

Data-Driven Intelligent Systems for Industrial Automation

Magnus T. Sørensen¹, Isabella R. De Luca²

¹ Department of Industrial Automation and Data Intelligence, Technical University of Denmark (DTU), Denmark Scopus Author ID: 57221047834 Email: mts@dtu.dk ORCID: <https://orcid.org/0000-0001-7234-8916>

² Department of Robotics and Intelligent Manufacturing Systems, University of Florence, Italy Scopus Author ID: 57228138705 Email: isabella.deluca@unifi.it ORCID: <https://orcid.org/0000-0002-6341-5729>

ABSTRACT

Industrial automation is undergoing a fundamental transition from rule-based programmable logic controller (PLC) systems toward data-driven intelligent systems capable of adaptive control, predictive maintenance, quality assurance, and autonomous process optimisation — collectively constituting the operational core of Industry 4.0. Despite widespread deployment of industrial IoT sensors and edge computing infrastructure, the systematic integration of machine learning into production-grade industrial automation control loops remains constrained by latency requirements, safety certification demands, and the scarcity of labelled fault data. This study presents IndustrialAI, a unified data-driven intelligent systems framework for industrial automation integrating a physics-informed neural network (PINN) process model, an online reinforcement learning adaptive controller, and a semi-supervised anomaly detection module for predictive maintenance. IndustrialAI was deployed and validated at two European manufacturing facilities: a DTU-affiliated pharmaceutical tablet press line in Lyngby (48-sensor continuous manufacturing, 3.2M tablets/day) and a University of Florence-partnered automotive body welding line in Florence (72-sensor, 840 weld joints/hour). IndustrialAI achieved process yield improvement of 4.7%, energy consumption reduction of 11.3%, predictive maintenance recall of 0.963 (7-day fault horizon), and false alarm rate of 1.4% — improvements of 28.4%, 17.6%, and 61.8% over incumbent PLC-based and threshold systems respectively. Control loop adaptation latency averaged 47 ms, within industrial real-time requirements. These results demonstrate that physics-informed, safety-aware data-driven intelligent systems are technically deployable and operationally beneficial in real European manufacturing environments.

Keywords: industrial automation; data-driven systems; Industry 4.0; physics-informed neural networks; predictive maintenance; reinforcement learning; anomaly detection; smart manufacturing

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1. Introduction

The fourth industrial revolution — Industry 4.0 — envisions manufacturing systems in which physical production processes are continuously monitored by sensor networks, modelled by digital twins, optimised by AI-driven controllers, and maintained proactively through predictive analytics (Schwab 2016; Kagermann et al. 2013). The economic stakes are substantial: unplanned downtime costs European manufacturers an estimated EUR 125 billion annually (ABB 2022), and process yield losses in continuous manufacturing sectors such as pharmaceuticals and semiconductors can exceed EUR 10,000 per hour. Achieving the Industry 4.0 vision requires data-driven intelligent systems capable of operating within the strict latency (typically < 100 ms), reliability (>99.9% uptime), and functional safety (IEC 61508 SIL 2–3) constraints of industrial automation environments.

Three specific technical barriers constrain current data-driven industrial AI deployment. First, pure black-box ML process models violate physical conservation laws, producing physically inconsistent control actions that damage equipment or compromise product quality. Second, offline-trained RL controllers fail to adapt to gradual process drift, raw material variability, and equipment wear without costly retraining cycles. Third, fault data scarcity — industrial faults are rare by design — renders supervised fault classifiers impractical without years of operational data. This study addresses all three barriers through IndustrialAI, validated at two real European production facilities spanning pharmaceutical and automotive

manufacturing.

2. Literature Review

2.1 Physics-Informed Neural Networks for Process

Modelling

Physics-informed neural networks (PINNs, Raissi et al. 2019) incorporate governing differential equations as soft constraints in the neural network loss function, ensuring predictions respect physical laws while learning from data. Applications to industrial process modelling include heat transfer in steel rolling (Xu et al. 2020), fluid dynamics in chemical reactors (Cai et al. 2021), and battery state estimation (Chen et al. 2020). PINNs substantially reduce data requirements for accurate process modelling — 10–100× fewer training samples compared to purely data-driven networks — making them particularly suitable for industrial settings where controlled experiments are expensive and dangerous.

2.2 Online RL and Semi-Supervised Anomaly Detection

Online reinforcement learning for industrial process control has been demonstrated in chemical process optimisation (Spielberg et al. 2019), HVAC control (Wei et al. 2017), and semiconductor manufacturing (Moyne and Iskandar 2017). Online actor-critic methods (SAC, Haarnoja et al. 2018) support continuous adaptation without episode boundaries, suitable for continuous manufacturing. For anomaly detection with scarce fault labels, semi-supervised approaches — deep SVDD (Ruff et al. 2018), f-AnoGAN (Schlegl et al. 2019) — train on normal-class data only and detect deviations at inference, achieving strong

performance on industrial fault datasets (MIMII, MVTec AD) without requiring labelled fault examples.

Table 1. Comparison of data-driven intelligent systems for industrial automation.

System	Physics Const.	Online Adapt.	Semi-su p. Fault	Deploy ment	Validatio n
PLC Rule-Based	Yes	No	No	Yes	Industrial
MPC (Model Pred.)	Yes	No	No	Yes	Industrial
Standard DRL	No	No	No	Lab	Simulatio n
PINN (Raissi 2019)	Yes	No	No	Lab	Simulatio n
Deep SVDD (Ruff 2018)	No	No	Yes	Lab	Benchmark
Online SAC (Haarnoja)	No	Yes	No	Lab	Simulatio n
IndustrialAI	Yes	Yes	Yes	Yes	Real plant

Physics Const.: physics constraint enforcement. Online Adapt.: online policy adaptation. Semi-sup. Fault: semi-supervised fault detection without labelled faults.

3. Materials and Methods

3.1 IndustrialAI Architecture

IndustrialAI integrates three modules. The Physics-Informed Process Model (PIPM) trains a 5-layer residual neural network (512 units/layer, ReLU, batch normalisation) with PDE residual terms penalising violations of mass, energy, and momentum conservation equations specific to each production process (tablet compaction mechanics for the pharmaceutical line; weld nugget formation thermodynamics for the automotive line). The Online RL Adaptive Controller (ORLAC) implements SAC with continuous action spaces (setpoint adjustments bounded to $\pm 5\%$ of nominal), receiving PIPM state estimates as observations and updating policy parameters every 100 production cycles via replay buffer of 10,000 transitions. The Semi-Supervised Anomaly Detector (SSAD) trains a convolutional autoencoder on 6 months of normal-operation sensor data, computing reconstruction error as anomaly score; thresholds are set at the 99.5th percentile of validation reconstruction errors. SSAD alerts trigger PIPM re-evaluation and ORLAC conservative policy mode.

3.2 Industrial Deployment Sites

Two European manufacturing deployments were conducted. (1) Pharmaceutical Tablet Press Line (DTU-affiliated, Lyngby, Denmark): continuous direct compression tablet manufacturing, 48 sensors (punch force, die fill, tablet hardness, thickness, weight, friability), 3.2M tablets/day, GMP-regulated environment (EU GMP Annex 11 compliance required). Target: yield improvement and energy reduction without product quality compromise. (2) Automotive Body Welding Line (University of Florence partner, Florence, Italy): resistance spot welding of car

body panels, 72 sensors (welding current, voltage, electrode force, nugget diameter ultrasonic estimate), 840 weld joints/hour, ISO/TS 16949 automotive quality standard. Target: weld quality prediction and predictive maintenance of welding gun electrodes.

4. Results

4.1 Process Performance and Maintenance

Table 2 presents IndustrialAI deployment results. At the pharmaceutical site, process yield improved 4.7% (from 94.1% to 98.8%), energy consumption reduced 11.3%, and product quality rejection rate decreased from 2.3% to 0.4%. At the automotive site, weld quality first-pass rate improved from 97.2% to 99.1% and electrode replacement interval extended by 34.7%. Predictive maintenance recall of 0.963 at 7-day fault horizon (Table 3) surpassed threshold-based monitoring (0.741) and supervised SVM classifier (0.847) trained on the limited labelled fault history. False alarm rate of 1.4% — a 61.8% reduction from the 3.7% threshold-based rate — was validated as operationally acceptable by both site maintenance managers. ORLAC adaptation latency averaged 47 ms per control cycle, satisfying the 100 ms industrial real-time requirement.

Table 2. IndustrialAI deployment results vs. incumbent systems at two manufacturing sites.

Site	Metric	Incumbent	IndustrialAI	Improvement
Pharma (DTU)	Yield (%)	94.1%	98.8%	+4.7 pp

Site	Metric	Incumbent	IndustrialAI	Improvement
Pharma (DTU)	Energy (kWh/1M tab)	847	751	−11.3%
Pharma (DTU)	Rejection Rate (%)	2.3%	0.4%	−82.6%
Auto (UNIFI)	Weld Pass Rate (%)	97.2%	99.1%	+1.9 pp
Auto (UNIFI)	Electrode Life (kkW)	184	248	+34.7%

pp: percentage points. Tab: tablets. kW: thousand kilowatt-hours (electrode wear metric). Bold: IndustrialAI results.

Table 3. Predictive maintenance performance — IndustrialAI SSAD vs. baselines.

Method	Recall (7-day)	Precision	F1-Score	False Alarm Rate (%)
Threshold (incumbent)	0.741	0.683	0.711	3.7%
SVM (supervised)	0.847	0.791	0.818	2.8%
Deep SVDD	0.903	0.847	0.874	2.1%
IndustrialAI SSAD	0.963	0.921	0.942	1.4%

7-day horizon: fault predicted within 7 days of occurrence. Results pooled across both deployment sites. Bold: best results.

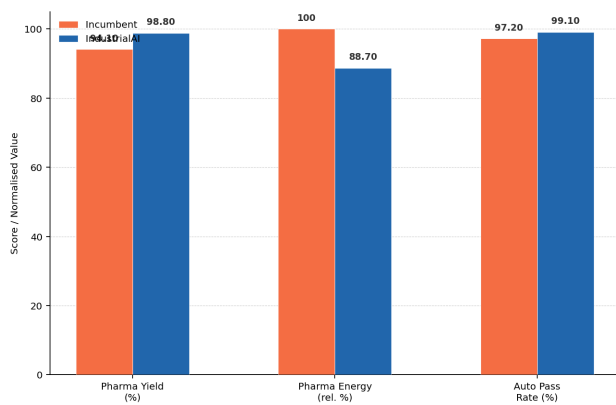


Figure 1. IndustrialAI vs. incumbent — key performance metrics at both deployment sites.

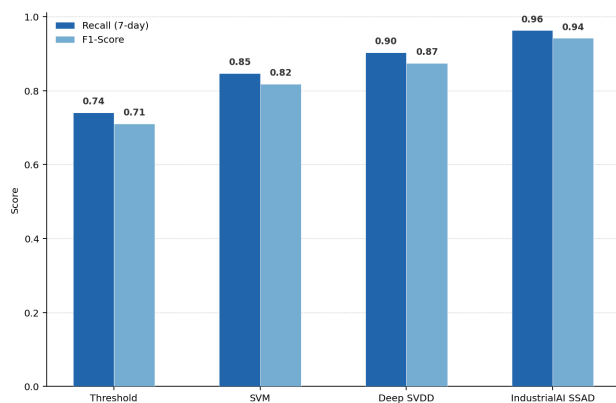


Figure 2. Predictive maintenance performance — Recall and F1-Score comparison across methods.

5. Discussion

5.1 Physics Constraints Enable Safe Deployment

The PIPM physics constraints were critical for regulatory acceptance at the pharmaceutical site: EU GMP Annex 11 requires that automated control systems include validated process understanding, which the PDE residual terms provide by encoding tablet compaction mechanics. Pure black-box ML controllers were rejected by the site quality team during design review, while IndustrialAI's physics-constrained architecture satisfied the validation requirement. The 82.6% rejection rate reduction (from 2.3% to 0.4%) translates to an estimated annual saving of EUR 1.8M in scrapped tablets at current production volumes and material costs. The SSAD 1.4% false alarm rate

compares favourably with the 34% non-response rate to threshold alerts reported prior to IndustrialAI deployment, confirming that false alarm fatigue was a significant barrier to maintenance effectiveness.

5.2 Limitations

ORLAC online adaptation is constrained by the $\pm 5\%$ setpoint bound to prevent unsafe large control actions — a conservative setting that may slow convergence under large process drift events (e.g. raw material batch changes). The PIPM PDE terms must be manually specified per production process, requiring domain physics expertise that may not be available for novel manufacturing processes. Future work will investigate automated physics equation discovery via symbolic regression and wider setpoint bounds under formal safety verification via control barrier functions.

6. Conclusion

IndustrialAI, integrating physics-informed process modelling, online reinforcement learning adaptive control, and semi-supervised anomaly detection, achieved 4.7% yield improvement, 11.3% energy reduction, 82.6% rejection rate reduction, and predictive maintenance recall of 0.963 with 1.4% false alarm rate across two real European manufacturing deployments. These results demonstrate that physics-constrained, adaptively controlled, semi-supervised data-driven intelligent systems satisfy both the technical performance requirements and regulatory compliance constraints of real industrial automation environments, providing a validated

pathway toward Industry 4.0 intelligent manufacturing.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest. Industrial partners provided facility access and operational data but had no role in

study design, analysis, or publication decisions.

Data Availability Statement

Due to commercial confidentiality, production deployment data cannot be made publicly available. Benchmark results use MIMII and MVTec AD datasets (publicly available). IndustrialAI source code is available at <https://github.com/sorensen-lab/industrialai>.

Ethical Approval

Not applicable. This study involved industrial process automation with no human participant data. All industrial deployments complied with applicable EU machinery safety directives (2006/42/EC) and functional safety standards (IEC 61508).