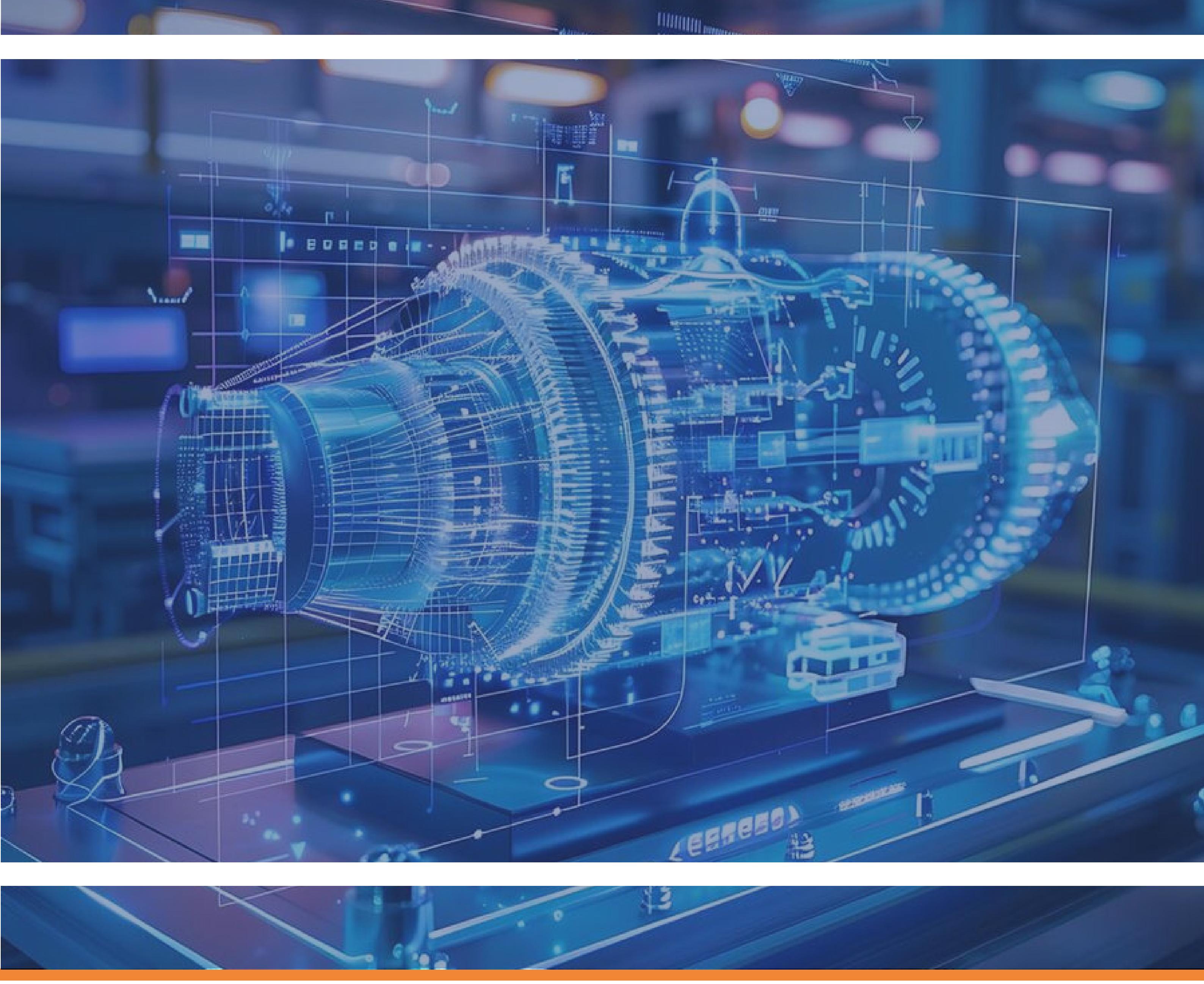


WHITE PAPER

Fit for AI? - Why Technical Data Holds the Key to AI Success in Mechanical Engineering

AI success is driven not by data volume, but by data quality and interoperability. This requires technical information to be continuously maintained, linked across systems, and kept consistently available in high quality.

simus systems

What to Expect from This White Paper

Artificial intelligence can only deliver economic value in mechanical engineering if the underlying data is reliable, consistent, and usable across systems. This is precisely where many companies face a bottleneck: it is not a lack of ideas that slows down AI adoption, but rather master data and CAD data that are scattered across systems, inconsistently maintained, and only limited in their interoperability. This white paper explains why the data foundation plays a decisive role in the success of AI projects, which data sources are particularly relevant, and how companies can build a robust basis for AI step by step. At the same time, it shows that investing in data quality not only supports AI applications, but also drives broader digital transformation initiatives forward.

Contents

1. AI in Mechanical Engineering - Why Companies Need to Act Now

If you are responsible for design, work planning, or master data in the mechanical engineering industry, AI has long been more than just a topic for the future. Many companies are currently developing concrete ideas: finding technical information faster, evaluating variants more effectively, automating cost estimates, leveraging knowledge from existing data sets, and reducing the workload on employees through intelligent assistance systems.

Our experience consistently shows that the bottleneck rarely lies in a lack of use cases. The real challenge usually begins earlier – with the question of whether the available technical data is complete, unambiguous, and usable across systems. Particularly in established CAD, PDM, and ERP environments, while a great deal of information is available, it is maintained in different ways, structured inconsistently, or can only be analyzed with a significant amount of manual effort.

A recent study by VDMA and Strategy& confirms that AI has become a strategic priority for the mechanical and plant engineering industry. Four out of five companies are already using Generative Artificial Intelligence (GenAI) or plan to do so.[1] 89 percent view it as a key driver of profitability in the industry.[2] At the same time, only 7 percent have systematically rolled out GenAI company-wide.[3] This is precisely where this white paper comes in. It shows why AI can only realize its full potential in mechanical engineering if the technical data foundation is structured, consistent, and usable across systems.

Only 7 percent of companies have systematically rolled out GenAI company-wide.

[1] Strategy& / VDMA Software and Digitalization, GenAI im Maschinen- und Anlagenbau, 2025, p. 15
[2] Ibid., p. 13
[3] Ibid., p. 21

2. Where AI Can Deliver the Greatest Value in Mechanical Engineering

AI is particularly valuable in mechanical engineering when large amounts of technical information need to be analyzed, recurring decisions need to be prepared, and existing knowledge needs to be made available more quickly. In practice, this applies especially to design, work planning, cost estimation, and purchasing. In all these areas, data is generated daily that would be valuable – but it is often stored in different systems, formats, and structures.

In design and development, for example, AI can help find similar parts more quickly, evaluate variants more effectively, or reuse existing solutions in a more targeted manner. In work planning and cost estimation, technical characteristics, geometric information, materials, work steps, and comparable parts can be used to speed up calculations and make more informed decisions. In procurement, potential savings can be realized, for example, by consolidating the purchase volume of similar parts, optimizing bidding processes, or implementing should-costing solutions. Concrete use cases also arise in the areas of production and service, such as in quality monitoring or predictive maintenance.

Based on our expertise, the benefits arise not solely from the AI application itself, but from the technical context of the data. This is because a similarity search, an automated calculation, or an assistance system can only deliver reliable results if relevant information from CAD, PDM, and ERP systems is clearly described, comparable, and usable across systems. This is precisely why the path to the effective use of AI often begins not with the model, but with the preparation of the technical database.

> **!** The necessary technical information must be available in a quality that makes robust AI applications possible in the first place.

The study by VDMA and Strategy& confirms that research and development is a key area of application for AI in the mechanical and plant engineering sector. 43 percent of the companies surveyed expect significant impacts in this area.[4] However, a decisive factor for implementation remains whether the necessary technical information is available in a quality that actually enables reliable applications.

[4] Strategy& / VDMA Software and Digitalization, GenAI im Maschinen- und Anlagenbau, 2025, p. 26

3. Why AI Success Depends on the Data Foundation

In mechanical engineering, AI projects rarely fail due to a lack of ideas, as there are plenty of starting points in most companies. The real challenge, however, arises when these applications need to access existing technical data.

In practice, this data has often accumulated over the years and is stored in various systems. PDM/PLM, ERP, or CAD systems are typically used, while production-related information is sometimes recorded in other applications. In addition, descriptions are maintained inconsistently and incompletely, resulting in duplicates. For humans, much of this can still be interpreted with experience. For AI applications, however, this quickly becomes a problem.

AI applications require not only data, but also reliable correlations.

This is because AI requires not only data, but also reliable correlations. If components are described differently across various systems, similar parts cannot be identified as such, or if important characteristics needed for cost estimation, searching, or evaluation are missing, this inevitably leads to unreliable results. Consequently, projects get stuck in the pilot phase, require a significant amount of manual verification, or produce results that specialist departments do not trust.

The realization that data-related issues are a major obstacle to AI implementation is evident not only in many projects but is also confirmed by a recent KPMG study. According to the study, 56 percent of manufacturers report difficulties of this kind.[5] For mechanical engineering companies, this means that the actual bottleneck often lies not in the AI model itself, but in the question of whether a consistent, analyzable, and reliable information base can be created from existing CAD, PDM, and ERP data.

[5] KPMG International, Intelligent Manufacturing, 2025, p. 6

4. What AI-Ready Data Looks Like Depends on the Use Case

Not every available dataset is automatically usable for AI. For mechanical engineering companies, therefore, the goal is not necessarily to feed as much data as possible into an AI system, but rather to provide the right data for a clearly defined use case. For example, automated cost calculation requires different information than a similarity search, a quality analysis, or a service assistance system.

The goal is not to feed as much data as possible into an AI system, but to provide the right data.

For many AI applications in mechanical engineering, technical master data and CAD data are of particular importance. Master data describes materials, parts lists, classifications, and often also manufacturing-related information. It is typically stored in ERP, PDM, or PLM systems and is sometimes supplemented by Excel spreadsheets, databases, or ad hoc solutions that have evolved over time. CAD data comes from design systems and includes not only 3D models but also drawings with geometric specifications as well as product- and manufacturing-related details.

With this type of data in particular, it is often the case that some product-related knowledge is contained in the CAD model, some in the material master, and other information in parts lists, documents, or routings. For humans, these connections can often be established through experience and by asking questions. For AI, search, cost estimation, or automation, however, these connections must be more clearly described, structured, and accessible across systems.

It is not necessary to start by analyzing the entire dataset. In many cases, it makes more sense to begin with a clearly defined use case and a representative sample of data. This approach allows you to more quickly assess the quality of the available information, identify typical gaps or inconsistencies, and determine which data preparation steps will yield the greatest benefits. As a result, initial results become apparent early on, without requiring that all of the company's data be fully cleaned in advance.

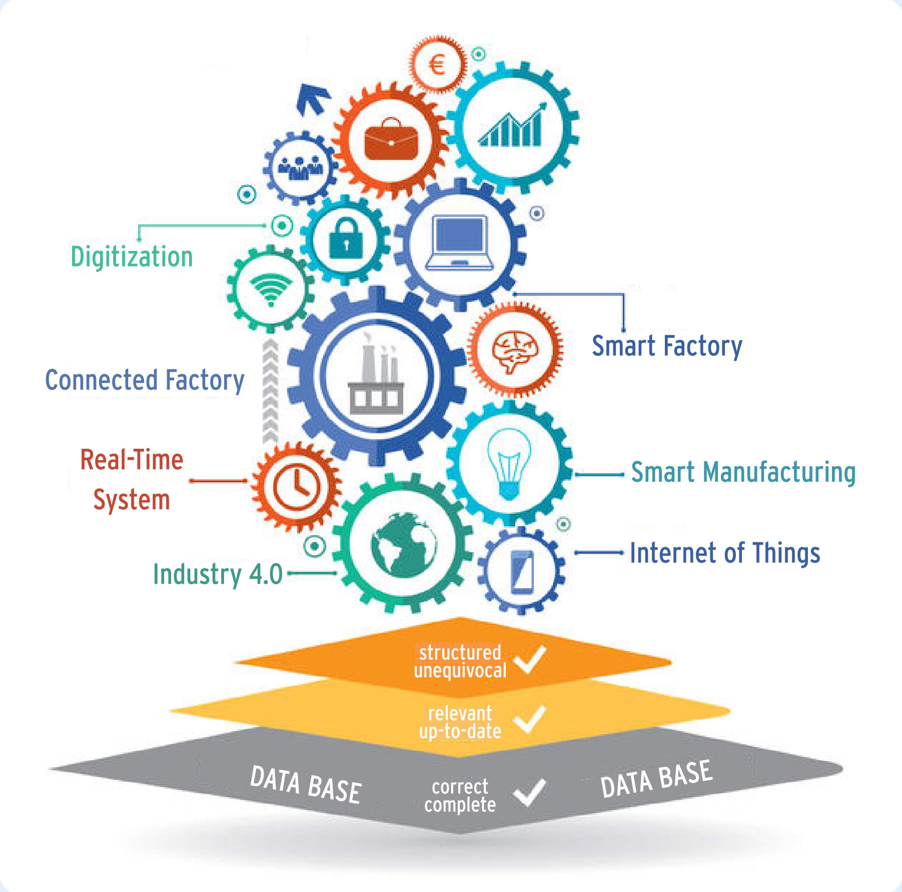
A pragmatic approach, starting with a clearly defined use case and a representative sample of data, is crucial.

That is why it is crucial to take a pragmatic approach, starting by clarifying the use case and then reviewing and specifically preparing the relevant data sources. This way, data optimization does not become an abstract, large-scale project, but rather a concrete step toward usable AI applications.

How simus systems Makes Technical Data Ready for AI Applications

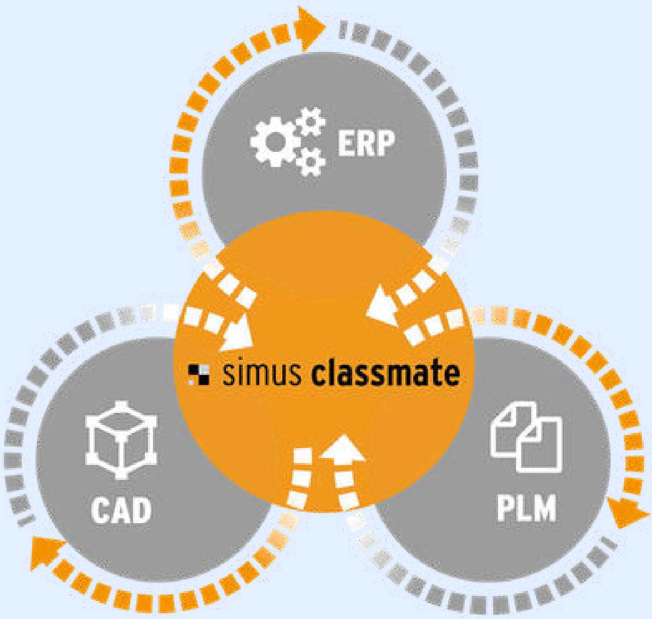
simus systems helps mechanical engineering companies prepare technical master data and 3D CAD data – including technical drawings – so that they can serve as a reliable foundation for AI applications and other digital processes. The simus classmate software suite analyzes, structures, enriches, classifies, and systematically makes existing data sets usable.

To this end, simus systems relies on proven rule-based AI methods that have been used in industrial data optimization for more than 20 years. The advantage of these methods lies in their transparency. This is because mappings, classifications, and data cleansing are performed based on clearly defined rules that can be individually tailored to the specific requirements of each company. This allows large volumes of data to be processed automatically without losing professional control over the results.



When it comes to technical master data, simus classmate identifies and eliminates, among other things, inconsistent spellings, duplicates, missing descriptions, and differing attribute structures. The data can be converted into a consistent target structure, existing classifications can be utilized, or new class models can be created. If necessary, proven standards can be applied. The tool processes data from ERP and PDM systems as well as structured external sources, such as XML, Excel, or databases. Interfaces and synchronization with SAP and other systems support integration into existing IT landscapes.

CAD data can also be systematically extracted using simus classmate. 3D models and their geometric information are automatically analyzed, classified, and stored in a structured manner. This allows existing parts to be found more quickly based on geometric similarity, reused, and systematically organized within the database. The rule-based AI methods are specifically supported here by generative AI for the digitization of technical drawings.



In this way, simus classmate integrates information from CAD, PDM, and ERP systems, making technical data accessible across system boundaries. Distributed data sets are consolidated into a consistent information base – for AI applications, search, reuse, cost calculation, and further steps in the digital transformation process.

5. How to Ensure Lasting Data Quality

Structured data preparation lays the foundation for AI applications, search, reuse, cost calculation, and other digital processes. However, the task is not complete there, as technical data is constantly changing. New items are created or modified, CAD models are generated, parts lists are updated, and classifications are expanded. If clear rules are not in place, the same problems that were previously resolved at great effort will quickly resurface.

For many mechanical engineering companies, this is precisely where the challenge lies. While data sets that have accumulated over time are cleaned up during projects, new data continues to be generated according to different logic. Definitions of terms are inconsistent, required information is missing, characteristics are interpreted differently, or data is maintained in individual systems without being reliably usable for other applications. This is particularly critical for AI applications because they rely on consistent, up-to-date, and trustworthy information.

Data quality must therefore be embedded in the organization. This includes clear objectives, defined responsibilities, and rules for the ongoing maintenance of new and existing data. It is also important that quality is not merely checked after the fact, but is established as early as possible in the process – for example, when creating new materials, importing CAD data, or classifying items based on technical characteristics. This prevents new duplicates, data gaps, or conflicting information from accumulating in the database.

> **!** Data optimization is becoming an ongoing component of digital value creation.

Data optimization thus becomes an ongoing component of digital value creation. Those who ensure that technical data remains structured, unambiguous, and usable across systems not only create better conditions for individual AI projects. They also lay the groundwork for implementing additional applications more quickly, expanding existing solutions more easily, and operating new digital processes more reliably.

6. What Value a Strong Data Foundation Creates in Practice

For mechanical engineering companies, the primary benefit of a robust database lies in the ability to implement AI applications more quickly, more cost-effectively, and with more reliable results. When technical information on materials, components, features, geometries, parts lists, and routings is consistently maintained and available across systems, AI-powered applications can access it much more effectively. Scattered data becomes a foundation upon which search, evaluation, classification, assistance systems, and automated decisions can be meaningfully built.

This benefit becomes particularly evident in cost calculation. It is a good example of how AI and data-driven automation create tangible added value in mechanical engineering. Reliable cost estimation depends on having relevant information – such as material data, dimensions, geometric information, manufacturing processes, machining steps, batch sizes, and reference parts – available in a complete and comparable format. If this data is inconsistent or incomplete, assumptions must be made, information must be gathered manually, or results must be painstakingly verified.

> **!** The cost analysis shows how AI and data-driven automation create tangible added value.

With a structured database, however, calculations can be performed more quickly, with greater transparency, and in a more reproducible manner. AI-supported or automated processes can identify similar parts, incorporate existing routings and empirical data, evaluate technical characteristics, and make cost drivers transparent. This creates a solid foundation for decision-making – for example, for preparing bids, evaluating variants, making make-or-buy decisions, or assessing new components.

Well-structured data becomes a reusable building block for other digital applications.

The benefits extend beyond individual use cases. The same database that enables reliable calculations can also be used for intelligent search, reuse, classification, assistance systems, quality analyses, or predictive maintenance applications. This reduces the effort required for individual AI projects, as central preparatory work does not need to be repeated for every use case. Well-prepared data thus becomes a reusable building block for further digital applications.

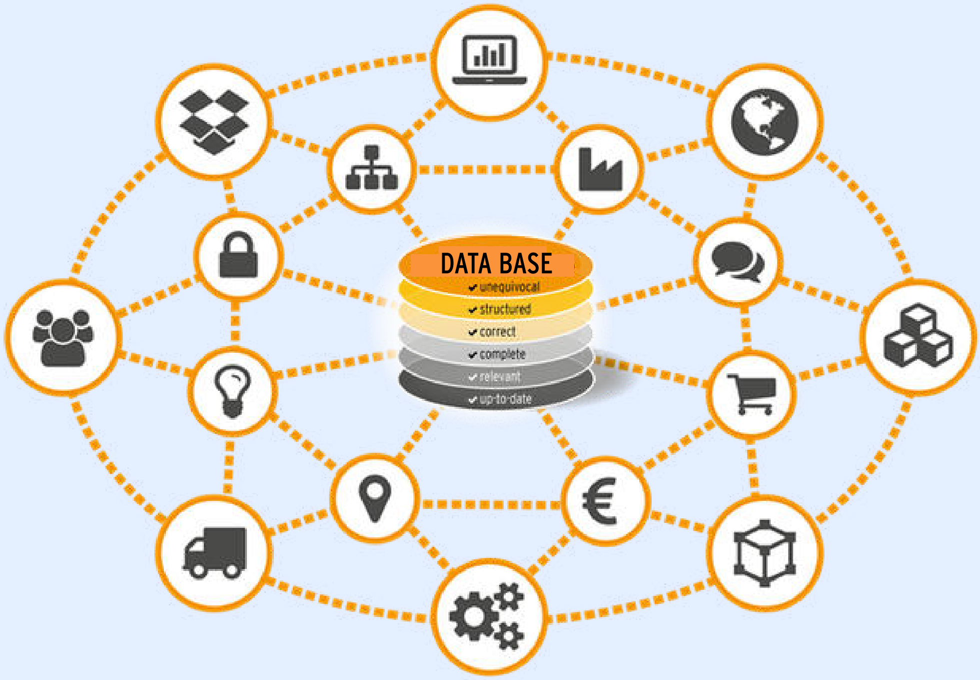
This is also strategically relevant: In a study, VDMA and Strategy& identify additional profitability potential of up to 10.7 percentage points through the use of GenAI in the mechanical and plant engineering sector.[6] At the same time, the study shows that support from top management is a key success factor for implementation. Investing in data quality not only creates better conditions for individual AI projects but also strengthens the ability to leverage AI in a sustainable and cost-effective manner.

Investing in data quality strengthens the ability to leverage AI in a sustainable and cost-effective manner.

[6] Strategy& / VDMA Software and Digitalization, GenAI im Maschinen- und Anlagenbau, 2025, p. 26

How Data Optimized by simus systems Delivers Cross-Functional Value

Optimized technical data delivers benefits beyond a single area. When product, master, and CAD data are structured, unambiguous, and available across systems, many departments within the company benefit – from design and work planning to cost estimation, purchasing, sales, and management.



simus classmate makes technical information from CAD, PDM, and ERP systems centrally accessible, comparable, and usable. Product and CAD data are consolidated into a single interface, clearly visualized, and linked to additional information from related systems. This simplifies access to reliable data, reduces search times, and helps users reuse existing parts, assemblies, or solutions more quickly.

In the design phase, simus classmate helps identify similar parts and avoid duplicate designs. Work planning can access structured technical information and make better use of existing routings or empirical data. In cost estimation, consistent material, geometry, and process data provide a more reliable basis for evaluating manufacturing costs. Purchasing and sales benefit from the fact that technical information is available more quickly and decisions can be made based on a uniform data set.

For mechanical engineering companies, this means less manual work, fewer back-and-forth inquiries between departments, and greater reuse of existing data and solutions. Processed master data and CAD data thus become not only the foundation for individual AI applications, but also a shared information space for end-to-end digital processes.

Case Studies from User Projects with simus systems

Time Spent on Work Planning Cut in Half

- Industry: Tooling for household appliances
- Project: Digitization of work planning
- Results:
  - Planning time per component reduced by 50 percent
  - Over 10,000 components fully planned and costed digitally

Read more >>

99 Percent of the Materials Are Classified for Successful Migration

- Industry: Refrigeration systems
- Project: Master data preparation for migration to SAP S/4HANA
- Results:
  - Quality-assured master data foundation for migration to SAP S/4HANA
  - 99 percent of materials covered by the new classification

Read more >>

Transparent Cost Information for 1.5 Million Components

- Industry: Food processing equipment
- Project: Cost transparency and standardized routings
- Results:
  - Approximately 1.5 million routings and cost estimates were automatically generated and made reusable; this corresponds to 305,000 manual work hours
  - Significant time savings through automation processes

Read more >>

7. Your Path to AI-Ready Data

The successful use of AI in mechanical engineering does not depend on making as much data as possible available. What matters is whether the relevant information for a specific use case is available in a complete, unambiguous, and cross-system manner. Only then can AI applications deliver reliable results – for example, in design, work planning, cost estimation, manufacturing, or procurement.

This makes data quality a key prerequisite for the economically viable use of AI. Clean master data and CAD data not only improve individual applications but also create a foundation on which further digital processes can be built. These range from intelligent search and reuse to automated cost estimation, assistance systems, standardization, and automation.

You don't have to start with a large-scale project. As a first step, it makes sense to conduct a structured assessment:

- What use cases are relevant?
- What data sources are available for this?
- Where do the biggest weaknesses currently lie in terms of quality, structure, and consistency?

That's exactly where the path to AI-ready data begins. It's pragmatic, manageable, and offers clear benefits for further implementation.

Get Your Data Ready for AI

If you want to use AI in mechanical engineering in a cost-effective way, you need a clear understanding of your own data. In a proof of concept, simus systems works with you to determine which data is relevant to your use cases, where specific opportunities lie, and what a practical first step toward AI-ready data might look like.

simus systems

We develop software that supports mechanical engineering companies with digitalization.

Software Bundesverband IT-Mittelstand Made in Germany
100% Service Quality Future

Optimize data structure

Keep costs and emissions under control

Automate processes

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