Model-Based Engineering and Semantic Interoperability for Trusted Digital Twins Big Data Connection Across the Product Lifecycle

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Abstract With the rising complexity of modern products and a trend from single products to Systems of Systems (SoS) where the produced system consists of multiple subsystems and the integration of multiple domains is a mandatory step, new approaches for development are demanded. This chapter explores how Model-Based Systems Engineering (MBSE) can benefit from big data technologies to

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implement smarter engineering processes. The chapter presents the Boost 4.0 Testbed that demonstrates how digital twin continuity and digital thread can be realized from service engineering, production, product performance, to behavior monitoring. The Boost 4.0 testbed demonstrates the technical feasibility of an interconnected operation of digital twin design, ZDM subtractive manufacturing, IoT product monitoring, and spare part 3D printing services. It shows how the IDSA reference model for data sovereignty, blockchain technologies, and FIWARE open-source technology can be jointly used for breaking silos, providing a seamless and controlled exchange of data across digital twins based on open international standards (ProStep, QIF), allowing companies to dramatically improve cost, quality, timeliness, and business results.

Keywords Interoperability · Semantic data model chains · Industry commons · Model based design · IDSA · QIF · FIWARE · Pro-STEP · Digital twin · Digital thread · Testbed · Trial · Maintenance 4.0 · Metrology 4.0 · ZDM

1 Introduction

With a rising complexity of modern products and a trend from single products to Systems of Systems (SoS) where the produced system consists of multiple subsystems and the integration of multiple domains is a mandatory step, new approaches for development are demanded. One of these approaches is Systems Engineering (SE).

> Systems Engineering is a transdisciplinary and integrative approach to enable the successful realization, use, and retirement of engineered systems, using systems principles and concepts, and scientific, technological, and management methods. *(INCOSE)* [1]

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To tackle this challenge Model-Based Systems Engineering (MBSE) has been introduced.

> Model-based systems engineering (MBSE) is the formalized application of modeling to support system requirements, design, analysis, verification and validation activities beginning in the conceptual design phase and continuing throughout development and later life cycle phases. *(INCOSE Technical Operations 2007)* [2]

With the advent of Model-Based Definition (MBD) and Model-Based Engineering, the 3D CAD model carries details for both human and machine interpretation, taking legacy 2D drawings and practices and updating them to twenty-first century evolutions leading to automation, AI, and improved products and cost savings. In general, parametric modelling and optimization techniques supported by MBSE methods contribute significantly to the process of building CAD simulations. Several design parameters and probably density factors are taken into consideration for simulation sequence. These simulations are very important in analyzing different factors such as sensitivity, optimization, and correlation of the design or structure. Moreover, the rapid growth of the Internet and wireless technology has led to an influx of raw, unlimited data. Companies that are able to collect, analyze, and execute upon internal data have become cultural and business revolutions, such as Google, Facebook, and Amazon. As more industries refine their data, breakthroughs in artificial intelligence, automation, Internet of Things, and predictive analytics begin to showcase the influence of big data—especially the ability to connect different data sets and provide actionables that can impact the bottom line and society. Nearly a quarter of the way into the twenty-first century, while many new industries are creating digital transformation and older industries embracing it, today's manufacturing enterprise is still stuck with last century's practices and mindset, especially when it comes to data that is disconnected and disorganized. Though terms like Industry 4.0, Industrial Internet of Things, and Model-Based Enterprise outline a fundamental need for digital transformation and a basic understanding of its importance—for manufacturing, it is still more theory than practice. And nothing highlights this better than the different data file formats used from design to manufacturing. Additionally, many practical problems usually have several conflicting objectives that need optimization.

Boost 4.0 [3] is the European lighthouse project that has trialed at large scale over 13 industrial leading factories, 40 business processes, and 7 manufacturing sectors a unified standardized big data reference architecture, highly replicable advanced big data solutions, and sovereign industrial data spaces for Industry 4.0. As the implementation of Boost 4.0 large-scale trials have evidenced, the *real big data challenge for Factory 4.0* does not lie just in the actual "storage of data or exchange of assets across digital platforms" but primarily on the speed, transparency, and trustfulness in which highly heterogeneous and multi-domain interoperable data networks can be established and accessed, as well as the real-time synchronization of such data networks across the many cross-sectorial big data lifecycles. In other words, the ability to effectively support the implementation of cross-sectorial data value chains along the product lifecycle and across connected factories; i.e., *seamless "digital*

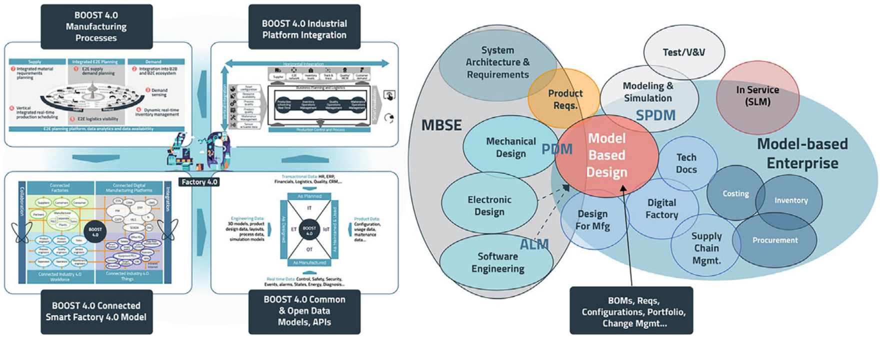


Fig. 1 Model-Based Systems Engineering (MBSE) BOOST 4.0 pillars for digital thread and connected digital factories 4.0

threads" among connected designers, connected suppliers, connected machines, connected boardrooms, connected products, and connected customers. To ensure a unified approach and high replicability, within Boost 4.0 a number of pilots have applied the model-based engineering paradigm, thereby enhancing the capability for multi-objective optimization introducing machine learning and lightweight deep learning architectures to address this issue taking into account significant production features.

BOOST 4.0 is not just a project dealing with factories implementing isolated big data processes. In fact, over the last few years, many Factories of the Future (FoF) projects have already shown that Industrial Internet and big data can bring clear business value to isolated factory operations. However, the connected smart Factory 4.0 is a paradigm shift towards optimizing how data and information are leveraged across new value chains (becoming more integrated and more complex) with interoperable digital manufacturing platforms as central to its vision. The connected smart factory 4.0 pillars (see Fig. 1) *integrate* digital platforms and industrial things and foster *collaboration* across factories and workforce. Factories 4.0 industrial platform horizontal and vertical integration leads to E2E real-time business planning with support of extended data availability and big data analytics for *real-time production scheduling*, dynamic *real-time inventory management* based on demand sensing, and production *quality and maintenance automation and optimization*. Such competitive advantages for European factories can only be made possible through *industrial data model convergence* at many levels, i.e., OT, IT, ET, and IoT and a *core capability in Industry 4.0 frameworks for big data and data analytics*.

This chapter relates mainly to the technical priority Data Management Engineering of the European Big Data Value Strategic Research & Innovation Agenda [4]. It addresses the horizontal concerns of semantic annotation, semantic interoperability, and data lifecycle management of the BDV Technical Reference Model. It addresses the vertical concerns of standardization of big data technology areas to facilitate data integration, sharing, and interoperability. The work in this chapter relates mainly but not only to the Knowledge and Learning cross-sectorial technology enablers of the AI, Data and Robotics Strategic Research, Innovation & Deployment Agenda [5].

This chapter will initially present in Sect. 2 the Boost 4.0 approach to big data-driven smart digital model-based engineering. This section will also address how such an approach has been realized in the Internet of Things Solutions World Congress (IoTWC) [6] testbed. This testbed has been built to highlight the feasibility of integrating model-based engineering methods with big data technologies and Boost 4.0 European industrial data space technology to leverage digital twin and digital thread continuity. Thus, the benefits of model-based engineering to improve the interoperability and data sharing capabilities for trusted digital twin's big data connection across the product lifecycle can be materialized in a concrete workflow and product, in this case a Mars rover.

This demonstrator has then inspired and motivated a number of large-scale pilots that capitalize on the digital thread continuity technologies at scale. The trials showcase the impact of enhanced engineering practices in the machine tool sector. Section 3, presents the large-scale big data trial conducted by FILL GmbH machine tool builder, addressing next-generation machine-tool engineering and digital service provisioning. Section 4, presents an overview of the large-scale pilot conducted by George Fischer's Smart Zero-Defect Factory, focusing on data-driven production improvement for milling machine spindle component manufacturing. Finally, Section 5, presents Trimek large-scale big data pilot for zero defect manufacturing powered by massive metrology that showcase how new big data technologies can significantly increase the capacity for 3D quality control of very large pieces and components in automotive through model-based design and intensive use of QIF (Quality Information Framework), as an open standard developed to enrich CAD models with additional process-related information.

2 Boost 4.0 Testbed for Digital Twin Data Continuity Across the Product Lifecycle

The aim of this section is to introduce the Boost 4.0 approach to big data-driven model-based engineering and the testbed built to demonstrate the feasibility of digital twin and digital thread implementation across design, production, and product operation lifecycle. There is a special bond between the digital twin and the physical world it represents. The digital twin has largely been a PLM concept for design and performance simulation of discrete products. Now, new kinds of digital twins are available to support and improve specific manufacturing plant production processes through Cyber Physical Systems (CPS) and obtain a better understanding of the product performance in operation through IoT. Each of these various kinds of digital twins have been developed as siloed solutions, each dealing with different manufacturing processes across the product lifecycle. The data exchange among digital twins breaking these silos opens manufacturers

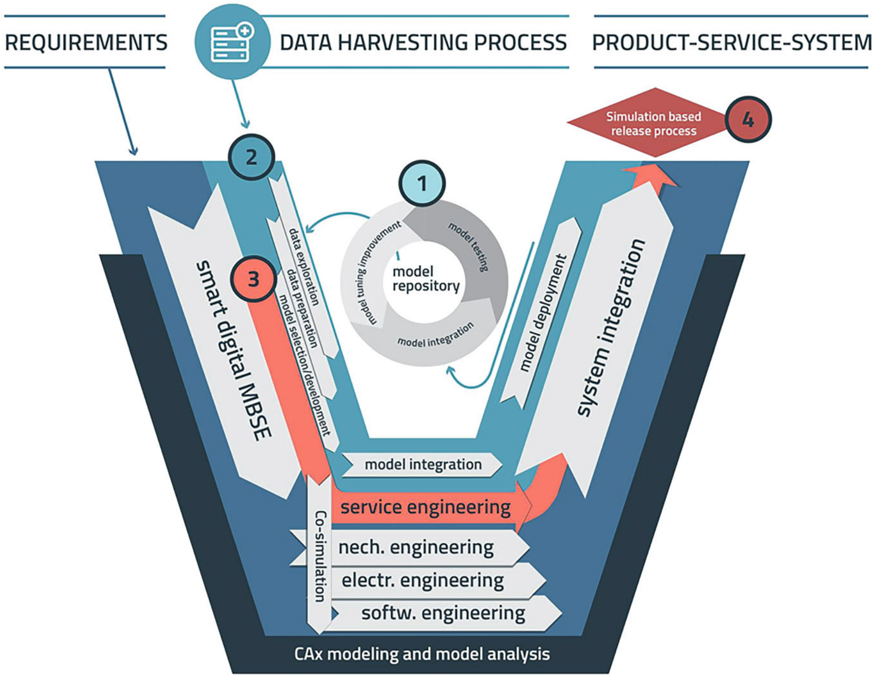


Fig. 2 Boost 4.0 smart digital engineering process using big data (based on VDI 2206)

the door to unprecedented insights, visibility, and automation opportunities leading to efficiency improvements in product design, product performance, behavior and manufacturing process operations like never before.

The approach implemented by Boost 4.0 to leverage data continuity across product lifecycle has been twofold. On one hand, the adoption of an agile V development model (based on VDI 2206) enhanced with big data (Fig. 2). A metadata representation approach has been integrated to define the structure and the relations (i.e., the connections) between the various data sources across the full process lifecycle. The Boost 4.0 smart digital engineering process is interacting with the model-based engineering process, a model repository (1) for trusted digital twins using big data, (2) for better service design, (3) and a simulation-based release process (4) to create product-service-systems (PSS) across the lifecycle.

On the other hand, to support the interconnection of metadata representation across the full lifecycle, the Boost 4.0 approach has been the extension, adoption, and demonstration of ProSTEP chain of Industry 4.0 standards with QIF capabilities (Fig. 3). This would ensure the semantic interoperability across not only product and process design/engineering but also quality control and production system commissioning and optimization.

As illustrated in Fig. 4, the Boost 4.0 testbed demonstrates how ProStep [7] model-based engineering approach, the QIF semantic framework, IDSA data space

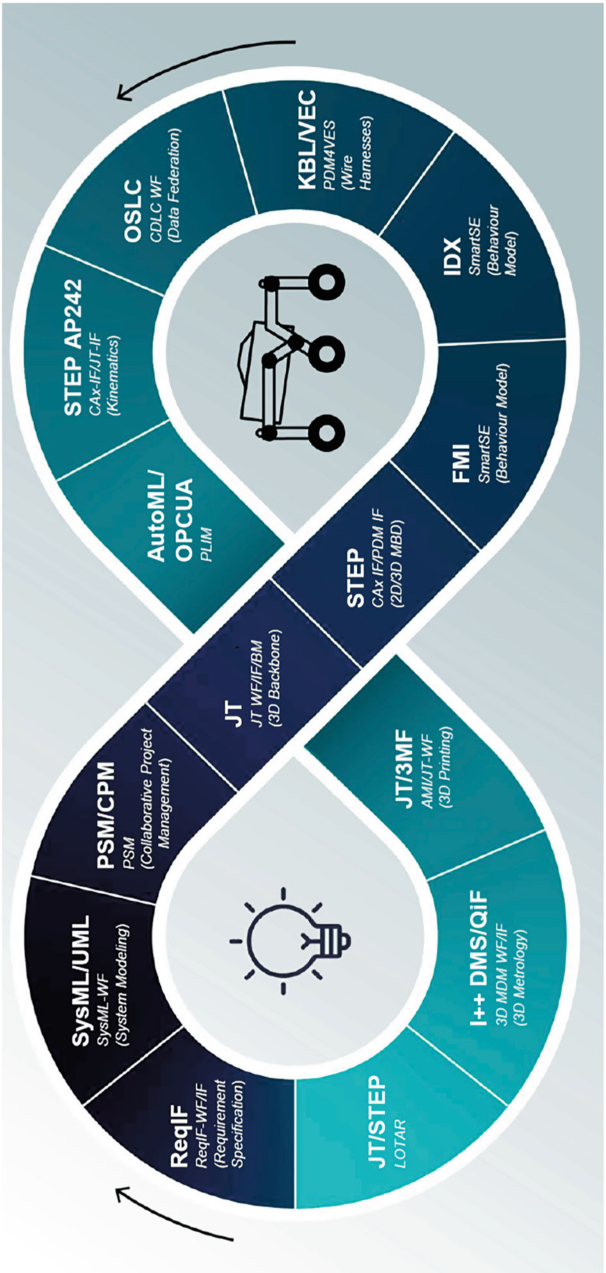


Fig. 3 Boost 4.0 ProSTEP interoperable semantic data model standards chain

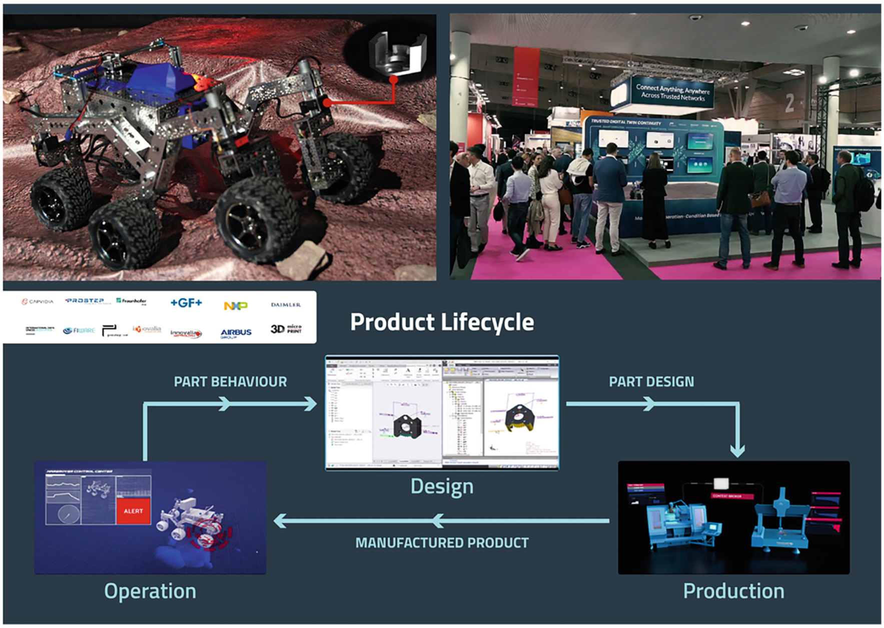


Fig. 4 A Mars rover vehicle trusted digital twin continuity testbed. IoTSWC 2019

[8] technology, and FIWARE NGSI Context Broker [9] open-source technology can be integrated for providing a seamless and controlled exchange of data across digital twins based on open international standards, allowing companies to dramatically improve cost, quality, timeliness, and business results through enhanced traceability, process workflow automation, and improved product and manufacturing process knowledge.

Machines chained to a shop floor as part of the manufacturing setup are typically working as information silos. They are "physically" connected since the part treated by one machine is passed to the next machine in the chain, which in turns treats this part and passes it to the next. Each of those machines generates a large amount of data, which so far has been used to monitor and improve the processes and tasks each machine performs. However, systems associated with each machine are not designed to exploit data from others when improvements can be gained if the data from one machine "feeds" the systems connected to the other and if such exchange is made in a way that is secure: access control terms and conditions established by each individual machine provider are preserved and the shop floor operator is also the final decision-maker, defining what is exchanged and what for, and whether it goes out of the factory.

In the context of the Internet of Things Solutions World Congress that took place in Barcelona in 2019, a group of companies that partner in Boost 4.0 (Capvidia, EPFL, FIWARE Foundation, +GF+, IDSA, Trimek, and Innovalia), in collaboration with key ProStep IVIP partners, presented a testbed that demonstrated

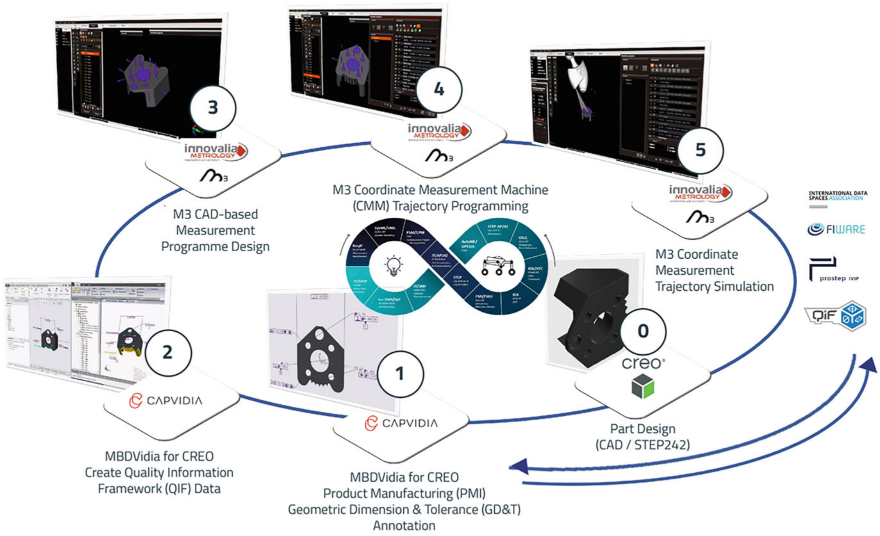


Fig. 5 The Mars rover big data-driven model-based engineering process and federated digital manufacturing platforms chain (PTC, CAPVIDIA, INNOVALIA METROLOGY)

how factories can benefit from IDS concepts and FIWARE open-source technology by bringing enhanced functionalities for the improvement of processes or the support of smart decisions, through management of context data shared across the product lifecycle.

This testbed demonstrator uses the example of a specific component of the Mars rover exploration vehicle to visualize the benefits of how companies can collaborate throughout the product lifecycle. As illustrated in Fig. 5, thanks to the combined exploitation of model-based engineering (MBE supporting standardized open PLM STEP standards [10] and Quality Information Framework (QIF) semantics [11]), *digital threads* and *digital twin* technologies based on *European industrial data space trusted connector technology* that allows product and process information sharing in an environment of trust.

The testbed is focused on the production of a specific component that is a very sensitive piece in the suspension of the Mars rover. In this case, it is manufactured by a +GF+ milling machine. As shown in Fig. 6, this milling machine is connected, through an IDS connector, to a predictive maintenance system deployed at +GF+ cloud systems, so information about the status of the milling spindle is constantly sent to the predictive maintenance system to be analyzed, and maintenance tasks are programmed to avoid breakdowns that force to stop the production.

After the piece is produced, an Innovalia Metrology coordinate measuring machine (CMM) takes care of the dimensional quality control. This machine measures millions of points in a very short period of time, producing what is called a point cloud (a high-resolution, high-fidelity, micron-resolution digital replica of

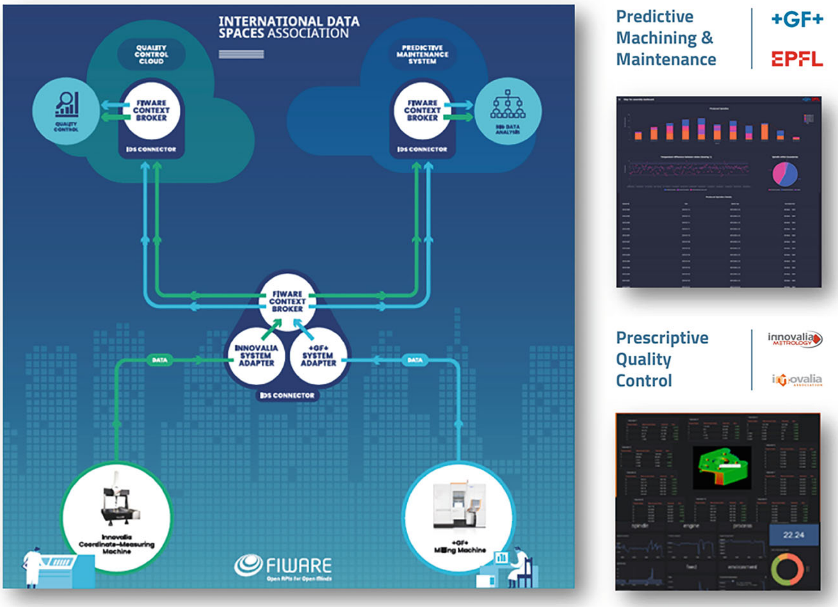


Fig. 6 The Mars rover digital manufacturing excellence threads and integrated decision support dashboards

the physical part). This information is sent to Innovalia's quality control cloud (M3 Workspace) through trusted IDS connector technology, and there it is compared with the 3D CAD model to identify deviations. The result of this analysis is a 3D model with color mapping, which allows the operator to easily find out if these deviations are within the allowed range.

The IDS connector in this setup is the same for both machines. Prior to use the IDS connector, each machine adapter had to be deployed across all machines that have to engaged in secure data sharing to enable trusted communication and data exchange among the machines. Thanks to the privacy-by-design defined by the IDS Reference Architecture, the communication between the machines and their respective cloud systems is isolated and independent.

As part of the demonstration, and to showcase the benefits of using the IDS connector to share information in a trusted and sovereign way, Innovalia can configure the IDS connector to allow +GF+ predictive maintenance systems to gather data from Innovalia's CMM. This would allow the system to enrich their algorithms to include the deviation's information in the analysis, so the system can cross this information with the machine status, improving the predictive maintenance system. In a similar way, +GF+ can allow Innovalia to request specific information from the milling machine to add new functions to the quality management system. The overall schema of the use case is depicted in Fig. 4.

3 FILL GmbH Model-Based Machine Tool Engineering and Big Data-Driven Cybernetics Large-Scale Trial

The expansion of competitiveness and sustainability are fundamental goals of companies. To achieve these, every business needs to deploy digital technologies in a variety of areas, including customer relationships and services, productivity, business model, IT security, and privacy. Digitization and networking are playing an increasingly important role, as the digital data volume will increase significantly.

The growth speed of the data volume, the diversity of data, and the various data sources pose many challenges, such as a collection of sensor data and the mapping of model data underlying the machine, and their integration and interpretation into a structured database system.

The FILL trial builds on the Boost 4.0 testbed concepts and technologies described in Sect. 2, i.e., advanced model-based engineering coupled with product digital thread and digital twin implementations applied to machine tool products. The main achievement of the trial is to demonstrate that such an approach (big data-driven V-model engineering and semantic data model chains) can be applied under real production scenarios, with clear benefits and that the approach can scale to effectively deal with the complexity of machine tool production lines. Semantic information is integrated across the full lifecycle from machine operation to machine design and manufacturing.

Within the Fill trial, it is possible to record the data of their machines standardized by OPC UA data model [12], including semantic information and metadata to be used in analyses and optimizations. Utilizing standardized communication technology (e.g., MQTT, HTTP, REST) the existing specific solution Machine-Work-Flow-Framework is generalized and used for further customer requests. In doing so, Fill, and the pilot partners took a big step forward in the digitization of the data flow on the shopfloor with the expanded machine state model. The Fill pilot pursues the following goals:

1. Cost reduction expected by reducing the time spent on future development and customer projects.
2. Development of data-driven business models in service and support.
3. Identification of optimization potentials in the engineering process for long-term reduction in the development times of machines.

The Fill pilot primarily serves the engineering process of the machine builder. It allows for a better understanding of machinery by detecting cause-and-effect relationships due to anomalies and patterns (semantic interoperability). In addition, maintenance intervals and cycles are optimized and, as a result, quality improvements of the production and the product are achieved.

3.1 Big Data-Driven Model-Based Machine Tool Engineering Business Value

Within the CAx systems, the optimization of products, e.g., machine tools, are done by engineer's expertise and their empirical knowledge. Several loops are performed to optimize products and production processes to fit customer needs. Thus, customization is resource and time-consuming. During the sales and project-planning phase in many cases, no simulations of the process or valid process data are available for frontloading to minimize the risk for the machine builder.

During the engineering process, the start of the project is when the order is placed. Several simulation models in different software tools are generated to avoid failures in the early project phases. The models exist mostly independently and have to be modified by hand if there is a change in the requirements.

In general, parametric modelling and optimization techniques contribute significantly to the process of building CAx simulations. Several design parameters and probability density factors are taken into consideration for simulation sequences. The simulations are most important for analyzing different factors such as sensitivity, optimization, and correlation of the design or structure. Many practical problems usually have several conflicting objectives that need optimization. In these multi-criteria optimization problems, a solution is found iteratively and systematically.

The production concept and the machines engineering solve the multi-criteria equipment effectiveness optimisation function. The machine physical behavior sets the quality of the part and the production time. The material flow concept implemented solves the interaction of production steps and provides the overall logistic concept. These concepts are most important for overall equipment effectiveness.

3.2 Implementation of Big Data-Driven Machine Tool Cybernetics

The V-model (Fig. 2; compare VDI 2206 [13]) describes the development of mechatronic systems based on a systematic analysis of the requirements and a distribution of the requirements and loads among the individual disciplines. The detailed development then takes place in parallel and independently of each other in the individual disciplines. The results are then integrated into subsystems and systems and validated regarding compliance with the requirements. The new proposal for an integrated business process for smart digital engineering using big data extends the V-model by (Fig. 7):

1. Agile model management and development process (model repository)
2. Data analytics process (involving data analysis and machine learning methods)
3. Service development process
4. Simulation-based release process for product service systems

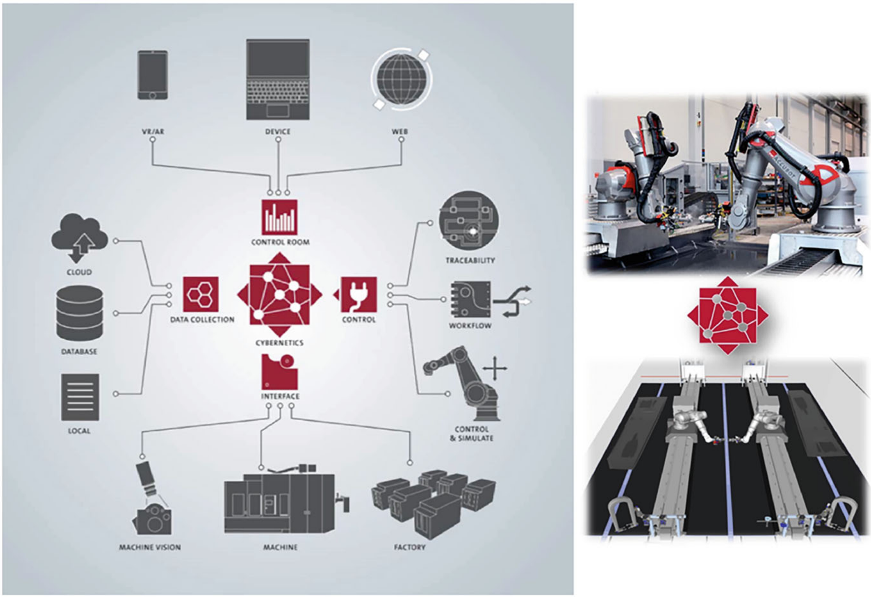


Fig. 7 The Fill big data cybernetics trial and semantic data integration based on Industry 4.0 standards. Digital twin and real line agile production engineering setups

Within the Fill pilot, TTTech provides the edge computing platform that provides real-time data harvesting services and enables the data-driven model approach. The resulting Product Service System (PSS) applications enhance shopfloor functionality utilizing machine data with significantly decreased latency and increased interoperability. To exploit the full potential of big data (and Industry 4.0), companies in the value-added network are willing to cooperate and share data. Openness and trust are crucial factors since the long-term strategy aims to create partner ecosystems, where different productions of different companies in the value-added network are connected, and individual processes across the companies are coordinated. The availability of process data across companies opens up great potential for agile production systems.

The main tasks of RISC in the Fill trial are focusing on the selection of the appropriate machine learning and data analysis methods that are suitable for very large data and that have the potential for parallel implementation (step (2) from above). An architectural concept [14] that combines big data technologies (such as Apache Spark [15] on Hadoop) with semantic approaches (Apache Avro [16] and SALAD [17]) has been defined to facilitate the exploration and analysis of large volumes of data from heterogenous sources, adhering to the Boost 4.0 unified big data pipeline and service mode proposed in the chapter "*Big Data Driven Industry 4.0 Service Engineering Large Scale Trials: The Boost 4.0 Experience* of this book.

3.3 Large-Scale Trial Performance Results

The Boost 4.0 large-scale trial impact has been assessed in the engineering process on Fill products, accurate robotic NDT systems Accubot®, and machine tools Syncromill ®, addressing four key performance indicators.

Long-term Reduction of Machine Development Times (Estimated: 15%, Achieved: 26.4%) or the Option for Better, More Innovative Concepts
Reducing time-to-market of innovative customized products is a key success factor for industrial companies. Integrating big data feedback information from operation and maintenance phases into the engineering phases shortened the time for real plant or factory commissioning in lot-size-1 production facilities. The new engineering process is shorter in time: in several projects of 2019/20 the time-to-market was reduced by 26.4% compared to 2015/16 before the implementation. In addition to a reduction in time, optimization loops can be also dedicated to increasing the quality, efficiency and flexibility of the machines. Thus, it is definitely a cost-saving issue, but also a key to attract customers because of fast ramp-up of production. Especially the reduced time gives extra time for innovative new concepts and to fulfill SDGs.

Unplanned Downtimes (Estimated: 20%, Achieved: 20.8%)
To use this new model-based and big data-driven process engineering methodology it is essential to establish a pattern and anomaly detection framework. With this framework, different behavior models as well as artificial intelligence and machine learning algorithms are developed and provided in a model repository. The models are used in the engineering process to get better insights of the physical, logistics, or other behaviors. This accelerates the reduction of unplanned downtimes and therefore improvements in the sense of time, quality, and costs. The models are stored in a model repository and can be further used by the customer, e.g., as virtual sensors. This leads to new business models, such as "Model as a Service." Since the period of Boost 4.0, the amount and duration of downtimes due to maintenance actions at the customer's site was reduced by 20.8%.

Service Cost Reduction (Estimated: 15%, Achieved: 19%)
The pilot focuses on three states: as-engineered (state after the engineering was finished) as-manufactured (state after manufacturing and in-house commissioning), and as-operated (how the customer operates the production system, simulate historical and real-time data). In order to extend the field of application from pure simulation and monitoring usage, the requirements of service design and service engineering has been integrated into the digital twin. This enables requirements analysis for new projects, failure analysis, and designing a service process with focus on service cost reduction. The measured projects in Boost 4.0 achieved a reduction of 19%; this is mainly due to designed remote service actions and failure prevention concepts in the engineering phase.

Simulation-Based Release Process Reducing Commissioning Time (Estimated: 10%, Achieved: 14.7%)
With the efficient use of CAD models, interfaces between Visual Components simulation tools and the engineering management tools of Fill have been established; thus a better integration of the simulation process into the proposed engineering process has been achieved. This led to a simulation management in which saving, loading, and version control are well integrated. Moreover, design changes are updated faster in the simulation. The use of virtual commissioning was measured in a reduction of commissioning time by 14.7%. In future, the target from Visual Components is to create a generic PLM interface which can be tailored with add-ons for the PLM solutions in the market.

> "Beside the Fill Pilot that we have been involved in, by realizing customized solutions in simulation, our customers benefit in reductions of commissioning time in the range of 15–25%." (Fernando Ubis (Visual Components).

3.4 *Observations and Lessons Learned*

The development of innovative, highly customized production systems is generally based on a customer-centric approach. Furthermore, for the machine builder, the operations process knowledge is a key success factor. This is mostly expertise and empirical knowledge and is usually built during the operating phase and used in follow-up projects. The intended feedback loop should accelerate the buildup of knowledge and make it possible to secure customer needs and even wishes earlier and increases customer satisfaction. This leads to fewer delays in the business process, like customer-dependent approval processes, e.g., design approval, delivery approval, etc.

"Fill is a grown family-owned company and focused on its customers success. With the new approach of closing the gap of digitalization between customers and the Fill engineering we also can feel a higher customer satisfaction, which is brought to me by feedback of our customers. Beside the facts and figures of measured KPIs, it is about the people working and their motivation. I think the digitalization and its approach is mandatory to benefit but it is about the mindset to see digitalization as a chance and not a threat. With the transparency on the process and the trust we have built up with our partners and customers we are best prepared for the factory of the future!" Alois Wiesinger (CTO of Fill).

4 +GF+ Trial for Big Data-Driven Zero Defect Factory 4.0

This section presents the +GF+ trial and the Boost 4.0 concepts adopted for model-based engineering, in particular the semantic information framework to deal with product quality information (metrology data) and digital factory/process information. The trial is intended to demonstrate how the implementation of semantic information representation supported by cutting-edge digital platforms and

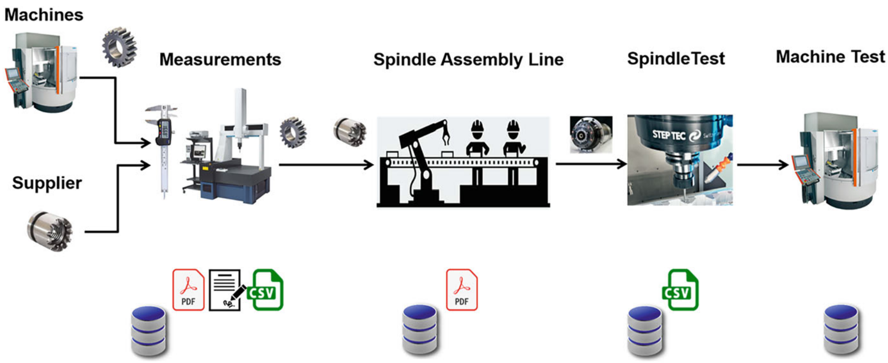


Fig. 8 GF milling machine spindles assembly process

based on agreed standards can break the silos, implement federated workflow and pipelines, and lead to a cost-effective implementation of advanced decision support systems and production cost reduction.

The trial is focused on the manufacturing of the most critical component on +GF+ machine tools, i.e., +GF+ Milling Spindles. These are critical components conveying the highest value in production processes. Their assembly processes currently generate data in isolation, which can be identified in the diagram showed in Fig. 8.

1. Factory machines produce some critical parts, which are measured with different systems producing data in different formats (from manual devices to CMM machines). One key issue is to link all those measurements to one part and avoid dealing with multiple reports.
2. The data acquired on the assembly line is among the most critical ones. It is currently collected by hand, what makes it, it difficult to aggregate and analyze.
3. The quality testing of each spindle also produces data, which today is stored as a .csv file and not correlated to any other data in the process.
4. The data related to the assembly of the spindle into the machine itself is stored into a PostgreSQL database, again not aggregated for analysis.
5. Finally, there is also data coming from service records and sensors (spindles which are returned by the assembly of the machine or by the end customer), with unexploited key information on the component quality.

While the quantity of data created is not a problem nowadays, the major challenge is the complexity to structure and aggregate it so as to have a comprehensive understanding of their meaning, in order to improve the manufacturing process and even machine operation through predictive maintenance applications.

4.1 Value of a Quality Information Framework for Dimensional Control and Semantic Interoperability

QIF (quality information framework) [18] is an open-standard CAD format made specifically for introducing twenty-first-century concepts such as digital transformation, digital thread, and IoT (Internet of Things) to computer-aided technology and engineering applications. The two main points of QIF are interoperability and traceability throughout the entire product lifecycle. From design to planning to manufacturing to analysis, full metadata can be mapped back to the "single source of truth" (native CAD).

QIF is built on the XML framework for easy integration and interoperability with other systems, web/internet applications, and other formal standards – a unified and universal approach.

- **Structured Data**: featured-based, characteristic-centric ontology of manufacturing quality metadata.
- **Modern Approach:** XML technology—simple implementation and built-in code validation.
- **Connected Data**: information semantically linked to model for full information traceability to MBD.
- **Standard Data:** approved ISO and ANSI interoperability standard.

It also contains holistic, semantic PMI (product manufacturing information)/3D product definition and other metadata that is both human-readable and computer-readable for MBD (model-based definition) implementation. QIF is an ANSI and ISO 23952:2020 standard managed by the Digital Metrology Standards Consortium (DMSC), an international leader in the field of metrology. QIF supports Design, Metrology, and Manufacturing as it enters the Industry 4.0 initiative: data that is semantic, machine-readable, standard, and interoperable to enable the smart factory. QIF is a key conversation starter for companies beginning the MBD/MBE (model-based enterprise) process, especially for metrology-related information in PLM (produce lifecycle management) and PDM (product data management).

As the Boost 4.0 + GF+ trial has evidenced, a semantic approach to data integration across the product and process lifecycle has very clear benefits:

1. **Automation**: Defined business process and software compatibility leads to the possibility of automation.
2. **Interoperability**: Enables authority CAD file to be reused on different software by different departments and companies.
3. **Single Source of Truth**: Derivative models for robust, semantic PMI, metrology features, and mapping back to any native CAD model.
4. **Big Data:** Manufacturing data is moved upstream for analytics and design improvements.
5. **Faster Time to Market**: Automation and decreased manual translation and validation begets shorter production cycles.

6. **Cost Savings**: Up to 80% of total hours saved for annotation, control planning, and inspection processes together, meaning less resources needed for a particular task, reducing overhead.
7. **Work Efficiency**: Automation is repeatability, relying less on human involvement (and possible error), and freeing the engineer to focus on other value-adding work.
8. **Process Over Personnel**: Avoiding the "human-in-the-loop" method provides documented process-driven strategy.
9. **Better Product**: Faster time to market leads to more iterations and breakthroughs in product, process, or pricing.
10. **Better Bottom Line**: Automated work processes, less bottlenecks, and faster iteration and feedback for ideation all lead to savings in time and money.

On the other hand, many of today's manufacturing practices depend on disparate data sets and manual transcription and validation that impede the ability for automation. Not all data is created equal. Different data file formats (e.g., PDF, TXT, TIF, CSV, XLS, STEP, JT, IGES, PRT, QIF, XML, etc.) from different software are either proprietary or lacking robust data capabilities to produce true MBD. The incompatibility and inaccessibility prevents connecting data throughout the whole product lifecycle—traceability and automation in the digital thread. With multiple stakeholders throughout the supply chain with their own CAD, CAM, and CMM software and custom-made data, exchanging inoperable data with a disjointed approach results in multiple disconnections in the digital thread. As illustrated in Fig. 9, QIF is an MBD-ready, XML-based, CAD-neutral, and open standard that includes the following features: (1) PMI (Product Manufacturing Information), (2) GD&T (Geometric dimensioning and tolerancing), (3) Measurement plans, (4) Geometry, (5) Bill of Characteristics, (5) Inspection Plans, and (6) Other semantic data.

All these features allow seamless handoff of data downstream, enabling automation to quality control and production with full traceability to the single source of truth: the CAD model. It empowers businesses for a better product, faster process, and bigger bottom line. This is the purpose of MBD and MBE in manufacturing! And this all begins with quality information.

According to the Data Information Knowledge Wisdom (DIKW) Pyramid [19] & QIF stands in the information layer, data is a number while information is data with context. It is well known that decisions made from data require a "human-in-the-loop," while decisions made from information lead to automation. Anyone can collect data, but data in action is wisdom (Table 1).

4.2 Value of Semantically Driven Big Data Zero Defect Factory

The realization of the concept of zero defect factory that underpins the +GF+ trial relies on mastering four critical business processes: (1) spindle component

Fig. 9 QIF structure

Table 1 Decisions from data vs. information

Decisions from data	Decisions from information
Interpretation	Increases speed of task completion
Tedious process	Lowers cost due to decreased labor requirements
High cognitive load	Frees up valuable personnel for other tasks more suited for the human mind
More opportunities for error	Repeatable solutions
Costly solutions	Lower risks
Inconsistent solutions	

manufacturing, (2) spindle assembly and delivery to machine factory, (3) after-sales guarantee management, and (4) service contracts. For each of these processes, specific KPIs have been defined and are now constantly monitored. This will allow delivering well-defined benefits reaching nearly 1 M€/y only for the manufacturing and after-sales guarantee stages (Fig. 10).

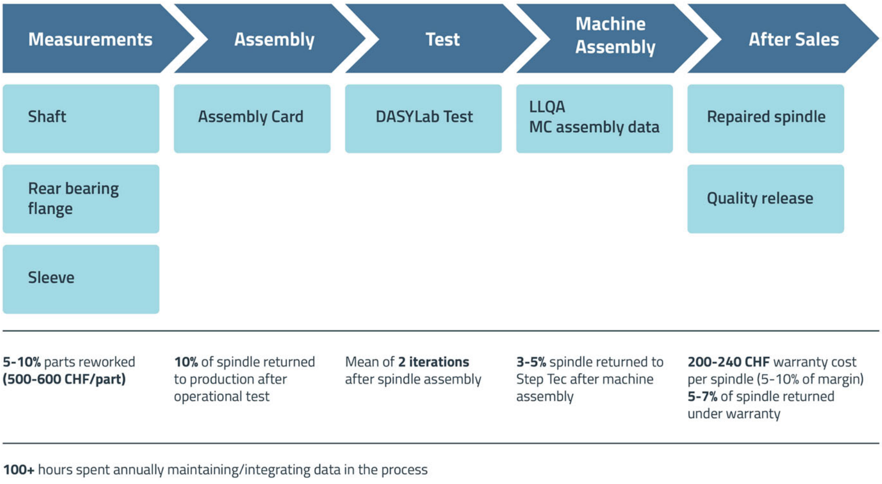


Fig. 10 Spindle component lifecycle and KPIs

4.3 Semantic Big Data Pipeline Implementation for Zero Defect Factories

The +GF+ big data pipeline has been built on the bases of three main types of data. Metrology, machine sensor data and assembly data.

Spindle Metrology Data QIF workflow was implemented on a typical +GF+ part—the main spindle. The part was designed with PTC CREO software and was used as input to the workflow, creating the QIF MBD representation with the help of Capvidia's MBDVidia for CREO software. The workflow was divided into steps. Step 1: the native CAD model is converted into the standard Model Based Definition (QIF). Step 2: the QIF file with the semantically linked Product Manufacturing Information (PMI) is verified for correctness of the Model-Based Design (MBD) definition (this check validates and corrects all semantics in the PMI definition). As a result we get MBD Ready data being 100% machine-readable for the next application (maintain the digital thread). Step 3: This MBD model is used for automatic generation of the First Article Inspection (FAI) document specifying what entities have to be measured in the quality control process. This is an inspection document to verify the quality of the manufacturing process confirming that the physical part complies with the design intent. As explained in the first part, today for one specific part, information about the measurement is spread between three documents most of the time (from different machines, operator measuring manually, etc.). The implementation of the QIF workflow reduces it to one document, making it easier for the quality team to check (Figs. 11 and 12).

In addition, the data, being fully digital, is now traceable and organized in a standard (QIF) data format, guarantying open access and transparency. They are

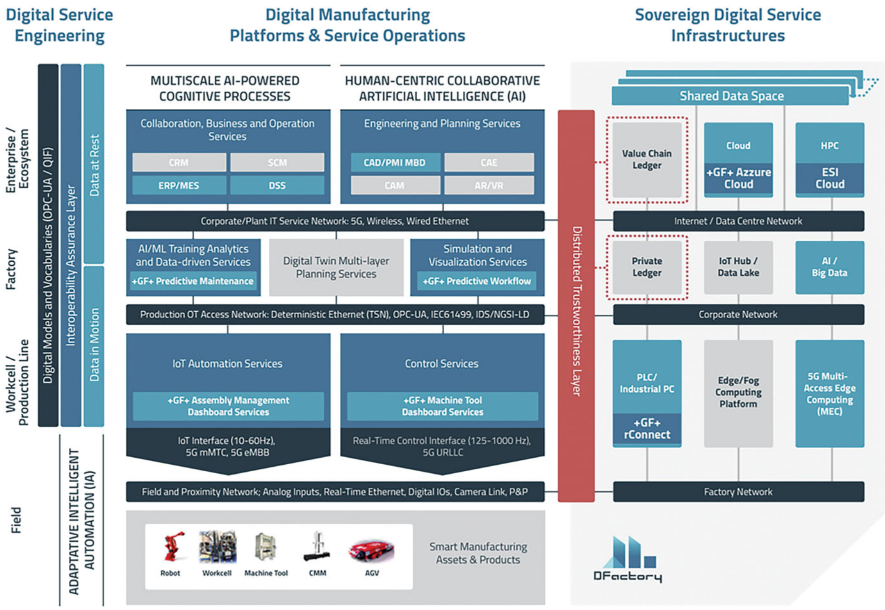


Fig. 11 +GF+ service development architecture

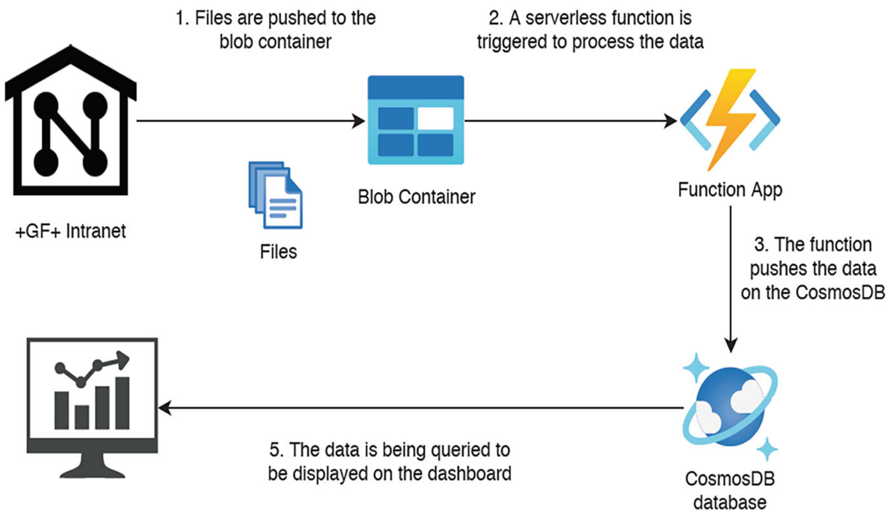


Fig. 12 +GF+ service development architecture and Azure Data Factory Pipeline

also uniquely linked with the physical part, which significantly simplifies the repair and maintenance activities.

Spindle Assembly Data Assembly cards, which contain all the needed information about the produced spindles, have been digitalized, and manual filling process suppressed. An Az-copy script copies these files from the +GF+ intranet to a blob container on a storage account on +GF+'s Azure platform. Information regarding the different parts of the spindles (the shaft, the front sleeve, and the rear bearing flange) is also saved in different CSV files, which are also copied to the blob container. This triggers a piece of logic called an Azure Function App. This app contains two functions: one for processing the assembly cards and one for processing the CSV files containing information to update the spindle parts. The first function reads the assembly card, retrieves the data, transforms it to add the semantics, and pushes the transformed data to the database in order to create a new spindle. The second one read the files containing information about the spindle's parts, and for each part, retrieves the corresponding entity from the database, updates it, and saves the changes to the database. The database is a CosmosDB database which uses the Gremlin API, so as to operate with graph data, which allows us to store data with its semantic metadata. Thanks to this platform, all the information about the produced spindles is now digitalized and centralized into one single database, and can be easily understood and retrieved by all parties thanks to the semantics. It's then possible to query this data, in order to learn information about the spindles, and to display it on a dashboard. As another example, an Azure Data Factory Pipeline has been set up in order to retrieve all the information about all the spindles, and save them as a CSV file.

Finally, **Machine Sensor Data** is retrieved through OPC-UA channels and protocols from the field and specific modelling has been implemented in order to estimate the Residual Useful Time (RUT) of key components.

4.4 Large-Scale Trial Performance Results

The results of the large-scale trials (Fig. 13) are extremely positive in the following two dimensions.

Data Workflow and Visualization
The implementation of the digital data flow enabled keeping a self-service warehouse always up to date. This can be shown in a dashboard with the corresponding KPIs. The Capvidia solution (QIF model) shows also the potential benefit from easy data aggregation around a single model. It appears clearly that this provides value in a short term (time savings, transparency) and in the subsequent steps of analysis.

Machine Learning and Predictive Quality
Thanks to this program, it is possible to apply machine learning in order to detect 30% of manufacturing quality problems. Additionally, the benefit of having an interpretable model will enable us in the future to improve our design and our tolerances by understanding the root causes (Fig. 14).

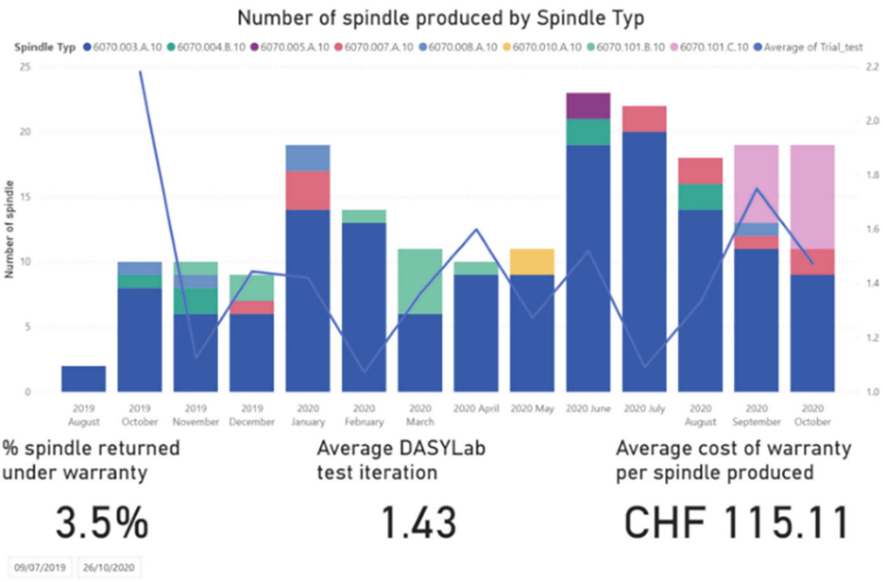
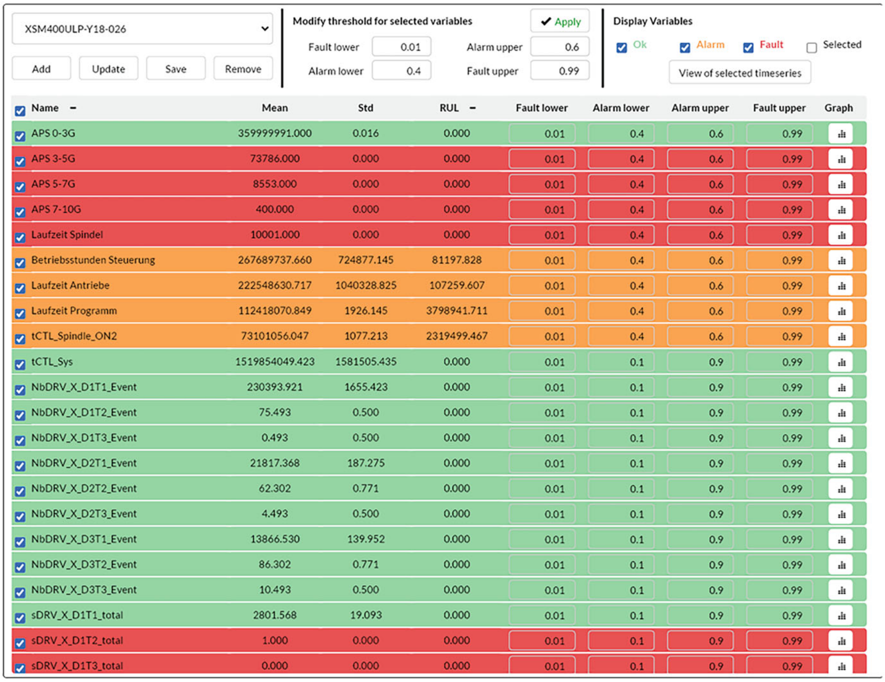


Fig. 13 Example of report showing the potential benefit



Name	Mean	Std	RUL	Fault lower	Alarm lower	Alarm upper	Fault upper	Graph
APS 0-3G	359999991.000	0.016	0.000	0.01	0.4	0.6	0.99	
APS 3-5G	73786.000	0.000	0.000	0.01	0.4	0.6	0.99	
APS 5-7G	8553.000	0.000	0.000	0.01	0.4	0.6	0.99	
APS 7-10G	400.000	0.000	0.000	0.01	0.4	0.6	0.99	
Laufzeit Spindel	10001.000	0.000	0.000	0.01	0.4	0.6	0.99	
Betriebsstunden Steuerung	267689737.660	724877.145	81197.828	0.01	0.4	0.6	0.99	
Laufzeit Antriebe	222548630.717	1040328.825	107259.607	0.01	0.4	0.6	0.99	
Laufzeit Programm	112418070.849	1926.145	3798941.711	0.01	0.4	0.6	0.99	
tCTL_Spindle_ON2	73101056.047	1077.213	2319499.467	0.01	0.4	0.6	0.99	
tCTL_Sys	1519854049.423	1581505.435	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D1T1_Event	230393.921	1655.423	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D1T2_Event	75.493	0.500	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D1T3_Event	0.493	0.500	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D2T1_Event	21817.368	187.275	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D2T2_Event	62.302	0.771	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D2T3_Event	4.493	0.500	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D3T1_Event	13866.530	139.952	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D3T2_Event	86.302	0.771	0.000	0.01	0.1	0.9	0.99	
NbDRV_X_D3T3_Event	10.493	0.500	0.000	0.01	0.1	0.9	0.99	
sDRV_X_D1T1_total	2801.568	19.093	0.000	0.01	0.1	0.9	0.99	
sDRV_X_D1T2_total	1.000	0.000	0.000	0.01	0.1	0.9	0.99	
sDRV_X_D1T3_total	0.000	0.000	0.000	0.01	0.1	0.9	0.99	

Fig. 14 Predictive maintenance testing environment on Scilab Cloud

Predictive Maintenance
Deployment is a key factor in big data knowledge inference. Preprocessing and further inference technologies (e.g., machine learning) must be performed at the data location. To do so, predictive maintenance algorithm has been deployed in a dedicated testing environment on a Cloud Solution. This application could be used to test and validate different predictive maintenance algorithms, and predictive capabilities can be accessed from the client platform, at the data location, via a dedicated API.

4.5 Observations and Lessons Learned

Bringing our data in one semantic model provides cost saving value in a short term and in the later steps of analysis. Boost 4.0 trialed and discovered also new ways and new standards to bring data together and set up a manufacturing digital twin, highlighting the benefits internally during the project.

As a result, some critical improvements are now possible: machine learning algorithms help to achieve unexpected accuracy (even with limited data) by detecting manufacturing issues; semantic and QIF standards give the possibility to link data together in an efficient way, and the cloud solution gives the possibility to deploy easily AI in testing environments and integrate them through APIs in any platform, making the full deployment swift and valuable.

5 Trimek Trial for Zero Defect Manufacturing (ZDM) Powered by Massive Metrology 4.0

Zero Defect Manufacturing (ZDM) powered by massive metrology is aimed at improving the performance and efficiency of the essential quality control processes in manufacturing lines, which have to deal with very large parts, e.g., automotive, aeronautics, renewable energy systems, and railways, and consequently have to deal with very heavy data and large volumes of 3D information. This trial also builds on the QIF (see +GF+ trial discussed earlier) semantic model and Boost 4.0 big data pipelines to implement a metrology 4.0 thread and data-driven digital twin analytics. The aim of this trial is to demonstrate how the Boost 4.0 big data-driven model-based approach can lead to increased automation of the quality control workflow through seamless interoperability among product design data, product GD&T information, and quality control process commissioning (Fig. 15).

The key pillars of this pilot are the implementation of high-definition inline metrology process to capture large volumes of 3D point cloud data, the integration and analysis of heterogeneous data, both quality and product data from different sources, incorporating to the metrology flow data coming from the product design steps, and finally the development of an advanced human-centric collaborative and

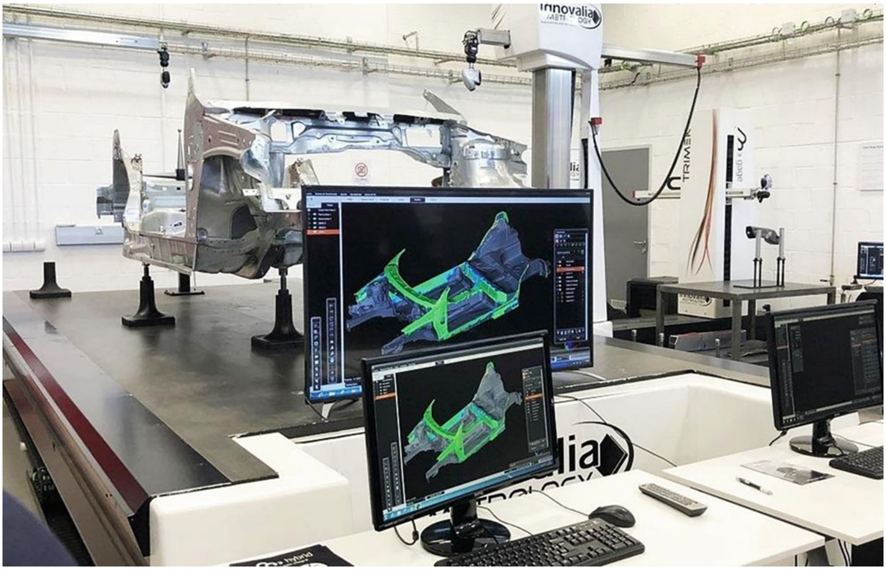


Fig. 15 Massive metrology 4.0 trial scenario

visual analytic process based on advanced color mapping. As a result, a connected and secure quality control process covering the whole metrology workflow and based on QIF standard has been implemented, with innovative and efficient visualization, processing, storage, and analysis capabilities, which definitely improves the decision-making process and reduces the number of defective parts. The ZDM Massive Metrology trial is based on the M3 Big Data Platform [20] for design and production data sharing and QIF standard as dimensional metrology data exchange. The M3 platform is poised to provide a structured solution for Metrology 4.0, an edge-powered quality control analytics, monitoring, and simulation system (Fig. 16).

5.1 Massive 3D Point Cloud Analytics and Metrology 4.0 Challenges

Up to now, the metrology results are usually only visualized in reports based on the Geometric Dimensioning and Tolerancing (GD&T) analysis, which is aimed only for metrology use and only a few control points are considered (10–100 points). Industry 4.0 in general and zero defect manufacturing in particular demand that metrology 4.0 processes scale up data acquisition, processing time, and visualization speed at various orders of magnitude. This is in accordance with the demand for more holistic, flexible, and fast metrology solutions—see requirements and trends from the VDI 2020 Manufacturing Metrology Roadmap.

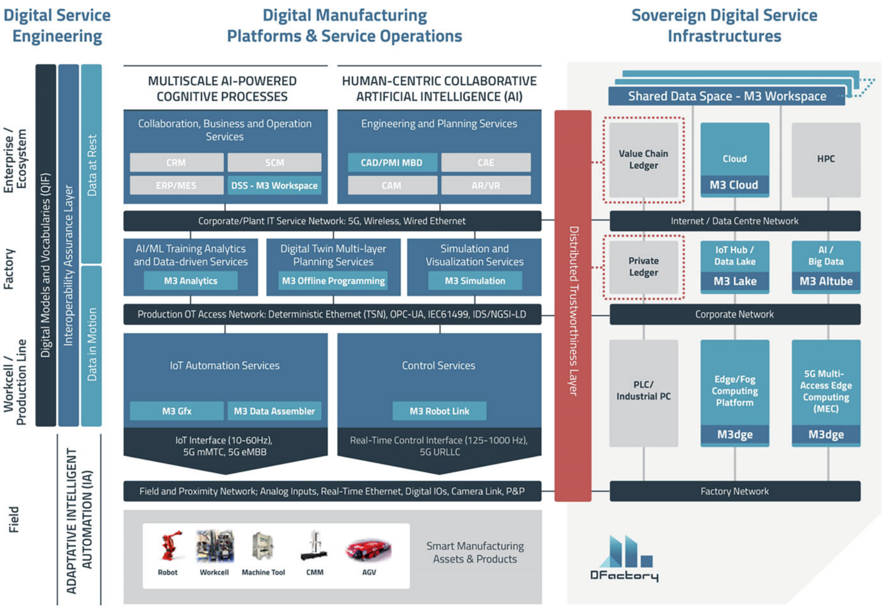


Fig. 16 Boost 4.0 reference model for massive metrology 4.0 based on the M3 platform pipeline

The Trimek trial exploits model-based engineering of metrology solutions to implement massive metrology 4.0 workflows that will address the need for holistic measurement systems capable of dealing with increasing information density, diversity, integration, and data processing automation in reduced measurement times.

The objective of the Trimek trial is to implement a rapid big data pipeline for processing and advanced high-speed high-resolution texturized colormaps for high fidelity visual analysis of massive 3D point clouds (from 10 to 100 million points) in less than 30 s. So the challenge is to demonstrate that future metrology 4.0 platforms can be used to assess and guarantee the fit, performance, and functionality of every part (irrespective of its size and tolerancing requirements) and support the targets of zero defect, zero waste, and carbon neutrality (Fig. 17).

5.2 *Implementation of Massive Metrology 4.0 Big Data Workflow*

The Trimek ZDM Massive Metrology 4.0 trial considers two main business processes for implementation:

- **High-density metrology**: This process has developed a system capable of rapid acquiring and processing big volume of 3D point cloud data from complex

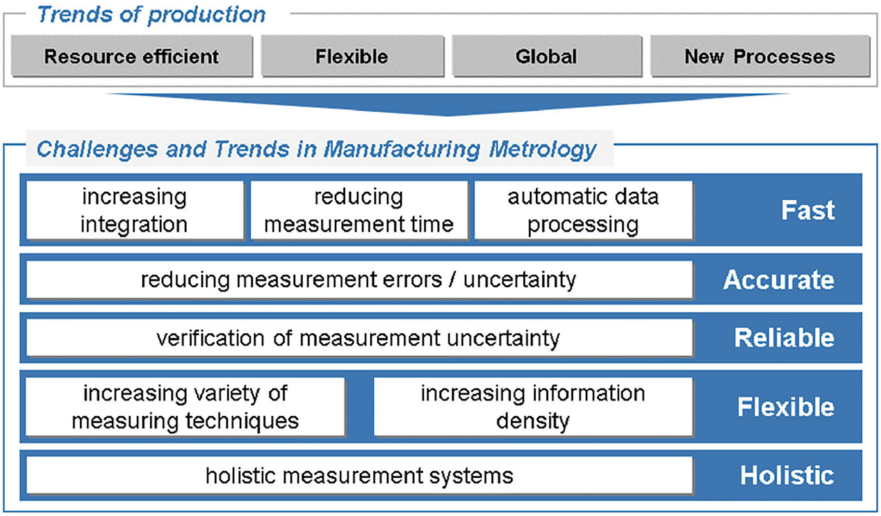


Fig. 17 Massive metrology 4.0 trial data analytics challenges

parts and analyzing massive point clouds coming from those parts by means of advanced 3D computational metrology algorithms, obtaining high-performance visualization, i.e., a realistic 3D colormap with textures.

- **Virtual massive metrology**: This business process has developed a digital metrology workflow and agile management of heterogeneous products and massive quality data, covering the whole product lifecycle management process and demonstrating an advanced semantic QIF metrology workflow (Fig. 18), enabling product design semantic interoperability with product quality control processes and advanced analysis and visualization of the quality information for decision support.

5.3 Large-Scale Trial Performance Results

The Trimek trial has allowed the implementation of advanced metrology 4.0 algorithms based on 3D computational capabilities to finally obtain a texturized mesh, instead of an annotated polygonal mesh, that is a more realistic visualization of the physical product for human-centered decision support process. Large pieces have been scanned and analyzed and the trial has demonstrated that the Boost 4.0 big data pipelines can process the whole body of a car (Fig. 19).

Table 2 summarizes the main system capacities.

These new big data capabilities have allowed the automotive industry to work fluently with 10 times larger CAD files and control beyond 600 geometrical features, which is important as having all the car modelized. The processing speed has also

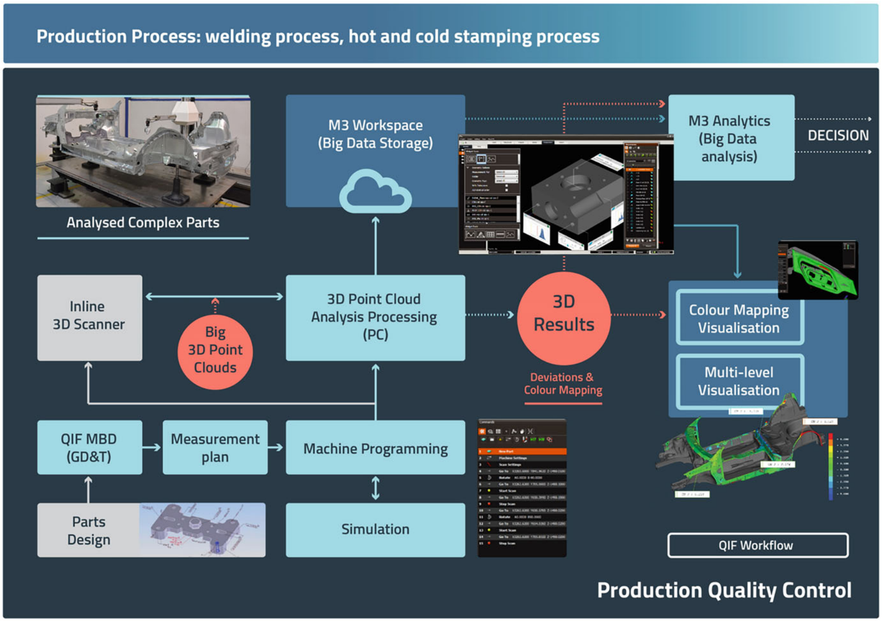


Fig. 18 QIF-ready semantic massive metrology big data analytics pipeline based on M3 platform

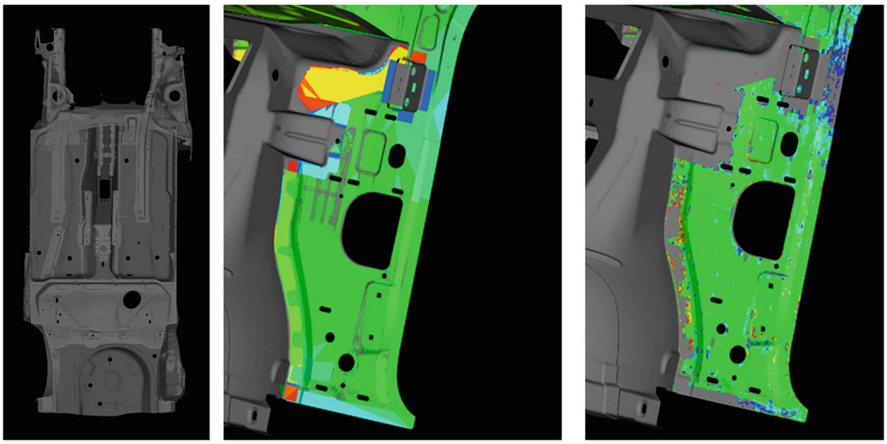


Fig. 19 Large-scale CAD file (left), annotated polygonal colormap mesh (middle), texturized colormap mesh (right)

been multiplied by 5, which allow a better performance and a more fluent analysis and visualization. Also, the time needed to program the scan of each piece has been reduced significantly, up to 80%, as having the whole car already modelized allows for a digital planification of the trajectories thus reducing the time needed to configure the scan. Overall, this derives a cost reduction of 10%.

Table 2 Trimek trial big data capabilities features for Metrology 4.0

Big data capability	M3	M3—big data
Data usage	32 bits CAD for 100 Mbs Point cloud size <six million	64 bits CAD for 400 Mbs Point cloud size >100 million
CAD file format	Mono CAD	Multi CAD
Part/CAD alignment	Mono-alignment algorithms	Multi-alignment algorithms
Region of Interest (RoI) extraction	Slow	Effective
Color mapping	Mono-core & Polygonal	Multicore & Texturized
Visualization	Monolithic	Adaptive

6 Conclusions

This chapter has discussed how Model-Based Systems Engineering (MBSE) can benefit from big data technologies to implement smarter engineering processes. The chapter has presented the Boost 4.0 testbed that has demonstrated how digital twin continuity and digital thread can be realized from service engineering, production, product performance, to behavior monitoring. The Boost 4.0 testbed has demonstrated the technical feasibility of an interconnected operation of digital twin design, ZDM subtractive manufacturing, IoT product monitoring, and spare part 3D printing services. It has shown how the IDSA reference model for data sovereignty, blockchain technologies, and FIWARE open-source technology can be jointly used for breaking silos, providing a seamless and controlled exchange of data across digital twins based on open international standards (ProStep, QIF), allowing companies to dramatically improve cost, quality, timeliness, and business results.

This closed-loop implementation allows the realization of advanced product-service processes that have been trialed by Fill, +GF+ and Trimek manufacturing equipment. The chapter has clearly presented how semantic data integration across the product and process lifecycle based on open international standards such as OPC-UA and QIF provide significant performance improvements in customization of complex machine tool installations, development of zero-defect factories 4.0, and massive product metrology 4.0. It has illustrated how QIF (Quality Information Framework) ISO-standard (ISO 23952:2020) meets MBD conditions and leverages interoperable data exchange between CAD, CAM, and other CAx systems for down-stream use. This chapter has described how big data trials leverage the possibility to map data back to a single source of truth; providing traceability and validation of intended and unintended changes/outcomes. QIF with PMI (Product Manufacturing Information, aka 3D annotations) can include GD&T, Bill of Materials, Process Plans, and more for data that is unambiguous and machine-readable—able to overcome human interpretation, thereby leveraging a new generation of data-driven digital twins.

This chapter has provided additional evidence that the Boost 4.0 service development reference architecture maintained by the Digital Factory Alliance and the Big Data Value Association (BDVA) reference architecture provide a unified framework to develop high-performance big data pipeline that allow for fast transfer, replication, and adoption of product engineering and manufacturing operational optimization.

As it has become apparent in this chapter, over the last few years the role of GD&T is gaining momentum in the definition of new generations of Industry 4.0 semantic models such as Automation ML. The need for increased levels of interoperability across OPC-UA, AML, and QIF standards calls for additional research that leverage higher manufacturing autonomy levels and facilitate more efficient and effective collaborative engineering processes for highly customized and complex products. The integration and alignment of such models will be a fundamental milestone in the development of increasingly cognitive and intelligent digital twin services that seamlessly interact not only between physical and digital work but also across the product and manufacturing process lifecycle.

Acknowledgments This research work has been performed in the framework of the Boost 4.0 Big Data Lighthouse initiative; a project that has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No. 780732. This data-driven digital transformation research is also endorsed by the Digital Factory Alliance (DFA) www.digitalfactoryalliance.eu

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