DIGITAL TWIN

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CERTIFICATE

This is to certify that this is a bonafied report on the seminar titled

DIGITAL TWIN

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during the year 2020-2021 in partial fulfilment of the requirements for the award of the degree, ***BACHELOR of TECHNOLOGY*** *in* ***MECHANICAL ENGINEERING*** *under A.P.J Abdul Kalam Technological University.*

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ABSTRACT

A digital twin is a digital representation of a physical object, process or service. The concept originated earlier the first practical definition of digital twin originated from NASA in an attempt to improve physical model simulation of spacecraft in 2010. Digital twins are the result of continual improvement in the creation of product design and engineering activities. Product drawings and engineering specifications progressed from handmade drafting to computer aided drafting/computer aided design to model-based systems engineering.

A digital twin can be a digital replica of an object in the physical world, such as a jet engine or wind farms, or even larger items such as buildings or even whole cities. As well as physical assets, the digital twin technology can be used to replicate processes in order to collect data to predict how they will perform. A digital twin is, in essence, a computer program that uses real world data to create simulations that can predict how a product or process will perform. These programs can integrate the internet of things (Industry 4.0), artificial intelligence and software analytics to enhance the output. With the advancement of machine learning and factors such as big data, these virtual models have become a staple in modern engineering to drive innovation and improve performance. The concept of digital twins is not exactly new – it was first presented by Dr Michael Grieves in 2002, and, prior to that, NASA had been using complex simulations of spacecraft for decades. But thanks to the explosion of the internet of things (IoT), and the subsequent lowering costs of associated technologies, digital twins are now more accessible than ever.

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ABBREVIATIONS

DT	Digital twin
IP	Internet protocol
AI	Artificial Intelligence
VR	Virtual reality
AR	Augmented reality
IoT	Internet of Things

CHAPTER 1

INTRODUCTION

The concept of digital twins is not exactly new – it was first presented by Dr Michael Grieves in 2002, and, prior to that, NASA had been using complex simulations of spacecraft for decades. But thanks to the explosion of the internet of things (IoT), and the subsequent lowering costs of associated technologies, digital twins are now more accessible than ever.

A digital twin is a virtual representation of a real-life object or device. If you think that sounds a lot like 3D renderings of computer-aided design (CAD) models, you'd be right. But where digital twins differ crucially from simple 3D models is that they also combine the physical elements and the dynamics of how that object or device operates in the real world. In other words, you can see, almost in real time, precisely how an object or device responds throughout its lifecycle. Just as an asset drifts in response to factors like the weather, the ambient temperature, operator idiosyncrasies, and so forth, so too does its digital twin.

Digital twins do this by combining data collected from sensors on the device, with knowledge related to the design, build, operation and servicing of the physical twin. Already, just from this data, you have a rich, highly detailed picture of the asset. Intelligence, in the form of analytics, physics, and machine learning, is then built on top of the data, acting as the "brain" of the digital twin, and making things like predictive modelling, optimization and early warning systems possible.

1.1 IMPORTANCE OF DIGITAL TWIN TECHNOLOGY

Digital twins are powerful technologies to drive innovation and performance. It is the most important product for technicians with the most advanced monitoring, analytical, and predictive capabilities at their fingertips. Its estimated that by 2018 companies who invest in digital twin technology will see a 30 percent improvement in cycle time of critical processes. Over the next five years, billions of things will be represented by digital twins. These representations of the physical world will lead to new collaborations and opportunities among physical world product experts and data scientists whose jobs are to understand what data tell us about operations. Digital twin technology help companies improve the customer experience by better understanding customer needs, develop enhancements to existing products, operations, and services, and can even help drive the innovation of new business.

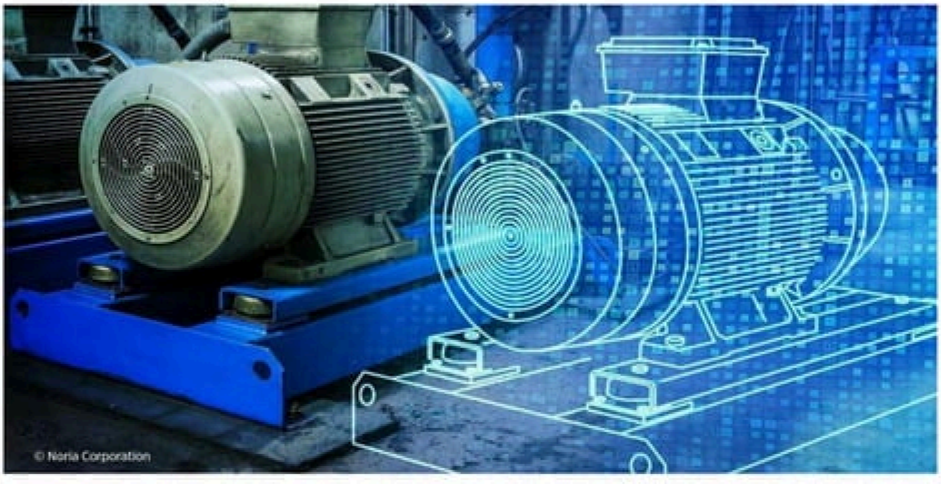
1.2 ESSENTIAL COMPONENTS OF A DIGITAL TWIN

Analytics at every step: A digital twin deals with a staggering amount of data, and its effectiveness is reliant on whether this data is:

- real-time,
- operational,
- high-quality, and
- predictive-orientated in its nature.

Open and federated data: The data has to be accessible from several sources, and be pulled together into a federated model, rather than being centralized in proprietary systems.

Applied industry context: Applying industry context is essential to getting maximum value out of a digital twin. In fact, it is possible to have two different digital twins for the same product that is being used in two different industries, because of how the industry context is applied to the twin.



CHAPTER 2

LITERATURE SURVEY

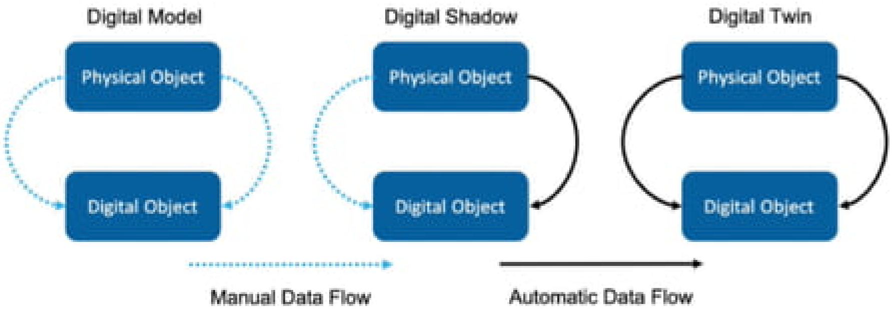
Since Dr. Grieves presented the concept, and NASA gave the first specific definition, large number of literatures regarding digital twin have been published, including six reviews. Holler et al. analyzed 38 articles. The review results provided an overview of established concepts, classified the existing body of literature, provided a lifecycle perspective on applications, and suggested directions for further research. Negri et al. conducted a comprehensive literature review to answer two questions: 'How does scientific literature define the digital twin?' and 'What role does it play in Industry 4.0?'. The review presented three possible uses of digital twin: analyzing health conditions to plan maintenance activities, managing the whole lifecycle of the physical object, and improving decision-making through engineering and numerical analysis. Krit- Zinger et al. reviewed digital twin in manufacturing from a categorical perspective. To clarify integration level of digital twin in existing researches, the author proposed three subcategories of digital twin according to data integration levels. The classified subcategories were Digital Model, Digital Shadow, and Digital Twin. Tao et al. reviewed the state-of-the-art of the digital twin researches thoroughly. The authors focused on the key components, the up-to-date development, and the major applications of digital twin in industry. They divided the development trend of DT research into three stages, which is formation stage (2003–2011), incubation stage (2011–2014), growth stage (2014-now). The paper reviewed the most relevant theories: (1) DT modeling, simulation, verification, validation, and accreditation (VV&A), (2) data fusion, (3) interaction and collaboration, and (4) service. Liu et al. compared and analyzed the DT models in the scientific publications. Digital twin models were retraced from the initial one to the most up-to-date one to find some principles of DT modeling. The paper reviewed relevant information on DT models according to the application purpose, model level, and model representation. For the analysis of Digital Twin applications, Enders and Hoßbach proposed a classification scheme with six dimensions to describe the applications identified. The six dimensions include industrial sector, purpose, physical reference object, completeness, creation time, and connection.

CHAPTER 3

DIGITAL TWIN MISCONCEPTIONS

1) Digital Model

A digital model is described as a digital version of a pre-existing or planned physical object, to correctly define a digital model there is to be no automatic data exchange between the physical model and digital model. Examples of a digital model could be but not limited to plans for buildings, product designs and development. The important defining feature is there is no form of automatic data exchange between the physical system and digital model. This means once the digital model is created a change made to the physical object has no impact on the digital model either way. Figure. illustrates a Digital Model.



2) Digital Shadow

A digital shadow is a digital representation of an object that has a one-way flow between the physical and digital object. A change in the state of the physical object leads to a change in the digital object and not vice versus. Figure illustrates a Digital Shadow.

3) Digital Twin

If the data flows between an existing physical object and a digital object, and they are fully integrated in both directions, this constituted the reference "Digital Twin". A change made to the physical object automatically leads to a change in the digital object and vice versa. Figure illustrates a Digital Twin.

These three definitions help to identify the common misconceptions seen in the literature. However, there are several misconceptions seen but they are not limited to just these specific examples. Amongst the misconceptions is the misconception Digital Twins have to be an exact 3D model of a physical thing. On the other hand, some individuals that think a Digital Twin is just a 3D model.

CHAPTER 4

HOW DOES DIGITAL TWIN WORK?

Digital Twin is a complex system that produces tremendous amount of data. All of this data from devices is descriptive in nature. That is, the data tells you what happened and when it happened. Using data analytics, you can exploit this data to be predictive and tell you when something will happen like a failure, for instance. In contrast, digital twin which is basically a virtual representation of the process, product or system will allow you to improve them to avoid a failure. Digital Twin technology integrate AI, software analytics and machine learning data to create a digital simulation models that update and change as their physical counterparts' change. This near real-time update and continuous learning from multiple sources represent the status, working condition or position of the physical asset. Digital twin contains sensors that collect data to represent real time data of the physical asset. The sensor data is collected, analyzed and used in predictive analytics by the digital twin to optimize the product's performance via a maintenance regime. Digital twin technology offers an interface that makes organizations familiar to past and present operation, and helps them to make predictions of the future. Various data sources contribute to the digital twins learning curve. This model learns from the historical data from past machine usage, processes, or system usage, from humans with relevant domain knowledge, from other sources.

4.1 STEPS TO IMPLEMENT DIGITAL TWIN MODEL

While it may seem easy to list out the steps to implement digital twins, it requires a lot of practical realities to make this possible. Businesses must check on the existing infrastructure, policies, organizational wide attitude, budget, and other mandatory requirements. There are four practical steps to get started with digital twin implementation

- Integrate smart components into new or existing products.
- Connect the products/services to a central (cloud-based) location with streaming, big data, in-memory, and analytic capabilities to capture sensor data and enrich it with business and contextual data.
- Constantly analyze the data to identify areas for improvements, new products

or even new business models.

- Use digital insights to create new services that transform the company.

CHAPTER 5

CREATING A DIGITAL TWIN

The creation of digital twin involves the following steps:

1. Create: The create step encompasses outfitting the physical process with myriad sensors that measure critical inputs from the physical process and its surroundings. The measurements by the sensors can be broadly classified into two categories:

• operational measurements pertaining to the physical performance criteria of the productive asset (including multiple works in progress), such as tensile strength, displacement, torque, and color uniformity;

• environmental or external data affecting the operations of a physical asset, such as ambient temperature, barometric pressure, and moisture level.

The measurements can be transformed into secured digital messages using encoders and then transmitted to the digital twin. The signals from the sensors may be augmented with process- based information from systems such as the manufacturing execution systems, enterprise resource planning systems, CAD models, and supply chains systems. This would provide the digital twin with a wide range of continually updating data to be used as input for its analysis.

2. Communicate: The communicate step helps the seamless, real-time, bidirectional integration/connectivity between the physical process and the digital platform. Network communication is one of the radical changes that have enabled the digital twin; it comprises three primary components: Industry 4.0 and the digital twin

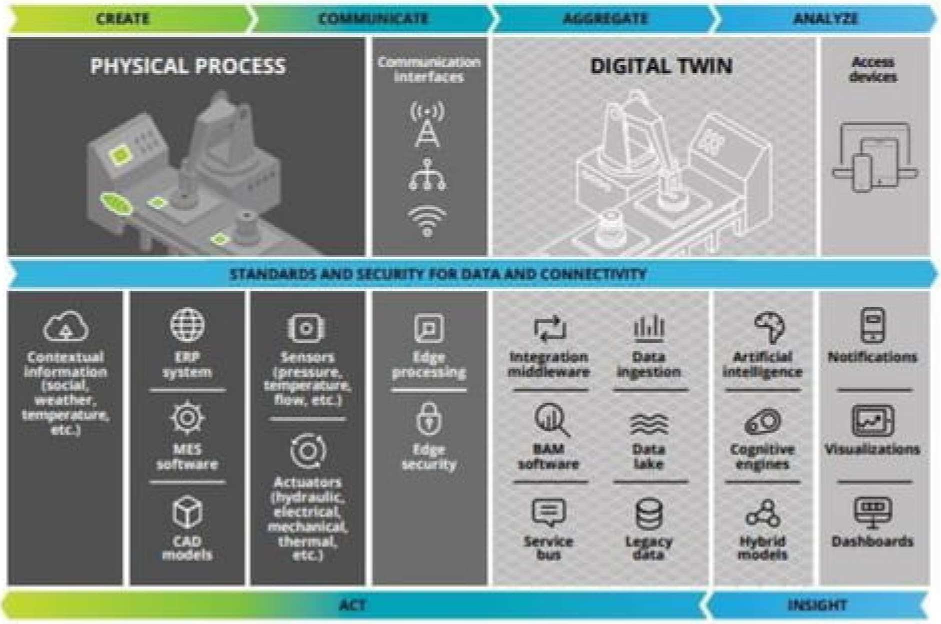
• Edge processing: The edge interface connects sensors and process historians, processes signals and data from them near the source, and passes data along to the platform.

• Communication interfaces: Communication interfaces help transfer information from the sensor function to the integration function.

• Edge security: New sensor and communication capabilities have created new security issues, which are still developing. The most common security approaches are to use firewalls, application keys, encryption, and device certificates. The need for new solutions to safely enable digital twins will likely become more pressing as more and more assets become IP enabled.

3. Aggregate: The aggregate step can support data ingestion into a data repository, processed and prepared for analytics. The data aggregation and processing may be done either on the premises or in the cloud. The technology domains that power data aggregation and processing have evolved tremendously over the last few years in ways that allow designers to create massively scalable architectures with greater agility and at a fraction of the cost in the past.

4. Analyze: In the analyze step, data is analyzed and visualized. Data scientists and analysts can utilize advanced analytics platforms and technologies to develop iterative models that generate insights and recommendations and guide decision making.



5. Insight: In the insight step, insights from the analytics are presented through dashboards with visualizations, highlighting unacceptable differences in the performance of the digital twin model and the physical world analogue in one or more dimensions, indicating areas that potentially need investigation and change.

6. Act: The act step is where actionable insights from the previous steps can be fed back to the physical asset and digital process to achieve the impact of the digital twin. Insights pass through decoders and are then fed into the actuators on the asset process, which are responsible for movement or control mechanisms, or are updated in back-end systems that control supply chains and ordering behavior—all subject to human intervention. This interaction completes the closed loop connection between the physical world and the digital twin.

The digital twin application is usually written in the primary system language of the enterprise, which uses the above steps to model the physical asset and processes. In addition, throughout the process, standards and security measures may be applied for purposes of data management and connectivity

CHAPTER 6

DIGITAL TWIN MATURITY MODEL

The maturity model for digital twins depends on the level of information that's known about a physical asset and its environment. This model shows that the digital model improve over time as more derivative information is accumulated. The recorded data and its storage intimates about the asset's current state and condition the level of Digital Twin maturity model include:

a) Partial

•At this level, the digital twin typically contains a limited number of data sources such as pressure, temperature and device state.

•The twin is useful to capture a key metric or state from a low power or resource-constrained asset, such as a connected light bulb that simply reports its current power state.

•This level is also seen in proof-of-connectivity development, as it enables quick development of device-to-platform functionality.

•This level contains enough data sources to create derivative data for further analysis. For example, if pressure is down but temperature is up, and linear regression identifies a correlation, a corresponding inference about the health of the asset can be made.

b) Clone

•This form of a digital twin contains all meaningful and measurable data sources from an asset.

•This level is applicable when a connected asset is not power or data constrained.

•This level is useful in prototyping and data characterization phases of IoT development.

c) Augmented

•The augmented digital twin enhances the data from the connected asset with derivative data, correlated data from federated sources, and/or intelligence data from analytics and algorithms.

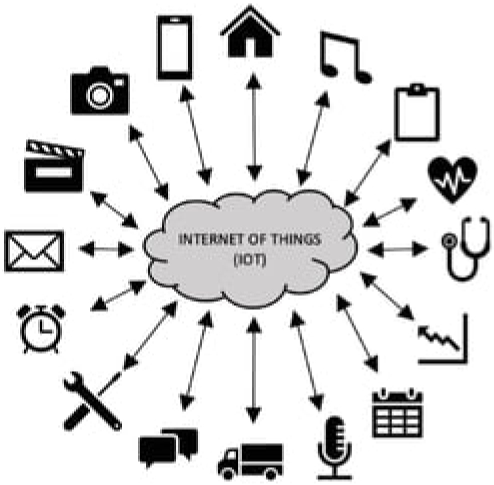
CHAPTER 7

UNDERLYING TECHNOLOGIES

The technologies which enable digital twin technology are given below

7.1 Internet of Things (IoT)

The Internet of Things is the term given to devices connected to the internet. It is about giving so-called "things" a sense of intelligence and the ability to collect information on their environment. The idea that all devices that are interconnected gives the developer the ability to track and monitor everything we do, thus leading to a smarter world. The number of IoT devices recorded year on year shows the considerable growth of this technology



7.2 Data Analytics

The term data analytics stems from the field of "Data Science", a multidisciplinary subject that covers a range of concepts, with an emphasis on collecting and presenting data for analysis to gain greater insight. To perform data analysis, the need for raw data is paramount. There are several actions needed to turn this data into usable information, ready for use in algorithms and statistical analysis. These being the requirements, collection, processing and cleaning. The requirements set out the necessary needs of the data and how it is used, ensuring that specific requirements are outlined, considering the intended use of the data. The second stage acts on the requirement of collecting the relevant data, identifying physically where and how the data

will be collected. The collected data will then go through a processing phase in which it is sorted according to specific requirements. The final phase and arguably the most important is the cleaning of data. Despite the data being collected and sorted, it may have significant gaps or erroneous data. This cleaning phase uses the imputation methods, previously identified as challenges to data analytics. These methods ensure that no missing data exists

7.3 Statistics

Statistics is the overarching term for the collection, classification, analysis, and interpretation of data. Briefly relevant in this case for data analysis as statistical models underpin machine learning algorithms. Statically inference and descriptive statistics are another way in which data analytics are used to describe observations in collected data. AI and the following topics below show the growth of advanced data analytics

7.4 Artificial intelligence

Artificial intelligence (AI) is a wide-ranging branch of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence. AI is an interdisciplinary science with multiple approaches, but advancements in machine learning and deep learning are creating a paradigm shift in virtually every sector of the tech industry. AI programming focuses on three cognitive skills: learning, reasoning and self- correction.

7.5 Machine Learning

A subsection of AI, machine learning is the creation of algorithms that can give the computer the ability to learn and act for the user without being directly programmed to do so. Machine learning is used to create programmes that use sophisticated algorithms to collect and analyze data autonomously. For more general analysis, machine learning can fit into two types of learning:

a) Supervised Learning This is the most popular form of machine learning. The algorithms use large amounts of labelled data to analyze and learn. The algorithm is tasked with learning and analyzing the labelled data to identify a given task correctly; image classification is one example. The algorithms learn from training data and are then given test data to see how well it is accurately predicting what an image is showing, presented through an accuracy percentage. The user then analyses these answers and any errors are corrected and re-learned, helping train the model and increasing the accuracy of a given algorithm

b) Unsupervised Learning Unsupervised learning is another form of machine learning, it does not require expensively marked-up data where for each input pattern the desired output has previously been determined: as is required for supervised learning Unsupervised learning algorithms learn using its own methods in categorizing and highlighting patterns within data instead of relying on user feedback. Clustering is one method of categorizing data. Algorithms learn to cluster unlabeled data sets together, potentially showing hidden patterns that were not explicitly identifiable

7.6 Deep Learning

Deep learning is another part of the field of data analytics and a subsection of machine learning. Deep learning algorithms learn unstructured and unlabeled data using complex neural networks with autonomous input feature extraction as opposed to manual extraction. These networks utilize machine learning to create deep learning models that can take longer to train because of the much larger neural networks, but this allows for greater accuracy. Another type of learning is semi-supervised learning, defined as having some labelled data, but more data is unlabeled to see how the algorithms can learn to be more accurate. Many more algorithms appear throughout the field of data science, but these are the most common.

7.7 Data Visualization

The final subtopic within data analytics is visualization, defined as a graphical representation or visualization of data or results. The type of data affects the way it is visualized. The most common being multidimensional data, which can be presented using graphs and charts, taking multiple variables, for instance, bar or pie charts. Another data type is geospatial; this involves data collected from the earth through location data, visualized through distribution maps, cluster maps, and more commonly, contour maps

7.8 Cloud computing

Simply put, cloud computing is the delivery of computing services—including servers, storage, databases, networking, software, analytics, and intelligence—over the Internet ("the cloud") to offer faster innovation, flexible resources, and economies of scale. You typically pay only for cloud services you use, helping lower your operating costs, run your infrastructure more efficiently and scale as your business needs change

7.9 API and open standards

An open API (often referred to as a public API) is a publicly available application programming interface that provides developers with programmatic access to a proprietary software application or web service. APIs are sets of requirements that govern how one application can communicate and interact with another.

7.10 virtual reality

Virtual reality (VR) is a simulated experience that can be similar to or completely different from the real world. Applications of virtual reality include entertainment (e.g., video games), education (e.g., medical or military training) and business (e.g., virtual meetings). Other distinct types of VR-style technology include augmented reality and mixed reality, sometimes referred to as extended reality or XR.

CHAPTER 8

ADVANTAGES

The advantages of digital twins are incredibly far-reaching, and extend throughout a product's entire lifecycle, from design, to build, and finally to operation. The main benefit of digital twin is to provide an integrated outlook of any project to any user at any point of the product lifetime. This single source of factual truth allows organizations to foster collaboration across various teams and departments, and even outside the organization. Digital twin technology can drastically reduce the product development time and cost by up to 50%. Through lean development cycles, increased collaboration between external and internal partners and the suppliers, businesses can effectively change the design, manufacturing, sales, and maintenance of complex products in multiple industries. With real-time mirroring, engineers can simulate the behavior of complex system to predict and prevent mechanical breakdowns

Here are just some of the advantages of digital twins:

1. Improved design: Digital twins allow you to quickly test designs using simulations, without the need for costly prototypes.

2. Improved build: Digital twins allow you to project how a change in the manufacturing process might impact things like efficiency, quality and yield.

3. Better early detection and warnings: Digital twins can quickly alert you to any abnormalities or failures in the asset, allowing you to address before it becomes a major (and potentially costly) problem.

4. Predictive maintenance: Digital twins not only gives you real-time insight into how an asset is performing, but it also allows you to model your interventions, so you can see the full-scale of their impact and minimize downtime losses.

5. Aggregated data: Aggregated data is valuable. As Dimitri Volkmann of GE

notes: "If your organization is monitoring multiple systems of the same type of assets, for instance a fleet of jet engines (each of which has an individual digital twin), you can start to learn

from all of them as a cohort, find similar patterns or trends, and that analysis can lead to refining models for higher fidelity in the future."

6. Post-manufacturing visibility of products: For many products, once they leave the factory, there is no more insight into how that product is being used by consumers – until something goes wrong, that is. Digital twins can change that, by giving manufacturers visibility into their real-world usage, allowing them to further optimize the product, predict when it might be in need of service, and quickly fix any problems that do arise.

7. Continuous refinement of design and models through data captured and easily crossed referenced to design details

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CHAPTER 9

DISADVANTAGES

The main disadvantage of digital twin technology is that it only works with one type of measurement. For example, velocity and displacement measurements cannot be accurately converted to an absolute value. Digital representation requires a different type of measuring device.

Other limitation of the digital twin method is that it cannot produce a velocity or displacement measurement at the same time, in the same area. This means that there may be two or more measurements to be taken, and they will not be converted correctly into an accurate value.

Other disadvantages include:

- The requirement for complex measuring equipment
- Expensive equipment and software.
- There is also the need to provide a large number of digital measurement points, and more space for storing measurement results.
- Highly qualified professionals are needed for executing the digital twin model.
- The success of technology is dependent on internet connectivity.
- The security is at stake.
- The digital twin's concept is based on 3D CAD models and not on 2D drawings.
- Digital twin will be required across entire supply chains.
- The challenges involved here include globalization and new manufacturing techniques. Managing all these design data for digital twin among partners and suppliers as the physical product evolves will be a challenge.

CHAPTER 10

APPLICATIONS

Digital Twin technology eliminates the guesswork from determining the best course of action to service critical physical assets. Asset-centric organizations that have focused on combining traditional operational technologies with IT governed technologies will now have easy access to this unique blend of deep knowledge and intelligence about their assets, and pave the road to optimization and business transformation. The increasing adoption of IoT is ideal for enterprises to leverage digital twin platforms to boost their services and processes. A new market category will emerge that will see the outcome-based applications being more versatile.

Improve customer experience:

Customers play a key role in influencing the strategies and decisions in any business. Enhancing your customer's experience to retain and explore new customer base, is the ultimate goal for businesses. By directly creating a digital twin of the customer facing applications, they can get feedback that boost the services directly offered to customers.

Performance tuning:

A digital twin helps to determine the optimal set of actions that can help maximize some of the key performance metrics, and also provide forecasts for long-term planning. For example, the performance of a scientific device, which is deployed on a spacecraft, can be tuned from Earth using digital twin as a 3D real-time visualization.

Digital machine building:

A digital twin is used as a digital copy of the real machine that is created and developed simultaneously. Data of the real machine is loaded into the digital model to enable simulation and testing of ideas even before actual manufacturing starts

Healthcare:

A digital twin can help virtualize a hospital system in order to create a safe environment and test the impact of potential changes on system performances. Not just operations, digital twins can also help improve the quality of health services delivered to patients. For example, a surgeon can use a digital twin for a digital visualization of the heart, before operating it.

Smart cities:

A digital twin can be used for capturing the spatial and temporal implications to optimize urban sustainability. For instance, 'Virtual Singapore', a part of the Singapore government's Smart Nation Singapore initiative, is the world's first digital twin of an existing city-state, providing Singaporeans and effective way to engage in the digital economy.

Maintenance:

A digital twin is capable of analyzing performance data collected over time and under different conditions. For example, with a digital twin, a racecar engine can be visualized to identify the required maintenance, such as a component that is about to burn out. With a digital twin, your business can integrate the insights generated in a system, allow visibility into current and future machine states, and trigger appropriate remedial business workflows.

CHAPTER 11

CONCLUSION

The growth in Digital Twin use has seen a shift in recent years, facilitated by an increase in the number of published papers and industry leaders investing heavily in developing Digital Twin technology. It would not be possible without the same growth in the AI, IoT and IIoT fields, which are becoming key enablers for Digital Twins. The majority of the Digital Twin research is focused on the manufacturing field. The number of papers found in manufacturing is noticeably higher compared to papers discussing Digital Twins for smart cities and healthcare, highlighting gaps in the research for these areas.

AI is becoming a component within Digital Twins and exploring where these algorithms can be applied is another avenue of open research. The effects of AI combined with Digital Twin are topics amongst the publications but on a small scale. The exciting and inevitable future research will explore scaling up smaller successful Digital Twin and AI projects. An important finding is the lack of standardization and misconceptions with definitions for Digital Twins. Addressing the challenges with standardization ensures future developments are actually Digital Twins and not wrongly defined concepts.

The digital twin may drive tangible value for companies, create new revenue streams, and help them answer key strategic questions. With new technology capabilities, flexibility, agility, and lower cost, companies may be able to start their journeys to create a digital twin with lower capital investment and shorter time to value than ever before. A digital twin has many applications across the life cycle of a product and may answer questions in real time that couldn't be answered before, providing kinds of value considered nearly inconceivable just a few years ago. Perhaps the question is not whether one should get started, but where one should start to get the biggest value in the shortest amount of time, and how one can stay ahead of the competition. What will be the first step, and how will you get started? It can be an overwhelming task to get there, but the journey starts with a single step.

CHAPTER 12

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