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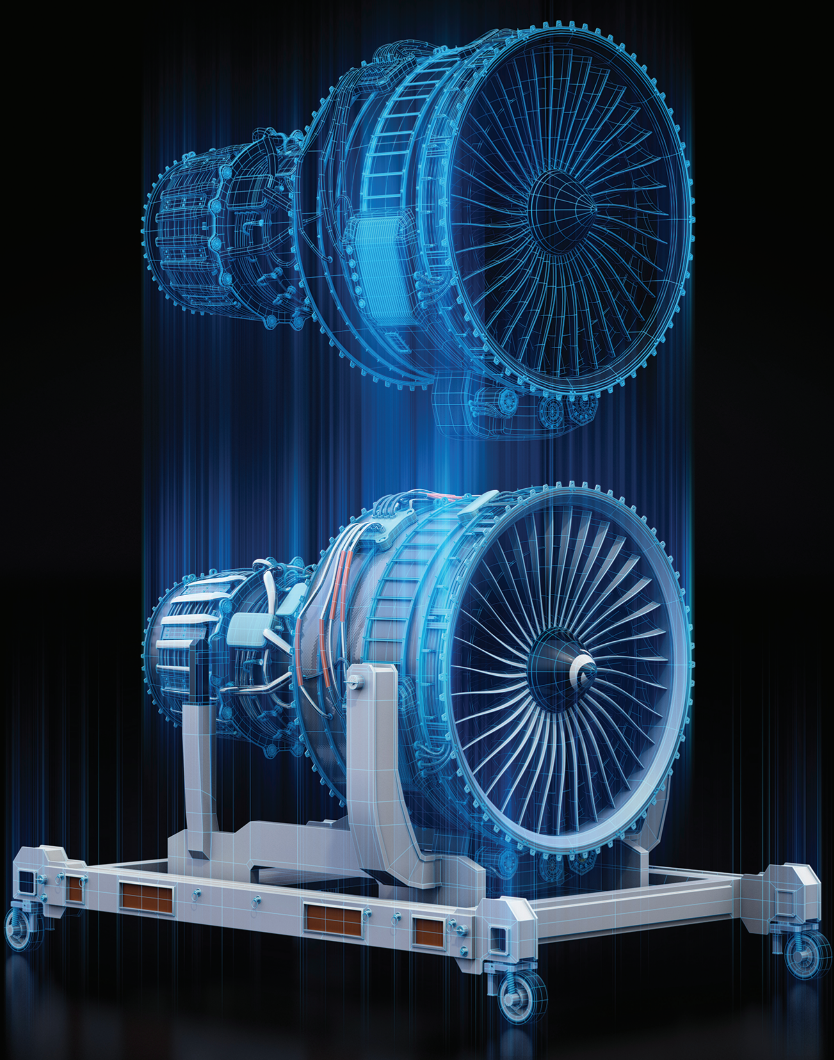
DIGITAL TWINS

CREATING DIGITAL OPERATIONS TODAY TO DELIVER BUSINESS VALUE TOMORROW



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Executive Summary

- A digital twin is a virtual model and detailed representation of a system (e.g., product design) or entity (e.g., fatory) that can be used to understand performance, improve processes and create revenue opportunities from services
- A digital copy or replica of the real thing is a means to an end, for example, to optimize the operations of a plant or validate the expected behavior of product design
- Companies that own or operate products and facilities face an uphill battle when implementing their digital twin strategy due to virtual copies that don't match reality; a lack of third party data for a comprehensive operational picture; or unstable "ground truth" that is continuously changing
- Successful companies are laser focused on creating value from digital twins by embarking on discrete projects and solving for technology, architecture and organizational change management

HOW TO CREATE VALUE NOW AND PREPARE FOR DIGITAL OPERATIONS FOR TOMORROW

"Digital twins allow companies to improve a variety of business processes, whether its boosting production efficiency of a factory or optimizing the performance of products in the field. Digital twins also begin to position companies for the next dimension of computing that is spatial, interactive and intelligent."

- Walid Negm, Group Chief Innovation Officer, Altran

Introduction

Creating digital copies of physical products or facilities including software components allows for improved design considerations, realtime status transparency, greater visibility into parts and the balancing of production to quickly respond to supply chain disruptions as they occur. For example, in the automotive sector, PSA Group expects digital mockups of new designs to save 50% of product development costs between 2015 and 2020 by removing all physical work. Also, PSA is moving to virtual engine development, which eliminates the prototype phase and reduces cost by 30% over the same timeframe.[1]

Companies in almost every industry are looking to implement a holistic digital twin strategy where a "virtual backbone" that spans the entire product development life cycle, including production and manufacturing drives meaningful business outcomes. The objective is to:

- Drive faster, safer and more cost effective "virtual" validation of product functionality and accelerate the alignment of manufacturing to customer expectations
- Understand the impact of new designs and explore the consequence of changes to processes without disrupting customer operations
- Allow more accurate predictions and what if scenarios from usage (e.g., machine learning models) that can identify the cause of quality issues, anticipate performance failures, or optimize production output

A digital twin is a virtual model or representation of a system such as product design, process or a factory that can be used to understand performance better, improve processes or create revenue opportunities from services.

[1] https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/

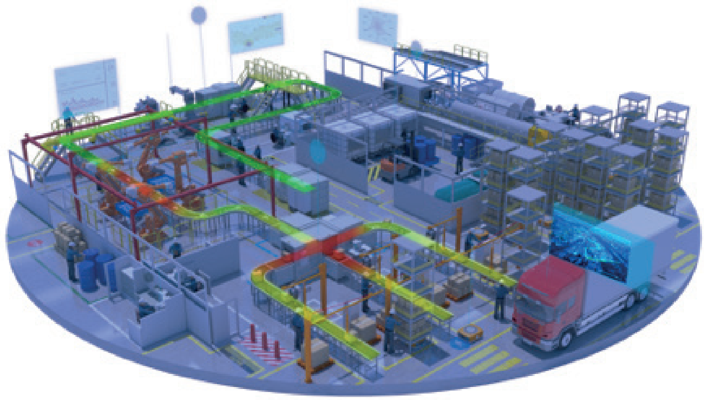

Figure 1: Example of Digital Twin

Digital twins allow companies to imagine a host of new and innovative services that tap in field data to provide valuable insights to customers. In 2019, Gartner ranked the digital twin model fourth in its top 10 strategic technology listing. Gartner estimated the size of the global digital twin market to be $6 billion across all industry sectors and forecasted the market to grow at a 40% CAGR to $16 billion by 2023.[2]

However, getting digital twins up and running and generating value needs management discipline, including:

- A clear vision of the expected business benefits and a realistic assessment of the costs involved
- A profound knowledge of the industry use case and operating domain
- Technology strategy and architecture that can be scaled to meet diverse requirements
- An understanding of new human machine interfaces to drive new ways of working

Whether standing up a twin of a production facility or a product, a virtual model will play an important role in the life cycle of the entity that it represents even if it does not match the physical lifecycle. (See Figure 2.) Thus, twins will typically have several possible states at any given times:

[2] https://www.gartner.com/smarterwithgartner/gartner-top-10-strategic-technology-trends-for-2019/

- **As designed,** representing the intended structure and performance of the real world entity
- **As built,** representing the output of the manufacturing and assembly process
- **As used and maintained,** representing the status of the physical object in operation

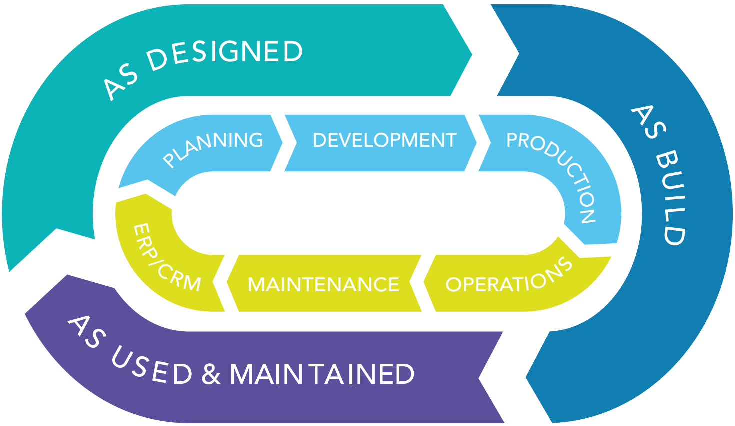

Figure 2: Digital twin life cycle

The optimal life cycle of a digital twin will depend on the expected benefits and use cases such as design time applications, production applications and operational applications. In turn, where a digital twin "operates" in a product lifecycle will have a significant impact on the effort and cost of creation. For example, maintaining the current state of an as used twin, particularly as maintenance is carried out, may prove to be difficult if there is a low degree of sensor deployment, real time connectivity or situational intelligence.

Low Hanging Fruit : Digital Twins in Manufacturing

There are many use cases in the manufacturing domain for which a digital twin is extremely useful. From our own industry experience, the most high impact in terms of expected returns include:

- **A digital twin** of a production process where operating parameters are mapped to expected outcomes to predict the performance. For example, a digital twin of a batch reactor production process can be used to:
  - Define the most appropriate conditions for maximum performance of the process (e.g., cycle time, first pass yield, etc.)
  - Implement continuous monitoring of the current parameter values to steer the variables in real time to effectively obtain the maximum performance. Real time data are required to build the model for this use case on top of historical data. Benefits include an increased production rate and better quality
- **A digital twin** of a manufacturing system to monitor (in real time) the status of production progress and make decisions about short-term scheduling and staffing. Benefits include increased utilization of assets and resources
- **A digital twin** of a manufacturing system to model the medium to the long term behavior of the system and generate "what if" scenarios (e.g., change in demand mix, production rates, etc.) to optimize the allocation of CAPEX and OPEX. Usually, only historical data is required to build the model. Benefits include optimized CAPEX and OPEX
- **A digital twin** of a production machine or line to evaluate, in advance, the interactions with other machines or operators, so that potential interference or ergonomic issues can be addressed in advance. Another application is to facilitate remote training of operators even when the line is not physically present at the site or not to disturb daily operations with training activities. Usually, no real time data is required; only the design model is needed. Benefits include shorter commissioning time and reduced time to competency for operators
- **A digital twin** of the operation of a machine or facility to anticipate modes of performance degradation and intervene with maintenance routines when applicable, including both predictive and on condition maintenance. Real time data, on top of historical data, is required to build the model. Benefits include increased machine availability and reduced maintenance costs

Activating the Organization to Adopt Digital Twins

A digital twin, as a virtual replica of reality with all its immediacy, offers all the richness and complexity of the real thing. There are at least six challenges that are associated with designing and ensuring an enduring digital twin:

Rising Complexity

A production line is a complex system with many undocumented, ad hoc behaviors and interactions between people, processes and machines across the value chain. The temptation is to reduce the scope of the digital twin model to reduce the complexity, but this will only lead to failure. The digital twin must be designed to cope with the complexity. Otherwise, the model will address only limited parts of the system and be of limited practical use.

Schinkelbruggen is one of the most complex movable bridges in the Netherlands, consisting of eight bridges carrying a highway, mainline rail and metro rail around Amsterdam. Because of the volume of human and goods traffic on the bridge at any given time, the bridge operator required a digital twin that adhered to a “right first time” approach to minimize risk. The solution was to develop an operational model that included simulation, a mock up of the operator’s screens and interactive 3D visualization. The simulation included both core and nominal behavior, allowing the user to explore the design, giving full coverage while testing the software. This approach allowed better training and organization of the operations team before the bridge was commissioned. The complexity of the digital twin was determined by stakeholder communities highway, water transport and two independent railways and by the bridge operator’s expectations of what “right first time” meant for a system that was yet to be built and so lacked critical behavioral data. This was addressed by developing a comprehensive system and environmental models, including interactive visualizations.

Inertia and Lack of Agility

The transactional systems often found in typical manufacturing processes share only enough information and context get the job done. This level of integration binds the systems to each other, making it difficult to change one system without also changing the others. Adopting the same approach for the digital twin will add even more restrictions and layers of complexity that will make it even more cumbersome to drive any form of positive change. What is required is a platform that supports the plan do check act (PDCA)[3] process of continuous improvement that will drive lean, agile manufacturing.

- A major manufacturer of gas turbine engines collected, selected and analyzed data from aircraft engines that allowed it to develop predictive maintenance regimes based on the operational behavior of the physical engines. These capabilities extended from the development of certification grade software for onboard monitoring units to the preparation of fleet maintenance reports.

- A health monitoring technology of complex systems has evolved rapidly in recent years. Model and data requirements for accurate predictions are driven based on experience and the requirement that features deployed can be changed frequently. One healthcare company deployed a modular architecture for the customer that allowed configurations to be defined and developed in an agile manner.

An Incomplete Picture

The data needed for a digital twin project is often unavailable, inaccessible, of poor quality or a combination of all three. Data models are often incompatible or do not exist in a digital format. These data challenges lead to long drawn out digital twin roadmaps, as strategies are created to massage the data into usable and standardized formats and implement sensor strategies. These delays can take years to address, which in turn delays the creation of a digital twin and results in a competitive disadvantage. There are proven ways to accelerate the process of improving the volume and quality of data.

One example is a reaction vessel modeling approach that a chemicals company used to improve its access to usable data. The problem the company faced was that batch efficiencies for a new product were wildly variable. Without suitable industrial standardization, the product could not be brought to market profitably. To address this challenge, the company implemented analytical models of chemical reaction rates as functions of the physical environment. It created a reactor wide model to determine the variables that had a major influence on batch wide efficiency. A unique electro optical sensor was procured and customized that allowed data to be collected for verification. The collected data were then analyzed using a wide range of techniques to identify the cause of batch variability and the company introduced operational modifications that rectified the issue.

[3] PDCA – Plan, Do, Check Act, W. Edwards Deming (https://en.wikipedia.org/wiki/PDCA)

The challenge of identifying and obtaining the necessary data was addressed by the creation of the fundamental scientific model, targeting the business requirements of improved efficiency, and procuring a custom sensing solution to collect verification data. These three actions provided adequate data to allow the final analysis to proceed.

Identification of Data and Codifying Relationships

To manage complex integration requires making sense of multisource, multiformat data and correlating it to other data where there is no obvious link. A traditional approach is to code the relationships through logic. Unfortunately, it is only possible to code a limited number of obvious direct correlations, which do not adequately capture the complexity of reality. The alternative to manual coding is to train machine learning (ML) and artificial intelligence (AI) algorithms on the data.

However, this only solves one aspect of the problem, such as correlating causal events, to adopt predictive maintenance. AI and ML do not provide a way to understand the business or shape the outcomes by adjusting the inputs, all of which are critical aspects of a digital twin solves one aspect of the problem, such as correlating causal events, to adopt predictive maintenance. AI and ML do not provide a way to understand the business or shape the outcomes by adjusting the inputs, all of which are critical aspects of a digital twin.

A real world example of managing complexity is the Train Automatic Performance Analysis System (TAPAS), used by commuter rail services that demand high reliability of their trains. For example, Southern, a railway operating company in the UK was experiencing train cancelations and penalties due to in service failures of door mechanisms. Southern utilized a team of data science experts that leveraged statistical techniques, including ML models, of the real world equipment driven by data collected from the trains which allowed Southern to identify potential failures before they occurred. As a result, Southern was able to optimize maintenance and achieve a 63% reduction in delays, a 66% reduction in cancellations and a 50% reduction in the depot effort required for maintenance.

In another example, a life sciences company had a problem with a centrifuge that was prone to catastrophic failures, which resulted in costly batch losses. The failures were attributed mainly to a lack of understanding of the system behavior. To understand the causes of the failures, an analytics team examined all centrifugal data, including test, production and cleaning cycles. Using the data, the team deduced the cause of failure was overshadowed by the noise of the production data but was apparent in simpler cycles of testing and cleaning. The underlying challenge of obtaining enough data to identify the problem was resolved by taking a sufficiently general definition of the data that included testing and cleaning cycles. A predictive analysis model was developed that could identify centrifuges that were likely to fail during subsequent production runs, which allowed rectification of the problem before a production run. The team was able to eliminate failures in production runs, which saved the customer millions of dollars.

Maintaining Up to date Information

Creating a one time model of a physical asset is just one part of the process of building a digital twin. It is necessary to ensure that the digital model is supplied with sufficiently accurate and timely data about the real world for it to remain useful and make accurate predictions. There are several points at which data continuity must be established and maintained, including during design and manufacturing to capture the design intent of the asset and as built conditions. This is addressed by using the digital continuity approach that starts with the creation of information flows through the design and manufacturing processes based on a common, synchronized set of models, rather than the cumbersome transfer of limited data from system engineering to manufacturing to the shop floor to enterprise planning silos.

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One example of a successful digital continuity approach is a collaboration of major tool vendors, including Dassault Systèmes and Siemens, that together with enterprise level customers integrated digital design data onto platforms such as 3DExperience and Teamcenter. In operations, traditional data collection may be insufficient to support the predictive models. Data from many sources such as engineering and enterprise IT, shop floor systems and live sensors must be continuously captured and integrated while respecting the security and integrity requirements attached to each. Modern network platforms can achieve the integration needed but require configuration for the data sources used by an enterprise.

In the transition phase to the digital twin model which requires evolving configurations and changing technologies within the life of a facility or asset it is unsafe to assume that a database schema developed during product design will remain applicable. Adaptable data architectures support this evolution, such as the Altran Scalable Elastics Knowledge Graph (SEKG). Statistical techniques and models can be used to estimate parameters that cannot be directly observed and replace them with approximations or ghost data.

An Airbus team developed a digital proof of concept for an industry 4.0 production environment dubbed Deep Tech Sparkle with full end to end digital representation and monitoring of a factory of the future. The platform supports comprehensive real time data integration from IT systems (ERP and MES), shop floor systems (PLC and SCADA) and IoT devices. It supports applications in monitoring and altering, predictive maintenance and virtual reality training, which allows Airbus to embrace a fully agile production methodology. Data flexibility is provided by a plug and play interface for analytics tools, and the standards compliant IoT platform that can interface with many different technologies, such as an EEG helmet, virtual reality tools and IoT analytics for customized early warning systems.

The challenge of maintaining and updating a complex model such as an entire digital factory arises from the volume and diversity of data that needs to be captured. The solution framework provides both a highly scalable data architecture and a flexible data capture mechanism, including an IoT platform.

Mindset

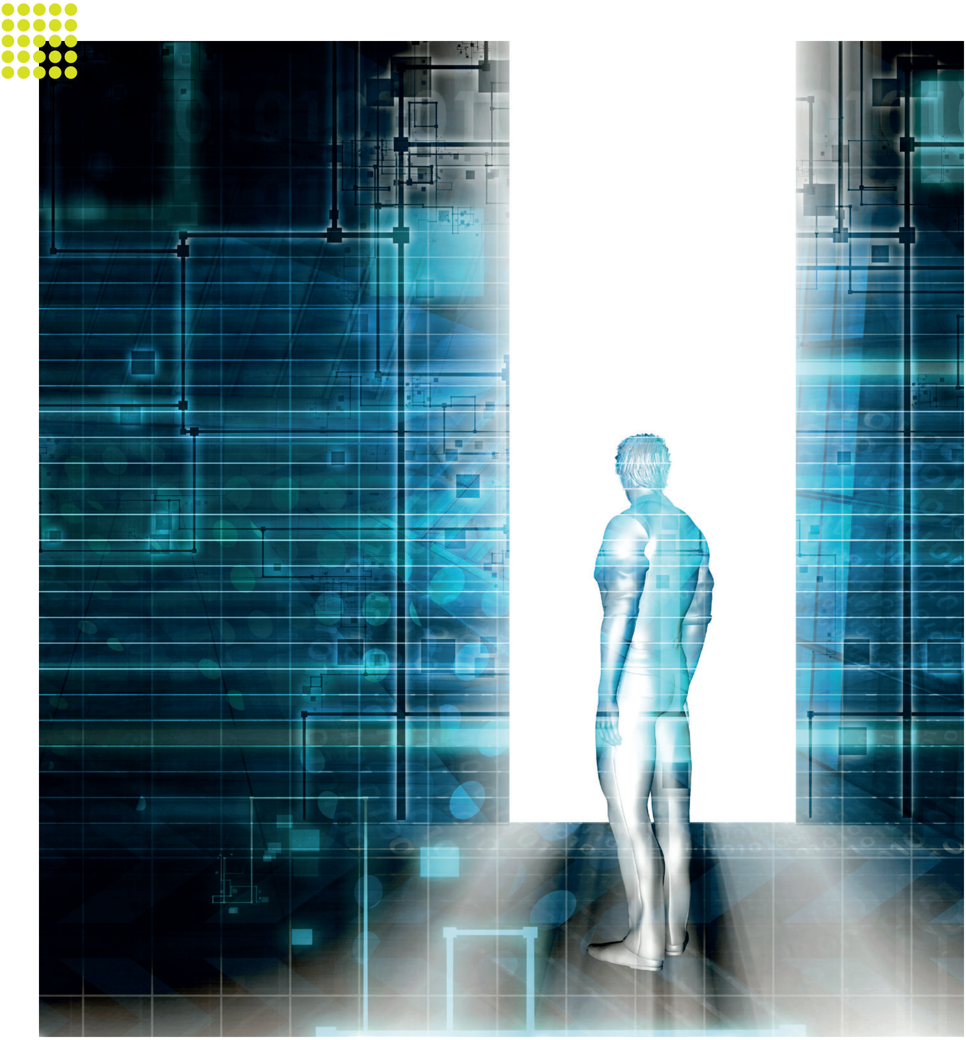
The implementation challenges described above demand a completely different architecture and an entirely different business mindset compared to the traditional model. The conventional mindset relies on:

- Taking a reductionist approach to minimize complexity
- Using a traditional integration approach for the main systems, which increases inertia and reduces agility
- Coding the relationships between the different datasets which creates gaps and cannot manage dynamic, constantly changing relationships

Conversely, the digital twin mindset is based on:

- Data that is not owned but shared
- Shifting from transactional systems and processes to cooperative systems and processes
- Intelligence that is developed incrementally and contributes to value creation
- Asset life cycle management that is both process centric and data centric

Consequently, change management and corporate culture reform needs to be part of the process on the journey to developing and implementing digital twins as they address the vitally important issue of transforming the organizational mindset.



An Agile and Trustworthy Digital Backbone

Companies are aware they must be able to adapt operations across all business processes to account for changing customer expectations. This requires consistently engaging with customer satisfaction data and link the feedback and reviews to adjust manufacturing processes. The enterprise's internal processes from marketing to innovation and design to production must be closely aligned with the customer's journey so they can share information back and forth quickly and fluidly.

From an organizational perspective, it should be possible to view and assess various internal processes from different vantage points. In this context, a digitals twin can be visualized as covering many of the enterprise's value streams, from production to maintenance and operation and include marketing and sales. (See Figure 3.)

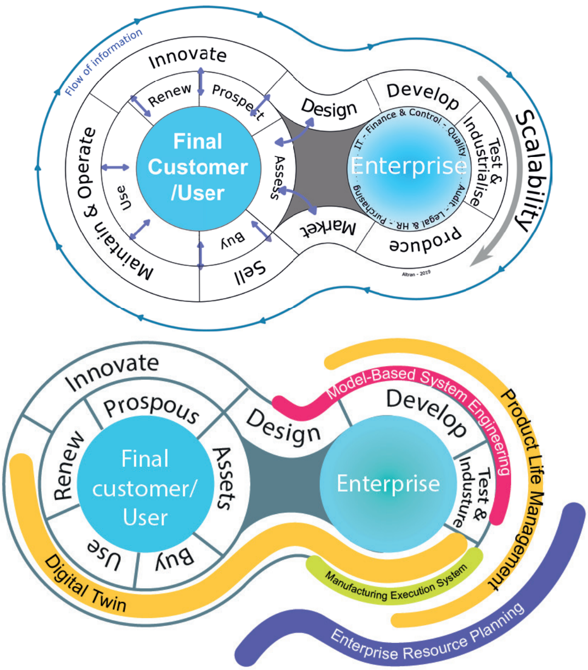


Figure 3:Digital Continuity and the place of digital twin

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Adopting a thoughtful digital twin architecture can help deal with roadblocks and challenges. For example, any delay in retrieving and processing data to provide insights will lead to a time lag in visual display, hampering the benefits of the digital twin. The architecture must also be able to deal with data heterogeneity, redundancy, interoperability and dataset evaluation to ensure the digital twin becomes scalable, open, flexible and robust.

The key building blocks for a digital twin architecture include:

- **Connectivity and Networks**: The ground truth for a digital twin is only possible by putting in place a means to connect customers with products and assets. A digital twin network feeds on sensor data and requires connectivity as well as a robust "data harvesting" strategy. For example, traversing IoT devices to feed operational data into models that can accurately replicate real world scenarios in a virtual environment
- **Data Intelligence**: This requires a data management strategy that helps transform raw data into insights based on customer and stakeholder needs. An AI based data science DevOps model is critical to ensure trust, especially in critical, complex systems. For example, an effective data management strategy in the TAPAS project helped the team build the right statistical models using the data collected from the trains. It allowed the train company "Southern" to identify potential failures before they occurred and take preventive actions for maintaining high availability of the train services
- **Simulation**: This is the process of modeling using physics, math and ML models so issues can be debugged without affecting physical systems. For example, advanced simulation can help chemicals company determine chemical reaction rates, understand the underlying cause of batch variability and remediate the issue of batch efficiencies, which can bring products to market cost-effectively
- **Human machine interfaces**: This requires the use of digital technologies such as augmented and virtual reality (AR and VR), mobile, etc. to increase efficiency and enhance the way one visualizes and interacts with processed information. For example, VR was used as a human machine interface for an Airbus virtual factory project, which provided an immersive experience for factory personnel to remotely interact with the industrial environment As the digital twin is a virtual representation of physical components and processes, it is critical to adopt the appropriate computational and representational model. This model is built upon three different channels, or pipelines, for transmitting the data:

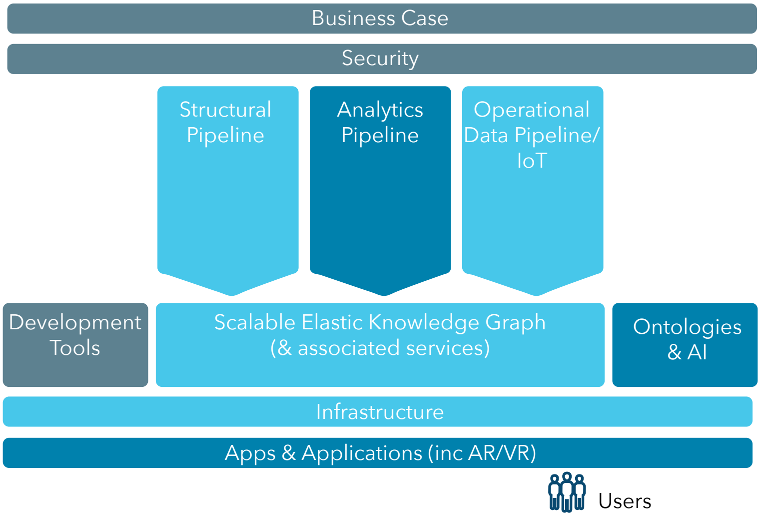


Figure 4:Digital twin high-level architecture diagram

Structural Pipeline

Representation of a real world physical model into a virtual world with 3D data obtained by various tools and modeled in the digital twin editor after processing. These models help replicate real world scenarios to understand and solve real world problems.

Analytics Pipeline

Representation of business processes that help predict and mitigate risk beforehand without impacting the business.

Operational Data Pipeline

Computation of operational data gathered from various sources that are monitored using dashboard visualization that forecasts and detects anomalies using ML to generate alerts so that preventive actions can be taken proactively.

Finally, the infrastructure that functions as the plumbing and runtime environment should be a microservices based architecture that provides interfaces for transactional systems, a query interface for users and support for digital twin applications that deliver a seamless experience for users connected via AR and VR devices.

A Roadmap to capture Value from Digital Twins

The first step in launching a digital twin network is simply getting it up and running. Once in place, it not only reflects the physical world but can "see" into potential future scenarios to anticipate issues and complications. Actions can be taken preemptively to manage dynamic, day to day events such as supply chain disruptions, machine failures, urgent orders and unanticipated customer requirements.

To codify the often complex system of interactions between people, tools and process require a process or methodology to quickly and effectively make sense of what companies already possess (i.e., data) and leverage what they already know (i.e., processes and knowledge) by using ontologies and intelligent automation through machine learning. An example of such a methodology is the Collect, Localize, Organize, Network and Engage (CLONE) process:

- **Collect**: Workshops with subject matter experts in business and IT identify data sources and how they can collect the data. The data combines structural data (e.g., CAD, BIM, GIS and company structures) with process data (e.g., ERP, MES and CRM) and sensor and control data (e.g., IoT, SCADA and PLCs). Importantly, it is not necessary to start by collecting all the different types of data. There is no specific place to start. Instead, an additive approach works best, where the readily accessible data is collected and other data can be added later. Strategies can be explored for dealing with data that is not available using 3D scanning, implementing additional sensors and using algorithms to extrapolate or create ghost data. Through one on one interviews, teams can codify what the subject matter experts know into ontologies, keeping the impact on both business and IT to a minimum

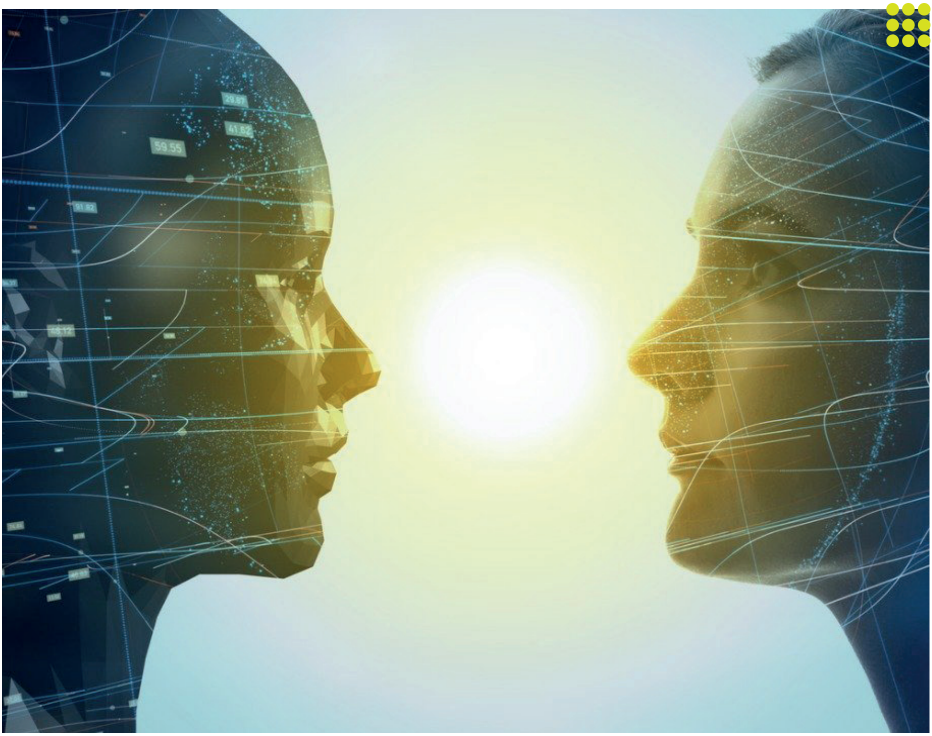
- **Localize:** This requires the automated ingestion and correlation of data from all sources using industrial strength tools that handle vast quantities of data. AI uses the ontologies to break down and combine the data from all the sources into the SEKG to make the initial version of the digital twin. The target is to produce early visualizations to play back to business stakeholders so they can see a reflection of what they see in the physical world

- **Organize:** This requires the team to work iteratively to finalize and apply the various ontologies to the data. The process automatically structures the digital twin to reflect the complexity of the entire system while enabling powerful visualization systems and hiding the complexity. Agile methods can be used to produce digital prototypes to meet the use cases. The business stakeholders can see reality and understand why they see it

- **Network:** This step brings together all the components of the digital twin online. It initiates live data processing and establishes user interfaces with the production of the minimum viable product (MVPs) to satisfy the use cases and objectives using agile approaches

- **Engage:** The final phase scales the digital twin to include the whole organization as part of the digital transformation

The ability to capture the full complexity of interactions between product, processes and people and to codify the relationships between datasets is not an easy task. Also, cultural challenges must be addressed. Companies should focus on "what they have" and "what they know" to drive the implementation process that provides a clear roadmap for designing, implementing and running a digital twin, while considering the existing context and objectives of the user.



The Future of Digital Twins

The digital twin as an "operating model" will continue to proliferate and is expected to become a critical and mainstream part of manufacturing soon. By the end of 2020, IDC projects that 65% of manufacturers will be using simulation and digital twins to operate products and assets, reducing the cost of quality defects and service delivery by up to 25%. [4]

Today, there are many startups, such as Twaice[5] and Cognata[6], innovating in the automotive sector. Twaice uses digital twins to create the future of mobility by increasing battery life and reliability while reducing development and testing costs. Cognata relies on digital twins for autonomous driving and ADAS simulation.

Figure 5 depicts a subset of emerging technologies that will likely influence the adoption rate and progression of digital operating models.

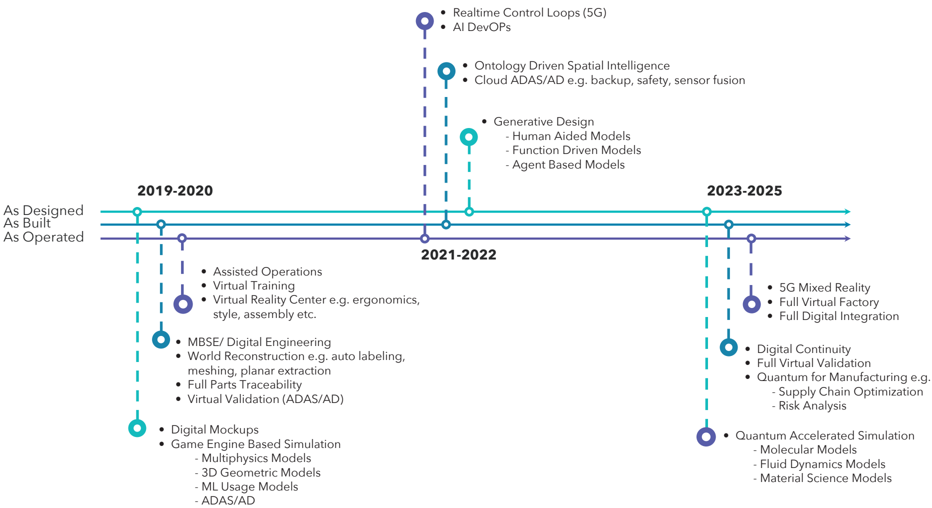


Figure 5 : Future Technologies for Digital Twin

[4] https://www.idc.com/research/viewtoc.jsp?containerId=US43153217
[5] https://twaice.com/
[6] https://www.cognata.com/

The following are several examples of technology trends shaping the future of digital twins:

- **Virtual validation** is an approach that engineers and designers use to place a replica of a product "under test" to meet regulatory requirements, quality assurance or functional safety. The use of virtual validation is growing in the automotive industry as automakers seek to test new digital technologies in electric and autonomous vehicles. Estimates from Toyota indicates that 8.8 billion miles of testing would be required to validate autonomous vehicles, which is impossible.[7] Instead, automakers are combining virtual (i.e., totally computer simulated), semi virtual (i.e., real vehicles in a simulated environment) and physical (i.e., normally driving) for validation of autonomous vehicles
- **Generative design** is gaining popularity and will define how future digital twins are created and deployed. For example, Airbus already uses generative design to explore thousands of variations for the partitions that divide airplane cabins. In one case, the design was half the weight of the previous design, which saved millions of dollars in fuel costs while continuing to meet safety requirements. The new design also proved to be stronger and performed better than the heavier original design that had flown for decades[8]
- **AIDevOps** is all about composing and deploying decision models from training data in an automated way. It is in the same paradigm as software continuous integration (CI) and continuous deployment (CD) methodologies. And a digital twin whether a multi physics simulation, what if scenario using ML, or an edge inference requires a disciplined approach for version control and production deployment. The emergence of AIDevOps tools allows engineers to take models into production across multiple compute targets and ensure simulations and predictions are running the latest model versions. The "digital heart twin," developed by Siemens Healthi-neers, is one example of how medical device makers are using AI to help doctors make precise diagnoses as medicine enters an increasingly personalized age.[9] This solution will need AIDevOps to scale and make it available for a large number of patients in the future. AIDevOps is also known as AutoML. Leading public cloud providers such as Microsoft Azure and Google GCP offer various AutoML capabilities as a service as part of their AI toolkits[10]
- Quantum computing is not yet enterprise ready, but the technology is moving forward at a rapid pace and is expected to be available in mainstream models within five years. In an early quantum computing application, Biogen has developed a first of its kind quantum enabled molecular comparison application in collaboration with Accenture and 1Qbit, a quantum software firm, that could significantly improve the advanced molecular design and speed up drug discovery for complex neurological conditions such as multiple sclerosis, Alzheimer's, Parkinson's and Lou Gehrig's Disease[11]

[7] https://www.forbes.com/sites/alanohnsman/2016/10/03/toyotas-robot-car-line-in-the-sand-8-8-billion-test-miles-to-ensure-safety/#475aa43116f0
[8] https://www.autodesk.com/redshift/bionic-design/
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[11] https://www.linkedin.com/pulse/quantum-computing-solving-difficult-problems-life-new-anne-o-riordan/

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About Altran

Altran ranks as the undisputed global leader in Engineering and R&D services (ER&D), following its acquisition of Aricent.

The company offers clients an unmatched value proposition to address their transformation and innovation needs. Altran works alongside its clients, from initial concept through industrialization, to invent the products and services of tomorrow. For over 30 years, the company has provided expertise in aerospace, automotive, defense, energy, finance, life sciences, railway and telecommunications. The Aricent acquisition extends this leadership to semiconductors, digital experience and design innovation. Combined, Altran and Aricent generated revenues of €2.9 billion in 2018, with some 47,000 employees in more than 30 countries.

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