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LEARNING-BASED ADVANCED PROCESS CONTROL: A REVIEW

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Abstract. Advanced Process Control (APC) is undergoing a fundamental transformation driven by the rapid integration of data-driven modeling and learning algorithms into industrial control architectures. While classical model-based approaches-most notably model predictive control (MPC)-have provided structured optimization, constraint handling, and stability guarantees, their effectiveness increasingly depends on accurate process models that are difficult to derive for highly nonlinear, large-scale, and time-varying systems. The proliferation of industrial data and advances in machine learning have enabled a new generation of learning-based APC strategies that enhance modeling flexibility, prediction accuracy, and adaptability. However, the deployment of such approaches in safety-critical chemical and industrial processes raises significant concerns regarding stability, robustness, interpretability, and constraint satisfaction. This review provides a systematic and critical synthesis of learning-based advanced process control methods published since 2020, with a particular focus on the progression from data-driven modeling to safe reinforcement learning. The literature is organized according to the functional role of learning within the control loop: (i) data-driven process modeling using neural networks and Gaussian processes, (ii) learning-based MPC frameworks that retain explicit constraint handling, (iii) safety-aware reinforcement learning approaches augmented with stability conditions or MPC supervision, and (iv) advanced soft sensors enabling reliable state estimation and monitoring. Across these categories, we analyze trade-offs among prediction accuracy, computational complexity, data efficiency, safety guarantees, and industrial maturity.

Keywords: Advanced Process Control (APC); Learning-based Control; Data-driven Modeling; Model Predictive Control (MPC); Learning-based MPC; Gaussian Processes; Neural Networks; Safe Reinforcement Learning; Stability and Constraint Satisfaction; Soft Sensors; Industrial Process Control; Safety-Critical Systems

Annotatsiya. Ilg‘or jarayon boshqaruvi (Advanced Process Control – APC) sanoat boshqaruv arxitekturalariga ma’lumotlarga asoslangan modellashtirish va o‘rganish algoritmlarining jadal integratsiyasi natijasida tub transformatsiyani boshdan kechirmoqda. An’anaviy modelga asoslangan yondashuvlar – ayniqsa

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model prognozli boshqaruv (Model Predictive Control – MPC) – tuzilmali optimallashtirish, cheklovlarni hisobga olish va barqarorlik kafolatlarini ta’minlab kelgan bo‘lsada, ularning samaradorligi tobora yuqori darajada nochiziqli, katta masshtabli va vaqt bo‘yicha o‘zgaruvchan tizimlar uchun hosil qilish qiyin bo‘lgan aniq jarayon modellariga bog‘liq bo‘lib bormoqda. Sanoat ma’lumotlarining ko‘payishi va mashinani o‘rganish sohasidagi yutuqlar modellashtirish moslashuvchanligi, prognoz aniqligi va adaptivlikni oshiruvchi o‘rganishga asoslangan APC strategiyalarining yangi avlodini shakllantirdi. Biroq bunday yondashuvlarni xavfsizlik jihatidan muhim bo‘lgan kimyoviy va sanoat jarayonlarida qo‘llash barqarorlik, mustahkamlik (robustlik), talqin qilinuvchanlik va cheklovlarga rioya etish bilan bog‘liq muhim muammolarni keltirib chiqarmoqda. Mazkur adabiyotlar tahlilida 2020-yildan buyon chop etilgan o‘rganishga asoslangan ilg‘or jarayon boshqaruvi usullarining tizimli va tanqidiy tahlilini taqdim etadi hamda ma’lumotlarga asoslangan modellashtirishdan tortib xavfsiz mustahkamlovchi o‘rganishgacha bo‘lgan evolyutsiyaga alohida e’tibor qaratadi. Adabiyotlar o‘rganishning boshqaruv siklidagi funksional roliga ko‘ra quyidagicha tasniflanadi: (i) neyron tarmoqlar va Gauss jarayonlari asosidagi ma’lumotlarga asoslangan jarayon modellashtirish; (ii) aniq cheklovlarni saqlab qoluvchi o‘rganishga asoslangan MPC arxitekturalari; (iii) barqarorlik shartlari yoki MPC nazorati bilan boyitilgan xavfsizlikka yo‘naltirilgan mustahkamlovchi o‘rganish yondashuvlari; (iv) ishonchli holat baholash va monitoringni ta’minlovchi ilg‘or yumshoq sensorlar. Mazkur toifalar doirasida prognoz aniqligi, hisoblash murakkabligi, ma’lumotdan foydalanish samaradorligi, xavfsizlik kafolatlari va sanoatga joriy etilish darajasi o‘rtasidagi muvozanatlar (trade-off) chuqur tahlil qilinadi.

Kalit so‘zlar: Ilg‘or jarayon boshqaruvi (APC); o‘rganishga asoslangan boshqaruv; ma’lumotlarga asoslangan modellashtirish; model prognozli boshqaruv (MPC); o‘rganishga asoslangan MPC; Gauss jarayonlari; neyron tarmoqlar; xavfsiz mustahkamlovchi o‘rganish; barqarorlik va cheklovlarga rioya etish; yumshoq sensorlar; sanoat jarayonlarini boshqarish; xavfsizlik jihatidan muhim tizimlar.

Аннотация. Продвинутое управление процессами (Advanced Process Control, APC) переживает фундаментальную трансформацию, обусловленную быстрой интеграцией методов моделирования на основе данных и алгоритмов обучения в архитектуры промышленного управления. Классические подходы, основанные на моделях, – прежде всего модельно-прогнозирующее управление (Model Predictive Control, MPC) – обеспечивали структурированную оптимизацию, учет ограничений и гарантии

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устойчивости. Однако их эффективность в возрастающей степени зависит от точных моделей процессов, получение которых затруднено для сильно нелинейных, крупномасштабных и нестационарных систем. Рост объёмов промышленных данных и достижения в области машинного обучения способствовали формированию нового поколения стратегий APC на основе обучения, повышающих гибкость моделирования, точность прогнозирования и адаптивность. Вместе с тем внедрение таких подходов в химических и промышленных процессах, критичных к безопасности, вызывает серьёзные опасения, связанные с обеспечением устойчивости, робастности, интерпретируемости и соблюдения ограничений. Настоящий обзор представляет систематизированный и критический анализ методов продвинутого управления процессами на основе обучения, опубликованных с 2020 года, с особым акцентом на эволюцию от моделирования на основе данных к безопасному обучению с подкреплением. Литература структурирована в соответствии с функциональной ролью обучения в контуре управления: (i) моделирование процессов на основе данных с использованием нейронных сетей и гауссовских процессов; (ii) архитектуры MPC на основе обучения с сохранением явного учета ограничений; (iii) подходы к обучению с подкреплением, ориентированные на безопасность и дополненные условиями устойчивости или супервизией MPC; (iv) продвинутые программные (soft) сенсоры, обеспечивающие надёжную оценку состояния и мониторинг. В рамках указанных категорий анализируются компромиссы между точностью прогнозирования, вычислительной сложностью, эффективностью использования данных, гарантиями безопасности и степенью промышленной зрелости.

Ключевые слова: продвинутое управление процессами (APC); управление на основе обучения; моделирование на основе данных; модельно-прогнозирующее управление (MPC); MPC на основе обучения; гауссовские процессы; нейронные сети; безопасное обучение с подкреплением; устойчивость и соблюдение ограничений; программные сенсоры; промышленное управление процессами; системы, критичные к безопасности.

INTRODUCTION

Advanced Process Control (APC) [1] has long been a central pillar of industrial automation, enabling the safe, efficient, and economically optimal operation of complex processes in the chemical, energy, water, and manufacturing industries. Classical APC strategies [2], most notably model predictive control (MPC) [3], have achieved widespread success by explicitly accounting for multivariable interactions [4], operational constraints [5], and process objectives

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within a rigorous optimization framework. When accurate first-principles or identified models are available, MPC and its nonlinear extensions can deliver robust performance [6] and provable stability properties. However, the increasing complexity of modern industrial systems [7], combined with stricter environmental regulations, sustainability targets, and the need for flexible operation under varying conditions [8], has exposed fundamental limitations of purely model-based APC approaches [9]. Over the past decade, industrial plants have experienced an unprecedented growth in data availability driven by advances in sensing technologies, distributed control systems [10], and large-scale data historians [11]. This data-rich environment has fundamentally altered how process understanding and control design are approached. Instead of relying exclusively on mechanistic models [12] derived from physical laws, practitioners increasingly exploit historical and real-time data to construct models [13], estimate unmeasured variables, and adapt control strategies. As a result, APC has undergone a gradual but profound evolution toward learning-based formulations, in which data-driven models and learning algorithms play a central role in control synthesis and implementation.

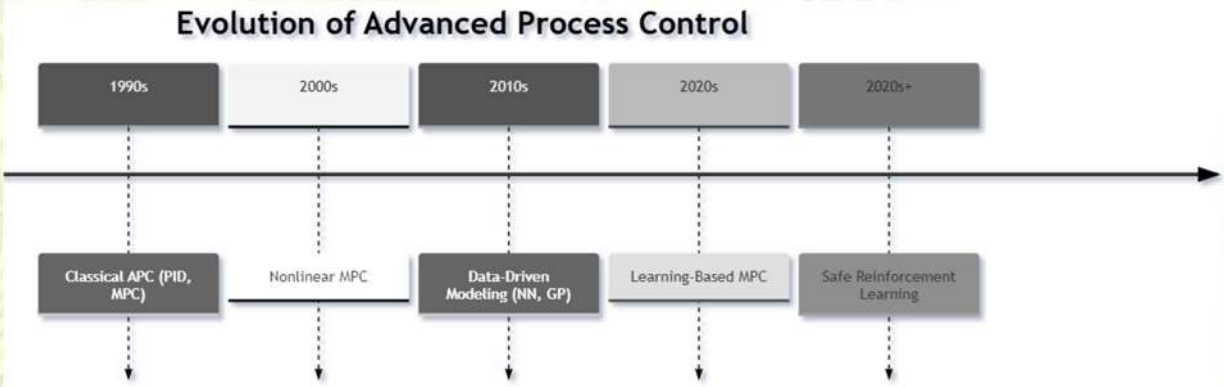


Figure 1. Evolution of advanced process control toward learning-based and safety-aware frameworks

Figure 1 illustrates the conceptual evolution of advanced process control from classical model-based approaches to modern learning-based and safety-aware control frameworks. The progression highlights the increasing role of data-driven modeling, learning-enhanced predictive control [14], and reinforcement learning [15], as well as the growing emphasis on safety and stability in industrial applications. Neural networks [16], Gaussian processes [17], and other machine learning methods [18] have demonstrated strong capabilities in representing highly nonlinear and coupled process dynamics that are difficult to capture using first-principles modeling alone. These models have been successfully integrated into predictive control frameworks, leading to learning-based MPC schemes [19] that can outperform classical controllers in terms of tracking accuracy, economic

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efficiency, and adaptability. In parallel, advanced soft-sensor systems [20] based on learning techniques have significantly enhanced process monitoring, fault diagnosis, and state estimation, further strengthening the foundations of data-driven APC. Industrial case studies, including wastewater treatment plants, semiconductor manufacturing [21], and large-scale energy systems [22], have illustrated the practical benefits of such approaches in terms of improved performance and sustainability metrics. Despite these promising developments, the transition from classical APC to learning-based APC introduces challenges that go beyond incremental performance improvements. The most critical of these challenges are safety and stability. Classical APC methods are deeply rooted in control theory, where stability, robustness, and constraint satisfaction can often be analyzed and enforced explicitly [23]. In contrast, learning-based models are inherently approximate, data-dependent, and valid only within regions covered by training data. Model uncertainty, limited extrapolation capability, and the lack of physical interpretability can result in unpredictable closed-loop behavior [24] when learning-based controllers are deployed in real processes.

These issues become particularly acute in safety-critical industrial environments [25]. Chemical reactors, separation units, biological and wastewater treatment systems, and automated manufacturing lines operate under tight safety and quality constraints, where violations may lead to environmental damage, equipment degradation, or risks to human health. Even minor deviations from safe operating conditions can propagate through interconnected process units, amplifying their impact. Consequently, while learning-based APC methods may offer superior nominal performance, their industrial adoption remains limited unless safety and stability can be guaranteed with a level of confidence comparable to that of classical control strategies. Reinforcement learning (RL) [26] represents a further step in the evolution of learning-based APC [27], offering the possibility of learning control policies directly from process interaction rather than relying on explicit models. In principle, RL can handle complex nonlinear dynamics and long-term objectives in a unified framework, making it attractive for advanced industrial applications. However, standard RL algorithms are typically data-intensive, rely on exploration strategies that may violate safety constraints, and provide no inherent guarantees of stability or constraint satisfaction. These characteristics are fundamentally misaligned with the conservative design philosophy traditionally adopted in process control engineering. In response to these concerns, recent research has increasingly focused on the development of safe and stability-aware learning-based control methods. Hybrid frameworks that combine the structure and guarantees of MPC with the adaptability of learning algorithms have emerged as a

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particularly promising direction. Examples include learning-enhanced MPC schemes that preserve constraint handling, Gaussian process–based controllers that explicitly quantify uncertainty, and reinforcement learning approaches augmented with safety filters, Lyapunov-based conditions [28], or MPC supervisors. These methods aim to reconcile performance gains from learning with the reliability and predictability required for industrial deployment.

Given the rapid expansion of the literature in this area since 2020, a systematic synthesis of learning-based APC methods is both timely and necessary. Existing contributions are scattered across control theory, machine learning, and application-oriented journals, often using different assumptions, performance metrics, and validation strategies. Without a unified perspective, it is difficult to assess the maturity of the field, identify common principles, and distinguish methods that are ready for industrial adoption from those that remain primarily of academic interest. The purpose of this review is to provide a coherent and critical overview of learning-based advanced process control, with a particular focus on the progression from data-driven modeling to safe reinforcement learning. Drawing on recent contributions across APC, soft sensing, learning-based MPC, and safety-constrained RL, the review aims to clarify how learning techniques are currently used in process control, what benefits they offer, and what limitations remain.

METHODS

The methodological approach adopted in this review is designed to ensure rigor, transparency, and relevance while remaining consistent with best practices for systematic narrative reviews in process control and industrial automation. As this work is a review rather than an experimental study, the methodology focuses on literature selection, screening, and conceptual organization, with the objective of synthesizing recent advances in learning-based advanced process control into a coherent and analytically meaningful framework. The literature selection process was guided by a clear temporal, thematic, and application-oriented scope. Only peer-reviewed journal articles and refereed conference papers published from 2020 onward were considered. This temporal restriction was deliberately chosen to capture the most recent phase of development in learning-based APC, which has been shaped by rapid progress in machine learning, increased industrial digitalization, and the growing emphasis on safety, sustainability, and industrial deployability. Earlier foundational works were not included, except insofar as they are implicitly reflected in the post-2020 literature, allowing the review to focus on current trends and open challenges rather than historical development.

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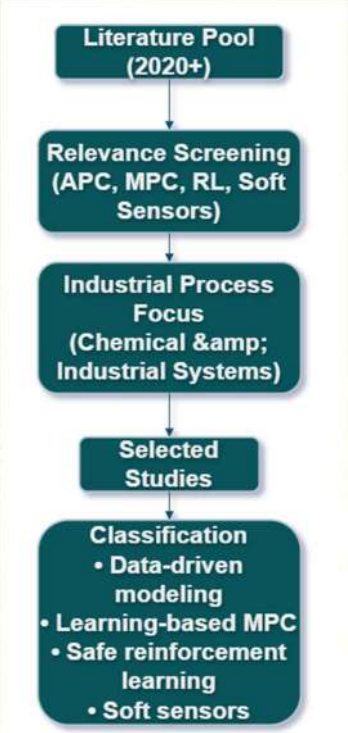


Figure 2. Literature selection and classification workflow used in this review

Figure 2 illustrates the workflow adopted for selecting and organizing the literature reviewed in this paper. Studies published from 2020 onward were screened based on relevance to learning-based advanced process control and industrial applicability, and subsequently classified into four functional categories. This workflow ensures transparency and consistency in the review process. The thematic scope of the review centers on advanced process control and its learning-based extensions [29]. Articles were selected if they addressed at least one of the following topics: data-driven or learning-based modeling for process control, learning-enhanced or learning-integrated MPC, reinforcement learning applied to process or chemical systems, advanced soft-sensor design for monitoring and control, or explicit treatment of safety, stability, and constraint satisfaction in learning-based control. Particular emphasis was placed on works that go beyond algorithmic novelty to address issues relevant to closed-loop operation, such as robustness, uncertainty handling, and practical implementation considerations.

From an application perspective, the review prioritizes chemical and industrial processes, including but not limited to chemical reactors, separation processes, wastewater treatment systems, semiconductor manufacturing, and large-scale energy or sustainability-related processes. This focus reflects the domain in which APC has traditionally played a central role and where safety and stability considerations are most critical. Papers dealing exclusively with robotic systems, autonomous vehicles, or purely benchmark control problems without a clear connection to industrial or chemical processes were excluded, even if they

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employed similar learning techniques. The selected papers were analyzed and organized using a classification framework that reflects both the functional role of learning in APC and the increasing emphasis on safety and reliability. Rather than grouping papers by algorithmic families alone, the classification focuses on how learning is embedded within the control loop and what guarantees are provided. Four primary categories were identified.

Table 1.

Classification criteria adopted for learning-based advanced process control approaches

Category	Role in APC	Representative Techniques	Main Evaluation Focus
Data-driven modeling	Process representation	Neural networks, Gaussian processes	Prediction accuracy, uncertainty
Learning-based MPC	Constrained control	NN–MPC, GP–MPC	Feasibility, stability
Safe reinforcement learning	Policy learning	RL with safety layers, MPC supervision	Safety, robustness
Soft sensors	State estimation	NN-based and hybrid models	Monitoring reliability

Table 1 summarizes the classification criteria used to organize the reviewed literature. The categories reflect the functional role of learning within the APC framework and the extent to which safety and reliability considerations are explicitly addressed. The first category comprises data-driven modeling approaches, including neural networks and Gaussian processes, used to represent process dynamics, estimate unmeasured states, or support prediction in APC frameworks. The second category includes learning-based MPC methods, where data-driven models or learning mechanisms are integrated into MPC formulations while retaining explicit constraint handling and optimization-based decision making. The third category encompasses safe reinforcement learning approaches, in which learning-based control policies are combined with mechanisms that enforce safety, stability, or constraint satisfaction, either explicitly or through supervisory structures. The fourth category focuses on advanced soft sensors, which play a critical enabling role by providing reliable estimates of key process variables and supporting monitoring, fault diagnosis, and safe control operation.

This classification framework is intentionally conceptual rather than purely algorithmic. Many recent contributions span multiple categories, for example by

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combining soft sensing with learning-based MPC or embedding reinforcement learning within an MPC safety layer. Such overlaps are explicitly acknowledged and discussed in the review, as they reflect an important trend toward hybrid and integrated control architectures. By structuring the literature in this manner, the methodology supports a systematic comparison of approaches, highlights common design principles, and facilitates the identification of research gaps related to safety, stability, data efficiency, and industrial applicability. The methodological approach adopted in this review is intended to provide a structured yet flexible foundation for synthesizing recent advances in learning-based advanced process control.

RESULTS

The reviewed literature published since 2020 reveals a clear and consistent shift in advanced process control toward learning-centered formulations, with data-driven models, learning-based MPC, reinforcement learning, and advanced soft sensors emerging as tightly interconnected components rather than isolated research directions. Across chemical and industrial applications, learning is no longer treated merely as an auxiliary tool for model identification, but as an integral element of the control loop whose role ranges from prediction and state estimation to policy optimization and decision making. Data-driven modeling constitutes the foundation of most learning-based APC frameworks. Neural networks and Gaussian processes are the two dominant model classes used to represent process dynamics, each reflecting different design philosophies and trade-offs. Neural network models, including feedforward, recurrent, and deep architectures, are widely adopted due to their strong approximation capability and scalability to high-dimensional nonlinear systems. Studies in semiconductor manufacturing, chemical reactors, and nonlinear process control demonstrate that NN-based models can significantly outperform linear or simplified mechanistic models when sufficient data are available.

Table 2.

Comparison of learning-based advanced process control approaches

Approach	Model Type	Safety and Stability Handling	Data Efficiency	Industrial Maturity
Classical MPC	First-principles / linear models	Explicit constraints, proven stability	High	High
NN-based APC	Neural networks	Implicit or heuristic	Medium–Low	Medium

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GP-based APC	Gaussian processes	Probabilistic constraints, uncertainty-aware	Medium–High	Medium
Learning-based MPC	NN or GP within MPC	Explicit constraints, stability via MPC	Medium	Medium–High
Reinforcement learning (model-free)	Policy learning	Typically none	Low	Low
Safe reinforcement learning	RL with safety layers / MPC supervision	Explicit or Lyapunov-based guarantees	Medium	Emerging

Table 2 provides a comparative overview of learning-based APC approaches reviewed in this paper. The comparison highlights differences in modeling paradigms, safety and stability handling, data requirements, and current levels of industrial maturity, thereby supporting a structured interpretation of the reported results. Gaussian process models offer a complementary perspective by embedding uncertainty quantification directly into the modeling framework. GP-based models are especially prominent in applications where data efficiency and safety are prioritized over raw approximation power. The probabilistic nature of GPs allows prediction uncertainty to be propagated into control decisions, enabling more cautious and robust operation. In learning-based APC, GP models are frequently used to represent residual dynamics on top of nominal models or to support constraint tightening strategies. Nevertheless, the reviewed literature also points to practical challenges associated with GPs, including computational scalability and limitations when dealing with very large datasets or high-dimensional systems. As a result, many recent contributions favor hybrid approaches that combine neural networks for expressiveness with GP-inspired uncertainty handling. Learning-based MPC emerges as a central theme in the reviewed works, reflecting a convergence between classical APC structure and modern learning techniques. Neural network–based MPC schemes typically replace or augment first-principles models with learned predictors, enabling more accurate state and output predictions in nonlinear regimes. These approaches consistently report improved tracking performance and economic efficiency compared to traditional MPC, particularly in processes characterized by strong nonlinearities or poorly understood kinetics. At

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the same time, constraint handling remains one of the main advantages of MPC-based formulations. Even when learning-based models are used, the optimization-based structure of MPC allows explicit enforcement of input, state, and output constraints, which is essential for industrial deployment.

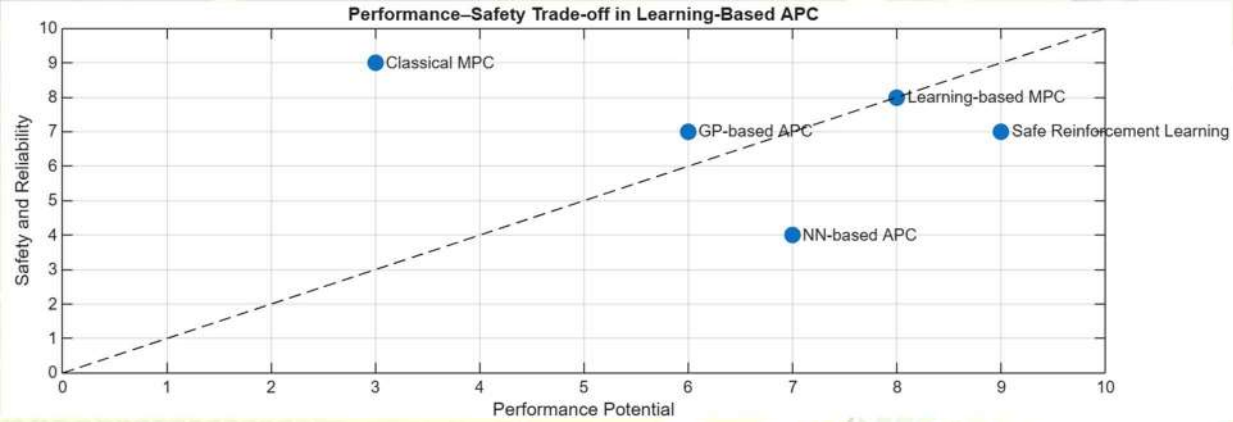


Figure 3. Conceptual performance–safety trade-off of learning-based advanced process control approaches

Figure 3 illustrates a conceptual trade-off between performance potential and safety for different learning-based APC approaches. The relative positioning reflects general trends reported in the recent literature rather than quantitative performance metrics.

Gaussian process–based MPC further strengthens this connection between learning and reliability. By incorporating model uncertainty into the prediction and optimization stages, GP–MPC frameworks enable probabilistic constraint satisfaction and robustness against modeling errors. The reviewed studies show that such approaches are particularly effective in safety-critical processes, where conservative behavior is preferable to aggressive performance optimization. However, computational complexity remains a recurring concern, motivating research into approximations, sparse representations, and hierarchical control structures that preserve safety guarantees while reducing online computational burden. Reinforcement learning represents a more radical departure from classical APC, as it seeks to learn control policies directly from interaction with the process. The reviewed literature distinguishes clearly between model-free and model-based RL approaches. Model-free RL methods, while conceptually simple and flexible, are generally regarded as ill-suited for direct industrial application due to their high data requirements and lack of inherent safety guarantees. In contrast, model-based RL approaches, which leverage learned or nominal models to guide policy optimization, exhibit stronger alignment with APC principles and are more amenable to integration with existing control infrastructures.

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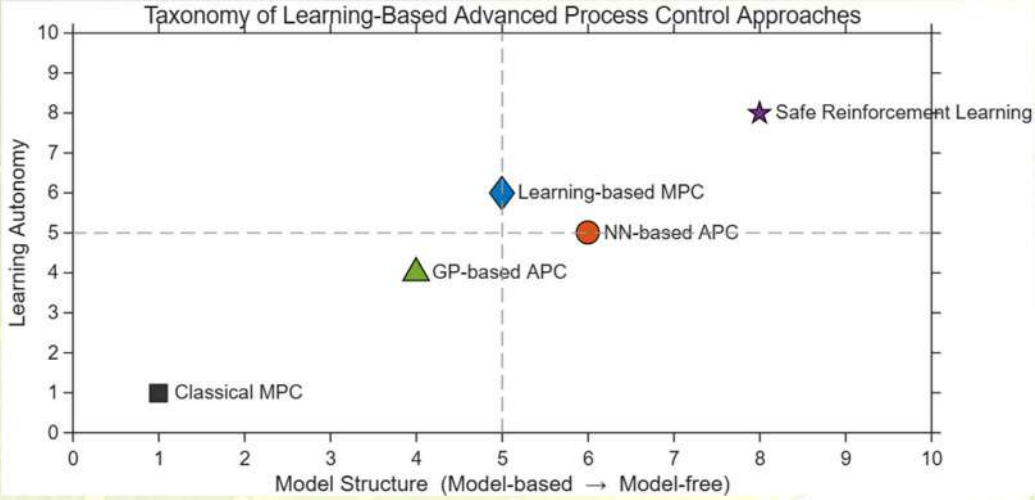


Figure 5. Taxonomy of learning-based advanced process control approaches based on model structure and learning autonomy.

Figure 5 presents a qualitative taxonomy of learning-based advanced process control approaches according to their reliance on explicit process models and their degree of learning autonomy. The relative positioning reflects conceptual trends reported in the literature rather than quantitative performance metrics. A dominant trend in recent work is the explicit incorporation of safety and stability guarantees into RL-based APC. Rather than relying on unconstrained exploration, safe RL frameworks employ mechanisms such as constraint projection, Lyapunov-based conditions, safety filters, or MPC supervisors to ensure that learned policies remain within acceptable operating regions. These approaches demonstrate that RL can be used not as a replacement for APC, but as an adaptive layer that enhances performance while respecting the safety envelope defined by classical control methods. The reviewed studies consistently emphasize that without such safeguards, RL remains unsuitable for chemical and industrial processes, regardless of its theoretical optimality. Advanced soft sensors play a critical enabling role across all learning-based APC paradigms reviewed. Learning-based soft sensors, particularly those using neural networks and hybrid data-driven models, provide reliable estimates of unmeasured or difficult-to-measure variables, such as product quality indicators, biological states, or internal concentrations. These estimates support improved monitoring, fault diagnosis, and control performance, especially when integrated with MPC or safety-aware RL frameworks. The reviewed literature shows that modern soft sensors are increasingly designed as dynamic, adaptive systems that evolve alongside the controller, rather than static estimators trained offline. Their integration into learning-based APC architectures contributes directly to safer operation by reducing uncertainty and improving situational awareness.

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The findings of this review indicate that learning-based APC has matured beyond isolated algorithmic demonstrations and is moving toward integrated, safety-conscious control architectures. Neural networks and Gaussian processes provide complementary modeling capabilities, learning-based MPC offers a structured pathway for industrial adoption, reinforcement learning introduces new possibilities for adaptability and optimality, and soft sensors underpin reliable operation. At the same time, the literature consistently underscores that performance gains alone are insufficient; safety, stability, and interpretability remain decisive factors in determining whether learning-based APC methods can transition from research prototypes to widely deployed industrial solutions.

DISCUSSION

The body of evidence reviewed in this work highlights a fundamental tension at the heart of learning-based advanced process control: the trade-off between performance enhancement and the preservation of safety and reliability. Learning-based methods consistently demonstrate superior nominal performance compared to classical APC, particularly in highly nonlinear, multivariable, and time-varying operating regimes. Data-driven models improve prediction accuracy, learning-based MPC enhances economic optimization, and reinforcement learning enables long-horizon performance objectives that are difficult to address with conventional controllers. However, these gains are often achieved at the cost of reduced transparency, increased uncertainty, and weakened analytical guarantees. The reviewed literature makes it clear that, in industrial process control, performance improvements are only valuable insofar as they do not compromise safety, stability, or regulatory compliance. From an industrial perspective, the applicability of learning-based APC depends less on algorithmic novelty and more on robustness, maintainability, and integration with existing control systems.

Reinforcement learning, while conceptually appealing, remains the most challenging paradigm to deploy in industrial settings. The literature shows that model-free RL is largely confined to simulation studies or tightly controlled experimental environments, due to its data requirements and lack of inherent safeguards. Model-based and safety-augmented RL approaches show greater promise, especially when combined with MPC supervisors or safety filters that constrain exploration and enforce stability conditions. Nevertheless, even these methods face significant hurdles related to validation, certification, and operator trust.

CONCLUSIONS

The rapid development of learning-based methods has fundamentally reshaped the landscape of advanced process control, offering new opportunities to

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address long-standing limitations of classical model-based approaches. This review has examined recent contributions that span the progression from data-driven modeling to safe reinforcement learning, with a particular focus on works published since 2020 and on applications relevant to chemical and industrial processes. Taken together, the reviewed studies demonstrate that learning is no longer a peripheral tool in APC, but an essential component of modern control architectures. Data-driven models based on neural networks and Gaussian processes have significantly expanded the modeling capabilities available for APC, enabling accurate representation of complex nonlinear dynamics and improved handling of process variability. When embedded within predictive control frameworks, these models support enhanced performance while retaining the structured decision-making and constraint-handling properties that make MPC attractive for industrial use. At the same time, advances in soft sensing have strengthened the reliability of learning-based control by improving state estimation, monitoring, and fault detection, thereby reducing uncertainty in closed-loop operation. Reinforcement learning has introduced a new paradigm for process control, emphasizing adaptability and long-term optimization. However, the literature reviewed in this paper makes it clear that unconstrained learning is incompatible with the safety-critical nature of industrial processes. Meaningful progress in this area has been achieved by integrating RL within safety-aware control structures, including MPC supervisors, stability constraints, and uncertainty-aware mechanisms. These hybrid approaches illustrate a broader trend in the field: learning-based APC is most effective when it complements, rather than replaces, classical control principles.

Despite substantial progress, several challenges remain before learning-based APC can be widely deployed in industrial practice. Ensuring robust safety and stability under learning-induced uncertainty, improving data efficiency, enhancing interpretability, and managing the lifecycle of adaptive control systems are all open issues that require further research. Addressing these challenges will demand closer integration between control theory, machine learning, and industrial engineering, as well as more extensive validation in real-world operating environments. Learning-based advanced process control represents a promising and evolving direction for industrial automation. By combining the expressive power of modern learning techniques with the rigor and reliability of classical APC frameworks, it is possible to achieve controllers that are both high-performing and trustworthy. Continued research focused on safety-aware design, industrial applicability, and systematic validation will be essential to translate the growing

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body of academic work into robust, deployable solutions that meet the demands of modern process industries.

REFERENCES

1. Huang, J., O'Connor, T., Ahmed, K., Chatterjee, S., Garvin, C., Ghosh, K., ... and Warman, M. (2021). AIChE PD2M Advanced Process Control workshop-moving APC forward in the pharmaceutical industry. *Journal of Advanced Manufacturing and Processing*, *3*(1), e10071.
2. Rani, K. D., Kumar, S., Ranjan, V., Kumar, B., and Dhiman, T. (2025). An Analytical Study of Consumption and Saving Functions: Interlinkages of MPC, MPS, APC, and APS in Economic Theory and Practice. *European Economics Letters*, *15*(4).
3. Schwenzer, M., Ay, M., Bergs, T., and Abel, D. (2021). Review on model predictive control: An engineering perspective. *The international journal of advanced manufacturing technology*, *117*(5), 1327-1349.
4. Shrier, I., Redelmeier, A., Schnitzer, M. E., and Steele, R. J. (2021). Challenges in interpreting results from 'multiple regression'when there is interaction between covariates. *BMJ Evidence-Based Medicine*, *26*(2), 53-56.
5. Valdés, L., and Caldentey, R. (2024). Financial hedging of operational risk constraints: A general framework. *Production and Operations Management*, *33*(9), 1912-1930.
6. Hanover, D., Foehn, P., Sun, S., Kaufmann, E., and Scaramuzza, D. (2021). Performance, precision, and payloads: Adaptive nonlinear mpc for quadrotors. *IEEE Robotics and Automation Letters*, *7*(2), 690-697.
7. Lewandowska-Ciszek, A. (2020). Complexity of a modern enterprise and its flexibility in the sector of industrial automation. *Bulletin of the Polish Academy of Sciences: Technical Sciences*.
8. Ding, S., Gu, W., Lu, S., Chen, X., and Yu, R. (2023). Improving operational flexibility of integrated energy systems through operating conditions optimization of CHP units. *CSEE Journal of Power and Energy Systems*, *9*(5), 1854-1865.
9. Rhinehart, R. R. (2024). *Nonlinear model-based control: using first-principles models in process control*. John Wiley and Sons.
10. Espina, E., Llanos, J., Burgos-Mellado, C., Cardenas-Dobson, R., Martinez-Gomez, M., and Saez, D. (2020). Distributed control strategies for microgrids: An overview. *IEEe Access*, *8*, 193412-193448.
11. O'Shea, E., Khan, R., Breathnach, C., and Margaria, T. (2020, December). Towards automatic data cleansing and classification of valid historical data an incremental approach based on mdd. In *2020 IEEE International Conference on Big Data (Big Data)* (pp. 1914-1923). IEEE.

ISSN 3030-3907

12. Au, H., Alptekin, H., Jensen, A. C., Olsson, E., O'Keefe, C. A., Smith, T., ... and Titirici, M. M. (2020). A revised mechanistic model for sodium insertion in hard carbons. *Energy and environmental science*, *13*(10), 3469-3479.
13. Mohsen, O., Mohamed, Y., and Al-Hussein, M. (2022). A machine learning approach to predict production time using real-time RFID data in industrialized building construction. *Advanced Engineering Informatics*, *52*, 101631.
14. Sha, X., Ma, Z., Sethuvenkatraman, S., and Li, W. (2025). Online learning-enhanced data-driven model predictive control for optimizing HVAC energy consumption, indoor air quality and thermal comfort. *Applied Energy*, *383*, 125341.
15. Shakya, A. K., Pillai, G., and Chakrabarty, S. (2023). Reinforcement learning algorithms: A brief survey. *Expert Systems with Applications*, *231*, 120495.
16. Li, Z., Liu, F., Yang, W., Peng, S., and Zhou, J. (2021). A survey of convolutional neural networks: analysis, applications, and prospects. *IEEE transactions on neural networks and learning systems*, *33*(12), 6999-7019.
17. Yang, G. R., and Wang, X. J. (2020). Artificial neural networks for neuroscientists: a primer. *Neuron*, *107*(6), 1048-1070.
18. Li, H., Lin, L., and Zeng, H. (2024). *Machine learning methods* (pp. 1-532). Singapore: Springer.
19. Hewing, L., Wabersich, K. P., Menner, M., and Zeilinger, M. N. (2020). Learning-based model predictive control: Toward safe learning in control. *Annual Review of Control, Robotics, and Autonomous Systems*, *3*(1), 269-296.
20. Han, C., Jeong, Y., Ahn, J., Kim, T., Choi, J., Ha, J. H., ... and Park, I. (2023). Recent advances in sensor–actuator hybrid soft systems: Core advantages, intelligent applications, and future perspectives. *Advanced Science*, *10*(35), 2302775.
21. Lin, Y. S., Chien, C. F., and Chou, D. (2022). UNISON decision framework for hybrid optimization of wastewater treatment and recycle for Industry 3.5 and cleaner semiconductor manufacturing. *Resources, Conservation and Recycling*, *182*, 106282.
22. Arabzadeh, V., and Frank, R. (2024). Creating a renewable energy-powered energy system: Extreme scenarios and novel solutions for large-scale renewable power integration. *Applied Energy*, *374*, 124088.
23. Barto, L., Bulín, J., Krokhin, A., and Opršal, J. (2021). Algebraic approach to promise constraint satisfaction. *Journal of the ACM (JACM)*, *68*(4), 1-66.
24. Daryanavard, S. (2024). *Real-time predictive artificial intelligence: deep reinforcement learning for closed-loop control systems and open-loop signal processing* (Doctoral dissertation, University of Glasgow).

ISSN 3030-3907

25. Ramos, I. F., Gianini, G., Leva, M. C., and Damiani, E. (2024). Collaborative intelligence for safety-critical industries: A literature review. *Information*, *15*(11), 728.
26. Shakya, A. K., Pillai, G., and Chakrabarty, S. (2023). Reinforcement learning algorithms: A brief survey. *Expert Systems with Applications*, *231*, 120495.
27. Lee, M., Yu, Y., Cheon, Y., Baek, S., Kim, Y., Kim, K., ... and Jeong, J. (2023). Machine learning-based prediction of controlled variables of APC systems using time-series data in the petrochemical industry. *Processes*, *11*(7), 2091.
28. Ahmadi, H., and Kazemi, A. (2020). The Lyapunov-based stability analysis of reduced order micro-grid via uncertain LMI condition. *International Journal of Electrical Power and Energy Systems*, *117*, 105585.
29. Zhang, T., Chen, J., Li, F., Zhang, K., Lv, H., He, S., and Xu, E. (2022). Intelligent fault diagnosis of machines with small and imbalanced data: A state-of-the-art review and possible extensions. *ISA transactions*, *119*, 152-171.

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