. Appl. Eng. Sci.*, vol. 28, no. 12, pp. 2541-2548, 2025.

[29] Z. Zhang, X. Yang, J. Huang, and Y. A. W. Shardt, “Graph-based predictable deep transfer network for soft sensing of dynamic industrial processes,” *Knowl.-Based Syst.*, vol. 318, p. 113495, 2025.

[30] X. Guo, S. Pan, and Y. Li, “Global dynamic features and information of adjacent hidden layer enhancement based on

autoencoder for industrial process soft sensor application," *Can. J. Chem. Eng.*, vol. 103, no. 5, pp. 2218–2233, 2025.

[31] Q. Li, K. Han, and W. Ba, "A novel ensemble coefficients LASSO transformer network algorithm for nonlinear dynamic soft sensor in time-delay industrial processes," *Can. J. Chem. Eng.*, p. cjce.70039, 2025.

[32] J. Liu, H.-C. Chien, D. S.-H. Wong, and C.-T. Hsieh, "Advanced process control for sulfur recovery units by artificial intelligence (AI) surrogate model," *J. Taiwan Inst. Chem. Eng.*, vol. 172, p. 106119, 2025.

[33] G. Wu, L. Chen, H. Wang, C. Peng, and K. Hao, "Adaptive multilevel regression integration with error compensation for online soft sensing of data streams," *Neurocomputing*, vol. 644, p. 130397, 2025.

[34] Y. Zhao, R. Yang, J. Ying, S. Wang, and Z. Zeng, "Enhancing online industrial quality index prediction with a general deep temporal feature extraction and incremental ensemble modeling framework," *Eng. Appl. Artif. Intell.*, vol. 156, p. 111104, 2025.

[35] X.-Y. Zhang *et al.*, "Self-attention embedded StyleGAN for virtual sample generation in sensing applications," *Chemom. Intell. Lab. Syst.*, vol. 267, p. 105519, 2025.

[36] L. Patanè, S. Graziani, and M. G. Xibilia, "Identification of finite-time delay and regressors for the design of soft sensors in the presence of input collinearity," *Control Eng. Pract.*, vol. 157, p. 106267, 2025.