Findings from six Years of Applied Research: A Foundation for AI Use Cases - Illustrated with Two Practical Examples

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Abstract

In engineering, the implementation of artificial intelligence (AI) methods serves as a critical tool for breaking down data silos and enhancing data processing in simulation-based design. Beyond the need for efficient and transparent data management, the ability to identify, map, and retain relationships between engineering data elements is essential. Contextualization plays a crucial role in this process, structuring data in a way that enhances its usability, making it ideal for AI applications to identify patterns, derive insights, and support informed decision-making.

This principle is the foundation of the Data Context Hub (DCH), a platform developed over six years at Virtual Vehicle Research (Graz) in collaboration with automotive and rail OEMs. DCH is designed to integrate information from Manufacturing systems, telemetry data streams, and enterprise storage solutions such as data lakes. It generates an explorable context map in the form of knowledge graphs, built from domain-specific data models. These models enable process streamlining, and the discovery of new insights within data-driven product development. Moreover, advanced AI models enhance the ability to analyse data, predict trends, and automate workflows within the engineering domain.

This paper presents key findings from six years of applied research on contextual graph databases and their impact on AI-driven engineering solutions. By illustrating two real-world use cases, we demonstrate how DCH enables organizations to bridge the gap between data sources and AI applications transforming fragmented data into clear, actionable insights.

The first use case explores AI-enhanced data retrieval in manufacturing, focusing on a rail industry application. In rail vehicle production, workers frequently need to retrieve specific assembly and wiring instructions from multiple enterprise systems, such as SAP. However, the manual search process

is both time-consuming and error-prone, requiring extensive navigation through PDFs, ERP records, and manufacturing databases. The DCH solution enabled workers to instantly access task-relevant information using a barcode scanner linked to a real-time knowledge graph. This approach reduced lookup times from 5–15 minutes to a few seconds, minimized SAP dependency, and improved overall production efficiency.

The second use case focuses on automotive buildability validation, where AI-driven contextualization has significantly reduced simulation times in configuration feasibility analysis. Automotive engineering relies on highly complex product configurations, involving millions of potential variants. Conventional tools and manual methods proved inefficient, as they required engineers to manually verify constraints, simulation results, and regional regulations. The DCH platform introduced an AI-based buildability checker, allowing engineers to capture, simplify, and query configuration dependencies in real time ultimately accelerating design iterations and improving efficiency.

By integrating AI-driven contextualization, graph databases, and retrieval-augmented generation (RAG) models, DCH facilitates structured, context-aware AI applications in engineering and manufacturing.

This research highlights how context-aware AI and knowledge graphs represent a paradigm shift in engineering data management, enabling industries to transition from fragmented data silos to interconnected, intelligent decision-making systems. Future advancements in predictive analytics, real-time data integration, and autonomous AI decision-support will further enhance the capabilities of platforms like DCH paving the way for faster innovation cycles and improved regulatory compliance

1. Current Situation

Over the past decade, engineering and manufacturing industries have faced an exponential increase in data generation, largely driven by digital transformation, automation, and simulation-based design. Statista reports that global data creation is projected to grow to more than 394 zettabytes by 2028 [1]. This surge in data presents both opportunities and challenges, while data has the potential to drive innovation and operational efficiency, many organizations struggle to effectively integrate and utilize their data.

A 2024 survey conducted by Bitkom, involving 603 companies across various industries, revealed that 60% of organizations do not fully leverage their data [3]. Alarmingly, only 6% of companies believe they are extracting maximum value from their data. The primary obstacles preventing effective data utilization include:

- Data Fragmentation: Engineering teams operate across multiple enterprise systems, such as Product Lifecycle Management (PLM), Enterprise Resource Planning (ERP), and specialized simulation databases. These systems work independently, storing inconsistent metadata, redundant information, and isolated insights, making cross-domain data analysis highly complex.
- Lack of Contextualization: Even when companies integrate data across systems, the relationships between data points are often not preserved. As a result, engineers must manually re-establish dependencies between design constraints, simulation results, and real-world manufacturing limitations, leading to inefficiencies and costly rework.
- Time-Consuming Data Retrieval: Engineers, analysts, and production teams spend excessive time searching for relevant information in distributed data sources. Studies indicate that professionals in data-intensive industries spend up to 30% of their time locating relevant data [4], impacting product development speed, regulatory compliance, and operational decision-making.

The transition towards a data-driven corporate culture requires not just better data integration, but also smarter, AI-powered data management. Modern AI techniques, like knowledge graphs and natural language processing (NLP), can help organizations break data silos, by establishing contextual relationships, and automating insight extraction.

However, generic AI base models are often insufficient for engineering applications. Generic Large Language Models (LLMs), such as ChatGPT, rely on vast general-purpose datasets, but lack domain-specific context, leading to incorrect inferences, misleading conclusions, and unreliable decision-making when applied to specialized engineering workflows. To be effective in engineering and manufacturing, AI must be grounded in structured, domain-specific knowledge representations that reflect real-world constraints, dependencies, and compliance requirements.

This is where the Data Context Hub (DCH) plays a pivotal role. DCH is a context-aware data integration and management platform that enables organizations to connect disparate data sources, establish knowledge relationships, and enhance decision-making with AI-driven insights. By using graph-based contextualization, AI-enhanced retrieval models, and automated data linking, DCH bridges the gap between raw data and actionable intelligence.

DCH has partnered with leading industry players, where it has enhanced data accessibility, streamlined engineering workflows, and improved manufacturing efficiency. The next section explores how DCH enables organizations to transform raw data into a competitive advantage, demonstrating its real-world impact through practical applications.

2. DATA CONTEXT HUB: Transforming Data into a Competitive Advantage

The Data Context Hub (DCH) was developed to address the growing complexity of engineering and manufacturing data. As industries move toward digital transformation, traditional database systems and document-based knowledge repositories are no longer sufficient for handling the scale, diversity, and interdependencies of modern data. Engineering data is often highly interconnected, requiring a system that can not only store information but also retain and retrieve contextual relationships efficiently.

DCH serves as an AI-powered data integration and management platform that helps organizations bridge data silos, establish structured knowledge networks, and enable AI-driven insights. Unlike conventional data storage systems, which rely on relational or document-based architectures, DCH is built around knowledge graphs—a more adaptive and scalable approach to managing engineering data.

Bringing Context to Data

In traditional data management systems, relationships between data points are often implicit and need to be manually reconstructed by engineers when analysing information. This approach is time-consuming, error-prone, and difficult to scale. DCH transforms this process by automatically structuring data into knowledge graphs, where every data point (node) is connected to other relevant data through explicit relationships (edges) (see Figure 1).

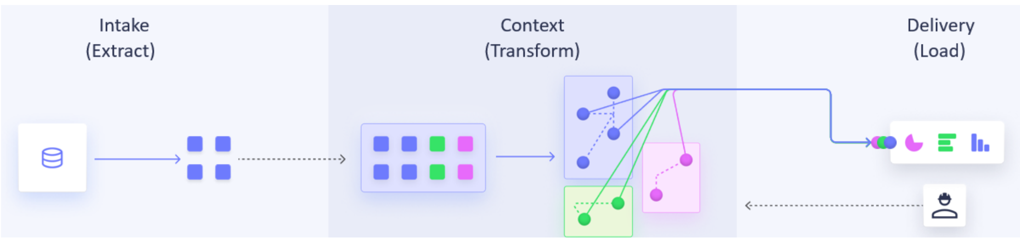

Figure 1 Basic Concept ICD - Intake, Context, Delivery

Key Features of DCH's Contextual Data Approach:

- Data Integration Across Systems: DCH connects data sources from PLM, ERP, simulation databases, telemetry, and enterprise data lakes, ensuring a unified view of engineering and manufacturing data.
- Preserving Data Relationships: Unlike conventional databases that store information in isolated tables, DCH maintains relationships between data elements, allowing engineers to trace dependencies, constraints, and past changes effortlessly.
- Semantic Data Enrichment: By applying domain-specific ontologies and metadata mapping, DCH enhances data discoverability and ensures consistency across different data sources.
- Graph-Based Querying: Engineers can navigate complex data interdependencies using intuitive graph queries, making it easier to retrieve relevant information without manual cross-referencing between systems.
- Scalability for Large-Scale Engineering Data: DCH's graph-based structure enables organizations to continuously add new data sources, allowing for more connected nodes across systems without compromising performance.

By implementing these principles, DCH provides a structured, contextualized foundation for AI applications allowing machine learning models and LLMs to understand and process engineering data with greater accuracy.

Seamless Integration with Generative AI

Generative AI has introduced new possibilities for automating engineering workflows, predicting system configuration, and optimizing decision-making. However, most general-purpose AI models lack the domain-specific understanding required for engineering applications. Without structured context, AI-driven insights can be inaccurate, or misleading.

To overcome this, DCH integrates generative AI techniques such as Retrieval-Augmented Generation (RAG), ensuring that LLMs retrieve relevant, structured information before generating responses.

How AI Enhances Data Retrieval in DCH:

- Knowledge Graph as Contextual Memory: DCH structures engineering knowledge into a graph format, making it easier for AI models to understand data relationships, constraints, and dependencies.

- Retrieval-Augmented Generation (RAG): Before generating insights, the AI searches the knowledge graph to retrieve relevant engineering data, ensuring that responses are based on traceable, context-rich information.
- Semantic Search and Querying: Instead of relying on traditional keyword searches, DCH enables semantic search, allowing AI models to identify conceptually relevant information, even if exact terminology differs.
- Explainability and Traceability: Every AI-generated recommendation or decision is traceable back to its source data, ensuring transparency and accountability in engineering workflows.

By combining AI-driven search capabilities with structured contextualization, DCH ensures that engineers receive accurate, data-driven insights reducing manual effort and enhancing decision-making efficiency.

3. Practical Applications: Real-World Use Cases

To demonstrate the real-world impact of Data Context Hub (DCH), we present two practical use cases from rail manufacturing and automotive engineering Customers. These examples show how AI-powered data contextualization and knowledge graphs transform complex, fragmented engineering data into structured, actionable insights.

Worker Guidance System for Rail Manufacturing

Background & Challenge

In rail manufacturing, ensuring proper assembly and wiring is important for safety and functionality. Workers rely on detailed instructions, including wiring diagrams, component placements, and connection details, to complete their tasks accurately. Traditionally, this information was stored within enterprise resource planning (ERP) systems such as SAP. To access these details, workers had to manually log into the system, navigate menus, and search through documentation to retrieve the necessary information.

This process presented several challenges. Retrieving instructions could take anywhere from 5 to 15 minutes per lookup, significantly slowing down the workflows. Additionally, many workers were not well-versed in using SAP, requiring training or frequent relearning. If the system underwent updates or changes, workers often faced difficulties finding required information, leading to further inefficiencies. Furthermore, workers repeatedly searched for the same information, leading to redundant effort and reduced productivity. The existing approach was not only time-consuming and complex but also inefficient, demanding a more efficient and user-friendly solution.

DCH Implementation

To address these inefficiencies, DCH was integrated into the rail manufacturer's data ecosystem, establishing seamless connections between SAP and Manufacturing Execution System (MES). The goal was to create an intuitive knowledge graph that could dynamically retrieve assembly and wiring information based on task-specific requirements.

The solution introduced barcode-driven data retrieval, allowing workers to simply scan a barcode on a component to instantly access all relevant instructions for that particular task. Instead of manually navigating through ERP menus, automated context extraction was implemented, ensuring that the system proactively gets the most relevant documents, specifications, and wiring diagrams. Additionally, a centralized knowledge access point was created, ensuring that all workers had access to up-to-date, standardized instructions without requiring direct ERP interaction (see Figure 2).

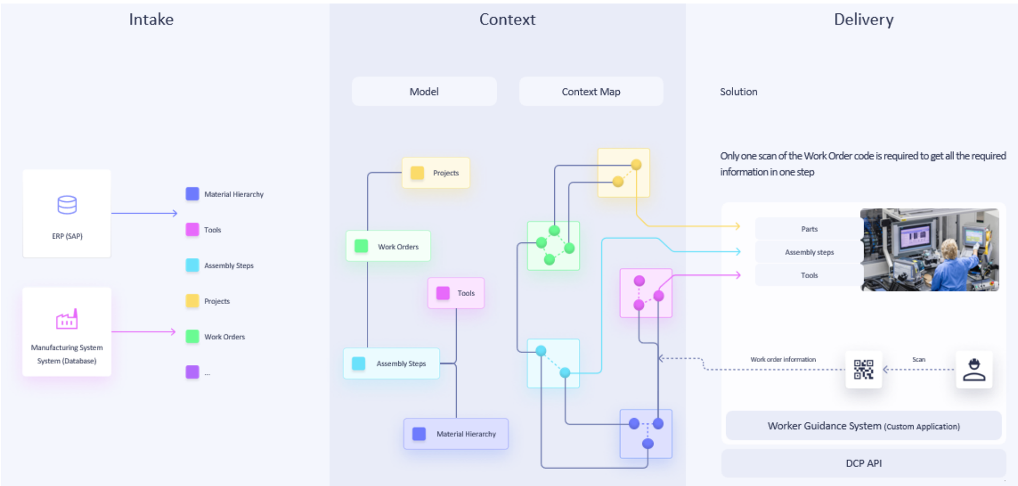

Figure 2 MES Integration - Solution Implementation

Impact

The implementation of DCH drastically reduced lookup times, bringing them down from 5–15 minutes to just a few seconds. By eliminating the need for manual searches in SAP, workers were able to focus on assembly rather than spending excessive time retrieving information. The system's ease of use led to rapid adoption across multiple production lines, and due to its efficiency, it was later integrated into additional manufacturing applications beyond its initial scope.

Moreover, the solution improved production accuracy, ensuring that workers consistently followed the latest assembly guidelines. This significantly reduced errors and rework, leading to smoother operations. In the end, the DCH-powered system enhanced efficiency, reduced dependency on specialized ERP training, and enabled a more agile manufacturing process.

Virtual Buildability and Engineering Data Exploration for Automotive Engineering

Background & Challenge

Automotive engineering involves managing highly complex vehicle configurations that must comply with regulatory, engineering, and production constraints. Validating whether a specific vehicle configuration can be manufactured under given constraints is a challenging and time consuming task. With millions of possible configuration variants, engineers must ensure that design specifications align with various regulations, production capabilities, and supplier dependencies.

For instance, regulatory compliance varies by region—certain markets may require climate-adaptive modifications, such as larger cooling systems in hotter climates or emissions compliance in areas with stricter environmental policies. Manufacturing constraints further complicate the process, as certain plants may have limitations on tooling, material availability, or production scheduling. Supplier dependencies can vary based on different markets, relying on specific component suppliers that may have availability constraints.

Previously, engineers relied on manual verification of buildability constraints, cross-referencing simulation models, regulatory data, and supplier information from over 100 databases. This approach resulted in long validation cycles, inconsistent decision-making, and difficulty in integrating new configurations. Every new vehicle configuration required repeated manual validation, which introduced inefficiencies and slowed down the product development cycle.

DCH Implementation

DCH was deployed to streamline configuration validation by integrating data from Product Lifecycle Management (PLM) systems, compliance databases, and manufacturing datasets. By structuring this information into an intelligent knowledge graph, engineers could navigate buildability constraints dynamically rather than manually verifying every condition.

The system introduced automated buildability checks, enabling engineers to query whether a given configuration could be produced under specific constraints in real time. Unlike traditional methods that required precomputed results, DCH performed dynamic validation, evaluating only the relevant constraints on demand. This approach eliminated the need to store millions of precomputed configuration scenarios, reducing data storage overhead while maintaining accurate and up-to-date feasibility assessments.

Additionally, the graph-based contextualization of engineering, compliance, and production data allowed engineers to trace dependencies and assess manufacturability with better precision. Instead of operating in silos, design teams could now collaborate seamlessly, accessing a unified, AI-driven validation workflow that streamlined decision-making (see Figure 3).

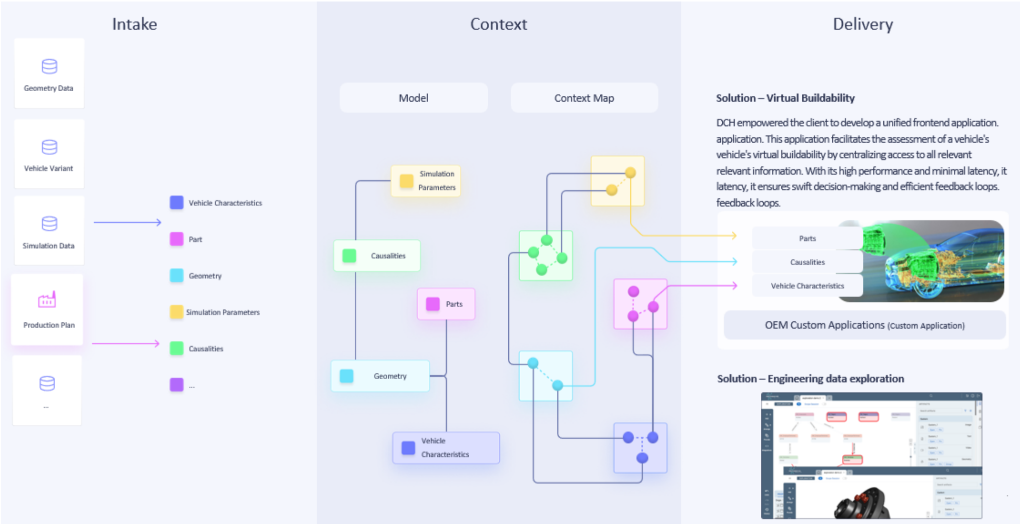

Figure 3 Virtual Buildability Tool - Solution Implementation

Impact

The deployment of DCH enabled real-time validation of vehicle configurations, eliminating the need for extensive manual cross-referencing. Engineers could now instantly verify whether a configuration complied with regional and production constraints, significantly reducing redesign efforts and accelerating the approval process.

By ensuring compliance with regulatory and production constraints upfront, the system helped minimize costly late-stage changes that often resulted from overlooked feasibility issues. The new approach also enhanced decision-making, allowing engineers to quickly assess buildability, reduce iteration cycles, and improve overall product development speed.

Furthermore, the AI-powered validation workflow provided an integrated, data-driven solution that optimized configuration analysis, ensuring that vehicles were designed with manufacturability and compliance in mind from the start. This reduced bottlenecks in engineering workflows and enabled more efficient product development in an industry where speed-to-market and regulatory compliance are critical competitive factors.

4. Conclusion

The findings from our research highlight that data fragmentation and lack of context remain major challenges in engineering and manufacturing data sources. As organizations generate and collect vast amounts of data across multiple enterprise systems, engineering tools, and production environments, the challenge is not only in storing data efficiently but also in connecting, contextualizing, and retrieving meaningful insights in real-time.

The Data Context Hub (DCH) answers these challenges by providing a structured, AI-enhanced approach to data management by integrating disparate data sources and establishing knowledge-driven relationships. The ability to preserve relationships between different types of engineering data ensures that users can navigate information in a way that aligns with real-world constraints, dependencies, and business objectives.

As artificial intelligence (AI) continues to evolve, the role of AI-powered contextualization will expand beyond just data retrieval and analysis. The future of AI-driven engineering knowledge systems can introduce:

- AI Agents for Interactive Data Exploration – Engineering teams will increasingly interact with their data ecosystems through intelligent AI agents, such as domain-specific chatbots, which will provide on-demand contextual insights based on natural language queries.
- Automated Reasoning and Decision Support – AI-powered systems will not only retrieve relevant data but will also be able to simulate configuration scenarios, suggest optimizations, and assist engineers in making informed decisions by analysing complex interdependencies.
- Seamless Collaboration Between AI and Human Experts – AI systems will act as assistants rather than replacements, enabling engineers to explore structured data interactively, validate AI-generated insights, and make adjustments based on their expertise.

By bridging traditional data silos with AI-enhanced retrieval and reasoning, DCH is setting the foundation for the next generation of engineering intelligence systems. As industries move toward AI-augmented design, simulation, and production workflows, structured knowledge graphs combined with AI agents will ensure that engineering data is not just stored but actively used to drive innovation and efficiency.

The transition from data management to knowledge-driven decision-making is already underway, and contextual AI systems like DCH will play a vital role in shaping the future of intelligent engineering and manufacturing.

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