Production of the Future

AI Meets Software-Defined Automation

Steven Vettermann and Marcus Röper*

The integration of software-defined automation with artificial intelligence (AI) holds the potential to revolutionize production. Software-defined automation can be characterized by its flexible, service-oriented architecture, enabling real-time monitoring and control of production processes. Combined with AI capabilities, it offers new levels of efficiency, flexibility, and safety for industry. This article provides practical insights into how these technologies can be applied in production together to enhance resilience, sustainability, and competitiveness.

Motivation

To shape the future of production, we must rethink it fundamentally. Both process and manufacturing industries often face significant challenges: Automation solutions insufficiently match digitalization possibilities [1], shortage of skilled labor [2], and increasing demands for flexibility, efficiency, and sustainability [3].

These requirements are driving the digital transformation of the industrial sector. However, traditional automation technologies have their limitations when it comes to fully taking advantage of the possibilities of modern information technologies to realize seamless and flexible information flows and location-independent interactions between humans and systems. Software-defined automation offers an alternative. It aims to replace the rigid automation pyramid with flexible, networked services [4]. By decoupling hardware and process control and shifting control to the software level, processes can be adapted and expanded in real-time, similar to apps on a smartphone.

AI integration, in particular, offers enormous potential: predictive fault detection, process optimization, and intuitive user assistance are just a few examples [4]. Software-defined automation structures and provides production-related data so the AI can derive valuable insights and optimizations. Simultaneously, software-defined automation enables the direct implementation of AI-driven insights into production processes. Thus, the combination of AI and software-defined automation is an essential lever for realizing the production of the future.

State of the Art

The following section briefly overviews the current state of AI and software-defined automation.

Principles of Software-Defined Automation

Given the growing complexity of production processes and labor shortages (in Germany alone, shortages of engineers and IT specialists cost an estimated 13 billion Euro annually [2]), it is increasingly important to efficiently network machines and systems, integrate AI-supported services, and create transparency across all corporate systems. Traditional automation technologies are reaching their limits, even when hardware, such as programmable logic controllers (PLC), is virtualized [5].

Decoupling Hardware and Process Control

As with software-defined networks (SDN), software-defined automation abstracts hardware, and production capabilities are controlled exclusively through software [4]. Decoupling hardware and software significantly increases flexibility. For instance, a welding robot only needs to know how to weld; the exact place of the welding point can be determined dynamically via IT services. Tasks such as welding, screwing, or transporting can be orchestrated flexibly – independent of the specific machine and without specialized on-site personnel [5].

Implementing IT Security

Software-defined automation creates a flexible network of IT services, replacing the rigid automation pyramid. When implementing this, the necessary cybersecurity protections must be addressed rigorously. Traditionally, production environments have been largely self-contained, with IT security applied selectively. Thus, addi-

* **Corresponding Author**
Dr. Steven Vettermann; ASCon Systems Holding GmbH; Curiestraße 5, 70563 Stuttgart;
Tel.: +49 (0) 711 258589–0, E-Mail: Steven.Vettermann@ascon-systems.de

Co-author
Marcus Röper; ASCon Systems Holding GmbH

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tional exposure, such as that caused by introducing software-defined automation, increases vulnerability within production [6].

Enforcing an organization's security policies centrally is a fundamental requirement for operational resilience [7]. The convergence of IT and operational technology (OT) that comes with software-defined automation also presents the opportunity to unify and standardize security measures across organizations and beyond [5]. This approach supports unified system governance with significantly lower system administration costs [8]. The EU's NIS2 (Network and Information Security) directive will play an increasingly important role here [9]. Although it is primarily aimed at IT operations and management, it can also be used to improve security measures in companies in general. Thus, it can be assumed that the NIS2 will seriously impact the OT in production too.

Digital Twins at the Core

Digital twins form the backbone of software-defined automation. They are virtual representations of real objects, maintaining live synchronization with their physical counterparts (Figure 1). This bidirectional connection allows real-time monitoring and control of production processes [10]. Digital twins are indispensable for applications like condition monitoring, prescriptive maintenance, as well as anomaly detection and safety assurance, enabling efficient production control, whether via cloud or edge computing.

Digital twins offer the capability to interact directly with AI. They can provide precise, context-based data from the production process, enabling AI to make accurate decisions [5]. Suggested process changes and optimizations can then be implemented in actual production through digital twins [4].

AI in Production

Introducing AI into production promises significant efficiency gains and innovation (Figure 1). However, successful AI integration requires a deep understanding of the technology and a targeted strategy that considers economic, technical, organizational, and cultural aspects. The following outline key requirements and steps for companies starting AI implementations.

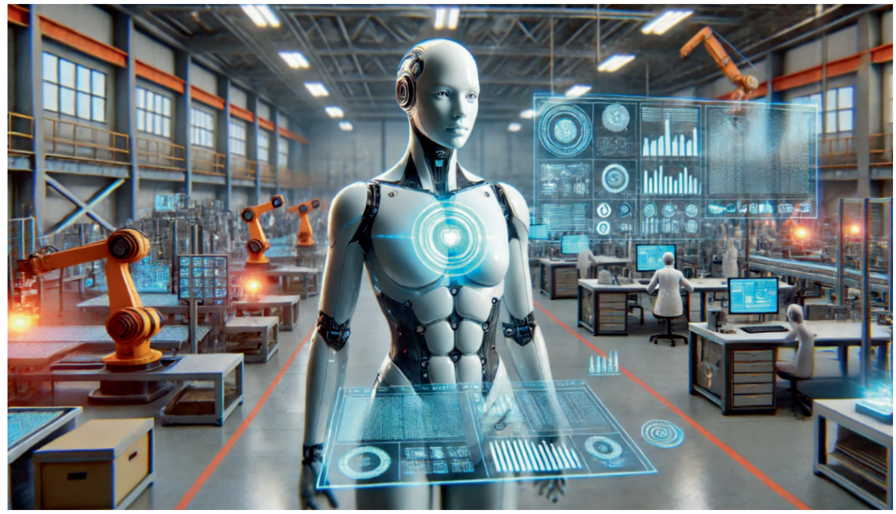

Figure 1. How ChatGPT might envision itself within a production setting if it had a physical form

Categorization and Fundamentals

AI refers to systems that independently learn from data through algorithms, handling cognitive tasks such as problem-solving and decision-making. Unlike Large Language Models (LLMs), which primarily focus on language-based tasks [11], a realization of an AI application essentially comprises three steps: Systematic data collection, model training, and integration into the production environment. You can find a more detailed breakdown in [12].

Implementing AI requires technical and domain-specific knowledge to adapt AI solutions to production requirements. Additionally, it should be considered to provide structured data in the process context rather than the mere provision of semantically poor data [13]. The „Periodic Table of AI" offers helpful guidance on industry application areas [14].

Successful AI Implementation

For companies beginning with AI, proof of concepts (PoC) can be used to test specific applications. The PoC approach aims to develop use cases with minimal effort and evaluate data availability and potential business benefits. Furthermore, the PoC phase reveals whether the project team possesses the necessary skills and how employees can be integrated into the process. Employee involvement is key, as close collaboration between the AI team and specialist departments is a foundation for success.

After a successful PoC phase, companies need to plan for the operation and scalability of AI solutions. Important questions include whether to use cloud-based or on-premises solutions, open or closed source, and whether to develop in-house or rely on external expertise [15]. Cost management is also crucial, especially with cloud solutions, where ongoing costs vary. In the long term, it is essential to establish mechanisms for maintaining and updating machine learning models to ensure consistent performance. Figure 2 presents this process in a flowchart.

Technical, Organizational, and Legal Constraints

Implementing AI in production is complex, involving numerous technical and organizational requirements. Verifying data availability and quality is essential. High data quality is crucial, as poor data can undermine model accuracy and jeopardize AI project success. Transparent data management and maintenance standards are needed to ensure a stable and reliable system. Data Mesh is a particularly effective standard for integrating AI systems into companies [16]. Risk management strategies also help to identify and address common pitfalls such as bias or overfitting.

Another key aspect is data protection, compliance with legal regulations, and the previously discussed cybersecurity measures. When handling personal or sensitive data, complying with the EU's

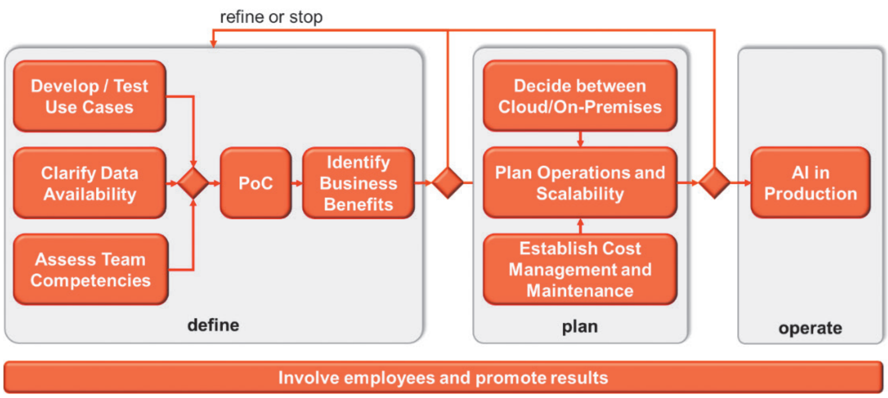

Figure 2. Flowchart for successful AI project implementation

GDPR (General Data Protection Regulation) is crucial. Wherever possible, data should be hosted within the EU. The EU AI Act also provides valuable guidance on legal risks [17].

Finally, transparent internal decision-making in AI models is essential to ensure traceability of errors and foster employee acceptance. Considerations around sustainability and ethics, such as efficient resource use and privacy protection, are also gaining importance as they reflect the company's social responsibility.

AI-Enabled Software-Defined Production

The convergence of software-defined automation with AI offers numerous advantages for modern production. For example, AI enables prescriptive analytics and process optimizations, reducing downtime, cutting costs, and improving efficiency [12]. Software-defined automation provides AI with necessary process-contextual data and can directly execute AI-driven insights. Both technologies are valuable on their own; together, they form the critical foundation for realizing future production. In the following, promising fields of application are given.

Quality Control and Process Agility

AI visual inspection and quality control applications reduce human errors and improve precision [18]. Image processing algorithms quickly and reliably detect defects, reducing waste and production costs – a considerable advantage in precision-focused industries such as automotive or electronics and pharmaceutical or food industries. Automated and digitally available results shorten processing times and increase efficiency.

In addition to visual inspection, supplementary sensors can be used to monitor processes more comprehensively. By combining data sources, AI gains more profound insights into process quality. For instance, inaccuracies from earlier process steps can be compensated for in subsequent steps [19].

Regarding this, software-defined automation provides the mechanisms to gather and communicate current and historical production-related data to AI. It provides the mechanisms to take the related feedback from AI for reconfiguring processes or providing actionable recommendations to personnel. In [5], a related application is described, where quality-related process information is gathered from a Body-in-White line and fed to the associated algorithms. The results are then applied at the line.

Anomaly Detection and Safety

AI will play an increasingly crucial role in anomaly detection in the highly regulated process industry to prevent production disruptions and accidents. As process complexity grows and unforeseen events become more frequent, AI algorithms demonstrate advantages over conventional analytics [4, 20]. This is particularly important in sectors with stringent safety and environmental regulations, where accidents can endanger lives and cause significant environmental and financial damage.

Real-time sensor data from software-defined automation enables AI to identify non-linear patterns indicating potential leaks, pressure spikes, or other hazardous states and recommend appropriate countermeasures. Software-defined automation can then directly implement these measures. In [21], more details on AI-based anomaly detection are given, and a case study is introduced. Meaningful publications from the industry currently seem to be kept secret to protect competitive advantage.

A further relevant aspect is „industrial aging": Aging equipment poses additional challenges, which AI addresses by predicting aging behavior and potential partial failures [22]. Software-defined automation can communicate context-specific data (current and historical sensor data, maintenance information, etc.) to the AI and execute the optimizations suggested by the AI.

Prescriptive Maintenance and Self-Healing

Predictive and prescriptive maintenance are essential for the manufacturing and process industries [5]. Unplanned downtime can be costly in continuous production environments, such as refineries or pharmaceutical plants. A single minute of downtime in the automotive industry can cost up to 20,000 euros. Combining AI and software-defined automation provides substantial advantages over traditional automation technologies.

As depicted in Figure 3, AI and software-defined automation go far beyond traditional automation technologies' possibilities. Implementation requires deep expertise, a trained AI model, data from current and past production runs, and the integration of relevant systems (e. g., maintenance, ERP, MES). It also requires the ability to influence the production process actively.

There are several stages of implementation. AI generally analyzes sensor data from machines and systems, e. g., to predict failures or wear before they occur. The stages differ in terms of what additional information is thereby considered by the AI and how the results are used in production actively.

Prescriptive maintenance incorporates dynamic strategies for specific aging and degradation behaviors. Based on this information, AI suggests targeted maintenance actions to ensure system reliability, allowing for more flexible and efficient maintenance planning than traditional static strategies [23]. Whereas related realizations can be found frequently in industrial applications (e.g. [5]), the following two can be seen as promising future trends. A review and a case study regarding the necessary self-reconfiguration capabilities are given in [24].

Proactive maintenance integrates maintenance and logistics knowledge, dynamically steering production to optimize maintenance timing. Self-healing advances this process by automatically detecting and resolving disruptions through corrective actions, process adjustments, or alternative logistics without manual intervention. These approaches require a bi-directional interaction between AI and software-defined automation.

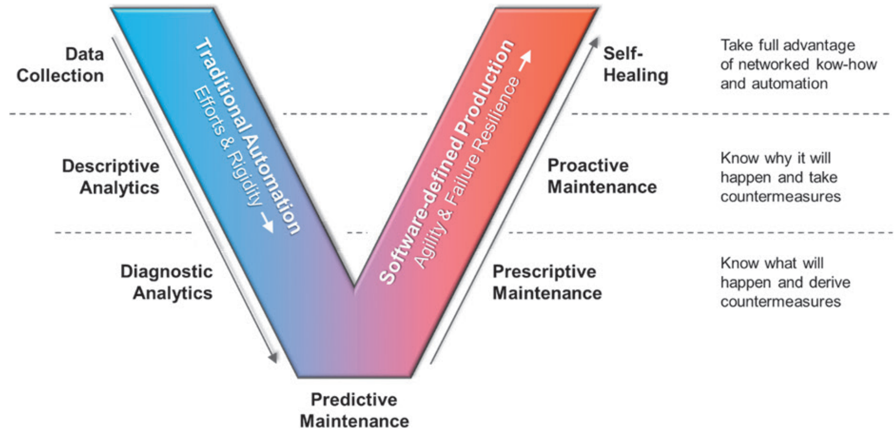

Figure 3. Unlocking new possibilities in maintenance through AI

Process Optimization, Supply Chains, and Sustainability

Machine-learning algorithms within software-defined automation enable real-time adjustments to process parameters to improve efficiency, product quality, and energy savings. In the process industry, AI-supported systems help reduce raw material consumption and maximize energy efficiency, reducing operational costs and the ecological footprint [25]. Similar benefits are observed in the manufacturing sector. A notable example is the publicly funded project E-KISS, which achieved nearly 30 percent savings in resources and energy [4].

AI can also optimize complex supply chains and enhance production processes. It improves demand forecasting, optimizes inventory, and enables flexible production adjustments. Software-defined automation provides the mechanisms for creating agile production and logistics environments.

New regulatory requirements further increase the need for real-time data availability. Real-time data, made available through software-defined automation services, can populate data spaces like Catena-X or Manufacturing-X in a structured and production-accompanying manner. In the future, such services and appropriately developed AI may also be used to achieve a global minimum of CO_2 emissions for specific products while simultaneously providing data relevant to future product passports.

Copilots in Production Planning

The application of AI delivers operational advantages in production and substantial benefits in production planning. AI-based copilots support planners by accessing experiential knowledge from past projects, providing helpful recommendations and handling repetitive tasks, allowing planners to focus on strategic decisions.

Production planning is a complex process that cannot be fully captured solely through the reasoning capabilities of a single language model [26]. However, it benefits significantly from enhanced reasoning abilities, enabling precise and efficient planning. The close integration of AI with cross-domain models creates a foundation on which changes in one domain can be automatically reflected in others. Figure 4 illustrates an example architecture for an agent-based logic system in production planning. This architecture incorporates vector embeddings to capture the nuanced relationships between different planning concepts and uses multiple specialized agents to handle various aspects of the complex planning process. It also includes a feedback loop using Reinforcement Learning from Artificial Intelligence Feedback (RLAIF) [27], which further sharpens the reasoning of the agent-based logic. The architecture was developed and successfully validated in a prototype, and an industry-ready application is in progress.

Active AI involvement can be structured so that a plan serves as a final output and seamless input for subsequent phases. When results—from engineering outputs, through production planning and virtual commissioning, to the services of software-defined automation—are bidirection-

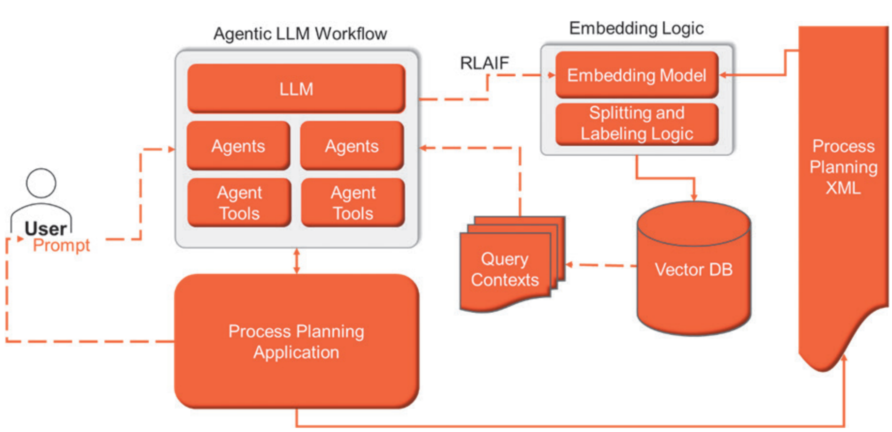

Figure 4. Architecture of an LLM-based agent system in production planning

Application	Objectives	Benefits	Computer Vision	LLM	Outlier Detection	Supervised Learning	Unsupervised Learning	Reinforcement Learning	Time Series Forecasting
Networking & Integration	• Transparency • Efficiency improvement	• Improved data availability		X	X	X			
Digital Twins	• Real-time monitoring • Process optimization	• Early error detection	X		X	X	X	X	
Condition Monitoring	• Condition monitoring	• Higher reliability			X	X			
Predictive Maintenance	• Efficiency improvement • Cost reduction	• Extended machine life • Reduced costs			X	X	X		X
Prescriptive Maintenance	• Process adjustments • Maintenance strategies	• Optimized maintenance planning			X	X		X	X
Anomaly Detection & Safety	• Safety • Quality monitoring	• Increased safety • Less errors			X		X		
Visual Inspection	• Process quality • Error reduction	• More accurate inspections	X						
Process Optimization	• Efficiency improvement • Production control	• Higher throughput • Reduced costs					X	X	X
Sustainability Initiatives	• Resource efficiency • CO2 reduction	• Improved environmental impact		X					X
Copilots	• Planning automation	• Improved planning accuracy		X					

Figure 5. Overview of AI technologies in production

ally interconnected, a well-trained AI system can ensure that changes in one domain are automatically updated in others. Such a solution could lead to an unprecedented efficiency boost in production.

Overview and Classification of AI Technologies

To illustrate and summarize the diverse applications of AI within the context of software-defined automation we discussed in this paper, Figure 5 presents the primary application areas and corresponding AI technologies in a compact table. It serves as a micro-overview, offering a quick reference for the various AI application areas, the respective goals, and the specific advantages achieved by integrating computer vision, large language models (LLM), outlier detection, supervised learning, unsupervised learning, reinforcement learning, and time series forecasting in production.

This illustration highlights how AI technologies can be strategically utilized to optimize processes, enhance operational safety, and achieve sustainability goals. Figure 5 shows that the intelligent use of AI can increase efficiency and quality in production, achieve significant cost savings, and reduce environmental footprints. An „x“ indicates where the AI technology applies to the specified automation application.

Summary and Outlook

Successful AI projects in the industry are characterized by addressing use cases with clear business benefits. The project team must possess the necessary skills, and employees should be involved initially. Additionally, data must be available at the required quality level, and IT security considerations are always relevant when it comes to data. Furthermore, the scalability and operational costs of AI in production must also be considered.

Insights from AI implementations offer valuable strategic and operational advantages. However, a much greater leap in innovation can be achieved by using these insights to enable the automated reconfiguration of production processes. This is made possible by software-defined automation solutions, which provide AI with real-time access to production-related data (both current and historical) as well as data from other systems (ERP, MES, maintenance, etc.) and enable the execution of the AI's resulting insights directly in production. This approach addresses the rapidly increasing demands for flexibility, resilience, and sustainability, helping to make the production of the future a reality.

Despite the extensive possibilities that technology offers, it's important to remember that humans will continue to play a critical role in the production environment of the future. Work itself will undergo fundamental changes. Software-defined automation and AI applications present enormous opportunities for the industry. However, beyond the technical challenges that must be overcome for widespread industrial use, a comprehensive, industry-wide change management strategy is essential. AI can play a crucial role in supporting humans and helping to accelerate progress in this transformative era.

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Authors

Dr. Steven Vettermann studied mechanical engineering at the Technical University of Darmstadt, where he also earned his doctorate in IT Security in Collaborative Product Data Management. Since 2022, he has been leading research activities at Ascon Systems with full responsibility. He is an author and speaker, dedicated to establishing solutions for AI, software-defined automation, and the industrial metaverse within the industry.

Marcus Röper studied computer science and physics at the University of Bonn and was involved in developing an award-winning AI product before assuming responsibility for AI strategy and innovations at Ascon Systems in 2024. His technical focus is on LLM agent systems in complex domains. He is committed to integrating the latest developments in AI into industrial applications and creating innovative solutions for complex challenges.

Abstract

Produktion der Zukunft: KI trifft Software-definierte Automatisierung. Die Verbindung von Software-definierte Automatisierung und Künstlicher Intelligenz (KI) bietet das Potenzial, die industrielle Produktion zu revolutionieren. Die Software-definierte Automatisierung bestiсht durch ihre flexible, Service-orientierte Architektur, die das Monitoring und Steuern von Anlagen in Echtzeit ermöglicht. Das mit den Möglichkeiten der KI kombiniert kann der Industrie neue Dimensionen an Effizienz, Flexibilität und Sicherheit erschließen. Der Artikel zeigt praxisnah, wie diese Technologien zusammen in der Produktion eingesetzt werden und dabei auch die Resilienz, Nachhaltigkeit und Wettbewerbsfähigkeit gefördert werden können.

Keywords

Software-defined Automation, Artificial Intelligence, Effectiveness, Efficiency, Safety, Sustainability

Schlüsselwörter

Software-definierte Automatisierung, Künstliche Intelligenz, Effektivität, Kosteneffizienz, Sicherheit, Nachhaltigkei

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