Generative AI and Agentic Architecture in Engineering and Manufacturing

Potentials and Practice of Scalable AI Solutions

Vlad Larichev,*
Jennifer Masek,
Prashant Chouhan and
Daniel Spiess

The integration of Generative AI (GenAI) and Agentic Architecture offers potential for scalability, automation, and improved decision-making in engineering and manufacturing. These technologies contribute to efficiency and process optimization but face challenges such as data fragmentation and interoperability. This paper examines the role of Agentic Architecture in addressing these issues, presenting scalable AI solutions, practical use cases, and strategic considerations for sustainable AI-driven innovation in industrial applications.

Introduction: The Transformation of Engineering and Manufacturing through AI

The integration of Artificial Intelligence (AI) and Generative AI (GenAI) in engineering and research & development (R&D) offers significant potential. *Ködding and Dumitrescu* emphasize that AI enables fundamental changes in strategic product planning by utilizing new technologies and data processing approaches to design complex systems [7].

Although GenAI is currently in the spotlight, it is only a part of the broader AI spectrum. Disciplines such as Machine Learning (ML), Natural Language Processing (NLP), and Data Science form the foundation of modern AI applications and play an integral role in industrial processes (Figure 1). However, GenAI expands this spectrum with capabilities for efficiently processing unstructured data, reasoning, and knowledge management beyond traditional data analysis.

Studies highlight that by 2025, GenAI will be used in 30 percent of companies for AI-supported development and testing strategies [3]. By 2026, over 100 million people could collaborate with AI-driven "AI colleagues", and 75 percent of companies plan to use GenAI to generate synthetic customer data.

However, the introduction of AI and GenAI in companies presents significant challenges. According to a 2022 study by Accenture, only 12 percent of companies worldwide can utilize AI and integrate it into their business processes effectively [1]. More than 60 percent of the surveyed companies are still experimenting and struggling to scale AI solutions sustainably [1].

These figures illustrate the complexity of implementation and the need for targeted strategies to integrate AI into business processes successfully. The lack of access to large, high-quality datasets, the requirements for explainable, accurate, and reliable AI processes, and the integration into existing, often complex IT landscapes complicate widespread integration. At the same time, there is often a lack of standardized interfaces to seamlessly incorporate AI technologies into existing systems and IT solutions along the value chain.

By training on enormous datasets and flexibly adapting GenAI applications using various techniques, this technology has the

* **Corresponding Author**
Vlad Larichev, M. Sc.; Accenture Dienstleistungen GmbH; Campus Kronberg 1, 61476 Kronberg im Taunus ; Phone: +49 (0) 170 464 1122, Email: vladislav.larichev@accenture.com

Co-authors
Jennifer Masek, M. Sc.; Accenture Munich
Prashant Chouhan, B. Tech., MBA; Accenture Dublin
Dipl. Wirtsch.-Ing. Daniel Spiess, M. Sc.; Accenture Munich

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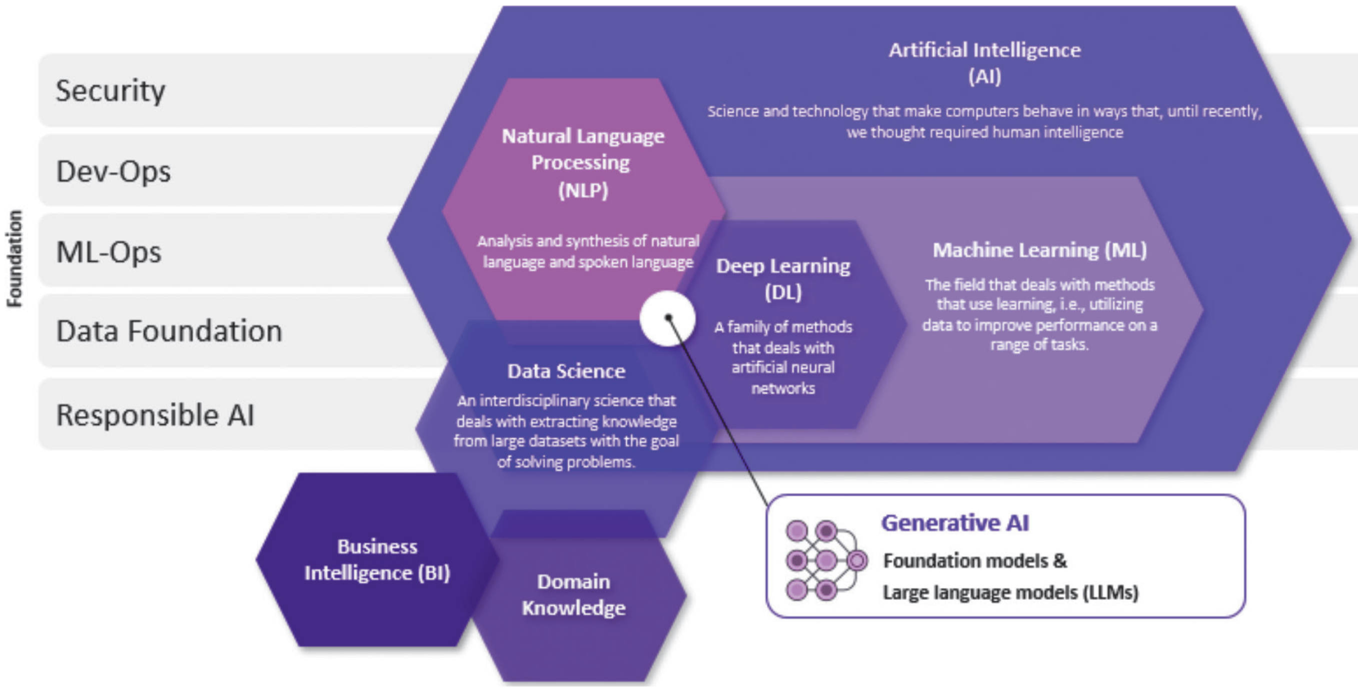

Figure 1. The AI Continuum: Positioning Generative AI within AI Disciplines and Supporting Foundations such as Data Management and ML-Ops (Accenture, 2024, modified)

potential to make development and manufacturing processes along the entire value chain more efficient, adaptable, and agile.

Despite these hurdles, a clear trend is emerging: the integration of AI and GenAI has the potential to sustainably transform not only engineering and manufacturing but the entire value chain. These technologies enhance productivity, optimize processes, and enable informed, data-driven decision-making in real time – a crucial competitive advantage for companies that embrace this change early on.

The following analysis highlights the potential of these technologies in the engineering and manufacturing landscape, which use cases are already being successfully implemented today, what architectural foundations are necessary to fully leverage their potential, and what companies need to do to sustainably benefit from this technology.

Status Quo: AI in Engineering and Manufacturing

Although AI is increasingly used in manufacturing and engineering, the adoption rate and penetration vary. According to a study commissioned by *IBM*, 32 percent of German companies with over 1,000 employees actively use AI, while another 44 percent are currently experimenting with AI or exploring its use [14].

In the manufacturing sector, AI is primarily used to optimize production processes. Machine learning and data analysis enable companies to automate production workflows and increase efficiency [5, 10]. Particularly in the automotive industry and electronics manufacturing, there are numerous applications where AI is used to predict machine failures and improve product quality [8]. The use of AI in many small and medium-sized enterprises in the DACH region is limited, as the necessary resources and expertise to effectively implement AI systems are often lacking [10].

In the area of R&D, a similar picture emerges. AI is increasingly being used as a supportive tool in generative design and research to analyze data and identify patterns crucial for developing new products or technologies [12]. Nevertheless, integrating AI into research processes often remains fragmented and heavily dependent on the respective discipline. In engineering, for example, AI is primarily used in design and simulation, while in other areas, such as materials research or product development, its application is not yet widespread [8].

In summary, the use of AI in engineering, R&D, and manufacturing in the DACH region is already established in specific disciplines along the value chain. However, comprehensive and widespread implementation is still pending.

Generative AI in Engineering: Potential and Main Use Cases

Generative AI represents a promising extension of existing methods in engineering and manufacturing. *Okuyelu and Adebayo* demonstrate that companies can reduce costs through GenAI, shorten time-to-market, and enhance their innovation capabilities [3, 11].

Large language models (LLMs) are evolving into powerful tools that go far beyond their original application in text processing. They can process classic text-based inputs and multimodal data sources such as images, videos, speech, structured production data, unstructured documents, and technical formats like CAD models (Figure 2). This diversity makes them particularly suitable for complex industrial use cases.

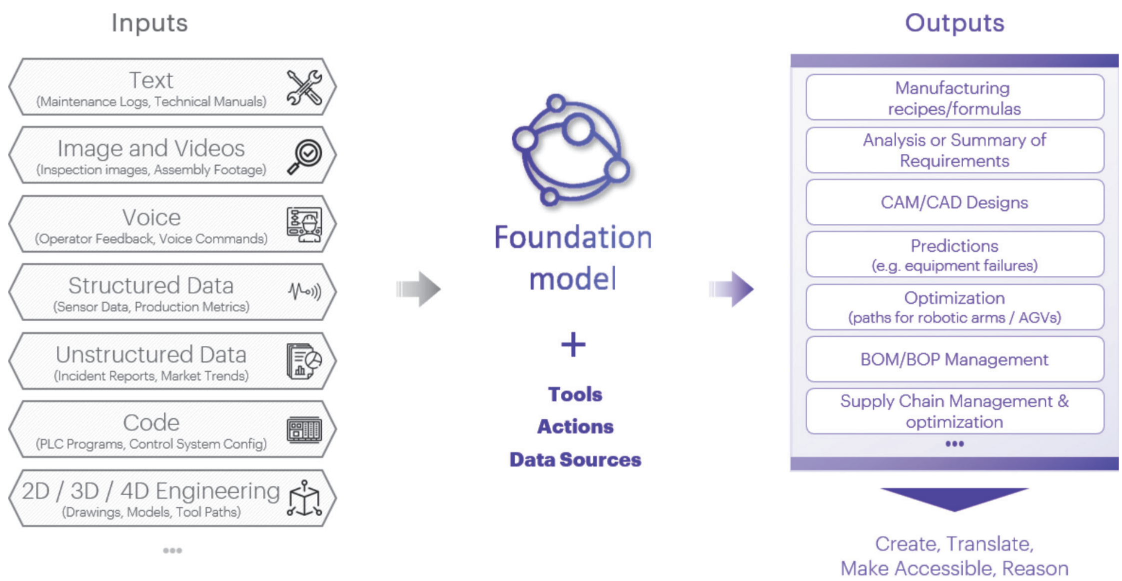

Figure 2. The Diagram shows how GenAI integrates various Data Types to generate usable Results (own representation)

In current industrial applications, the input data comes from various sources, including maintenance logs, ERP systems, technical manuals, inspection images, production data, software code, and 3D engineering data. GenAI systems can analyze these data, link them together, and derive informed insights.

The resulting outcomes include not only text content but also a variety of applications such as optimized production schedules, CAD/CAM designs, formulations, predictions of machine failures or quality deviations, proactive recommendations for action, and process optimizations, for example, through path planning for robotic systems or efficiency improvements in supply chain performance.

Large language models (Foundation Models) do not operate in isolation but can be further adapted with additional data to address certain domains or use cases. This can be achieved through fine-tuning, a targeted model development with domain-specific data, or specialized input instructions (Prompt Engineering). Furthermore, operational actions can be triggered through interfaces to existing IT systems such as ERP or PLM tools, making GenAI particularly effective in practice.

GenAI Along the Value Chain

Accenture estimates that Generative AI can increase the available resources in research and development along the value chain by up to 36 percent (Figure 3).

In early development phases, GenAI can provide significant support by acting as an intelligent assistant to facilitate idea generation, regulatory analyses, and technical feasibility studies. Its ability to analyze and structure large amounts of data in real time enables more efficient decision-making and accelerates the transition phase from research to conception.

GenAI optimizes iterative processes in the design and prototyping area by automatically simulating and evaluating various design options while considering requirements and regulations. This automation significantly reduces

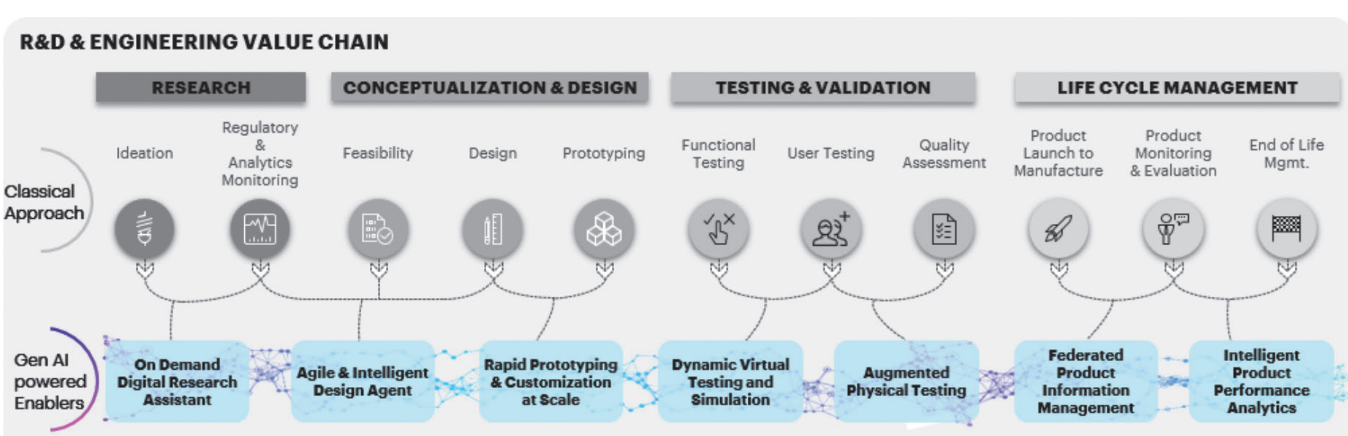

Figure 3. How Generative AI complements the Value Chain in R&D and Engineering (Accenture, 2024)

time and personnel effort, shortens development cycles, and accelerates time to market.

Also, in the testing and validation phase, GenAI unleashes its potential by augmenting traditional physical tests with virtual simulations. Weaknesses can be identified early on, and alternative solutions can be explored before physical prototypes are created. Hybrid approaches that combine simulation-based and physical testing ensure reliable results while also reducing costs

In lifecycle management, GenAI enables continuous optimization of products throughout their entire lifespan through data-driven analyses. Systems like Federated Product Lifecycle Management aggregate data from various phases of the product lifecycle to improve maintenance strategies and enhance product performance. This approach is mainly supported by technologies such as knowledge graphs, multi-agent systems, and cloud-based solutions. They make it possible to create robust federated systems while providing a centralized data view.

In summary, GenAI can become integral to modern engineering and manufacturing processes. By strategically deploying it along the value chain, companies can achieve significant efficiency gains and secure their market position through innovative products and processes in the long term.

Challenges of AI Integration in Engineering and Manufacturing

Despite the potential of AI in engineering and manufacturing, companies face numerous structural and technological hurdles that complicate the implementation and use of these technologies. According to a study by *Buxmann and Schmidt*, 95 percent of respondents believe AI will play a crucial role in their companies. Yet, the actual implementation lags behind these expectations [4].

The challenges associated with the introduction of AI are diverse, as summarized in the Figure 4. Companies are confronted with increasing complexity in data processing and the need to adapt their business models to meet the demands of digitalization [13, 7].

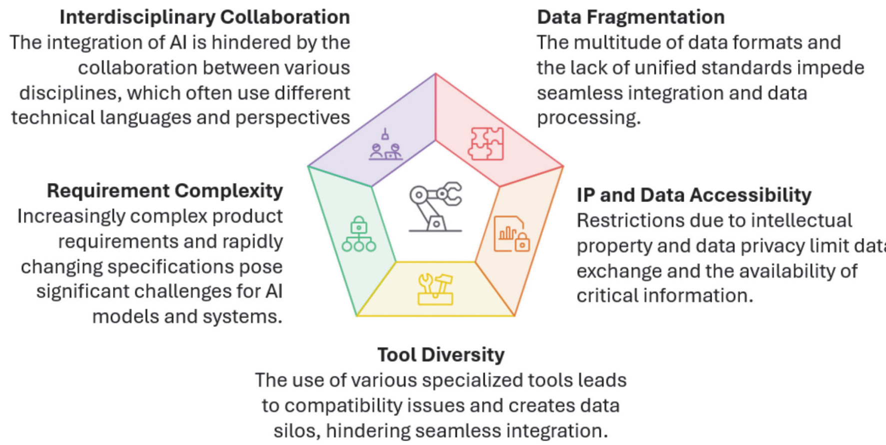

Figure 4. Central Challenges in the Engineering and Manufacturing Industry: Interdisciplinary Collaboration, Data Fragmentation, IP and Data Accessibility, Tool Diversity, and Requirement Complexity (own representation)

Heterogeneous Data Sources and Lack of Interoperability

Engineering and manufacturing processes generate data in various formats that are often not standardized. This ranges from CAD models to bills of materials to simulation data and test protocols, which exist in multiple versions and frequently incompatible formats.

The lack of consistent standards means that AI models struggle to integrate data from different sources seamlessly. This fragmentation hinders the development of a holistic view of the process and significantly restricts the interoperability of modern AI solutions.

Limited data availability and inaccessible documentation due to intellectual property and high data protection requirements

Data is often protected as intellectual property (IP) and cannot be shared outside of organizations or departments in the engineering and manufacturing sectors. Additionally, strict data protection regulations, particularly in Germany, complicate the processing of unstructured data, as it may contain potentially personal information. These restrictions limit the availability and quality of the data needed to develop AI systems such as LLMs.

Diversity of IT tools and media breaks

Development and manufacturing processes utilize various specialized software tools from different providers that are often incompatible. These tools cover specific areas such as CAD, PLM, ERP, or simulation software but usually operate in isolation.

Media breaks occur between these tools, complicating data transfers and require manual follow-up work. Classic AI solutions, such as application-specific “co-pilots”, can only help to a limited extent, as they are often focused on individual tools and do not enable comprehensive process integration.

Complexity of requirements and dependencies

The complexity of requirements for modern products is increasing rapidly. Across all industries, the demand for connected and modular products, which are increasingly defined by software (Software-Defined Products), is growing.

For example, software components such as over-the-air updates (OTA) must already be considered in the design and planning phase. At the same time, external factors such as regulations or sustainability requirements are also crucial.

Interdisciplinary Collaboration and Multimodality

Modern products require close collaboration between mechanical engineering, electrical engineering, software development, and manufacturing planning. Each discipline often uses its specialized language, and even similar terms like “security” have entirely different meanings in different contexts.

Additionally, company-specific terminology presents another challenge. Companies often use internal abbreviations, terms, and processes established independently of disciplines, which must be specifically trained to be correctly interpreted by AI systems.

These multimodality and discipline-specific nuances require modern AI systems to have the ability to interpret, distinguish, and contextualize specific domain knowledge accurately. However, current systems have only limited capabilities to seamlessly switch between domains in a "memory context", which restricts their ability to optimize complex processes comprehensively.

Architectural Foundations: Scaling GenAI in Engineering and the Role of Agent Systems

Integrating AI into engineering and manufacturing processes requires a robust and scalable architecture to overcome existing media breaks between tools and disciplines. Modern processes utilize various specialized software tools that often work in isolation. This lack of interoperability leads to data losses, inefficiencies, cumbersome integration, and difficulty for AI to access relevant information.

AI agents can overcome these media breaks by acting as intermediaries between tools and processes. They integrate data sources such as databases, document management systems, or real-time data streams into a unified digital process chain. By leveraging GenAI and an agentic architecture, companies can achieve higher efficiency levels, reduce operating costs, and improve product quality [6].

In particular, in a multi-agent system (MAS), autonomous agents represent specific machines, tools, or processes and can communicate and collaborate. This capability enables the dynamic optimization of production schedules, resource allocations, and process control. Studies show that MAS systems can significantly increase efficiency and flexibility in manufacturing environments [9, 15].

Furthermore, *Okuyelu and Adebayo* demonstrate that integrating generative AI and agentic architecture in engineering and the manufacturing industry increases productivity, optimizes processes, and enables real-time data-driven decision-making, providing companies with a crucial competitive advantage [11, 3].

Integrating GenAI into engineering and manufacturing requires a modern architecture capable of efficiently processing heterogeneous data sources and transforming them into valuable insights. This architecture is based on a multi-stage approach, including data collection (Figure 5), transformation, storage, and analysis.

The starting point is the integration of relevant data sources such as databases, emails, or technical systems. The data can be converted into a unified format optimized for AI models through methods like embedding and chunking. Subsequently, combining vector databases and knowledge graphs allows for data exploration and mapping of complex dependencies and relationships. At the end of the process, an orchestrated agent network performs tasks such as predictions, optimizations, or problem analyses and delivers actionable results by integrating external data sources and APIs.

Agentic Architecture as the Key to Efficiency

Agentic architecture plays a central role in applying generative AI to industrial processes. Agents enable seamless information exchange between systems, minimizing media breaks and improving collaboration between disciplines. Agents can harmonize different data formats and detect deviations early to avoid errors

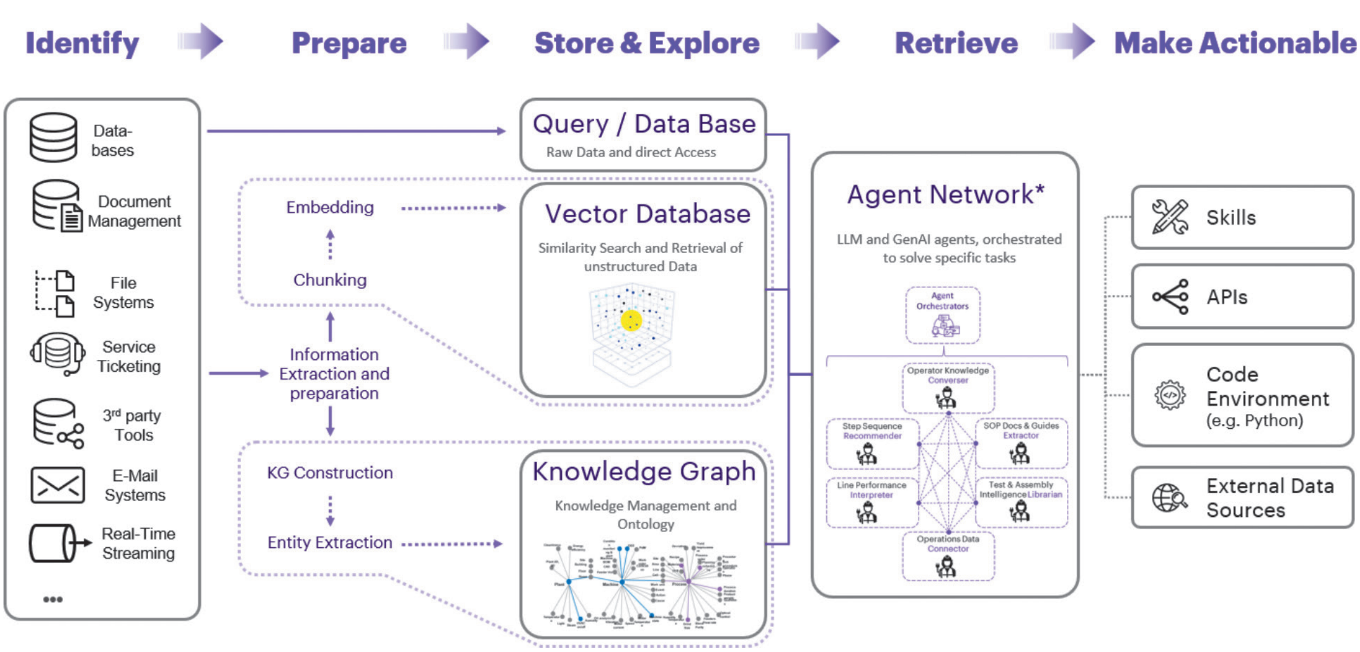

Figure 5. Modern AI Architecture: from Data Collection through Processing and Storage to Orchestration by Agent Networks – a Scalable Structure for Efficient and Action-Oriented Solutions (Accenture, 2024, modified)

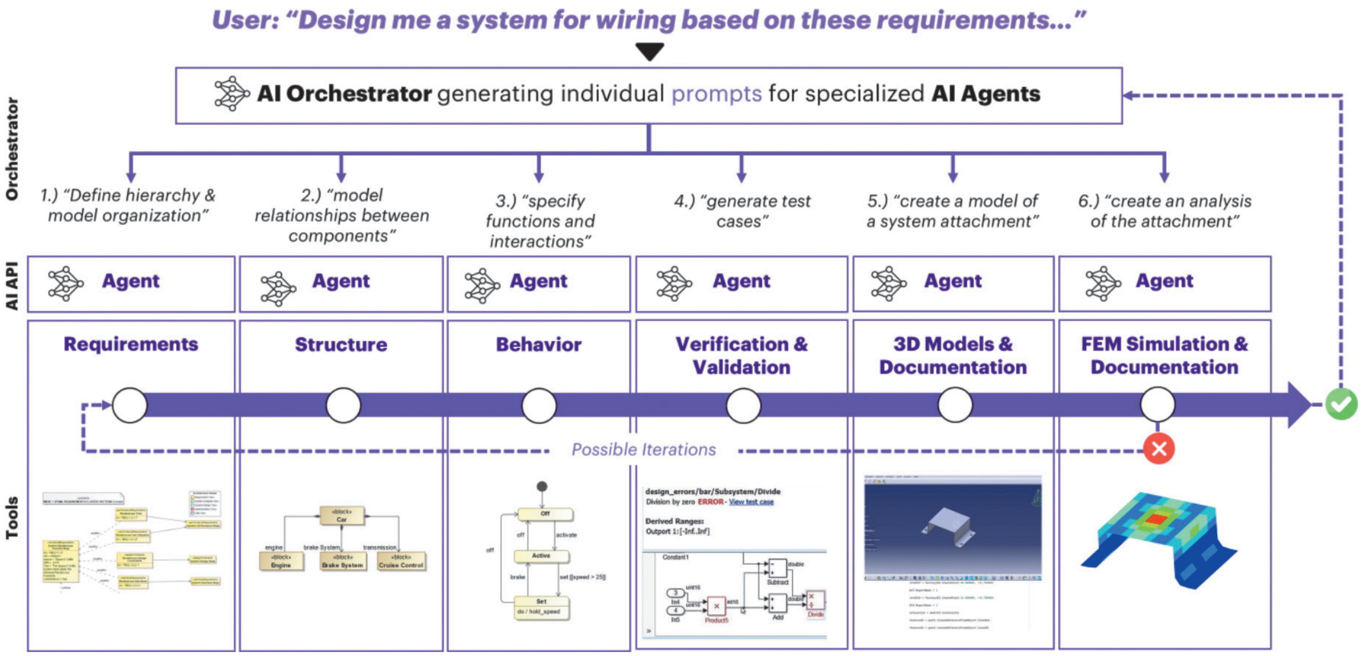

Figure 6. Architecture of a GenAI-based solution in engineering, consisting of a central orchestrator for task distribution and specialized agents for handling individual process steps, which collaborate iteratively (Accenture, 2024, modified)

and increase efficiency. This lays the foundation for flexible and scalable processes that dynamically adapt to changing requirements.

Due to their autonomy and communication capabilities, research confirms that MAS is well-suited to tackle complex industrial challenges [15, 16]. Applications such as optimizing production schedules or dynamic resource allocation demonstrate how these systems can help make production processes more efficient and resilient.

Use of GenAI Agents in in Engineering and Manufacturing

To address the challenges in engineering and manufacturing, a combination of robust reasoning systems and specialized GenAI agents has emerged as a best practice. This model combines the strengths of a central orchestrator with the specific capabilities of individual agents tailored to particular tasks and systems (Figure 6).

The orchestrator takes on planning, evaluation, and user interaction tasks. It manages the entire process, assigns tasks to the agents, and consolidates the results. In contrast, the GenAI agents focus on specific requirements and interfaces, such as understanding and utilizing IT solutions or processing particular data formats. Furthermore, the agents can consider lessons learned, best practices, and industry-specific and company-specific regulations, such as ISO standards. These agents do not require a comprehensive understanding of the overall process but work with a clearly defined, limited project scope. The results are reported directly to the orchestrator or other agents to solve complex tasks in iterative steps.

This modular concept allows for quick and cost-effective processing by utilizing powerful yet specialized tools for individual tasks. At the same time, the orchestrator ensures that all subprocesses are seamlessly linked and that the results are meaningfully integrated into the overall context. This combination of central control and specialized execution offers a robust and scalable solution that meets the specific requirements of modern engineering processes.

Recommendation: Competitive Advantages through a Company-Wide Digital Foundation

The ability to scale AI projects at the enterprise level is crucial for their long-term success. Companies that only use AI in pilot projects must address the scalability challenge to achieve sustainable effects.

However, using AI and GenAI solutions in practice is rarely possible "out of the box". For companies to benefit from the potential of these technologies, important prerequisites must first be established:

- *Data quality and availability*
  Companies must acquire relevant data and prepare it in a structured form.
- *Technological infrastructure*
  Powerful computing capacities, scalable cloud solutions, and the ability to integrate into existing systems through APIs and interfaces are central components for the successful use of GenAI. Additionally, flexible architectures are required to meet the demands of growing data volumes and complex models, as well as robust security measures to ensure data integrity and privacy.
- *Process adjustment*
  Internal processes and data flows must be optimized and aligned with the requirements of AI.
- *Staff training*
  Employees must be prepared to work with AI and GenAI and be continu-

ously trained. The study by Schönberger shows that successful integration of AI systems into existing workflows requires significant training and adjustment to ensure smooth collaboration between humans and machines [12]. This need for training and adjustment is often seen as one of the biggest hurdles companies must overcome to implement AI successfully.

- *Responsible AI*
  Companies should ensure that using artificial intelligence complies with ethical, legal, and social standards. This includes developing transparent models that ensure traceability and fairness and protecting sensitive data through robust security measures. Equally important is continuously reviewing AI systems to minimize unintended biases and risks.
- *Clear use cases and business value*
  Pilot projects should be purposefully selected and designed to be scalable to other areas of the company. Use cases that address specific challenges and create clear value for the company should be prioritized. Central management of use cases can also create synergies, avoid duplication of effort, and ensure strategic alignment.

The Right Approach: Focus on Use Cases with Value and a Strong Digital Foundation

An efficient entry into GenAI begins with implementing use cases that demonstrate measurable benefits. Examples include automating design processes, optimizing quality control, or predictive maintenance. These use cases can be effectively scaled in combination with a structured data foundation, a modern platform architecture, and especially a digital foundation – Digital Core.

Digital Core encompasses central technological elements such as cloud, data, artificial intelligence (AI), and security. It forms the basis for data-driven decisions, flexible integrations, and automation, essential for continuous transformation and adaptation to dynamic market demands. According to *Accenture* research, companies with an advanced digital core can achieve up to 60 percent higher revenue growth (from an average of 7.1 percent to 11.1 percent) and 40 percent higher profitability (14.2 percent to 19.4 percent) [2].

The introduction of generative AI should not be viewed as an isolated technological improvement but as part of a comprehensive strategic transformation. Companies must reevaluate their existing systems to enable AI-supported operations and align their organization with new possibilities. A digital foundation plays a key role here, as it strengthens collaboration between machines, humans, and systems, thus creating the basis for continuous innovation.

Conclusion and Outlook

Generative AI has the potential to transform engineering and manufacturing processes fundamentally. GenAI opens a new level of efficiency, flexibility, and innovation from conception to design to production and lifecycle management. Companies can overcome existing media breaks by integrating multi-agent systems, knowledge graphs, and modern platforms and establishing seamless digital process chains.

However, the successful introduction of generative AI requires careful planning and strategic decisions. Companies must:

- Structuring data and processes and aligning them with the requirements of AI.
- Start pragmatically by implementing use cases with measurable added value.
- Train employees to build the necessary knowledge for dealing with new technologies.
- Think long-term by establishing a scalable architecture and a robust digital foundation.

New technologies such as multi-agent systems will further expand the possibilities of GenAI. Companies that act now are laying the groundwork for a successful and innovative future.

Accenture GenAI Studio Munich: Experience Industrial Generative AI in Practice

The Accenture GenAI Studio Munich is our global center for Generative AI, specifically for the automotive and industrial sectors. Here, companies can experience the latest technologies and applications of GenAI live and test them hands-on. From workshops and tours to prototyping and co-innovation, the studio offers comprehensive opportunities to explore and customize the potential of Generative AI. Use cases include the Multi-Agent Engineering Assistant, Operation Twin Copilot, Generative Technical Publications, or the Virtual Mentor for Manufacturing. Visit us at the Balan Campus in Munich and discover how Generative AI can transform your processes. Our team looks forward to welcoming you on-site.

Summary

Integrating Generative AI and Agentic Architecture offers transformative potential for engineering and manufacturing processes. With its ability to process and analyze complex, multimodal data, Generative AI enables real-time decision-making, predictive maintenance, and process optimization across the value chain. This approach addresses challenges such as fragmented data, intellectual property constraints, and interdisciplinary collaboration. Businesses can unlock significant efficiency gains and enhance competitiveness by leveraging a robust digital core and modern architectures. Generative AI reshapes traditional engineering practices, setting the foundation for scalable, sustainable innovation.

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Authors

Daniel Spiess is the Managing Director of Digital Engineering at Accenture‘s Industry X division. In this role, he leads initiatives in digital engineering and business transformation, focusing on integrating advanced technologies into engineering processes. Before joining Accenture in January 2020, Daniel served as the Head of Virtual Development at MAN Truck & Bus AG in Munich, where he oversaw engineering architecture and program management. He also held the position of Head of PLM Business Consulting at Accenture GmbH for over a decade. Daniel holds degrees in Engineering and Business Management from the University of Greenwich and in Industrial Engineering from Hochschule Albstadt-Sigmaringen.

Jennifer Masek is an Industry X Associate Director, specialized in digital engineering. Starting as a Consultant 12 years ago, Jennifer gained extensive expertise in project management within engineering projects. For the past seven years, she has built and managed a Digitalization and Automation team within the engineering department. With this expertise, Jennifer now focuses on identifying new use cases for GenAI within engineering, with a particular emphasis on Digital Engineering and enhancing Engineering Efficiency.

Vlad Larichev leads Generative AI initiatives for Accenture Industry X in the DACH region, focusing on the integration of Data & AI solutions into industrial applications and the development of intelligent, connected products. He has a background in solution architecture, software development, and machine learning, with a specialization in Transformer models. Prior to his current role, he served as Business Development Manager at Umlaut and Head of Web & Software Development at ACT Translations.

Prashant Chouhan leads the Global Network Industry X Capability for Model-Based Engineering, Product Data Strategy, and Analytics, including AI and Generative AI solutions for the engineering and manufacturing value chain. With over 20 years of diverse industry experience, he has a proven track record of driving business growth and operational efficiency through digital and technology transformations. Prashant holds a Master’s degree in Business Administration and a Bachelor’s degree in Mechanical Engineering.

Abstract

Die Integration von Generativer KI (GenAI) ermöglicht Effizienzsteigerungen, Automatisierung und verbesserte Entscheidungsprozesse im Engineering und der Fertigung. Wesentliche Herausforderungen sind Datenfragmentierung, mangelnde Interoperabilität und notwendige organisatorische Anpassungen. Skalierbare Architekturen, insbesondere Agentic Architecture, sowie ein gezielter Fokus auf erprobte Anwendungsfälle bilden eine zukunftsfähige Grundlage für die nachhaltige Einführung von GenAI im industriellen Kontext.

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Keywords

Generative AI, Agentic Architecture, Engineering Manufacturing, Artificial Intelligence

Schlüsselwörter

Generative KI, Agentische Architektur, Engineering Produktion, Künstliche Intelligenz

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