Parameter Estimation of Fractional-Order Dynamic Systems Using PSO and Machine Learning Algorithms on Embedded Devices

Nerea Gómez Larrakoetxea[1,*], Ignacio Fidalgo Astorquia[1], Juan J. Gude[1]

[1] *University of Deusto, Faculty of engineering, Unibertsitate Etorb. 24, Deusto, 48007 Bilbo, Spain*

Abstract

Fractional-order models offer a more accurate mathematical representation of complex industrial processes compared to classical integer-order models, owing to their ability to capture memory effects and hereditary dynamics through non-integer differential operators. However, their real-time identification remains a significant challenge, particularly in resource-constrained edge computing environments. This work presents a hybrid framework that combines Particle Swarm Optimization (PSO) with machine learning techniques (including neural networks, Support Vector Regression (SVR), and Extreme Gradient Boosting (XGBoost)) to estimate reduced-order Fractional First-Order Plus Dead-Time (FFOPDT) models from step response data. PSO is employed to generate high-fidelity parameter estimates by minimizing the discrepancy between the high-order system response and the reduced model output, while the trained AI-based algorithms enable deterministic and rapid inference suitable for real-time deployment. The proposed methodology is validated on a custom-built thermal system, demonstrating that neural networks achieve R^2 values above 0.99 with inference times below 10 milliseconds on NVIDIA Jetson edge devices, compared to median PSO execution times exceeding 300 seconds. These results highlight a clear trade-off between estimation accuracy and computational efficiency, establishing the hybrid framework as a robust solution for real-time fractional-order system identification in industrial edge computing applications.

***K*eywords** Fractional-order systems · Edge computing · Reduced-order modeling 3

References

References

[1] Podlubny I., *Fractional Differential Equations*. Elsevier, 1998.

[2] Kennedy J., Eberhart R., Particle swarm optimization. *Proceedings of ICNN'95*, Perth, Australia, 1995, pp. 1942–1948.

[3] Gude J.J., García Bringas P., Proposal of a General Identification Method for Fractional-Order Processes Based on the Process Reaction Curve. *Fractal and Fractional*, 2022, 6, 526.

[4] Gude J.J., García Bringas P., Herrera M., Rincón L., Di Teodoro A., Camacho O., Fractional-order model identification based on the process reaction curve: A unified framework for chemical processes. *Results in Engineering*, 2024, 21, 101757.

[5] Åström K.J., Hägglund T., *Advanced PID Control*. ISA, 2006.

[6] Muresan C.I., Ionescu C.M., Generalization of the FOPDT model for identification and control purposes. *Processes*, 2020, 8, 682.

[7] Raubitzek S., Mallinger K., Neubauer T., Combining fractional derivatives and machine learning: A review. *Entropy*, 2022, 25, 35.

[*] *Corresponding Author's E-mail: abc@hbv.edu.tr*

[8] Miranda L.J.V., PySwarms, a research-toolkit for Particle Swarm Optimization in Python. *Journal of Open Source Software*, 2018, 3, 433.
[9] Breiman L., Random forests. *Machine Learning*, 2001, 45, 5–32.
[10] Chen T., Guestrin C., XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD*, San Francisco, 2016, pp. 785–794.
[11] LeCun Y., Bengio Y., Hinton G., Deep learning. *Nature*, 2015, 521, 436–444.
[12] Tepljakov A., Petlenkov E., Belikov J., FOMCON toolbox for modeling, design and implementation of fractional-order control systems. *Applications in Control*, De Gruyter, 2019, pp. 211–236.
[13] Gude J.J., García Bringas P., A Novel Control Hardware Architecture for Implementation of Fractional-Order Identification and Control Algorithms Applied to a Temperature Prototype. *Mathematics*, 2022, 11, 143.