Article:

de Souza Jr., M.B. and Rossiter, J. (2025) Recent developments in automatic control and systems engineering. Processes, 13 (8). 2406. ISSN 2227-9717

https://doi.org/10.3390/pr13082406

processes

Editorial

Recent Developments in Automatic Control and Systems Engineering

Maurício B. de Souza Jr. [1,2,*] **and John Anthony Rossiter** [3,*]

[1] Chemical Engineering Department, School of Chemistry, Universidade Federal do Rio de Janeiro (UFRJ), Rio de Janeiro 21941-914, RJ, Brazil
[2] Chemical Engineering Program, COPPE, Universidade Federal do Rio de Janeiro (UFRJ), Rio de Janeiro 21941-914, RJ, Brazil
[3] Department of Automatic Control and Systems Engineering, University of Sheffield, Sheffield S1 3JD, UK
* Correspondence: mbsj@eq.ufrj.br (M.B.d.S.J.); j.a.rossiter@sheffield.ac.uk (J.A.R.)

1. Introduction

The industry's pursuit of digitalization, with a focus on automating solutions, is presently being complemented by efforts to develop autonomous systems, where artificial intelligence (AI), advanced control, modeling and optimization play a significant role [1–3]. In this context, this Special Issue presents some recent developments in automatic control and systems engineering, including practical and experimental applications in various areas, ranging from autonomous vehicles to industrial processes. A core aim is to capture many of the important themes being pursued by researchers in this area, which in turn will allow new researchers to plan future research.

Computational methods and implementation challenges are two important sides of various works and include such topics as digital twins, hardware-in-the-loop (HIL) and software-in-the-loop (SIL) simulation techniques; real-time computing issues in model predictive control (MPC); edge computing for real-time control; and reinforcement learning (RL) for control and optimization. The continuing development of autonomous systems and their interactions with human expertise are also addressed, together with the use of machine learning and vision systems to support the real-time monitoring of industrial processes.

Received: 18 April 2025
Revised: 24 July 2025
Accepted: 25 July 2025
Published: 29 July 2025

Citation: de Souza Jr., M.B.; Rossiter, J.A. Recent Developments in Automatic Control and Systems Engineering. *Processes* **2025**, *13*, 2406. https://doi.org/10.3390/pr13082406

2. An Overview of the Published Papers

A common point of interest regarding automatic process control is the extent to which it is safe and efficient to allow machine autonomy, in comparison to human control and intervention. In the case of autonomous vehicles, as claimed by Yan and coworkers (contribution 1), human drivers and automated systems must still cooperate in a transition phase to autonomy. In this case, the question of "driver authority" is an import point of attention. The group of Xinyu Liu proposed a driving authority optimization framework using model predictive control for shared steering control. They presented simulations and experiments in order to evaluate their framework.

While the analogy with autonomous vehicles provides a relevant reference, the automatic control of industrial processes involves specific considerations. One core observation is the widespread benefits of model predictive controllers (MPC), which have led to their broad adoption and the need for computationally efficient algorithms for their implementation. Consequently, several papers in this Special Issue focus on MPC. For example, Mendes and coworkers (contribution 3) explored the use of a low-computational-cost

MPC-modified Takagi–Sugeno–Kang-based MPC (MTSK-MPC) embedded on a PLC (programmable logic controller) to control a pressure swing adsorption process (PSA). PSA is a cyclic method adopted for complex gas-phase separation. The authors showed the feasibility of their implementation through software-in-the-loop and hardware-in-the-loop simulations. In another work, Trentini and collaborators (contribution 7) investigated computationally efficient MPC for the control of a biphasic oil separator in the presence of slug flow using unrestricted horizon linear model predictive control (UHMPC). They used this unrestricted version of MPC to reduce the computational cost of the controller, avoiding the demand for expensive microprocessors, and compared their results via simulation with a linear quadratic regulator (LQR), with the UHMPC leading to more stable system behavior. Finally, and again on the same conceptual lines, Santanna and coworkers (contribution 6) addressed the practical dependence on limited hardware for the MPC of oil production processes equipped with an electric submersible pump (ESP). Two control strategies, namely robust infinite-horizon model predictive control (RIHMPC) and nonlinear model predictive control (NMPC), embedded in a microcontroller were evaluated and compared in terms of robustness and computational performance.

The next group of papers demonstrate the need for and benefits of tailored solutions that exploit existing control techniques for the improved control of specific applications. Gouveia and coworkers (contribution 4) developed an edge-computing-based modular control system and Yin and collaborators' (contribution 8) study focused on the automation of hydraulic drive pavers. Edge computing brings computation closer to the source of data generation, minimizing delays and improving system autonomy and reliability. The first study used data vibration signals from a real cement ball mill and aimed to test the system in different industrial process environments. The second investigation aimed to achieve constant speed control and reduce wandering deviation during paving operations, by proposing a control scheme based on a Global Navigation Satellite System (GNSS). The automation enhanced the efficiency and quality of paving operations.

An area of increasing interest in the community is the use of images for control (Image-based control (IBC)), given that algorithms and our ability to efficiently extract useful information from images are continually improving. While uses for autonomous driving are well known and widely reported, many other possible applications are becoming increasingly evident. Professor Durand's group (contribution 5) developed a testbed for IBC and analysis, consisting of a framework that integrates an open-source visualization software and process physics. The framework was applied to three different cases, demonstrating its potential.

Of course, no Special Issue on control would be complete without some discussion of artificial intelligence (AI) approaches. In the last few years, interest in using AI techniques in the field of process system engineering has grown significantly. Several developments in the design, monitoring, control and optimization of processes have been investigated (e.g., [4,5]) and it is clear that there is huge potential within this general area [3]. Within the Special Issue, we include AI work with an industrial application (Queiroz and co-workers, contribution 2) that synergistically integrated knowledge-based phenomenological models with a purely data-based artificial intelligence approach (the random forest tree-based algorithm) to develop soft-sensors for a sour water treatment unit (SWTU) in an oil refinery. The results allow the prediction of contaminants in the effluents of the SWTU and also the analysis of the input variables affecting them. Along the same lines, in transfer learning (TL), a deep learning model built from a source dataset is used to generalize the representations observed in another dataset. Professor Hedengren's group (contribution 9) presented a study on transfer learning (TL) and model predictive control. In Ref. [6], TL is applied in the context of MPC by using a pre-trained deep learning (DL) model of the MPC, and then fine-tuning the MPC training for a new automation task. The authors showed an illustration of the TL operation in which the behavior of the linear MPC of a liquid-level system is learned by a dynamic neural network (LSTM, long short-term memory) and then used to control a thermal system.

While learning-based methods could be considered as part of the broader AI family, one could also argue that reinforcement learning (RL) is to some extent a distinct area, one that is greatly facilitated by modern computer hardware and tools. Faria and coworkers (contribution 10) presented a review article on the application of reinforcement learning (RL) to process control [7]. According to the authors, unlike other review articles, their work examines RL from the perspective of simulation-based offline training, process demonstrations, and policy deployment with transfer learning. Finally, the challenges of integrating RL into online process control, including hyperparameter optimization, are also discussed, with a batch control experiment used to illustrate several proposed guidelines.

The important topic of process safety is also addressed in this Special Issue. Process safety involves strategies to avoid and mitigate incidents [8]; here, the procedures are based on process systems engineering approaches. Queiroz and co-workers (contribution 2) discussed the operational challenges and environmental concerns associated with SWTUs, particularly the removal of contaminants, and emphasized the role of soft sensors in real-time monitoring and control to prevent faults and ensure compliance with environmental regulations. In the work of Professor Durand's group (contribution 5), the use of image-based control systems and virtual testbeds to simulate and test monitoring and control strategies for chemical processes can help identify potential challenges and optimize control systems and cybersecurity strategies before implementation in real-world scenarios. Mendes and coworkers (contribution 3) and Santana and coworkers (contribution 6) ensured the safe implementation of MPCs in a PSA process and ESP-lifted oil wells, aiming to operate their systems within safe regions. Finally, Trentini and coworkers (contribution 7) discussed safety-critical issues posed by slug flow in offshore oil production control and developed a control strategy aiming to stabilize the process and mitigate disturbances, thereby enhancing its safety and reliability.

Finally, it is important to remember the future, and determine how the students of today might be encouraged to study the control challenges facing society [3] and take action. Consequently, the Special Issue also includes contribution 11, which addresses education and how, especially within the control arena, practice is changing to reflect current and future needs [9].

3. Conclusions

This Special Issue presents a rich panorama of approaches and applications, ranging from hydraulic drive pavers to oil and gas processes. Model Predictive Control (MPC) algorithms emerge as a widely used tool; however, the hardware limitations of many industries still constrain their application to simpler versions. While artificial intelligence tools hold great promise, their widespread adoption may require a transitional period where greater trust must be established before becoming fully realized. Nevertheless, the recent developments presented here demonstrate their potential in monitoring, control, and optimization. The authors hope this snapshot into control will promote more researchers to contribute to solving the challenges of the future.

Author Contributions: Writing—original draft preparation, M.B.d.S.J.; writing—review and editing, J.A.R. All authors have read and agreed to the published version of the manuscript.

Funding: Professor Maurício B. de Souza Jr. is grateful to financial support from CNPq (Grant No. 311153/2021-6) and Fundação Carlos Chagas Filho de Amparo à Pesquisa do Estado do Rio de Janeiro (FAPERJ) (Grant No. E-26/201.148/2022).

Conflicts of Interest: The author declares no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
DL	Deep learning
ESP	Electric submersible pump
GNSS	Global Navigation Satellite System
HIL	Hardware-in-the-loop
IBC	Image-based control
LSTM	Long short-term memory
LQR	Linear quadratic regulator
MPC	Model predictive control
MTSK-MPC	Modified Takagi–Sugeno–Kang-based model predictive control
NMPC	Nonlinear model predictive control
PLC	Programmable logic controller
PSA	Pressure swing adsorption
RIHMPC	Robust infinite-horizon model predictive control
RL	Reinforcement learning
SIL	Software-in-the-loop
SWTU	Sour water treatment unit
TL	Transfer learning
UHMPC	Unrestricted horizon linear model predictive control

List of Contributions

1. Yan, S.; Wei, Q.; Xie, X.; Zhao, D.; Liu, X. Driver–Automated Cooperation Driving Authority Optimization Framework for Shared Steering Control. *Processes* **2024**, *12*, 2313. https://doi.org/10.3390/pr12112313.
2. Queiroz, D.G.; Rodrigues, F.D.B.; Nogueira, J.N.P.; Melo, P.A.; Souza, M.B., Jr. Synergizing Phenomenological and AI-Based Models with Industrial Data to Develop Soft Sensors for a Sour Water Treatment Unit. *Processes* **2024**, *12*, 1900. https://doi.org/10.3390/pr12091900.
3. Mendes, T.P.G.; Ribeiro, A.M.; Schnitman, L.; Nogueira, I.B.R. A PLC-Embedded Implementation of a Modified Takagi–Sugeno–Kang-Based MPC to Control a Pressure Swing Adsorption Process. *Processes* **2024**, *12*, 1738. https://doi.org/10.3390/pr12081738.
4. Gouveia, G.; Alves, J.; Sousa, P.; Araújo, R.; Mendes, J. Edge Computing-Based Modular Control System for Industrial Environments. *Processes* **2024**, *12*, 1165. https://doi.org/10.3390/pr12061165.
5. Akkarakaran, L.A.; Gjonaj, G.; Rahman, M.; Durand, H.E. Virtual Test Beds for Image-Based Control Simulations Using Blender, *Processes* **2024**, *12*, 279. https://doi.org/10.3390/pr12020279.
6. Santana, B.A.; Matos, V.S.; Santana, D.D.; Martins, M.A.F. Embedded MPC Strategies for ESP-Lifted Oil Wells: Hardware-in-the-Loop Performance Analysis of Nonlinear and Robust Techniques. *Processes* **2023**, *11*, 1354. https://doi.org/10.3390/pr11051354.
7. Trentini, R.; Campos, A.; Salvador, M.A.; Scheuer, Y.M.; Santos, C.H.F. Unrestricted Horizon Predictive Controller Applied in a Biphasic Oil Separator under Periodic Slug Disturbances. *Processes* **2023**, *11*, 928. https://doi.org/10.3390/pr11030928.
8. Yin, X.; Yin, S.; Zhu, H.; Zhan, Z. Experimental Study on Constant Speed Control Technology of Hydraulic Drive Pavers. *Processes* **2023**, *11*, 477. https://doi.org/10.3390/pr11020477.
9. Munoz, S.A.; Park, J.; Stewart, C.M.; Martin, A.M.; Hedengren, J.D. Deep Transfer Learning for Approximate Model Predictive Control. *Processes* **2023**, *11*, 197. https://doi.org/10.3390/pr11010197.

10. Faria, R.R.; Capron, B.D.O.; Secchi, A.R.; Souza, M.B., Jr. Where Reinforcement Learning Meets Process Control: Review and Guidelines. *Processes* **2022**, *10*, 2311. https://doi.org/10.3390/pr10112311.
11. Rossiter, J.A. Modernising the control curriculum and delivery to meet 21st century needs. *Processes* **2025**, *13*, 531. https://doi.org/10.3390/pr13020531.

References

1. Daoutidis, P.; Megan, L.; Tang, W. The Future of Control of Process Systems. *Comput. Chem. Eng.* **2023**, *178*, 108365. [CrossRef]
2. Baldea, M.; Georgiou, A.T.; Gopaluni, B.; Mercangöz, M.; Pantelides, C.C.; Sheth, K.; Zavala, V.M.; Georgakis, C. From Automated to Autonomous Process Operations. *Comput. Chem. Eng.* **2025**, *196*, 109064. [CrossRef]
3. Annaswamy, A.M.; Johansson, K.H.; Pappas, G.J.; Alleyne, A.; Allgower, F.; Ames, A.D.; Amin, S.; Anderson, J.; Antsaklis, P.J.; Bagheri, N.; et al. Control for Societal-Scale Challenges: Roadmap 2030. IEEE Control Systems Society Publication. 2023. Available online: https://ieeecss.org/control-societal-scale-challenges-roadmap-2030 (accessed on 11 February 2025).
4. Ren, Q. AI in Chemical Engineering: A New Chapter of Innovation. *Engineering* **2024**, *39*, 1–2. [CrossRef]
5. Raven, D.B.; Chikkula, Y.; Patel, K.M.; Al Ghazal, A.H.; Salloum, H.S.; Bakhurji, A.S.; Patwardhan, R.S. Machine Learning & Conventional Approaches to Process Control & Optimization: Industrial Applications & Perspectives. *Comput. Chem. Eng.* **2024**, *189*, 108789. [CrossRef]
6. Munoz, S.A.; Park, J.; Stewart, C.M.; Martin, A.M.; Hedengren, J.D. Deep Transfer Learning for Approximate Model Predictive Control. *Processes* **2023**, *11*, 197. [CrossRef]
7. Faria, R.R.; Capron, B.D.O.; Secchi, A.R.; Souza, M.B., Jr. Where Reinforcement Learning Meets Process Control: Review and Guidelines. *Processes* **2022**, *10*, 2311. [CrossRef]
8. Mannan, S. (Ed.) *Lees' Loss Prevention in the Process Industries: Hazard Identification, Assessment and Control*, 4th ed.; reprinted through 2020; Butterworth-Heinemann: Oxford, UK, 2014.
9. Rossiter, J.A. Modernising the control curriculum and delivery to meet 21st century needs. *Processes* **2025**, *13*, 531. [CrossRef]