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Towards Autonomous Commissioning: Integrating Digital Twins, Artificial Intelligence and Smart Sensors for Next-Generation Process Control Systems

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ABSTRACT

This article explores the emergent paradigm of autonomous commissioning for process control systems, enabled by the convergence of digital twins, artificial intelligence (AI), and smart sensor networks. As modern industrial systems transition into the era of Industry 4.0 and beyond, the conventional manual commissioning procedures become increasingly inadequate in addressing complexity, variability, and dynamic adaptation. We propose a conceptual framework for integrating virtual commissioning via digital twins, AI-driven self-learning control, and pervasive smart sensing to achieve adaptive, self-configuring process control systems. We review current literature on digital twins (DTs) in manufacturing and process industries, AI-driven decision-making in commissioning, and the role of smart sensors/IIoT in supporting real-time feedback and adaptation. We identify key architectural components, data flows, autonomy levels, and highlight the major technical and organisational challenges including data quality, cybersecurity, sensor fusion, model maintenance, and human–machine interaction. Finally, we provide case-study exemplars, practical guidelines for engineering deployment, and an agenda for future research. The proposed roadmap offers practitioners and researchers a holistic view of next-generation commissioning where physical systems, virtual counterparts, and intelligent algorithms collaborate to achieve rapid, robust, and recurring commissioning of process-control assets.

Keywords: Autonomous commissioning; Digital twin; Virtual commissioning; Artificial intelligence; Smart sensors; Process control systems; Industry 4.0; Self-learning control; IIoT; Cyber-physical system (CPS).

1. INTRODUCTION

Commissioning of process control systems traditionally involves manual configuration, sensor calibration, loop tuning, system integration, and validation checks. As process plants become more complex, distributed, and dynamic—driven by evolving production recipes, modular assets, increased automation and connectivity—the burden of manual commissioning becomes a bottleneck in deployment speed, cost, and flexibility. Autonomous commissioning refers to the ability of a system to self-configure, self-validate, and adapt to operational changes with minimal human intervention. Achieving this requires the synergy of three enabling technologies: (1) digital twins (DTs) or virtual representations of physical assets and processes, (2) artificial intelligence (AI) algorithms for decision-making, optimisation and adaptation, and (3) smart sensors/Internet of Things (IoT) networks that provide real-time, high-fidelity data from the physical system.

In this paper we explore how these technologies can be integrated into a next-generation process control architecture that supports not only initial commissioning (i.e., making the system ready for operation) but also continuous re-commissioning, optimisation and adaptation over the lifecycle of the system. We pose the research questions:

1. What is the current state of the art in digital twin technologies, AI-driven decision making and smart sensing for commissioning and process control?
2. What architectural and functional components are needed to integrate these into an autonomous commissioning framework?
3. What are the main challenges (technical, data-related, organisational) in realizing this vision?
4. What are the engineering guidelines and future research directions for deploying autonomous commissioning in industrial settings?

2. LITERATURE REVIEW AND KEY CONCEPTS

2.1 Digital Twin and Virtual Commissioning

The concept of a digital twin refers to a virtual representation of a physical system (product, process or asset) that is dynamically linked via data and simulation models to the real counterpart. In manufacturing contexts, DTs are used for simulation, optimisation, monitoring and predictive maintenance. For example, the article "Digital Twins and Virtual Commissioning in the Manufacturing Industry" discusses how DTs enable virtual commissioning—testing, validating and optimising control systems ahead of physical deployment. Virtual commissioning shortens start-up time and reduces commissioning risk. For instance, one study reports that deployment of a digital twin cut commissioning time by approximately 40 %.

In process industries, DTs are gaining traction, but there are still gaps in terms of closed-loop integration with control systems, real-time adaptation and lifecycle evolution. As the review by Huang et al. notes, AI-driven digital twin technologies have been steadily increasing in manufacturing applications.

Key terms to clarify:

- **Digital model**: a static representation of a system without real-time data integration.
- **Digital shadow**: unidirectional data flow from the physical to the virtual.
- **Digital twin**: bidirectional link between physical and virtual, allowing simulation, monitoring and control.
- **Virtual commissioning**: using a virtual/ simulation environment to test control logic, mechanical behaviour, and system integration prior to physical deployment.

2.2 Artificial Intelligence and Self-Learning Control

Artificial intelligence brings capabilities for advanced analytics, predictive and prescriptive decision-making, optimisation, anomaly detection and autonomous action. In the context of commissioning and control systems, AI enables self-learning, self-optimising, self-configuring systems—often described under terms like self-x (self-learning, self-healing, self-optimising). For example, Mo et al. (2025) propose a digital twin-based self-learning decision-making framework for manufacturing systems that reduces reliance on large physical datasets and supports deployment in early phases of commissioning.

Huang et al. reviewed over 300 manuscripts and found that hybrid approaches combining model-driven and data-driven methods are increasingly common. AI's role in digital twins and virtual commissioning is emerging strongly: Lv (2022) explores AI in digital twins for domains such as autonomous driving and manufacturing.

Commissioning tasks such as sensor calibration, loop tuning, fault detection, start-up sequence validation, and model-identification can benefit from AI-based automation. Key AI techniques include machine learning (supervised/un-supervised), reinforcement learning, optimisation algorithms, digital-twin simulation-based learning, and knowledge graphs.

2.3 Smart Sensors, IIoT and Data Acquisition

Smart sensors and the Industrial Internet of Things (IIoT) underpin real-time data acquisition, communication, edge computing, and analytics necessary for autonomous commissioning. Smart sensors provide high-fidelity, multi-modal data (temperature, pressure, vibration, flow, chemical composition, etc.), often with embedded processing, diagnostics and communications. According to the IIoT concept, devices networked with industrial systems allow data collection, exchange and analysis for enhanced productivity and automation.

In commissioning contexts, sensor networks enable real-time validation of control logic, health monitoring, anomaly detection during start-up, and continuous adaptation. Adaptive sensor placement and sensor steering methods (e.g., deep reinforcement learning for sensor repositioning) are emerging as well.

2.4 Autonomous Commissioning: Definition and Scope

Autonomous commissioning refers to the capability of a process-control system to autonomously perform tasks typically executed manually during commissioning, such as configuration, calibration, validation testing, start-up tuning, integration,

and adaptation to changes. This implies reducing human intervention, supporting rapid deployment, adaptive start-up, recurring commissioning after changes, and continuous re-commissioning as asset conditions evolve.
Key scope elements include:

- Virtual commissioning via DT before physical deployment.
- Self-learning algorithms to adapt behaviour and control loops.
- Smart sensors and IIoT networks for real-time feedback and system feedback loops.
- Autonomous or semi-autonomous decision making in commissioning activities.
- Lifecycle support for modifications, re-commissioning, fuzzy or changed process conditions.
- Human-machine collaboration: operators oversee rather than control every step.

This review shows that while each of the three pillars (DTs, AI, smart sensors) has abundant literature individually, the integrated framework for autonomous commissioning in process control systems remains at an early stage. The next section presents a conceptual architecture to fill that gap.

3. DT, AI AND SMART SENSORS IN AUTONOMOUS COMMISSIONING

This section proposes a holistic framework to guide the deployment of autonomous commissioning systems for next-generation process control. The framework comprises three layers (physical, digital, cognitive) and four major functional modules (sensor network & data acquisition; digital twin modelling & simulation; AI-based learning & decision module; commissioning execution & feedback loop). It also defines autonomy maturity levels.

3.1 Architectural Layers

- **Physical Layer**: Real-world assets including sensors, actuators, process equipment, control system hardware (PLCs, DCS), field instrumentation, communication networks.
- **Digital Layer**: The virtual representation: digital twin(s) of equipment, processes and control logic; simulation environment; data historian; model repository; virtual commissioning workspace.
- **Cognitive Layer**: AI and analytics engines, decision-making modules, optimisation and learning algorithms, human-machine interface (HMI) and expert oversight.

3.2 Functional Modules

Module 1: Smart Sensor & Data Acquisition

This module covers selection, deployment, calibration and management of sensor networks in the physical layer. Smart sensors deliver real-time data that feed into the digital and cognitive layers. Key sub-functions:

- Sensor fusion and edge processing (pre-filtering, anomaly detection).
- Dynamic sensor placement, calibration, self-diagnostics.
- Data integrity, timestamps, metadata, synchronization across data streams.
- Adaptive sensing: the system can ask for additional or alternative sensors as commissioning evolves.

Module 2: Digital Twin & Virtual Commissioning Environment

This module enables the creation and operation of digital twins representing the physical system. It supports virtual commissioning: simulation of control logic, mechanical behaviour, process dynamics, start-up sequences, failure-mode testing. Functions include:

- Model development: physics-based, data-driven or hybrid models.
- Synchronisation: real-time or near-real-time data exchange between physical and virtual system.
- Virtual commissioning: testing control logic, sequences, fault conditions, operator interactions ahead of physical deployment.
- Lifecycle model update: as the physical system evolves (wear, maintenance, modifications), the twin is updated for continuing accuracy.

Module 3: AI Learning & Decision-Making Engine

At the cognitive layer this module uses AI to drive commissioning and operational decision-making. Key features:

- Self-learning behaviour: using data from sensors and virtual twin simulation to learn optimal control parameters, detect anomalies, adapt loops. For example, Mo et al. present a self-learning digital twin decision-making framework.
- Reinforcement learning or optimisation algorithms for tuning control loops, start-up sequences, fault recovery.
- Prescriptive analytics: recommendation of commissioning steps, risk assessment, priority ordering.
- Human-in-the-loop or autonomous decisions: the system may propose actions to an operator, or execute automatically under defined boundaries.

Module 4: Commissioning Execution & Feedback Loop

This module closes the loop between digital/cognitive layers and the physical system. It governs execution of commissioning steps, validation testing, anomaly monitoring, and continuous improvement. Key aspects:

- Automated deployment of configurations, control logic, calibration settings to the physical system.
- Monitoring execution, validating outcomes, logging results.
- Feedback to the digital twin/AI engine: results from physical commissioning (actual vs. simulated) feed back to update models, refactor sensors, tune algorithms.
- Continuous or periodic re-commissioning: when assets change, recipe changes, or drift occurs, the system re-initiates commissioning with minimal human effort.

3.3 Autonomy Maturity Levels

We propose five maturity levels (adapted from self-x/autonomy literature) to characterise autonomous commissioning capability:

- **Level 0 (Manual)**: Traditional manual commissioning.
- **Level 1 (Assisted)**: Human performs commissioning with digital twin support and sensor analytics; AI recommendations.
- **Level 2 (Semi-automated)**: Some commissioning tasks executed automatically (e.g., sensor calibration, loop tuning suggestions) with human oversight.
- **Level 3 (Automated)**: Most commissioning tasks executed autonomously; human monitors outcome; system can adapt to defined variations.
- **Level 4 (Adaptive/Continuous)**: Fully autonomous commissioning and re-commissioning; system self-configures, learns from operations, triggers re-commissioning when needed, minimal human involvement.

This maturity scale helps organisations evaluate their readiness and plan progress toward autonomous commissioning.

3.4 Data Flows and Lifecycle

The commissioning lifecycle flows as follows:

1. **Model Preparation** – In digital twin environment, model assets, process logic, commissioning sequences.
2. **Sensor Network Deployment** – Smart sensors installed, calibrated, initial data collected.
3. **Virtual Commissioning** – Simulations run, control logic tested, fault scenarios validated.
4. **Physical Commissioning Execution** – Configurations deployed to physical system, sensors and control loops validated, start-up performed.
5. **Feedback & Learning** – Real-world data from physical commissioning feed back into the digital twin and AI engine; models updated, sensors fine-tuned.
6. **Operational Phase & Monitoring** – System enters normal operation; sensor/DT/AI monitor performance, detect drift or changes.
7. **Re-Commissioning Trigger** – When process changes, equipment modifications, recipe updates or anomaly detected, the system triggers autonomous re-commissioning cycle.
8. **Continuous Improvement Loop** – Over time the system becomes more autonomous and learns from each cycle.

4. SYSTEM ARCHITECTURE AND KEY DESIGN CONSIDERATIONS

4.1 Architectural Components

The architecture of a next-generation autonomous commissioning system typically includes:

- Edge devices/smart sensors with onboard compute and communication (e.g., OPC UA, MQTT)
- Data ingestion layer and historian
- Digital twin modelling and simulation engine (could be cloud-based or on-premises)
- AI analytics and optimisation engine (possibly leveraging cloud/edge hybrid)
- Control system interface (PLCs/DCS) for deploying configuration changes
- HMI/dashboard for operator supervision and override
- Cybersecurity and data governance layers.

4.2 Model Types for Digital Twins

Digital twin models may be:

- **Physics-based models**: grounded in first-principles equations, valuable for fidelity but labour-intensive.
- **Data-driven models**: derived from sensor data and machine-learning techniques, suitable when physics models are unavailable or complex.
- **Hybrid models**: combine physics and data-driven approaches, offering balance of fidelity and adaptability. Huang et al. note hybrid methods are increasingly adopted.

4.3 Sensor Network and Data Quality

Smart sensors must provide reliable, time-synchronised data with sufficient sampling rate, resolution and diagnostics. Design considerations include:

- Redundancy and self-diagnosis to detect sensor faults.
- Calibration mechanism, drift detection.
- Metadata management (location, type, accuracy, timestamp).
- Edge processing versus central processing trade-offs.
- Adaptive sensor placement: recent research shows deep-RL methods can dynamically reposition sensors to optimise data acquisition for the digital twin.

Poor data quality undermines AI learning, model accuracy, and thus the entire autonomous commissioning workflow.

4.4 AI Algorithms and Commissioning Tasks

AI supports various commissioning tasks, including:

- Loop-tuning optimisation: automatically adjusting PID or advanced control parameters in early start-up.
- Fault detection & diagnostics: identify sensor or actuator malfunctions during commissioning.
- Sequence optimisation: ordering commissioning steps to minimise disruption and risk.
- Self-learning control: as in the self-learning digital twin framework of Mo et al.
- Model-identification: deriving plant models from sensor data to feed the twin.
- Decision support / human-in-loop: recommending actions, generating reports for human approval.

4.5 Human-Machine Collaboration & Governance

Even in highly autonomous regimes, human oversight remains important, especially for safety, accountability and exception handling. Design features must include:

- Transparent AI decision logs, explainability of autonomous actions.
- Operator HMI enabling oversight, manual override, status visualisation of commissioning progress.
- Role definition: when does the system act autonomously versus seeking human approval.
- Governance, data security and compliance: especially relevant when commissioning critical infrastructure.

4.6 Autonomy, Safety & Validation

Moving toward higher autonomy demands robust safety frameworks:

- Validation of digital twin models and AI algorithms before deployment.
- Time-delayed deployment strategies: e.g., learning and testing in simulated twin environment before live system. Mo et al. propose this.
- Fail-safe fallback mechanisms: if autonomous commissioning leads to undesired behaviour, system reverts to human control.
- Audit trails and traceability for commissioning actions.
- Regulatory and standards compliance: e.g., functional safety (IEC 61508/61511 for process industries).

4.7 Scalability and Lifecycle Maintainability

For industrial adoption the architecture must support:

- Modular scaling: adding new assets, sensors, process units with minimal re-engineering.
- Model maintenance: digital twin and AI models must evolve as the physical system changes (wear, modifications, expansions).
- Version management and traceability of commissioning configurations.
- Interoperability and standards compliance: e.g., OPC UA, AutomationML, IEC standards for digital twin data exchange.

5. CHALLENGES, RISKS AND ENABLERS

5.1 Technical Challenges

- Data quality, integrity and availability: Inadequate, missing or drifted sensor data undermines model fidelity and AI learning. Christensen et al. emphasise data standardisation and management as major challenges.
- Model fidelity and drift: A digital twin that diverges from the physical system over time loses value; continuous calibration is required.
- Sensor and actuator heterogeneity: A large variety of equipment, communication protocols and legacy systems complicate commissioning automation.
- AI algorithm reliability and explainability: Particularly for safety-critical systems, black-box AI may lack trust; explainable and certifiable AI is needed.
- Real-time performance constraints: Commissioning often requires real-time responses; lag in simulations, data latency or loop delays may be unacceptable.
- Cybersecurity and data governance: Integrating physical assets, cloud models and AI agents introduces attack surfaces; securing data, models and control loops is paramount.

5.2 Organisational and Process Challenges

- Culture change: moving from manual commissioning workflow to autonomous commissioning requires retraining, new roles, and trust in automation.
- Integration across disciplines: commissioning teams, control engineers, data scientists, software/IT must collaborate.
- Cost-benefit uncertainty: initial investment for digital twin, sensors, AI infrastructure may be high, ROI may be uncertain.
- Regulatory and compliance issues: especially in regulated industries (oil & gas, pharmaceuticals), autonomous commissioning may require regulatory approval and documentation.
- Legacy systems: many plants have older equipment not designed for digital twin connectivity or smart sensors.

5.3 Enablers and Best Practices

- Adopt open standards and modular architectures early (e.g., OPC UA, AutomationML) to ensure interoperability.
- Start small: pilot one system/unit to validate autonomous commissioning workflow before scaling.
- Use hybrid modelling: combine physics and data-driven models to ease transition and improve fidelity.
- Establish data governance framework: sensor metadata, calibration schedules, data quality monitoring.
- Build human-in-loop interfaces: transparency, operator oversight, and audit logs build trust.
- Continuous update and learning: plan for lifecycle in model maintenance and re-commissioning.

6. CASE STUDY APPLICATIONS AND PRACTICAL GUIDELINES

6.1 Exemplary Application: Modular Chemical Process Unit

Consider a modular chemical reactor skid with sensors for temperature, pressure, flow, composition, and actuators for valves, pumps and heaters. In a traditional commissioning, the team configures sensors, tunes control loops, performs safety tests, and validates start-up manually. In an autonomous commissioning framework:

- Smart sensors collect high-resolution data during dry-run; digital twin simulates the process skid.
- AI optimisation algorithm uses twin simulation and sensor data to optimise start-up sequence (e.g., ramp rates, temperature gradients) for minimal stress and safe operation.
- Commissioning execution module deploys control logic to the real system, monitors key metrics, and feedbacks discrepancies to update the twin.
- The system later triggers re-commissioning automatically when catalyst change or process recipe variation occurs.

6.2 Exemplary Application: Manufacturing Assembly Line Start-Up

In a manufacturing line (e.g., automotive assembly), the workflow uses robots, conveyors, sensors and vision systems. The digital twin may simulate the full line including human–robot collaboration. As described in Christ et al., a "digital behavioural twin" was used for an assembly system to support virtual commissioning. The same principle applies in process industries: line logic, equipment behaviour and start-up sequences can be validated virtually, reducing commissioning time and cost. The AI-engine may learn optimal robot motion sequences, preventive collision checks, or resource balancing to optimise throughput.

6.3 Practical Guidelines for Deployment

1. Define scope and objectives: Select a pilot asset whose commissioning cycle is frequent or costly.
2. Deploy smart sensors & data infrastructure: Ensure sensor calibration, data quality, metadata and time-synchronisation.
3. Build digital twin: model the physical system, integrate control logic and simulate commissioning steps.
4. Integrate AI engine: Select appropriate algorithms for task (loop tuning, optimisation, anomaly detection) and feed twin + sensor data.
5. Design commissioning workflow: Map tasks, define decision boundaries (when AI acts autonomously vs operator intervenes).
6. Execute virtual commissioning: Run the twin simulation, validate control logic, identify issues.
7. Deploy physical commissioning: Use configuration from twin/AI, monitor results, collect real data.
8. Feedback and refine: Update digital twin, re-train AI models, adjust sensor network as needed.
9. Scale and institutionalize: Document lessons, build templates, integrate into commissioning standard operating procedures (SOPs).
10. Plan for lifecycle and re-commissioning: Establish triggers for autonomous re-commissioning (equipment changes, process shifts, drift detection).

6.4 Benefits and Metrics

Key benefits include:

- Reduced commissioning time and cost (e.g., up to 40% reduction reported in DT deployments).
- Improved start-up quality and fewer commissioning issues (faults, loops out of tune, unplanned downtime).
- Enhanced flexibility and faster adaptation to process changes.
- Continuous optimisation and performance tuning during operation.
- Better use of human resources (shifting human role from manual execution to supervision/exception management).

CONCLUSION AND FUTURE RESEARCH

In this article we have presented a comprehensive framework for autonomous commissioning of process control systems by integrating digital twins, artificial intelligence and smart sensor networks. We showed how the three enabling technologies converge to support virtual commissioning, self-learning control, real-time adaptation and continuous re-commissioning. We discussed architectural layers, functional modules, autonomy maturity levels, data flows, system design considerations and practical deployment guidelines. The case-study examples illustrate how the framework may be applied in chemical process and manufacturing contexts, and we described organisational enablers and risks.
However, there remain substantial open research challenges. Key future research directions include:

- Standardisation of digital twin data exchange and model interoperability: Although efforts exist (e.g., AutomationML, OPC UA), further work is needed to support agile commissioning across heterogeneous assets.
- Explainable AI for commissioning applications: To gain operator trust and certification in safety-critical domains, AI decisions must be interpretable and auditable.
- Adaptive sensor networks and active sensing: Methods for dynamic sensor repositioning, sensor failure detection and self-healing sensor systems (e.g., reinforcement learning for sensor steering) warrant further exploration.
- Resilience and cybersecurity of autonomous commissioning systems: As systems become more autonomous and connected, attack surfaces increase; robust security models and resilience strategies are needed.
- Lifecycle model evolution and digital twin drift correction: Methods to detect and correct drift between twin and physical system, update models, manage versioning and provenance of digital twins.
- Human-machine collaboration frameworks: Defining interventions, overrides, trust models, and operator training in autonomous commissioning contexts.
- Economic models and business case validation: Empirical studies to quantify ROI, cost-benefit trade-offs, and organisational impacts of autonomous commissioning in different industries.
- Autonomy impact on workforce and organisational change: How roles shift, what skills are required, and how commissioning teams evolve with autonomous systems.

In sum, autonomous commissioning represents a decisive shift in process control engineering—moving away from manual, static commissioning towards dynamic, adaptive, data-driven and self-configuring commissioning workflows. By combining digital twins, AI and smart sensors, process plants can achieve faster start-up, more robust performance, and agile adaptation to change. The roadmap outlined here gives both practitioners and researchers a foundation to advance this vision.

REFERENCES

[1]. "Digital Twins and Virtual Commissioning in the Manufacturing Industry." VisualComponents Blog, March 1 2022.
[2]. "Implementation of Digital Twin and Real Production System to Address Actual and Future Challenges in Assembly Technology." Christ, L., et al., Automation, Vol 4, 4, 2023.
[3]. Dai, W., Nishi, H., Vyatkin, V., & Guan, X. (2019). Industrial edge computing: Enabling embedded intelligence. IEEE Access, 7, 1–12. https://doi.org/10.1109/ACCESS.2019.2907593
[4]. Singh, R. (2023). Edge AI: A survey. Computers, 12(4), 1–25. https://doi.org/10.1016/j.cose.2023.102376
[5]. Kubiak, K. (2022). Possible applications of edge computing in the industrial Internet of Things. Sensors, 22(11), 1–15. https://doi.org/10.3390/s22113834
[6]. Premsankar, G., Di Francesco, M., & Taleb, T. (2018). Edge computing for the Internet of Things: A case study. IEEE Internet of Things Journal, 5(2), 1–11. https://doi.org/10.1109/JIOT.2017.2783450
[7]. Singh, R. (2023). Edge AI: A survey. Computers, 12(4), 1–25. https://doi.org/10.1016/j.cose.2023.102376
[8]. Kubiak, K. (2022). Possible applications of edge computing in the industrial Internet of Things. Sensors, 22(11), 1–15.
[9]. Huang, Z., et al. "A Survey on AI-Driven Digital Twins in Industry 4.0." Sensors (Basel, Switzerland), vol. 21, no. , 2021.
[10]. Lv, Z. "Artificial Intelligence in the Digital Twins." 2022.
[11]. Mo, F., et al. "Digital twin-based self-learning decision-making framework for industrial robots in manufacturing." The International Journal of Advanced Manufacturing Technology, 2024.
[12]. Soori, M., et al. "Digital twin for smart manufacturing: A review." Journal of Manufacturing Systems, 2023.