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**A proposal process for building a functional Digital Twin model**

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**A proposal process for building a functional Digital Twin model**

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## ABSTRACT

**Digital Twin (DT)** is one of the most promising enabling technologies for realizing smart manufacturing and industry 4.0. DTs are characterized by the seamless integration between the cyber and physical spaces. The importance of DTs is increasingly recognized by both academia and industry. Keeping up to date with these demands, in particular, testing the products regularly could be testing for the manufacturers. The only way they can win this battle is by going digital.

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## 2. Abbreviations

- DT - Digital Twin
- VF - Virtual Factories
- CPS - Cyber-physical Systems
- MES - Manufacturing execution system
- FMUs - Functional Moke-up Units
- PHM - Prognostics and health management
- DTS - Digital twin shop floor
- IOT - Internet of thing
- VF - Virtual factory
- ERP - enterprise resource planning

### 3. Introduction to Digital twin

#### 3.1 Introduction

In the **Industry 4.0** era, the **Digital Twin (DT)**, virtual copies of system that are able to interact with the physical counterparts in a bi-directional way, seem to be promising enablers to replicate production systems in real time and analyse them. A DT should be capable to guarantee well-defined services to support various activities such as monitoring, maintenance, management, optimization and safety. Through an analysis of the current picture of manufacturing and a literature review about the already existing DT environment, till now we don't have final and approved concept of digital twin.

The introduction of information and communication Technologies (ICT) and the advent of the Industry 4.0 era have deeply changed the interpretation of simulation and its related role in manufacturing. Simulation is seen as the imitation of the real-world process or system over the time. From this perspective, simulation is used as an engineering tool for different purposes, from the early design phases to run time phases of complex systems resulting in higher efficiency, accuracy and economic benefits for companies. Generally speaking, Industry 4.0 provides with its tools new ways of thinking and doing business. Its related technologies such as Big Data, Cloud Computing, Internet of Things (IoT), Autonomous Robot and sensors introduce a new generation of Systems with integrated computational and physical capabilities called cyber physical Systems (CPSs) that can interact with human through many new modalities consequently, the introduction of CPSs in manufacturing systems reflects in the generation of big amount of data.

**“A digital twin (DT) is a real time digital replica of a physical device”**

The concept of the digital twin can be compared to other concept such as cross-reality environment of co-spaces and mirror models.

The correct management of this data potentially represent a big advantage for companies and reflect in a faster decision making process and can improve the productivity of systems. The continuous improvement of this kind of systems enable the real time monitoring of physical assets and the synchronization with virtual environment.

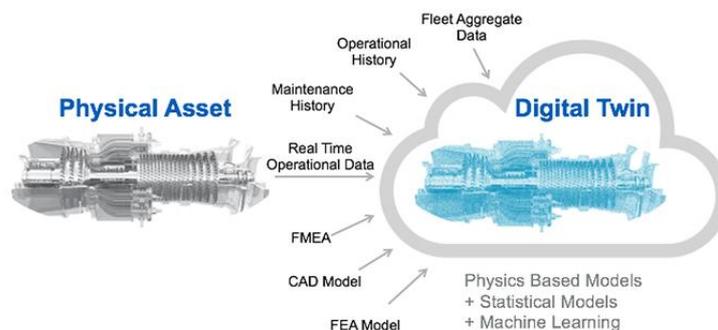


Figure 1: Digital Twin example

The Digital Twin (DT) can be identified as a simulation technique which differs from the traditional ones as it uses synchronized real data from the shop-floor, in order to get information, such as machine reliability and availability and to elaborate more accurate diagnostics and prognostics that use up-to-date field data, instead of leveraging on estimations by equipment suppliers.

Below **Figure 2** are given complete view of the definitions of the DT appeared in literature

Year	Definition of Digital Twin
2010 and 2012	An integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. The digital twin is ultra-realistic and may consider one or more important and interdependent vehicle systems.
2012	A cradle-to-grave model of an aircraft structure's ability to meet mission requirements, including submodels of the electronics, the flight controls, the propulsion system, and other subsystems
2012	Ultra-realistic, cradle-to-grave computer model of an aircraft structure that is used to assess the aircraft's ability to meet mission requirements
2013	Coupled model of the real machine that operates in the cloud platform and simulates the health condition with an integrated knowledge from both data driven analytical algorithms as well as other available physical knowledge
2013	Ultra-high fidelity physical models of the materials and structures that control the life of a vehicle
2013	Structural model which will include quantitative data of material level characteristics with high sensitivity
2015	Very realistic models of the process current state and its behavior in interaction with the environment in the real world
2015	Product digital counterpart of a physical product
2015	Ultra-realistic multi-physical computational models associated with each unique aircraft and combined with known flight histories
2015	High- fidelity structural model that incorporates fatigue damage and presents a fairly complete digital counterpart of the actual structural system of interest
2016	Virtual substitutes of real world objects consisting of virtual representations and communication capabilities making up smart objects acting as intelligent nodes inside the internet of things and services
2016	Digital representation of a real world object with focus on the object itself
2016	The simulation of the physical object itself to predict future states of the system

Figure 2: Definition of Digital twin in literature

### 3.2 Digital Twin (DT) and its applications

The concept of digital twin can date back to grieves presentation about product lifecycle management in 2003. However at that time the concept of digital twin is not mature enough because of technology limitations. Along with the data acquisition technology, processing technology, simulation technology and many other related technologies development, the concept of digital twin becomes more mature and specific.

Industry and academic define digital twin in many different ways. It is generally accepted that a digital twin is in an integrated Multiphysics, multiscale probabilities **ultra-realistic simulation of the systems** or products which can mirror the life of its corresponding twin using available physics models, history data real time data, etc.

Developed by NASA believe that digital twin is the model which can interact between autonomous system behaviours and the environment in the physical world. There are many other definitions in particular fields. In our opinion digital twin is a real mapping of all components in the product life cycle using physical data, virtual data and interaction data between them.

Because the digital twin can allow companies or users to have a complete digital footprint of the product they concerned from design and development through the end of the product lifecycle, so digital twin has increasing attention by both industry and academic. Existing primary applications of the digital twin in industry are briefly summarised as follows.

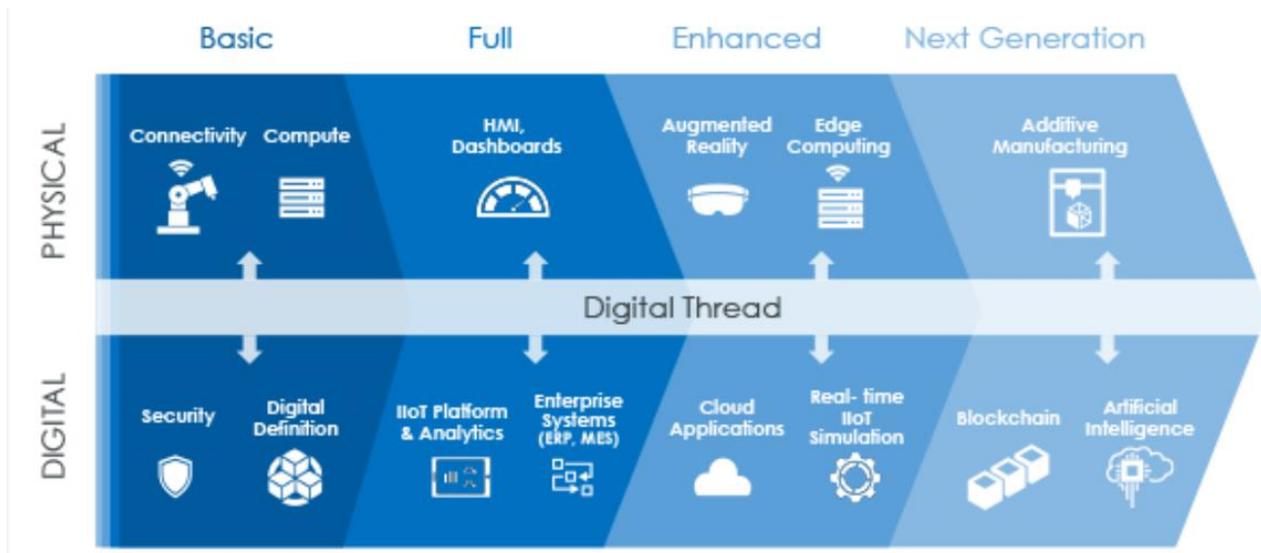


Figure 3: Evaluation of digital twin (Source: PTC)

The concept of DT was first proposed and primarily used in product or equipment **prognostics and health management (PHM)**. Typical applications are described in the following paragraph. DT used to predict the reengineering aircraft structural life. Seshadri and Krishnamurthy proposed a damage characterisation methods base on digital twin for aircraft structural health management , which demonstrated great advancement in predicting the damage location, size and orientation. Airframe Digital Twin (ADT) to assess the flight state which helps find the subsequent damage in a real-time way. Besides aircrafts, general Electric pays attention to using digital twin to forecast product health in product lifecycle, which can make operations and maintenance more accurate.

The notion of digital twin should be differentiated from cyber twin. Cyber twin is based on the conception of CPS. Generally speaking, the notion of cyber twin is derived based on development of **cyber physical system (CPS)**. Cyber space is defined as a networked space that consists of multiple interconnected cyber twins of critical objects. In other words, cyber twins purely exists and are merely meaningful within the cyber space. In sharp contrast, a complete DT must include a physical model, a virtual model, and connections between the physical and virtual methods. In other words, it emphasises interaction, communication and collaboration between physical space and cyber space.

Now a days as the application of new it in manufacturing, the smart manufacturing era has arrived. DT can be regarded as a critical milestone towards smart manufacturing and smart industry, while cybernetics provides the theoretical basis for DT. Cybernetics studies the concepts of control and communications in living organisms, machines and organisations, including self- organisation. It studies how a system processes information and depends on information to make decisions and take actions, with respect to automatic control and communication. Cybernetics provides the theoretical foundation for developing smart systems that are capable of collecting, processing and understanding various contextual information, based on which, DT can make ore contextually smart decisions. In short, relevant studies about cybernetics can be regarded as the technological backbones of DT.

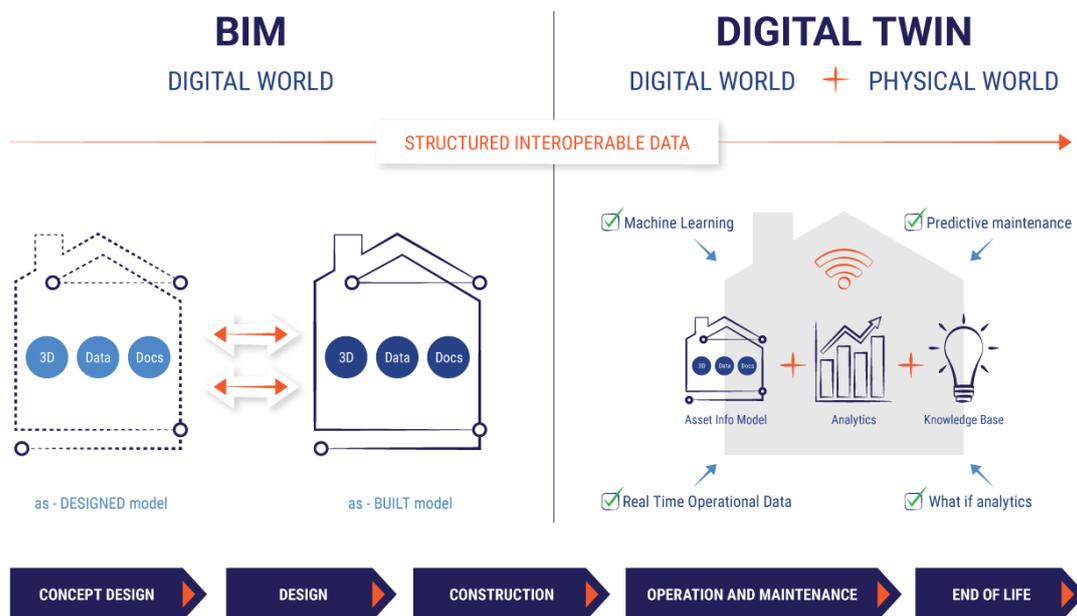


Figure 4: Digital twin applications

Some Countries proposed their national strategies such as industry 4.0, CPS-based Manufacturing, service-oriented manufacturing, and made in chine 2025. Throughout the above national manufacturing strategies, one common goal is smart manufacturing. In order to realise the intelligent management, digital twin was introduced into manufacturing stage.

For example, the concept of DT shop-floor (DTS) was proposed, and DTS characteristics, architecture, system composition, operation mechanism, and enabling key technologies are studied in detail. Vachalek investigated the application of digital twin in an industrial production line and analysed its superiority. Additive manufacturing’s digital twin and used It to make predictions about properties and serviceability of components.

Recently, studies shows digital twin-based real-time geometry assurance in individualised production. DXC company tries to build digital twin model to improve manufacturing efficiency and flexibility.

Furthermore, some researchers have studied the application of DT in **engineering optimisation**. DT application in optimising equipment operation and Bantegnie created a pump’s digital twin to optimise its performance in physical world. The above mentioned DT applications stay primarily in the production stage and after-product stage, and are heavily dependent on the product digital twin mode. Not much attention was paid to make use a digital twin in the first stage of product creation. As point out and stated by Dassault, there is huge potential of digital twin in product design. In addition, if one could establish the product DT mode from the design phase, then more related design data, marketing data , user experience data, etc., can be integrated into the product digital mode, and this will result in better serve for production stage and after-product stage.

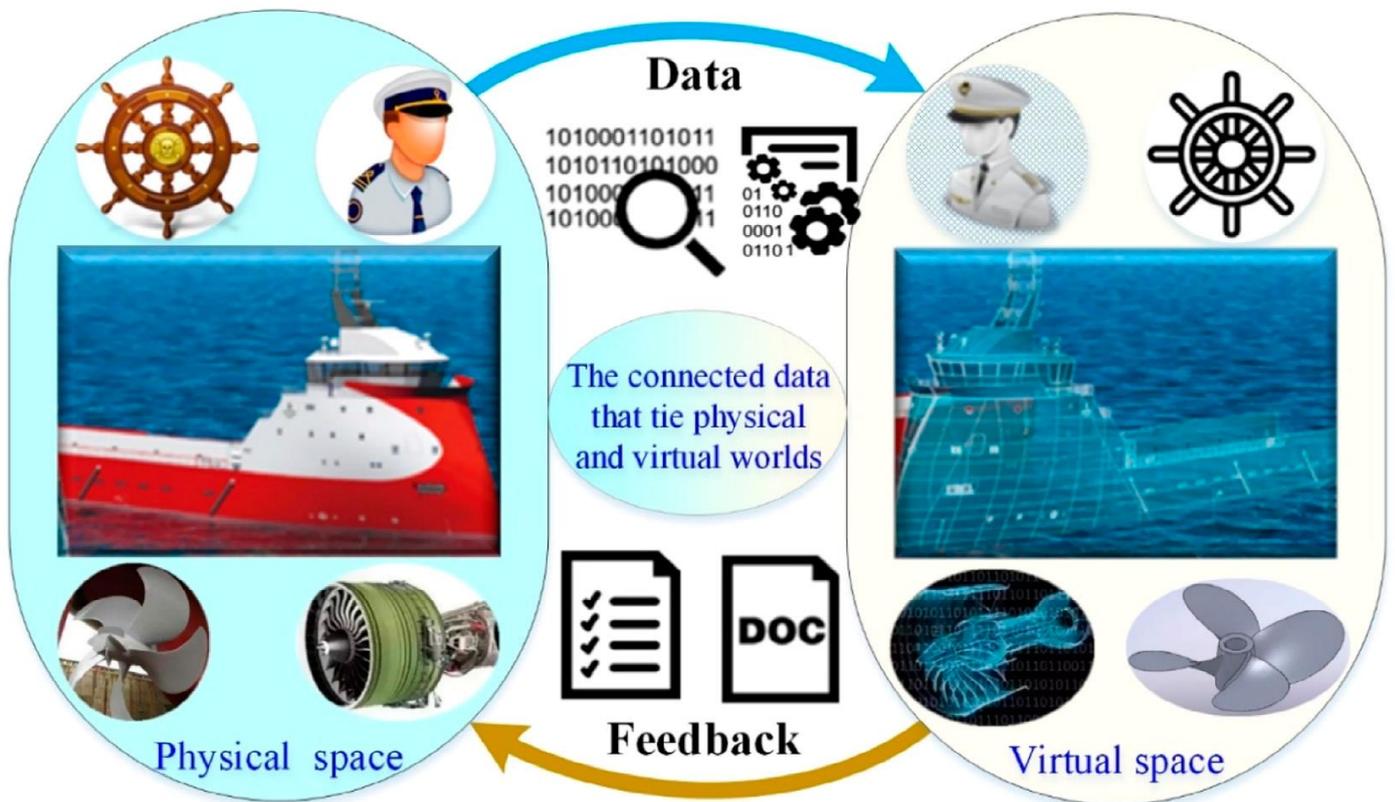


Figure 5 : General digital twin mode for a product

## 4. Industry 4.0

The term **Industry 4.0** was manifested for the first time at the Hannover Fair with the presentation of the "Industry 4.0" initiative. Following the first Industrial Revolution "Mechanization" as a result of the invention of the steam engine, the second "Mass production" with the help of electricity and the third "Digitization" by the use of Electronics and IT, this marks the dawn of the fourth Industrial Revolution through the use of cyber physical systems (CPS) and the Internet of Things and Services. In the field CPS, Germany has a leading role and can draw on almost **20 years of experience**. The integration of cyber technologies that make the products Internet-enabled facilitates innovative services to achieve, among other things, Internet-based diagnostics, maintenance, operation, etc. in a cost-effective and efficient manner. Moreover, it helps realization of new business models, operating concepts and smart controls, and focusing on the user and his or her individual needs. The goal of the Industry 4.0 is the emergence of digital factories that are to be characterized by the following features.

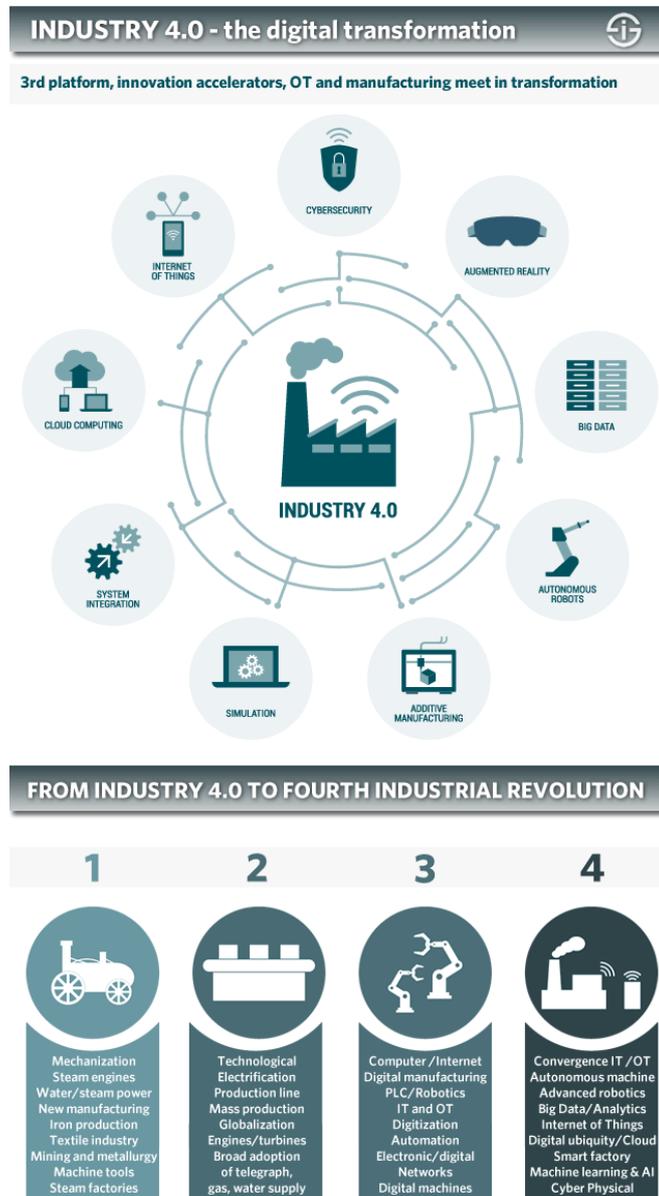


Figure 6: Industry 4.0 – digital transformation of manufacturing revolution (source: i-scoop.eu)

#### 4.1 Digitalization and simulation in Industry 4.0

With the technological evolution present in the last years, we have a scenario of radical changes that has been called the fourth industrial revolution. With this, many changes are being noticed in the production management models, where new ways of managing production appear. These made it possible to increase production customization, **make manufacturing processes more flexible**, support decision making with online data, improve resource efficiency, in addition to creating value.

One of the factors that triggered the fourth industrial revolution was the increased capacity for digitization of both factories and products.

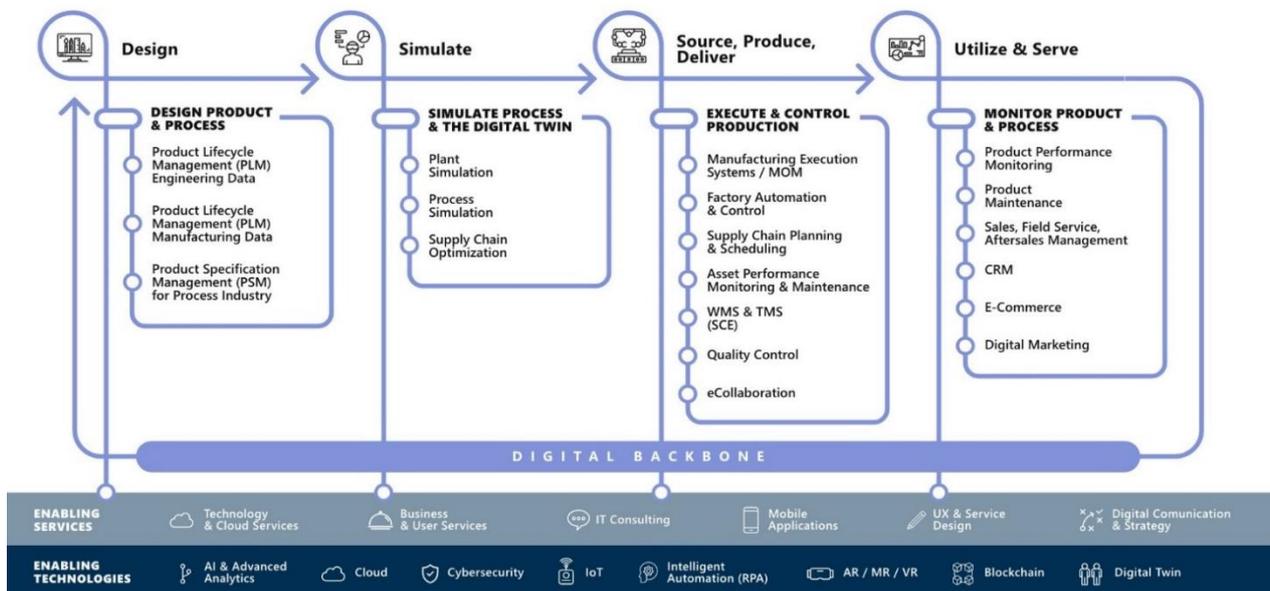


Figure 7 : Digitalization portfolio of digital industry (Source: Engusa)

**Digitization began in the 1970s** with the insertion of controls and microprocessors in factories, along with the evolution of information technology (IT). Today's digitization is broader and covers operations, product development as well as supply chain and customer relation. One of the challenges of digitization is to cover the entire supply chain.

Basically, digitalization consists of creating a twin computational model in a physical environment. This computational environment will serve to simulate and optimize conditions without intervention in the real environment, thus allowing the experiments to be extrapolated without consequences for the production system. This requires that digital transformation be based on four pillars: ability to collect, manage and analyse digital data; ability to work independently and organized; Supply chain connectivity and timing; and Digital customer access for more transparency and new products.

Due to the complexity of digital factories, it is necessary to build intelligent physical environments, combining physical and cyber technologies. Another important factor for the good functioning of the digital factory is the good architecture in mining and data storage in the Big Data concept. This data collection must be performed in real time, for this the **MES and RFID tools** stand out.

**Over the next five years**, it is estimated that digitalization will provide annual revenues of \$493 billion and a reduction in operating costs of \$421 billion. The key to this success comes from two factors: The Company's digital transformation in both the factory environment and customer relationships through products; Know-how protection that is the protection of the company's intellectual capacity.

The use of digitalization and simulation in Industry 4.0 **was demonstrated by Lee (2015)** in a framework that demonstrates the evolution levels of the production system beyond the attributes needed to make the factory level 4.0 this architecture can be seen in figure below.

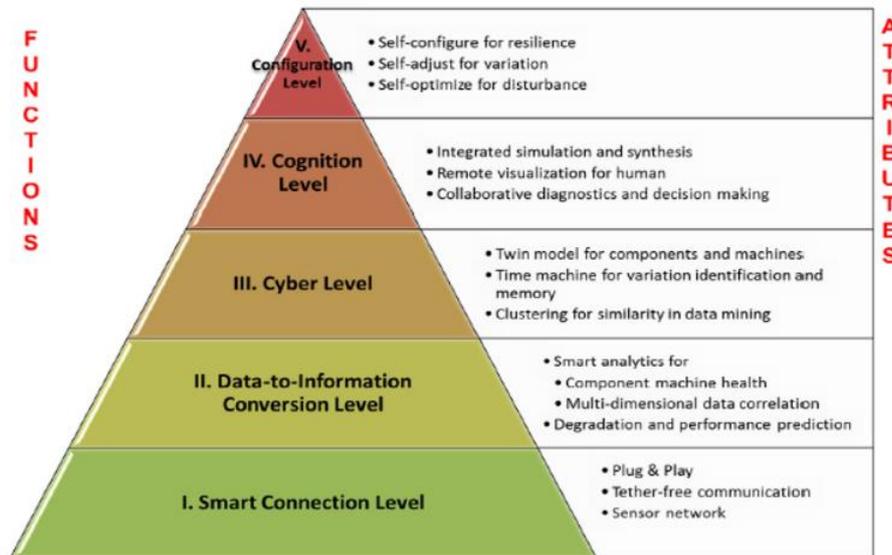


Figure 8: functions and attributers for industry 4.0

**Smart Connection Level:** To implement this level it will be possible to collect data from the production system in real time, for this it's necessary to install sensors that allow the collection of data and receivers that store this data.

**Data-to-Information Conversion Level:** At this level, machine life is known to be beyond performance, in this case use of sensors that monitor temperature, vibration, noise or wear are important.

**Cyber level:** At this level machines gain the ability to self-evaluate and compare current performance with other machines. This is possible because the data sent to the exchange compares it with the digital sister of the machine.

**Cognition level:** At this stage, the whole system is integrated, and decisions are made through graphs that cover the entire production system and all process variables. Comparative graphs are generated, individual equipment graphs, prioritization decisions to optimize the process. However, decisions are still made by users.

## 5. Digital Twin application in Manufacturing

### 5.1 CPS-based production systems

In recent years, the traditional manufacturing industry is challenged worldwide with the amazing growth and advancement in digital technologies that allow easy integration of interconnected intelligent components inside the shop floor, that is at the basis of the so-called industry 4.0 and that is made possible by the widespread adoption of information and communication technologies by manufacturing companies. Industry 4.0 has been recognized at international level as one of the strategical responses of the manufacturing companies to the economic crisis, to the tendency to delocalize production and to the increased market complexity. The technological basis of industry 4.0 root back in the **internet of things (IoT)**, which proposed to embed electronics, software, sensors, and network connectivity into devices, in order to allow the collection and exchange of data through the internet.

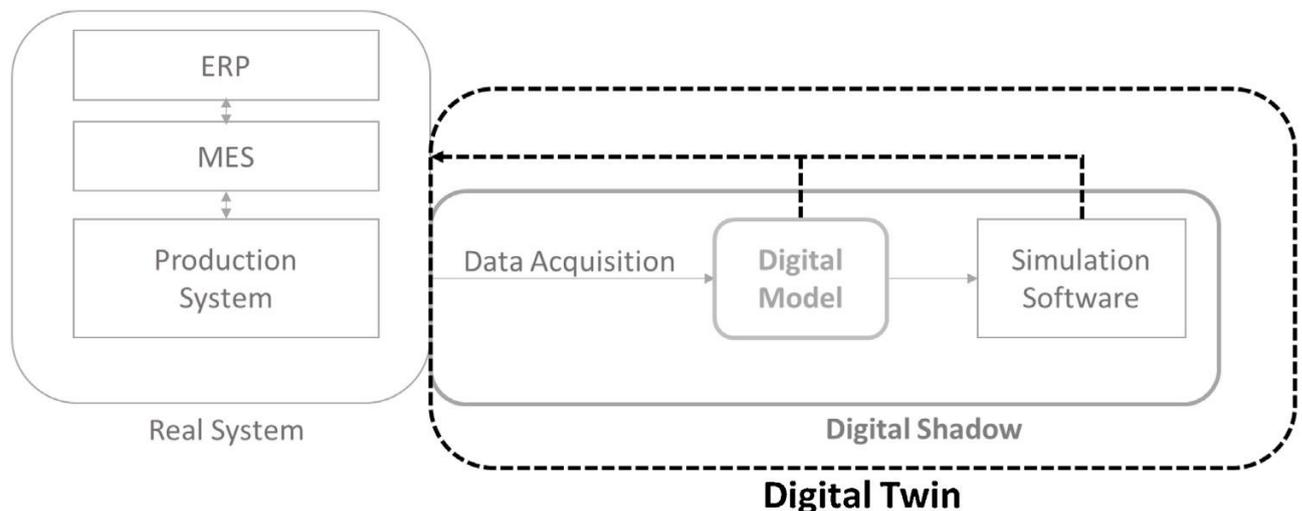


Figure 9: Digital Twin (DT) scheme

As such, IOT can be exploited at industrial level: devices can be sensed and controlled remotely across network infrastructures, allowing a more direct integration between the physical world and virtual systems, and resulting in higher efficiency, accuracy and economic benefits. Although it is a recent trend, Industry 4.0 has been widely discussed and its key technologies have been identified among which **Cyber physical systems (CPS)** have been proposed as smart embedded and networked systems within production systems.

They operate virtual and physical levels interacting with and controlling physical devices, sensing and acting on the real world. According to scientific literature, in order to fully exploit the potential of cps and IOT, proper data models should be employed. Such as ontologies, which are explicit, semantic and formal conceptualizations of concept in a domain.

They are the core semantic technology providing intelligence embedded in the smart CPS and could help the integration and sharing of big amounts of sensed data. Through the use of **Big Data analytics**, it is possible to access sensed data, through smart analytics tools, for a rapid decision making and improved productivity.

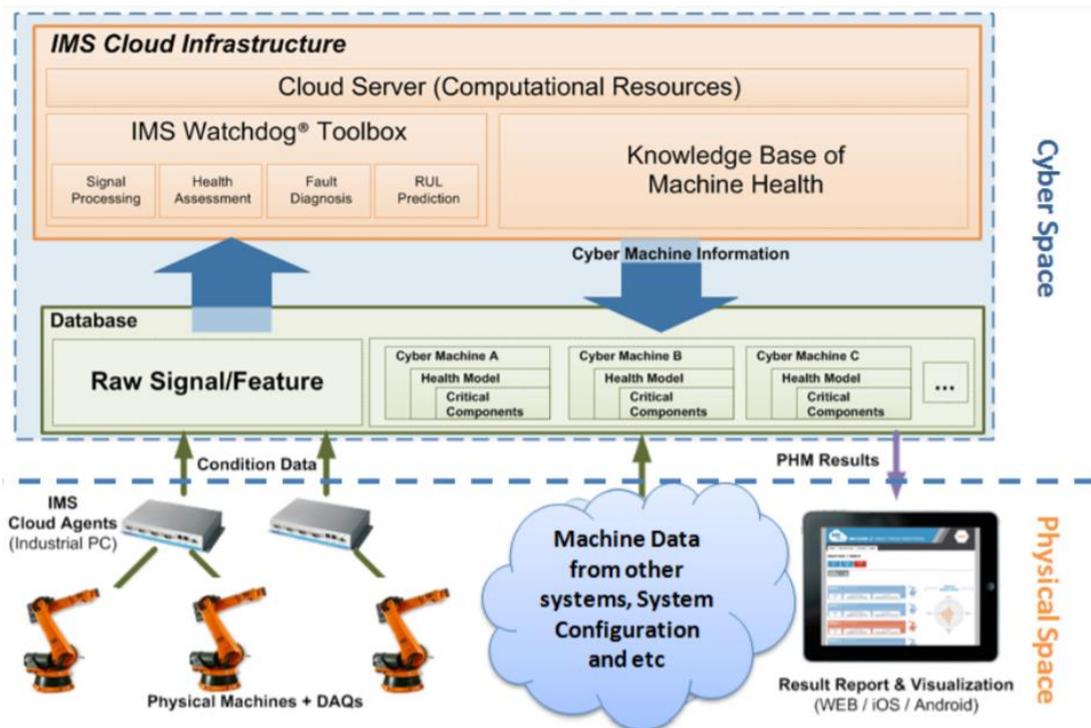


Figure 10: CPS- Model for industrial robot monitoring

With the use of these technologies, industry 4.0 opens the way to real-time monitoring and synchronization of the real world activities to the virtual space thanks to the physical-virtual connection and the networking cps elements. The DT is mean as the virtual and computerized counterpart of the physical system that can be sued to simulate it for various purposes, exploiting a real-time synchronization of the sensed data coming from the field, such a synchronization is possible thanks to the enabling technologies of Industry 4.0 and, as such, the DT is deeply linked with it.

The DT was first born in the aerospace field and only recently has been adopted also in manufacturing contexts such a term is used in industrial environments and in governmental research initiatives however, scientific literature that describes the contextualisation of the concept in the manufacturing domain is still at its infancy. A review of the contributions on this would be highly beneficial, in order to pave the way and clarify the conceptual foundations for future research works on the topic.

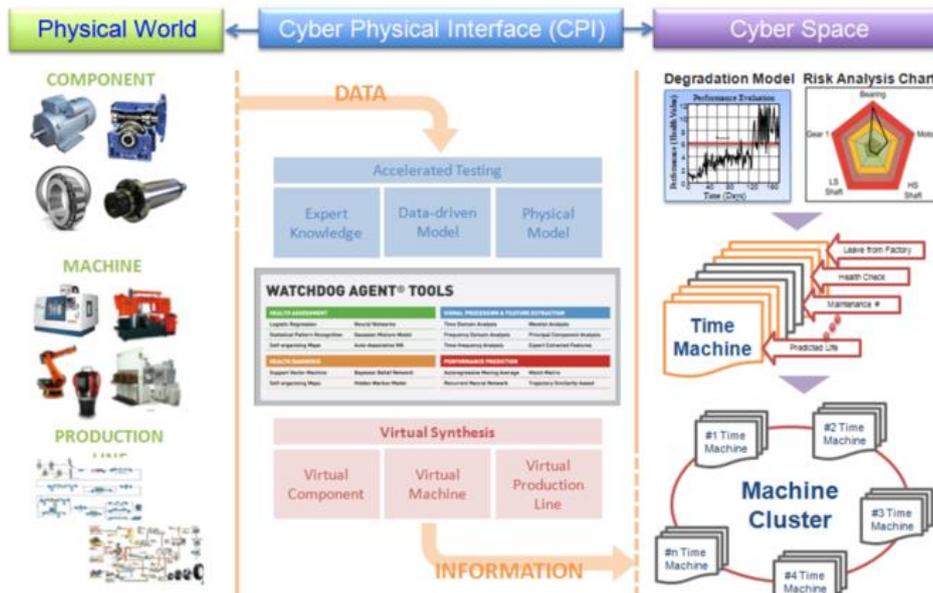


Figure 11: CPS based production systems

Research on the DT in manufacturing is an evolution of the already ongoing research stream about **Virtual Factories (VF)**. These are defined as the digitalization of the plant integrated with the real system coming in help to the production during all the lifecycle of each asset. In the robotics field, the simulations are mainly performed for the **Virtual Commissioning** to optimize the control algorithms for robots during development phase.

## 5.2 CPS in context of Industry 4.0

An interface to the Internet or a similar network is necessary to extend an embedded system, which is usually made of control units, sensors and actuators, to a CPS. In order to achieve this, there are various approaches that have been investigated in the context of this development and will be briefly presented below.

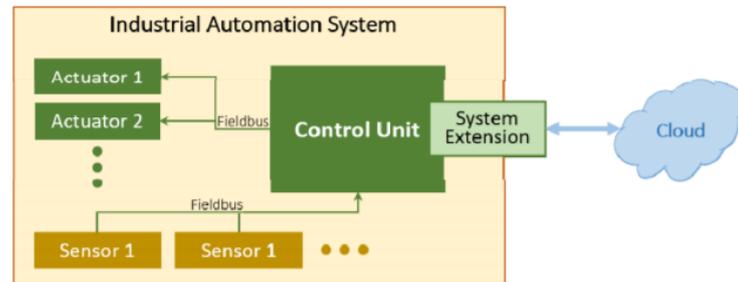


Figure 12: Direct system control

### Direct system extension

In this individualized solution variant, the embedded system, if not available yet, is extended by a communication interface to access the Internet and the software is changed accordingly to enable communication over the internet, e.g. with the cloud. To this end, all the sensor signals of the system must be transmitted by the control unit to the cloud. Methods should be implemented to control the actuators via Internet.

### System expansion by microcontroller board

In this solution variant, a microcontroller board that has the various communication interfaces such as **CAN**, **UART**, **WLAN**, Ethernet, etc. is developed. This is connected to the embedded system and takes over the communication to the Internet or a cloud. However, this requires uniform interfaces, over which the board can be connected to the embedded system. The software of the board must be adjusted separately to each system. However, the entire code need not to be rewritten every time, but only the mapping is to be reworked accordingly so that it is relatively easy to transfer this variant to other systems. This arrangement is demonstrated by the following figure:

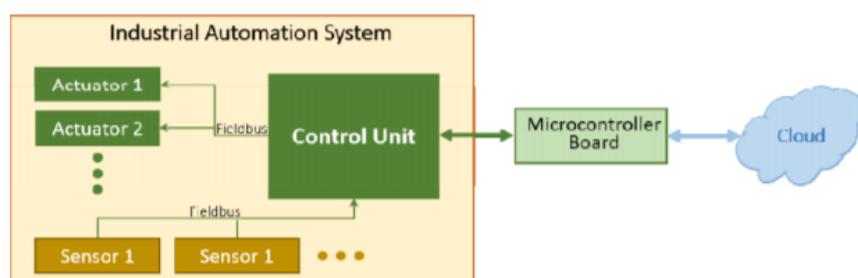


Figure 13: System extension by Microcontroller Board

### Extension by smart actuators and sensors

Traditional embedded systems usually consist of a control unit, several sensors and actuators, which are connected to the control unit via field buses. The control unit assumes the signal processing function in such systems. Should smart sensors and actuators be used now, the sensors take over even the processing of the signal and the actuators independently check their current status, and correct it, if necessary. These sensors transmit their data to a central control unit, e.g. via field buses. In order to extend such a system to a CPS, it would be conceivable to also send data from the sensors and actuators, which are sent via the field bus, to a cloud, and process it there. However, a high data volume is the result here and the cost of smart sensors and actuators must not be underestimated.

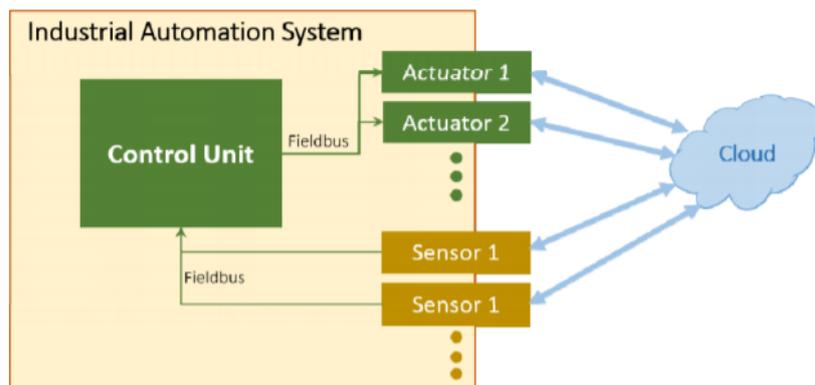


Figure 14: usage of intelligent actuators and sensors

### 5.3 Relation to the Automation pyramid

Each industrial automated process is commonly based on the automation pyramid, a centralized structure composed of five layers, on the left of the figure lies the automation pyramid. On the right the corresponding production management level the figure also shows the manufacturing execution system (MES) functions listed by the manufacturing execution system association.

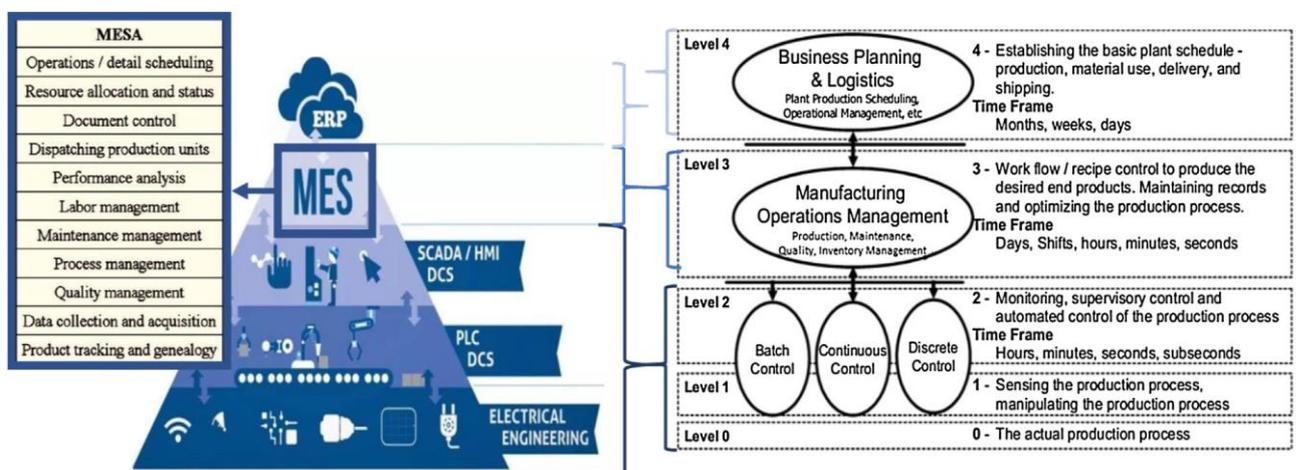


Figure 15: The automation pyramid

- (i) The three lower layers(0-1-2) are summarized as the control layer, including: electrical engineering layer, programmable logic controllers (PLCs) / Distributed control systems(DCS) and Scada/HMI Layers.
- (ii) The middle layer (3) is the manufacturing execution system (MES) that guides the process.
- (iii) Finally on the top there is the **enterprise resource planning(ERP)** layer (4) aimed at integrating organizational functional for better customer support and planning.

In this structure, the MES guides the manufacturing process, monitoring all the steps of a product in production system in a centralized way. Among the MESA- identified functions, some are directly linked to the production process (such as scheduling and quality control)., while others (such as resource management and traceability) are best described as cross functions, not strictly related to the production process but supporting a higher point of view. Thus, all MES functions are not on the same level.

## 6. The use of FMU's for the Digital twin

From literature emerges that a digital twin is a coupled model of a real system, that is stored in a cloud platform and represents its status based on data analysis and physical sensory information. The core simulation model is built with the representation of the pieces of equipment of the production system Each of these pieces will be connected to one or more modules that represent the specific behaviour of interest. The behaviour modules are black-boxes that take standard input data from both the simulated and field environments and that output computed data also in a standard format. **Functional Moke-up Interface (FMI)** standard is used for the black-box modules, creating **functional Moke-up Units (FMUs)**. The chosen standard allows the function to be exported to different simulation environments, in this way granting the independence of the FMU modules from to be exported to different simulation environments.

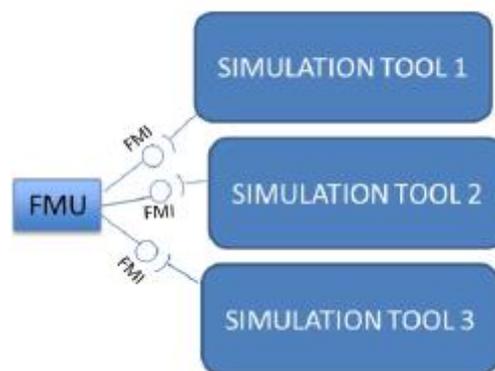


Figure 16: FMU module reuse in different simulation

in this way granting the independence of the FMU modules from the single simulation tool and allowing them to be reused with little arrangements. This standard has already been successfully used in CPS-based systems.

The FMU modules are created to be recalled by Discrete Event Simulation (DES) and constituted by a unique FMU zip-file composed of three main parts:

- an XML file to define the variables inside the FMU
- the equations used by the model (which is a set of C functions)
- other data, such as tables or comments about the model

The built FMU in the application case is created for a Discrete Event Simulation (DES) model and takes as an example of behaviour module the energy consumption computation. The energy consumption highly depends on the actual state each equipment piece is in at each moment, as shown in where the FMU is connected to the field to get information on the updated machine states

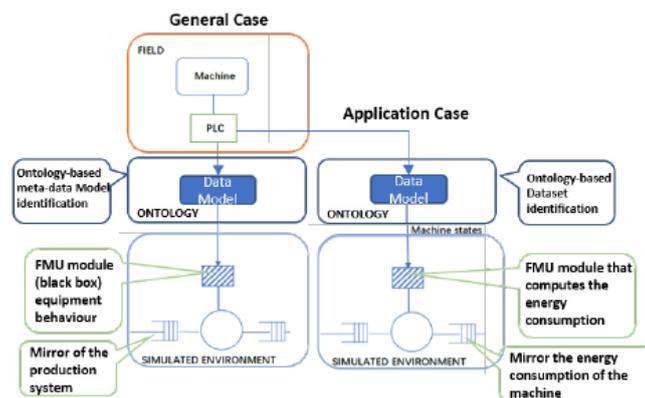


Figure 17: Relationship between field, ontology and simulated environment

## 6.1 Laboratory application

The proposed FMU modules approach, supported by a semantic data model, was tested in a laboratory environment: the industry 4.0 Laboratory (I40LAB) at Politecnico di Milano. The production line installed in the laboratory showed in Fig. below has been designed to assemble a mobile phone.

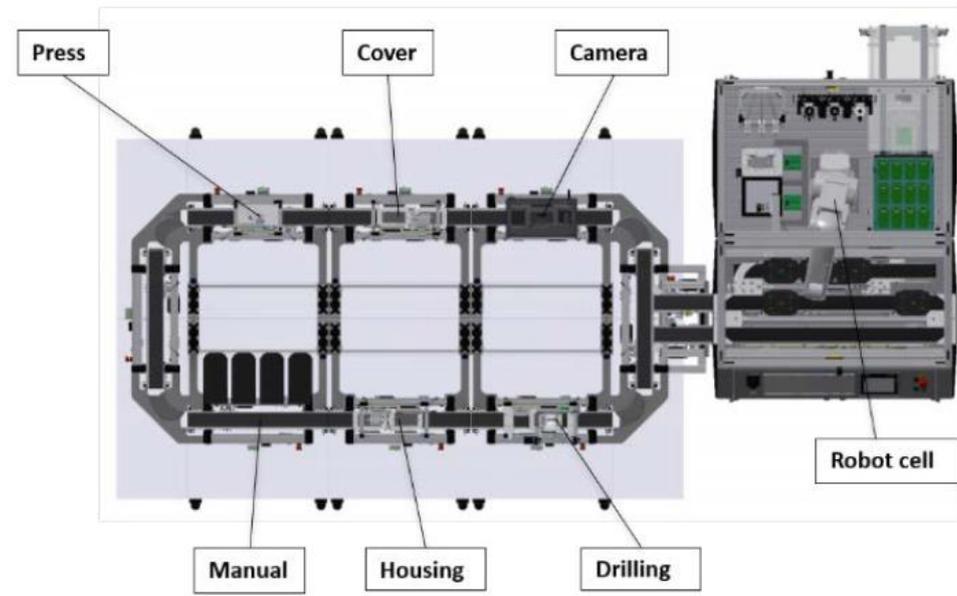


Figure 18: Production line installed in the I40LAB Polimi

The production line in the figure 18 is composed of six stations: Manual Load/unload station, housing, drilling station, robot cell, camera check station, back cover station, press station. In this system, a certain number of carriers moves around the line and are stopped in each module to read/write the information about them using the **RFID (radio frequency identification) technology**. Each machine in the I40LAB is equipped with a PLC server, that uses the open platform communications (OPC) **unified Architecture (UA)**, a machine to machine (M2M) communication. To enable the communication with non-windows computer applications, the new OPC UA specification introduced in 2009.

The laboratory gives the opportunity to realize a first implementation of a DT environment. The MATLAB Simulink environment was chosen to construct the FMU modules, and the OPC UA toolbox of MATLAB is used to establish the server/client connection and extract data from the system. The starting point is a single station of the production line in laboratory, since the embedded sensors are the same in each station. The next stations simulation will be obtained by replicating the first one. As said before, the energy consumption computation is based on the sum of the energy consumption in each machine state. The identified states of the machines in the laboratory are Idle, Working, Energy Saving and Fault mode.

## 6.2 FMU Simulation results

The first step is to model in the simulation environment the single states and their energy consumption curves in the FMU module. Then, through the OPC UA standard, the client/server connection can be established with the PLCs (Programmable Logic Controllers) of the line. The established connection allows to construct the ontology-based dataset used for the laboratory application, that is fundament to restrict the variety of the data present in the laboratory (i.e. at PLC level) into the relevant set of data used to replicate in a virtual environment the machine state. Once identified the dataset, the signals from the field that are part of it can be read directly in the

simulated environment and their combination reconstructs the actual state of the machine. Both the reconstructed machine states and the signals read directly from the PLCs can be used as an input of the FMU modules. In this way it is possible to replicate in real time both the states of the station and its energy behaviour in the virtual copy of the physical system.

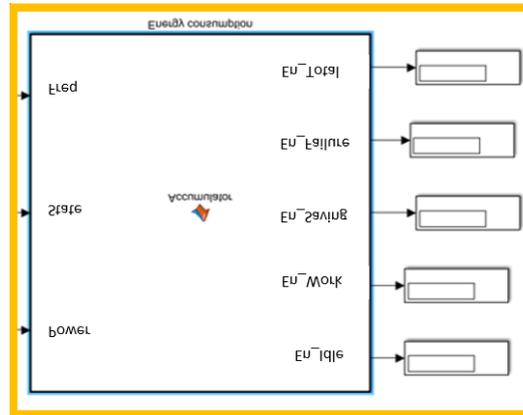


Figure 19: input and output signals of the FMU module

The connection with the PLCs of the line and the reconstruction of the machine state for each station are the basis to build a function that computes the energy consumption of the station. The FMU block of the application case built in the simulation environment is shown in figure. The inputs of the module in are the reconstructed states of the station, the sample frequency of the simulation and the instantaneous power at each sample time. The outputs of the function are the energy consumption for each of the machine states (Energy Idle, Energy Work, Energy Saving, Energy Failure) and the total amount of energy consumption, as the sum of the energy consumed in each state. In fact, the function stores the amount of time in which the station was in a determinate state and, according to the equation.

$$E_m = \int_{T_{m-1}}^{T_m} P dT = P_{avg} * (T_m - T_{m-1})$$

Computes the energy consumption for each state and the total one will be the sum of all  $E_m$ . (In the equation  $E_m$  is the consumed energy in the machine state  $m$  [J],  $P$  is the instantaneous power [kW],  $P_{avg}$  is the average power of the machine state  $m$  and  $T_{m-1}$  the initial time instant at which the machine state starts). This function can be then extracted from the simulated environment through the FMI standard and be used as a black box function that computes the energy consumption in different simulation environments.

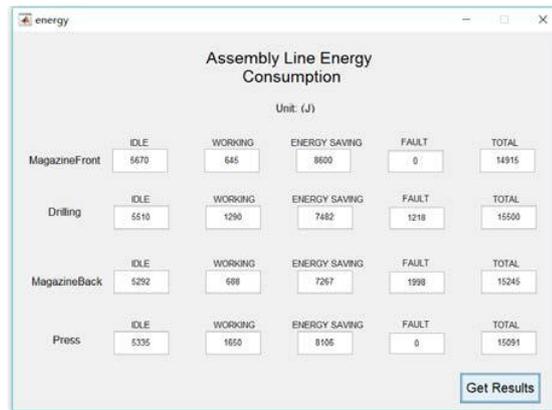


Figure 20: laboratory energy consumption results

## 7. New era of data-driven product design and manufacturing

Nowadays, the success of product design increasingly on manufacturing capability to handle data. Data can be accumulated through different phases of a product's lifecycle including design, production, distribution, usage, maintenance, upgrade and recycle. Some data are related to the products status, behaviour and performance (e.g. state sampling in utility, maintenance and failure information, upgrade information, degradation status, remaining values and recycle scheduling records). Some data are related to the context in which a product is being used with respect to for example, when, where, how, by whom and under what circumstances the product is used. Some data are related to customers in regards to their demographics information. The technological backbones of data-driven product design are IoT and big data analytics.

The **enabling technologies** of IoT include **sensors, software, electronics, actuator**, etc. The applications of IoT can be found in many fields such as healthcare, transportation, and smart city. IoT can lead to countless benefits, such as significantly enhanced automation, accuracy, efficiency and productivity. Made possible using the IoT technologies, data can be collected directly from the physical **products in real-time** a group of physical products can communicate and collaborate directly with each other; a physical product connected to IoT can interplay with an intangible service on the Internet; a physical product can be monitored, controlled, and upgraded remotely.

Big data are valuable information assets that are characterised by high volume, velocity and variety. Big data analytics aims to abstract useful information to facilitate a certain human creativity out of an enormous amount of highly unstructured and seemingly unrelated data. Design-related big data are richly available on the Internet and the Internet of Things. **On one hand**, some big data are generated by customers from the Internet. For example, countless text-heavy customer reviews are published on e-commerce platforms (e.g. Amazon.com) and social platforms (e.g. Facebook.com). On the other hand, made possible using advanced sensor technologies, big data can be collected from the physical products using Internet of Things.

## 7.1 DT- Driven Task clarification

In the task clarification phase, customer needs are translated into functional requirements under design constraints, where DT serves as an ‘interpreter’ to facilitate the ‘translation’ process.

**Firstly**, DT serves to deepen designers’ understandings about target customers and customer voices. So far, the vast majority of customer-related data are collected from various e-commerce, social and searching platforms based on the Internet. Increasingly, customer-related data (e.g. bio activities and personal habits) can be directly collected from various smart devices (e.g. smartphone, smart watch, smart coffee machine) based on the Internet of Things. The customer related information is useful for enhancing product personalisation and adaptability. The massive customer voices must be processed to be useful for task clarification. For example, a function recommender system can be incorporated into DT to recommend exciting new functions for a target product through analysis of readily available customer reviews published on e-commerce platforms.

**Secondly**, DT serves to guide designers to rationally formulate functional requirements. Functions can be represented as the input–output transformation of energy, materials and signal, all of which can be possibly detected by different sensors and analysed by DT. Furthermore, DT can provide key information such as how often the function is used, how long it is used every time, how many customers use the function, etc. According to the **Axiomatic Design Theory**, the information content of a product or its components can be calculated by measuring the overlapping area between the system curve and design range. The design range is determined by designers based on their estimations of the system curve. Based on the information directly collected from the physical product, a system curve (i.e. variance, mean value, bias) can be drawn in a much more precise manner. As a result, designers can adjust the design range accordingly .

**Thirdly**, DT serves to provide designers with affordance information. By definition, affordance refers to a possible action on a product performed by users in the real world. A fundamental difference between affordance and function is that the former is necessarily dependent on a particular artefact, whereas the latter can be artefact-independent (new functions can be formulated purely based on customer needs or abstracted entirely based on artefact behaviours). Traditionally, designers can only obtain affordance information through the time-consuming ethnographic observations and contextual inquires. Since affordance concerns with product–customer interactions, made possible by the DT, certain affordance information can be directly collected from various smart products. In the future, through the VR technologies, it is even possible to obtain affordance information based on customer behaviours in a completely virtual environment.

**Last but not least**, DT serves to clarify various design constraints imposed on a particular product. Since DT is oriented from product lifecycle management, it is potentially capable of synthesising a comprehensive collection of design constraints imposed by all the relevant stakeholders. Some examples of constraints include weight, size, budget, schedule, manufacturing capability, environmental standards, safety standards and government regulations. In the following conceptual design phase, designers can further validate whether and to what extent a new concept complies with various constraints through virtual verification. In the future, it is also interesting to explore how and in what ways constraint information can be collected by means of sensors directly from the physical product. For example, it is possible to utilise a car’s rear camera to detect various parking constraints in the physical world

## 8. Framework of digital twin-driven product design (DTPD)

Once a DT is successfully built, it can facilitate designers to perform different design activities. According to the design theory and methodology (DTM) classification by CIRP, DTM plays the role in generating new solutions, enrich functional information of design solution, and represent design knowledge. New solutions are generated based on creativity, combination and modification. DT is expected to be most useful for the combination-based design. The most commonly used combination-based DTM is the systemic design approach prescribed by Pahl and Beitz, which divides the design process into four phases: task clarification, conceptual design, embodiment design and detail design.

Each phase can be further divided into multiple sub-steps. Relevant DTMs can be incorporated into different phases of the systemic design process. For example, during the conceptual design phase, Axiomatic Design, TRIZ, Robust Design and Adaptable Design can be incorporated to reduce unnecessary design complexities, resolve undesirable design contradictions, make a product less sensitive to uncertainties, and increase a product's adaptability to changing Requirements, respectively. Since DTPD is characterised by the ability to make full use of data to build a virtual model, a specific design phase called virtual verification is proposed as the last phase of the design process. The complete process is shown in Figure 21. Various design activities and their associated data are divided into five parts, which correspond to the five design phases.

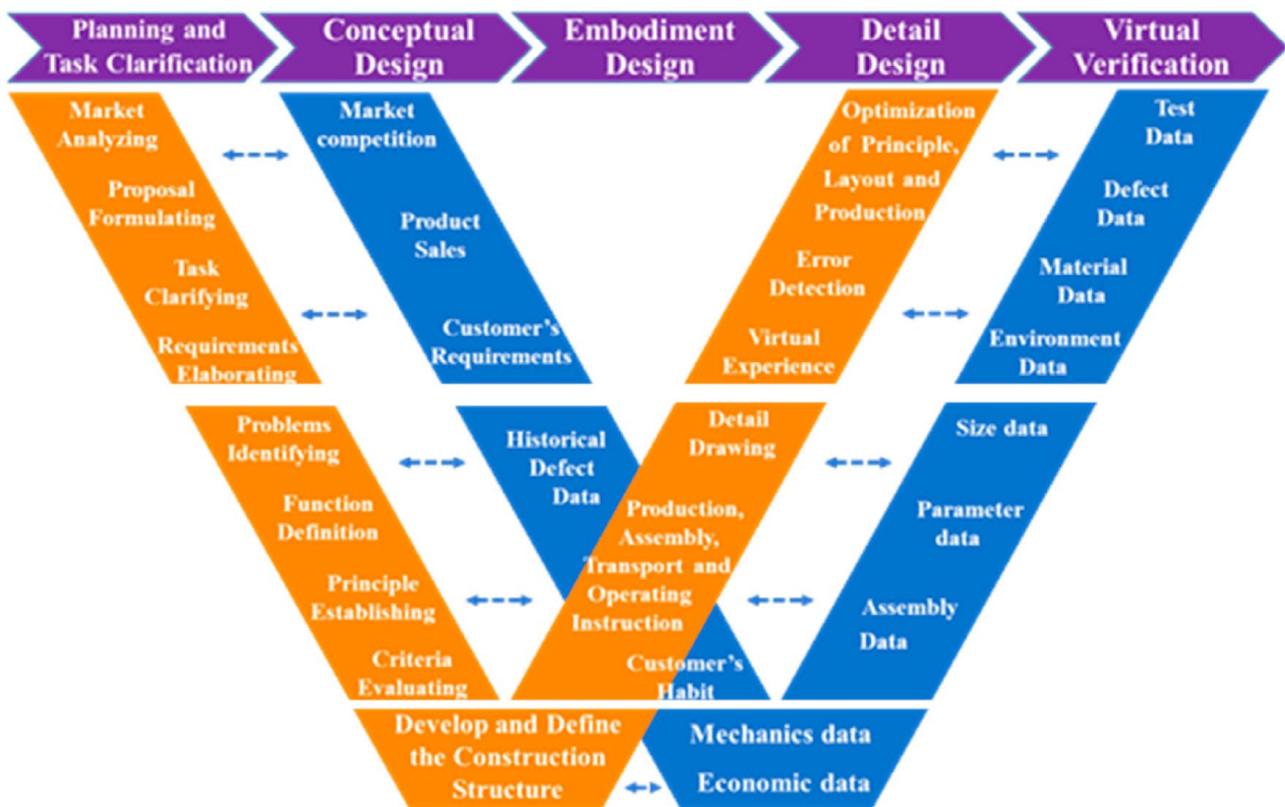


Figure 21: framework of DTPD

## 8.1 Theory support for DTPD

As illustrated in Figure 21, the proposed framework DTPD integrates relevant design theory and methodology (DTM), data lifecycle management (DLM), and digital twin (DT).

**Firstly**, DTPD develops based on existing DTMs. They are included to structure the design process and decide where, how, and in what ways different kinds of data are exploited for various design activities. In addition, DTMs explains the internal conflict and contact among the various design phases, which are conducive to coordinate the relationship between the design factors.

**Secondly**, design process becomes increasingly digital. DTPD depends on the massive amounts of historical and real-time data, etc., relevant studies about DLM can deal with the data throughout the product lifecycle. DLM can collect, transfer and storage the date from physical world. It also motivates the DTPD by integrating and processing the data, which promotes the communication and interaction of different kinds of data. In addition, it can make sure the purity and accuracy by cleaning, analysing and mining the data.

**Thirdly**, relevant studies about DT are included to explain how to build a digital twin to serve the data-driven design of consumer products. It can also make designers have a complete digital footprint of products through design. It should be noted that DTPD is essentially a design framework, in which, digital twin serves as an ‘engine’ to convert big data managed by DLM into useful information that can be directly utilised by designers to make informed decisions at different design phases as prescribed by DTM.

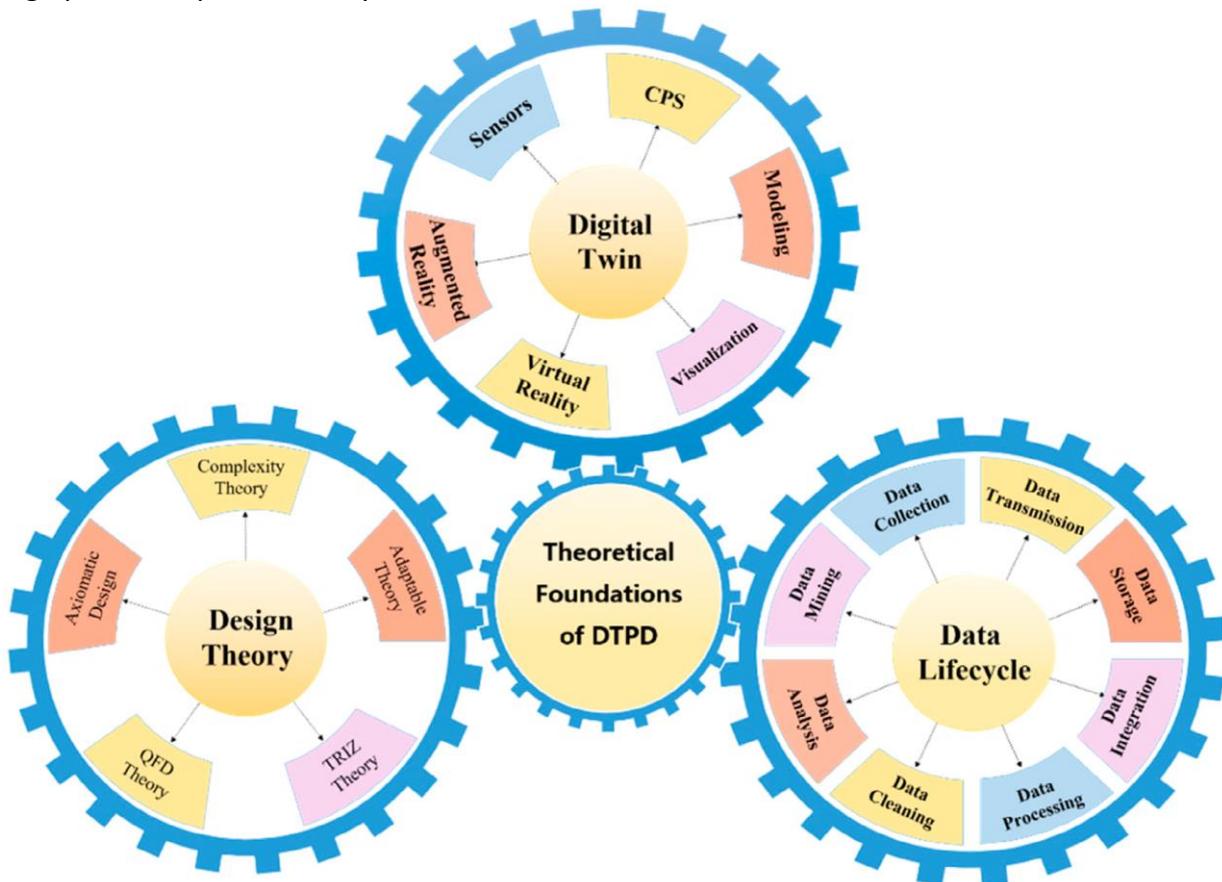


Figure 22: theoretical formulation of DTPD

## 8.2 Collaborative design between designers and digital twin in DTPD

From the perspective of design, DT can be regarded as a special kind of intelligent design machine, which is capable of providing designers with information, recommendation, and assessment throughout a product design process. If the design language is used to describe digital twin, it can be regarded as an overlapped representation of both designer's intentions and real-world realities. According to the situated **FBS framework design** involves back-and-forth interactions between three worlds expected world, interpreted world and physical world

product can be described with respect to its function, structure and behaviour in all three worlds. When a product is projected from the expected world to the interpreted world, and eventually to the physical world, more details and specifics are gradually added to the product.

**The product is moved to the physical world from the digital world (in the designer's mind)**, because practical uncertainties and constraints have been imposed on the product. The essence of digital twin is to create a digital representation of the physical product in the interpreted world. Note that this virtual product should be seen as a dual-reflection from both the expected world and the physical world. On one hand, as much as possible, the virtual product should reflect the designer's expectations on how the product ought to function, behave, interact with customers, respond to uncertainties, and be physically structured. On the other hand, as accurate as possible, the virtual product should reflect the real-time state of the physical product in the real world. Moreover, digital twin also enables the physical product and virtual product to communicate with each other in real-time and coevolve with each other over time.

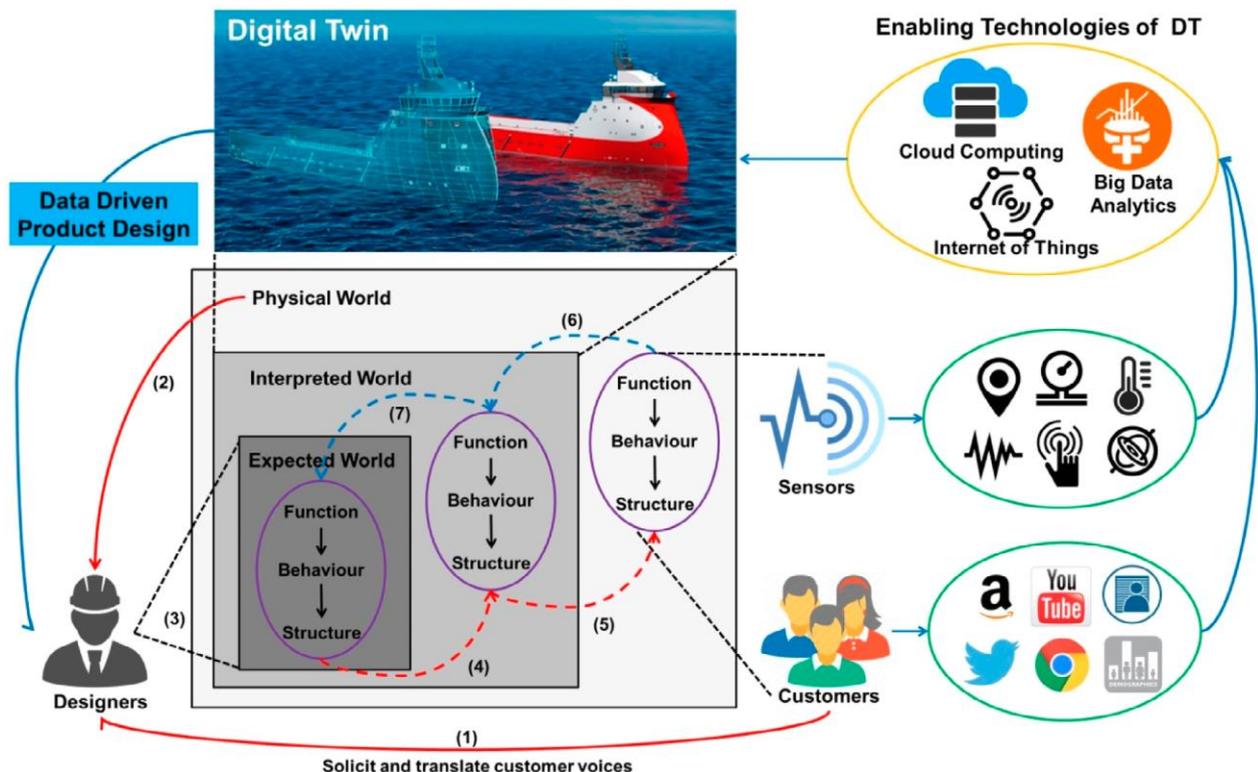


Figure 23: understanding of DT in the FBS framework

**Above figure:** illustrates the role played by DT in data-driven product design. In the expected world, based on their understanding of customers and knowledge of the physical world (arrow 2 in figure), designers propose a product's expected function, behaviour and structure ( arrow 3 in figure). Next, the expectations are visualised, simulated, analysed and optimised in the interpreted world (arrow 4 in figure), by means of CAD, FEM, 3D modelling, virtual prototyping and so forth. Then the product is projected from the interpreted world to the physical world (arrow 5 in figure). Traditionally, as the product enters the physical world, the designers will gradually lose the track of the various product-related information.

In particular, while a product is manufactured in outsourced factories, distributed by the third-party retailers, purchased by globally distributed customers, and maintained by third party dealers. As a result, designers have to employ design methods (e.g. survey, interview, lead-user theory, ethnography, etc.) to solicit feedbacks from customers, which are probably divided into two-ways, one is to collect the user's online comments on the website, like Amazon and YouTube, to understand the user's demand for the product; another is to collect product running data through the sensors to analyse the users' habits and preferences. The essence of digital twin is to create a digital representation of a physical product in the interpreted world (i.e. arrow 6 in Figure) and then reflect from the interpreted world back to the expected world.

some new values created through the communication between designers and digital twin, as well as the synergy between the virtual product and physical product (the subscript number indicates the product generations). The designers are guided to adjust their expectations based on those 'facts' that are cross-examined in both interpreted and physical worlds, and hence make more informed design decisions. The inconsistency among the expected product, virtual product, and physical product (with respect to their function, behaviour and structure) are gradually minimised. Lastly, the physical product is made more personalised and intelligent through various 'lessons' learned from the virtual product. Last but not least, the zigzagging interactions between the virtual product and physical product lead to a coevolution for the digital twin.

It should be noted that, unlike the complex systems, consumer products involve intensive back-and-forth interactions between product and user. Since DT is a real-time digital representation of the physical product, it can directly interact with end users and provide not only real-time product state information but also timely recommendations of utilisation, maintenance and upgrade services. In that regard, Thorsten et al. proposed the notion of 'product avatar', which is a digital representation of the physical product .

In order to interact with the end user on Facebook. Moreover, rich information is readily available on the Internet to build user profiles. In some sense, a user profile can be regarded as the digital representation of a certain user in the digital world. Therefore, it is also interesting to investigate the interplay between user profile with digital twin.

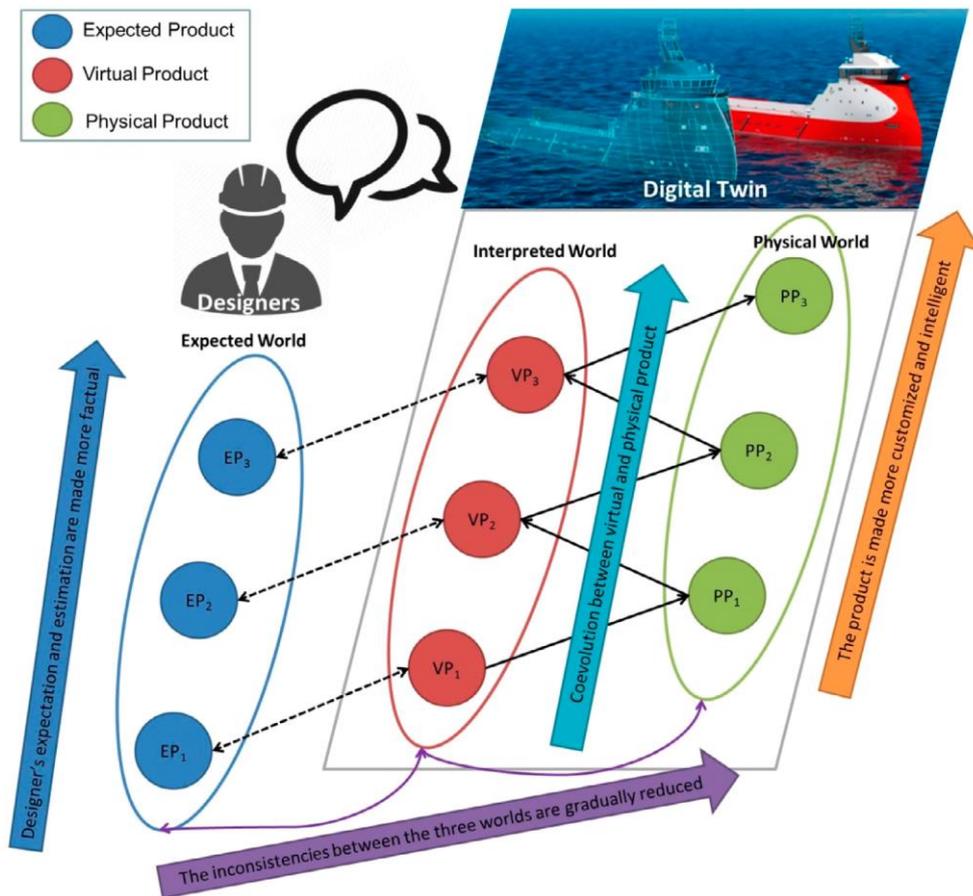


Figure 24: collaborative design between designers and DT in DTPD

### 8.3 Case study: Digital twin application in bicycle design

Recently, a new paradigm for bicycle use is rising in China, which is called ‘Bicycle-sharing’. The most famous companies are OFO and Mobike bicycle. They provide the users with bicycle as a kind of public service, and charge some cycling fee at a very cheap price, e.g. 0.5 RMB one time. The working flow of shared-bicycle paradigm is shown in Figure 25 below.

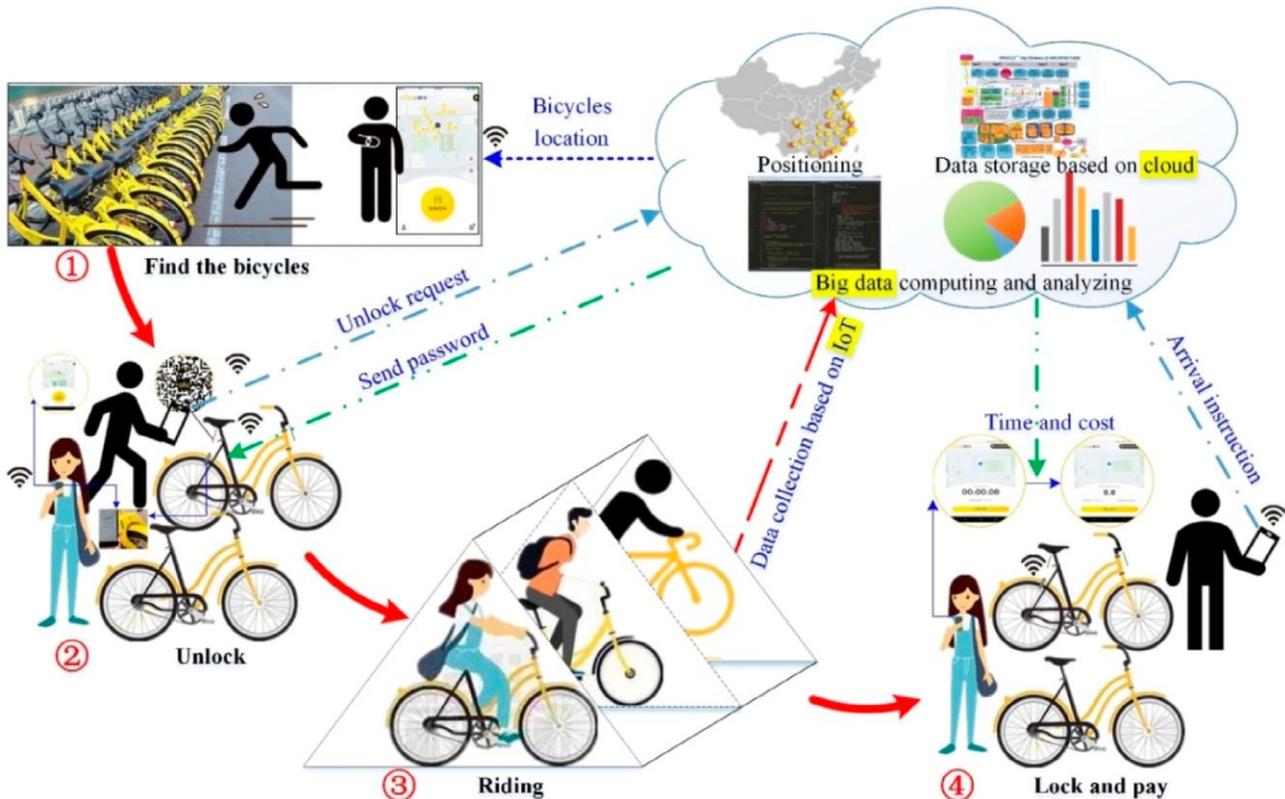


Figure 25: The use flows and interaction mode of shared bicycles

When a user wants to find a shared bicycle, he only needs to open the Mobike apps in his iPhone, then he will be told where to get a bicycle because of the automatic positioning function service. Next, after the shared bicycle is found, he scans the QR code on the plate. The password will be sent to his app interface, or the smart lock of the bicycle will automatically unlock. Then, he could ride the bicycle to his destinations. Last, when the user arrives at the destination, he just locks the bicycle lock and pays for riding via app. ‘Bicycle-sharing’ is a success case using New IT in public transportation.

lot of new ITs are used in ‘Bicycle-sharing’. For example, the real-time and physical-related bicycle data (e.g. location, route, status, etc.) can be collected and communicated using IoT during riding. Based on cloud computing, all the shared bicycles data storage, processing and analysis (such as computing, statistics and positioning, etc.) are implemented and finished in a ‘Sharing Cloud’. Mobile Internet connects the users, shared bicycles and ‘Sharing Cloud’. For instance, the users send the unlock request and arrival instruction to the ‘Sharing Cloud’. The ‘Sharing Cloud’ would feed the location, the password, as well as the time and cost back to the users. The user comments are also collected from apps through smart terminals (e.g. smart phones, PADS, etc.). With big data analysis, the bicycles are becoming smart, and are used more conveniently and efficiently. New IT has injected fresh energy to bicycles. Massive data of bicycles are acquired and analysed via New IT in

the new paradigm of ‘Bicycle-sharing’. These data would help build the digital twin for bicycles and support designer for bicycle redesign.

### 8.4 Digital twin (DT) driven bicycle redesign

Traditional bike design methods are mostly based on designers knowledge and experience. However, the digital twin paves a new way for bicycle design. As shown in figure 26 below, the digital twin for bicycle primarily consist three parts.

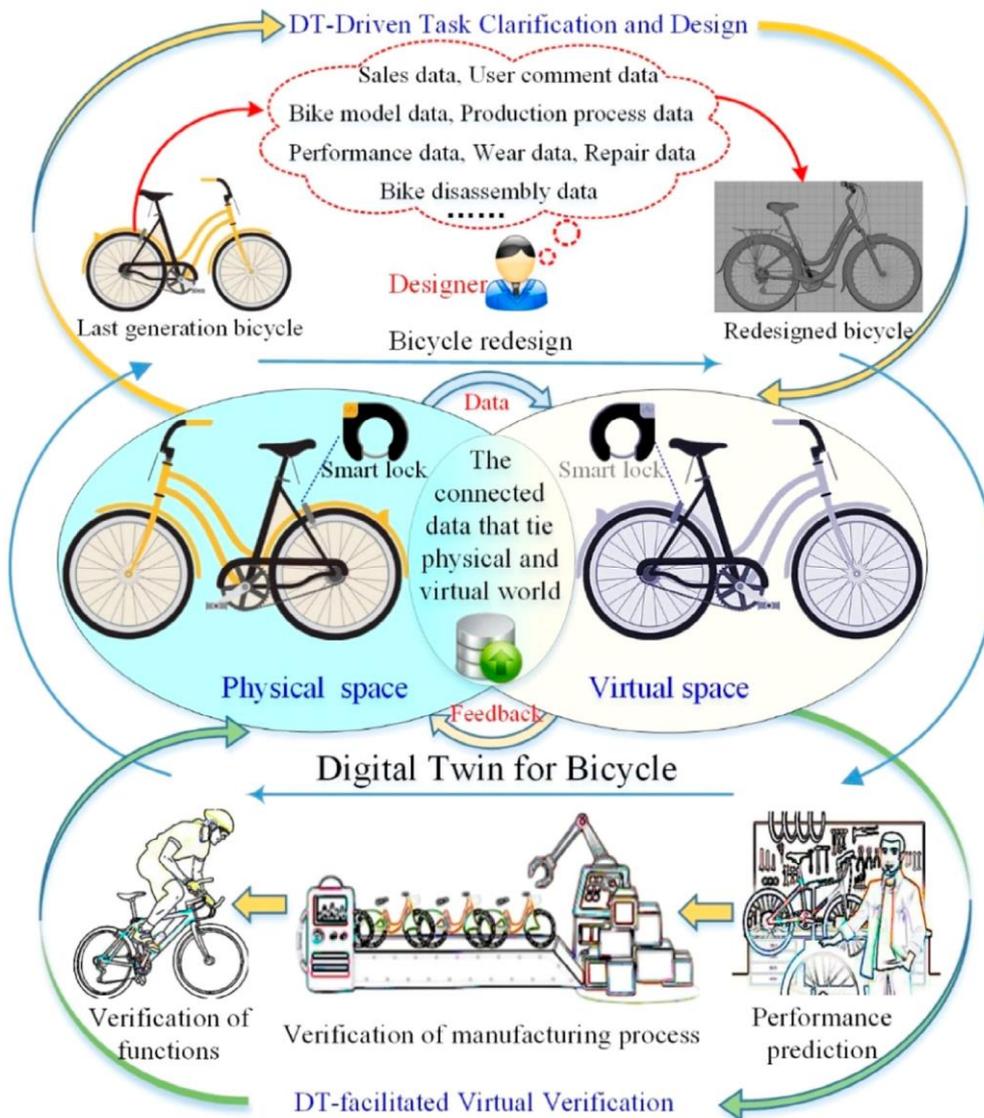


Figure 26: DT-driven bicycle design and virtual verification

The virtual bicycle in the virtual space, the real bicycle in the physical space, and the interactive data between virtual and real bicycle . Based on IOT and mobile internet, the virtual space could obtain a lot of data from the real bicycle, such as the speed, acceleration, wheel pressure, user comments,

as well as the relevant environment data, etc. with these data, a virtual model can be established in the virtual space, which is the real mapping and reflection of the real bicycle.

During the entire bicycle lifecycle, the virtual space would coevolve with the physical space. The virtual space would constantly collect, analyse and accumulate the data from the physical space, which could be use for design or redesign of next generation bicycle.

The lifecycle of bicycle includes the design, manufacturing, sales, maintenance and retirement, etc. designers can obtain all the data of the last generation bicycle through the digital twin, to redesign the next generation. In the task clarification phase, the designers could easily access the online user comments, rather than the questionnaire or telephone interview. By analysing these comments, the designers can discover the design flaws of the bicycle, the particular needs of the users, and the vision for the future development. Through the translation process based on the digital twin for the bicycle, the user demands are interpreted into functional requirements. For example, most of the shared bicycles do not have the backseats. So many users may make a request for the backseats, which are useful for carrying something or a friend. As a result, the designers would have a basic judgement that the design of the backseats should be considered.

Once the functional requirements are confirmed by the designers, they would be mapped to design parameters, working principles, and physical structures based on the digital twin for the bicycle. Taking the backseat design as example, the designers would compare the difference between the actual and the expected backseat, to deepen their understandings of the ideal and real contexts. With the digital twin-driven product design method, the designers could comprehensively compare and analyse the parameters of the bicycle, the height distribution of the user crowd, and the user comments about the use purpose. Eventually, the bicycle's backseat is designed to be an appropriate height based on the digital twin for the bicycle. Besides, as the backseat should be able to bear a certain weight, so the material selection of the backseat should be considered at the same time, as well as the shape, area, etc.

As shown in above figure, bicycle is still taken as an example to illustrate the virtual verification in DTPD, which includes three steps, namely performance prediction, verification of manufacturing process and verification of functions. In the performance prediction, the designers use the maintenance and failure history information, as well as the knowledge of engineering and material science, to simulate the various operations and predict the change of the performance indicators. For example, the digital twin for the bicycle could predict the change of the backseat wheels and tyre pressure, etc., when more weight is put on the backseat.

Next, in the verification of manufacturing process, designers use the digital twin model to simulate the manufacturing process of bicycles. On one hand, the specific links are optimised. Through simulation in virtual space, designers could determine the optimum process with the shortest time and print out the production instructor. On the other hand, the high defective rate steps would be reduced by accurate simulation. For example, through the simulation about key steps and a data relation mapping about material and equipment, the fractures of some components could be reduced. At last, the designed functions are verified.

For one thing, the ergonomics of the bike is verified by integrating the customer's physical data, and possible problems in design would be found. For another, the functions of the bicycles under different circumstance are verified by integrating various environment data. For example, the brake

distance, tyre wear speed, backseat life, etc., are tested in different weather condition through the digital model. In the virtual verification, once the unqualified problems are found, the design scheme would be improved through iteration of design process.

The digital twin for bicycle would facilitate the iterative optimisation of bicycle design. The design cycle, cost, etc., would be greatly decreased, and the design efficiency, satisfaction, security, etc., would be generally improved.

## 9. Process of Building functional digital twin model

In general, it takes six steps to create a fully functional digital twin but it could be more. It should be made explicit though, in practice, manufacturers may not strictly follow the sequence to build DTs. It is also possible that steps can be carried out concurrently.

### 9.1 Step(1): Build the virtual representation of the physical product

The enabling technologies of this **step are computer aided design (CAD) and 3D modelling**. Both are commonly used technologies in product design. The virtual includes tress aspects: elements, behaviours, and rules. At the level of elements, the virtual product model mainly includes the geometric model and physical model of the product, use the environment, etc. at the level of behaviours, the authors not only analyse the behaviour of products and users, but also focus on the analysis of the product and user interaction generated by the behaviour and modelling. At the rules level, it mainly includes the evaluation, optimisation and forecasting models established following the law of product operation.

### 9.2 Step(2): process data to facilitate design decision-making

Data collected from different sources mainly from the physical product, and also from the internet are analysed, integrated and visualised. Firstly, data analytics is necessary to convert data in to more concrete information that can be directly queried by designers for decision-making. Secondly, since product data are collected from diverse source, data integration is useful for discovering the hidden patterns that cannot be uncovered based on a single data source. Thirdly, data visualisation technologies are incorporated to present data in a more explicit fashion. Finally, advanced artificial intelligence techniques can be incorporated to enhance a DT's cognitive ability, so that certain relatively simple recommendations can be made automatically.

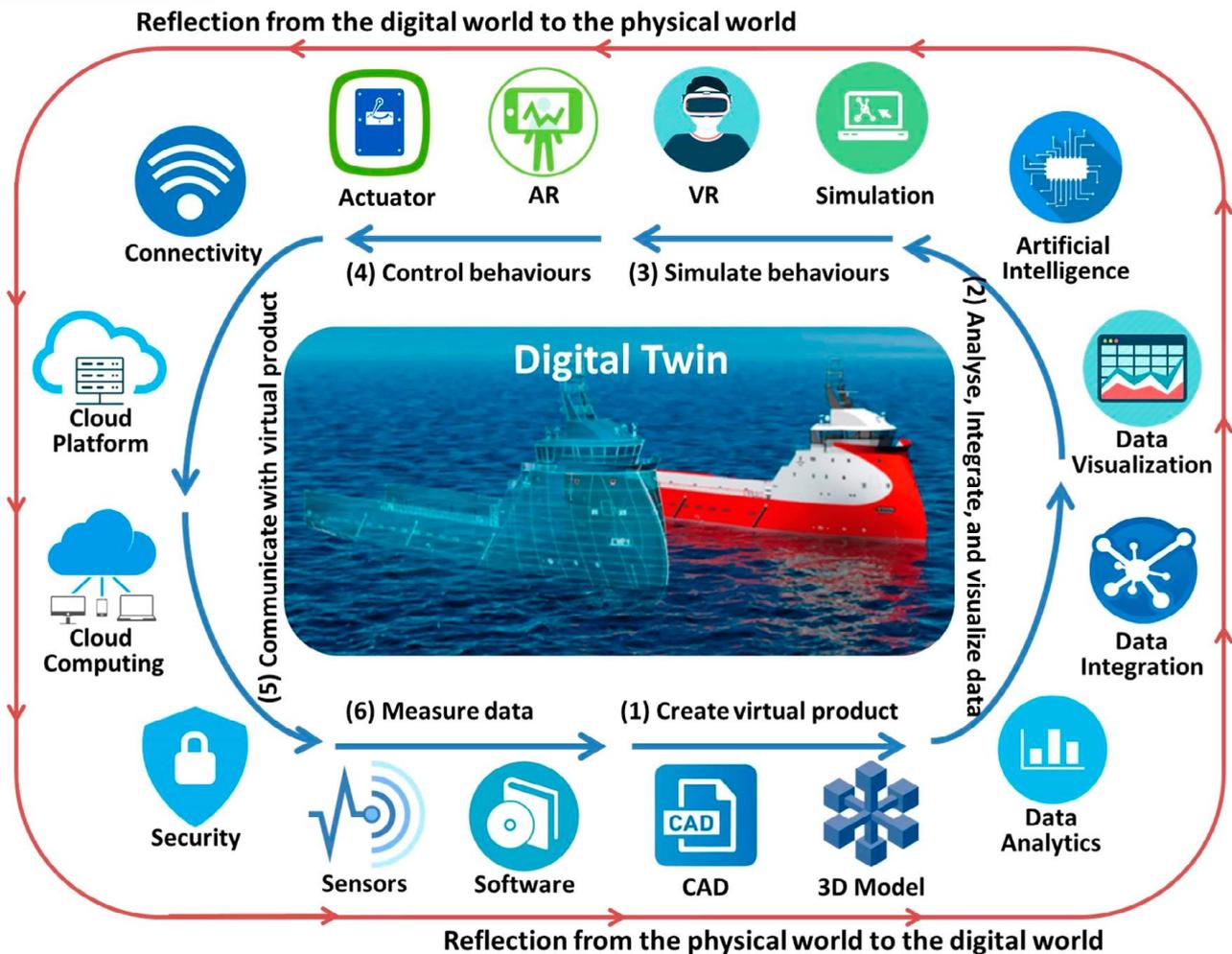


Figure 27: enabling technology of digital twin

### 9.3 Step(3): Simulate product behaviours in the virtual environment

The enabling technologies to this include simulation and **virtual reality (VR)**. The former is used to simulate key functions and behaviours of the physical product in the virtual world. In the past, simulation technologies are widely used in product design. On the other hand, virtual reality (VR). Technologies play the role of involving designers and even users to directly interact with the virtual product in the simulated environment. Recently, VR technologies are increasingly employed to support virtual prototyping and product design . Many readily available VR hardware devices can be directly adopted for digital twin.

### 9.4 Step(4): Command the physical product to perform recommended behaviours

Based on the recommendations of DT, the physical product is equipped with a capability, by means of various actuators, to adaptively adjust it function, behaviour and structure in the physical world. Sensors and actuators are the two technological backbones of a DT. The former plays the role in sensing the external world, whereas the latter plays the role in executing the desirable adjustments requested by DT. In practice, the commonly used actuators that are suitable for consumer products

include, for example, hydraulic, pneumatic, electric, and mechanical actuators. In Addition, augmented reality (AR) technologies can be used to reflect some parts of the virtual product back to the physical world. For example, AR enables end users to view the real-time state of their products. Recently, AR technologies are increasingly applied in the factory domain production engineering.

#### **9.5 Step(5): Establish real-time, two-way, and secure connections between physical and virtual product**

The connections are enabled using a number of technologies, such as network communication, cloud computing and network security. Firstly, networking technologies enable the product to send its ongoing data to the cloud to power the virtual product. The feasible networking technologies for consumer products include, for example, Bluetooth, QR code, barcode, wifi, Z-wave, etc. secondly, cloud computing enables the virtual product to be developed, deployed and maintained completely in the cloud, so that it can be conveniently accessed by both designers and users from anywhere with an internet access. Lastly, since product data are directly and indirectly concerning user-product interactions, it is critical to guarantee the security of connections. In light of the internet of Things (IOT), much effort has been devoted to connecting the physical and virtual product, which can be adapted for the DT research.

#### **9.6 Step(6): Collect all kinds of product-related data from different sources**

Generally speaking, there are three types of product-related data that should be processed by DT. For ordinary products, physical product data is usually divided into product data, environment data, customer data and interactive data. Product data contains customer comments, viewing and download records. Interactive data consist of user-product-environment interaction, such as stress, vibration, etc. using the sensor technology and IoT technology can collect some of above data in real time, and analyse from the product manual, web page customer browsing records, download records, evaluation feedback, etc. , can obtain the rest of the data. The collected data are fed to the step(1) in order to close the loop towards building more functional virtual product.

## 10. Data Exchange between Real Environment and Virtual Simulation Environment

The change in the behavior of global consumption and with the new technologies inserted in the products, demand that the production systems to adapt and become more and more agile. For this reason, some tools that contribute to the decision to change production systems are being used more frequently.

Among these tools, the Simulation of Discrete Events (DES) stands out, which has the function of reproducing the system studied in a digital environment. For this, the development of the model is based on the data collected, on the programming logic and on the validation of the results. Thus, the simulation model becomes an applicable tool in the evaluation of changes in production systems without any intervention in the production system.

### 10.1 Model Development (System Choice and Data Collection)

Achieving the goal of this work is to demonstrate the steps required to model a production system integrated with the virtual environment. In this sense, the work was developed in a small prototype (Big Loader Construction Set, from Tomy®) that represents the displacement of parts along a rail, passing through three workstations. In addition, the system is closed, and after delivery of the parts at the end point the entire process is repeated.

Thus, the necessary data were collected from the modeling of the system in a simulation software. The necessary data were: Total cycle time; Time between workstations; Distance between points; Transport speed between points; and Workplace failures analysis. Figure 28 shows the system chosen for this pilot model.

In addition, this prototype has components that collect data on its operation, these components are: Sensors capable of collecting time between workstations; data sharing system; data receiving system; car speed controllers along the way. Thus, this one is able to send and receive operating data in real time, thus, it is able to change its way of working according to the management needs of the system.

With the help of this system we can receive the data from sensors and check how many iteration have been done in specific time period. So, we can increase the production capacity of system and make required changing in the system.

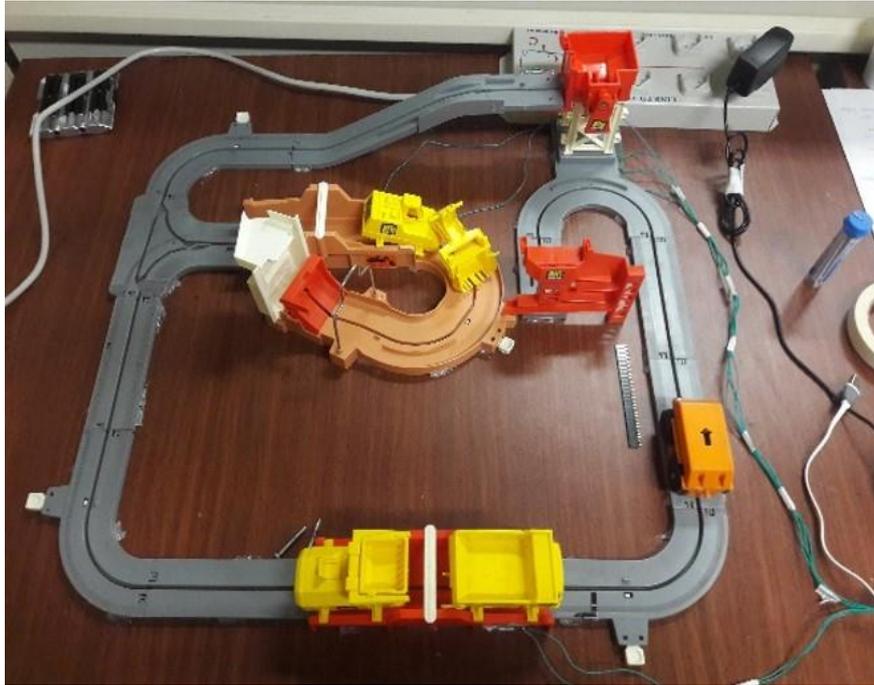


Figure 28: Production System prototype

## 10.2 Real time modelling and data collection

With the previously collected data it was possible to develop a simulation model that represent the real system. Figure 29 below demonstrates the simulation model.

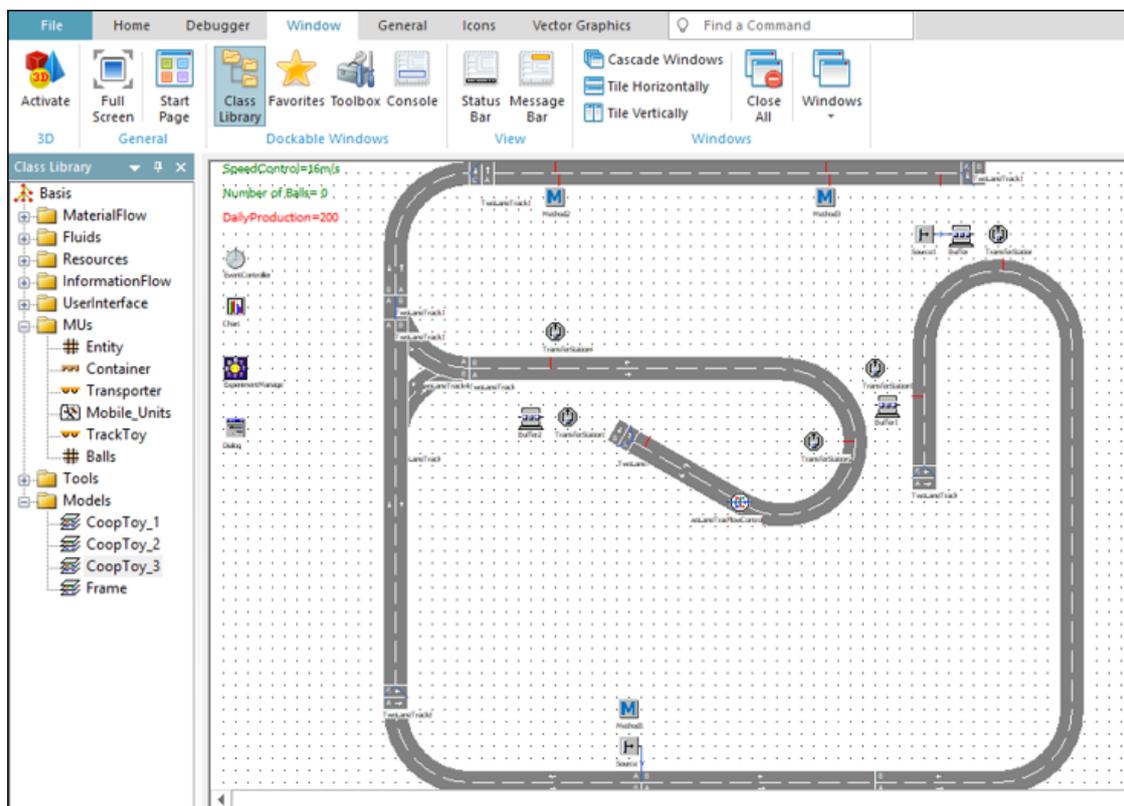


Figure 29: simulation model

For the development of the simulation model, we used Siemens Plant Simulation® software. This model was programmed to receive real time data from the physical model.

The data collection is made through sensors that identify the vehicle positioning and the real time of the displacement between the points, this happens similarly to the use of a MES System. All this information is stored in a database. During the process, the travel time may be influenced by discharging the batteries or by events along the way. Because in this prototype some events are deliberately provoked.

Thus, the data collected in the real system feeds the simulation model. So, the variables that control the speed of the vehicle cause it to change speed in the virtual environment automatically.

This model is also capable to receive programming data, which happens by reading into tables that can come from ERP. In this case, this information serves to evaluate whether work orders are being fulfilled correctly.

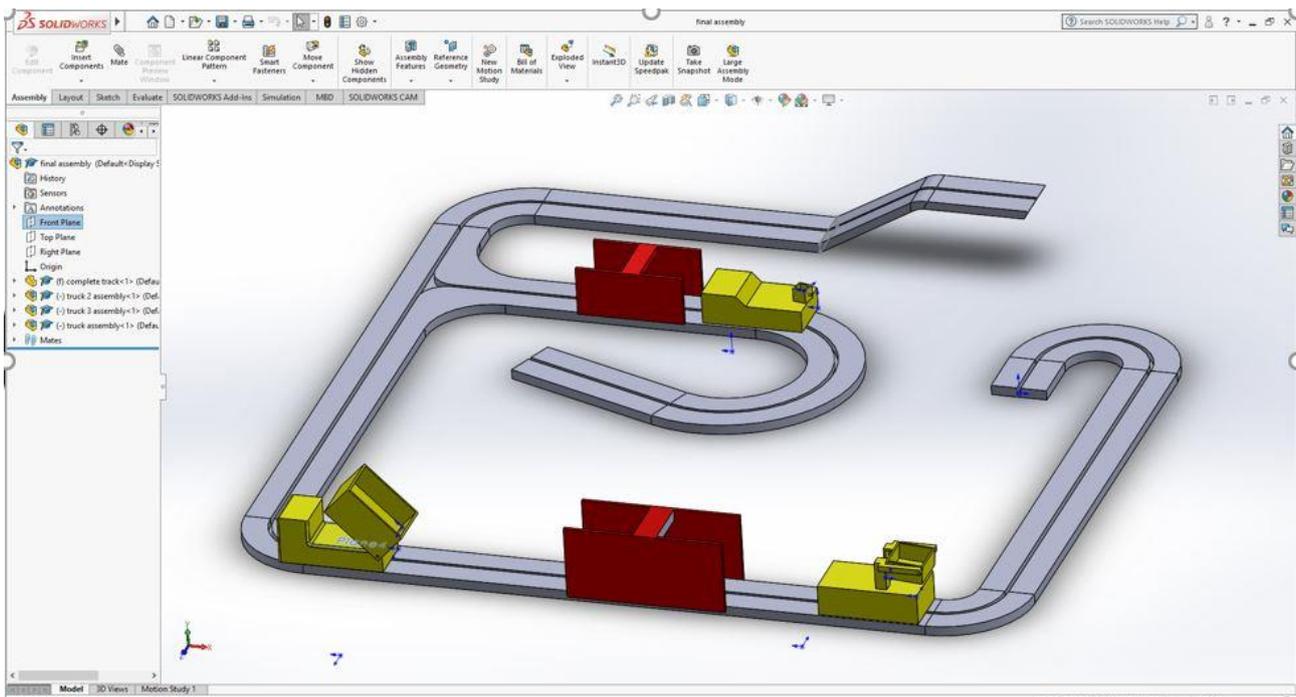


Figure 30: CAD model of production system prototype

### 10.3 Reprogramming proposal

As the simulation model receives data from both the real environment and the production schedule, the decisions made can be considered more accurate than the decisions made through simulation models that do not collect data in real time.

Thus, the main objective of this integration is to allow the optimizations generated in the virtual environment to be sent to the real environment. Figure 31 shows the proposal for exchanging information between real and virtual environments.

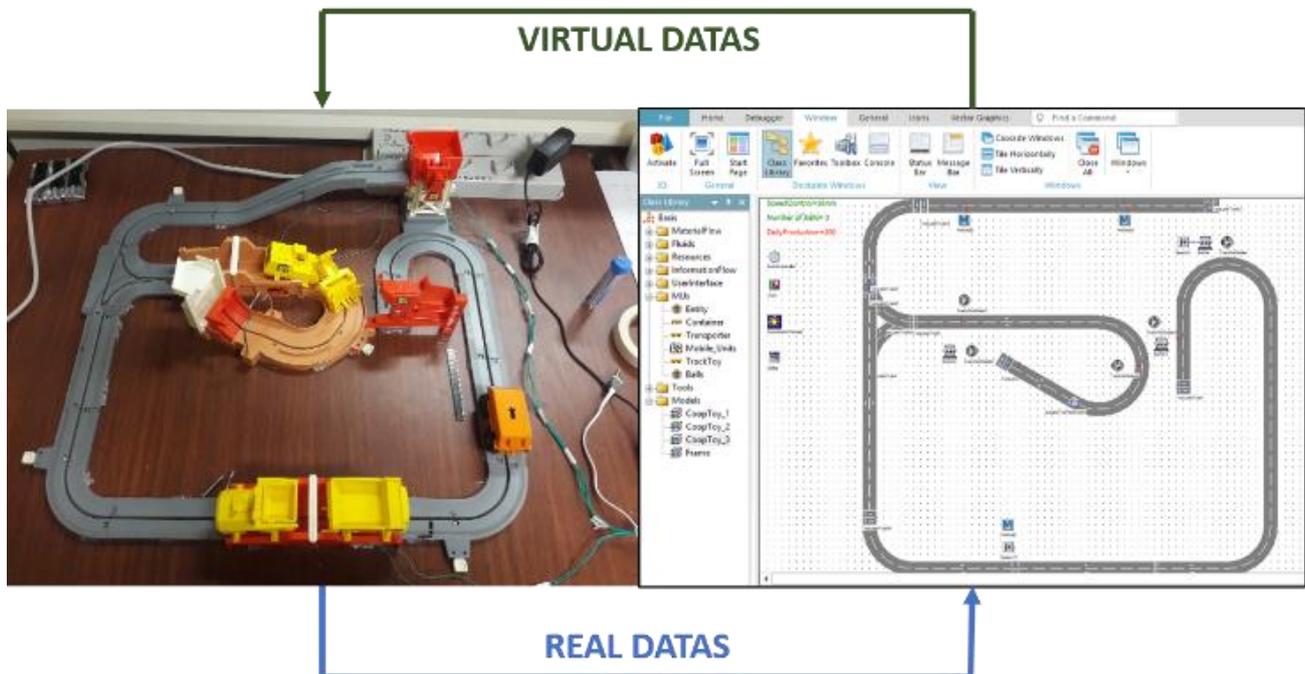


Figure 31: Data Exchange between environments

Assuming that the current system is delayed in fulfilling production orders, it is possible for the simulation model to determine the ideal vehicle speed to fulfill orders. In this proposal the vehicle will vary its speed in the real environment following the information from the simulation model. Thus, it can be said that the real environment has autonomy to reprogram itself without human intervention, only with data exchange.

Thus, the necessary steps for the development of a simulation model integrated with the production system:

- know the production system to be analyzed;
- Choose the main parameters of the production system;
- Develop a data mining system of the chosen parameters;
- Model the production system in simulation software;
- Develop an algorithm to insert the data collected in the simulation model;
- Create the optimization rules in the simulation model;
- Develop an algorithm that inserts the optimized data into the production system;
- Create production scheduling rules with new optimized data.

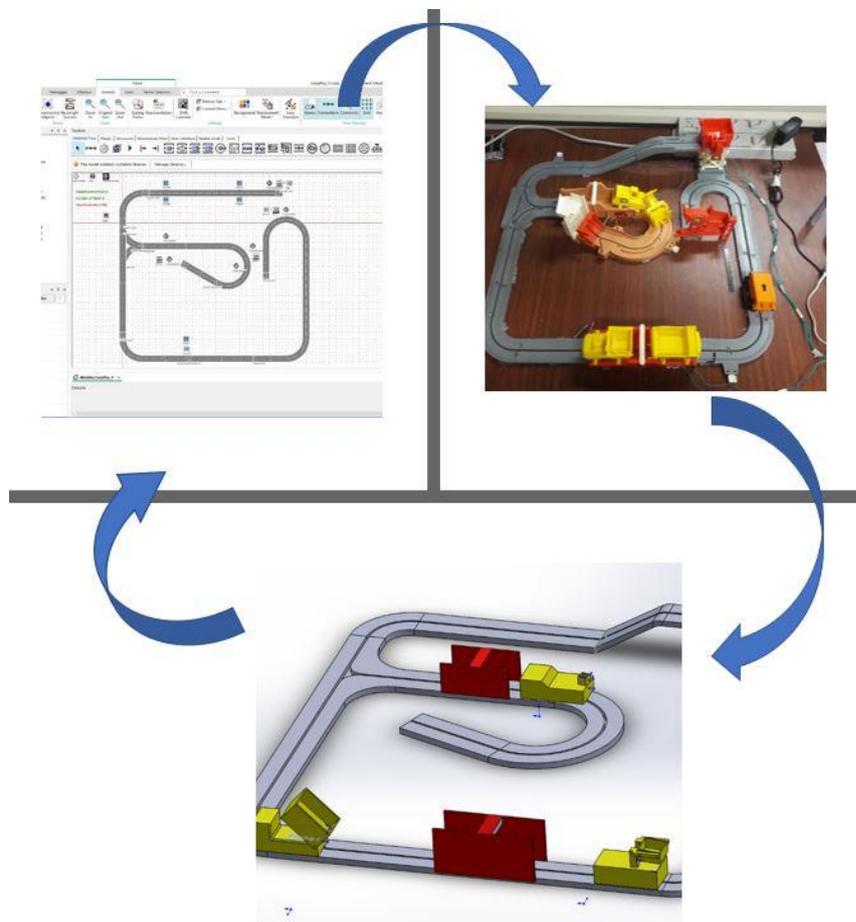


Figure 32: Digital twin cycle

It is important to certify that this work aims to show only the steps necessary for the development of a model with the highlighted characteristics. Thus, the results of this prototype are not valid, which should be presented in another work.

After building this simulation model, we want to research the advantages of decisions made with data exchanged in real time against decisions made with conventional models.



Figure 33: production line prototype at FEM-UNICAMP (Brazil)

## 10.4 Digital twin Based Scheduling Framework

The framework is supported by an architecture that lies at the basis of a scheduling tool represents its architecture that is composed of the following parts:

**REAL MACHINE** (or machine sub-system) feeds the database with signals about the interesting variables of the real behaviour of the analysed system. is being acquired from field devices from multiple sources such as add-on sensors, actuators, **PLC (Programmable Logic Controllers)**, **CNC (Computer Numerical Control machines)** etc. Signals could be data on different levels, as described in the **ISO 13374**. 1- Acquired data; 2- Manipulated data; 3- Detected state; 4- Assessed health; 5- Assessed prognosis.

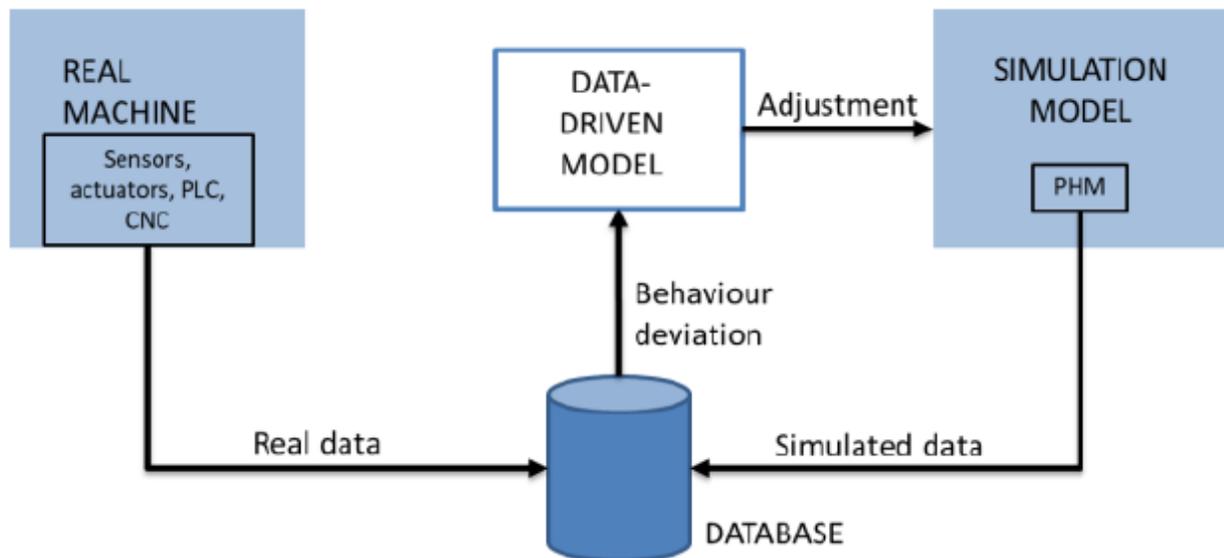


Figure 34: Architecture of scheduling tool

**SIMULATION MODEL** of the analyzed system feeds the database with the simulated signals replicating those generated by the real machine. The simulation model is a DT, as an EHI module is embedded and connected to the field devices that continuously update it according to the equipment health, through Prognostics Health Monitoring models, in order to carry out the reliability of the system, considering time and conditions variables.

**The DATABASE** collects data from both the real machine and the simulated model, decoupling the two levels of the DT (physical and cyber). By storing historical series of data from both the sources, it is possible to compare them and detect the deviations between the behavior of the real system and its simulation model.

**The DATA-DRIVEN MODEL** takes the behaviour deviations between the real and simulated system as input, which is detected in the historical series of data. The output of the data-driven model is an adjustment of the simulation model parameters. This adjustment provides incremental updates to the simulation model to synchronize it with the real system

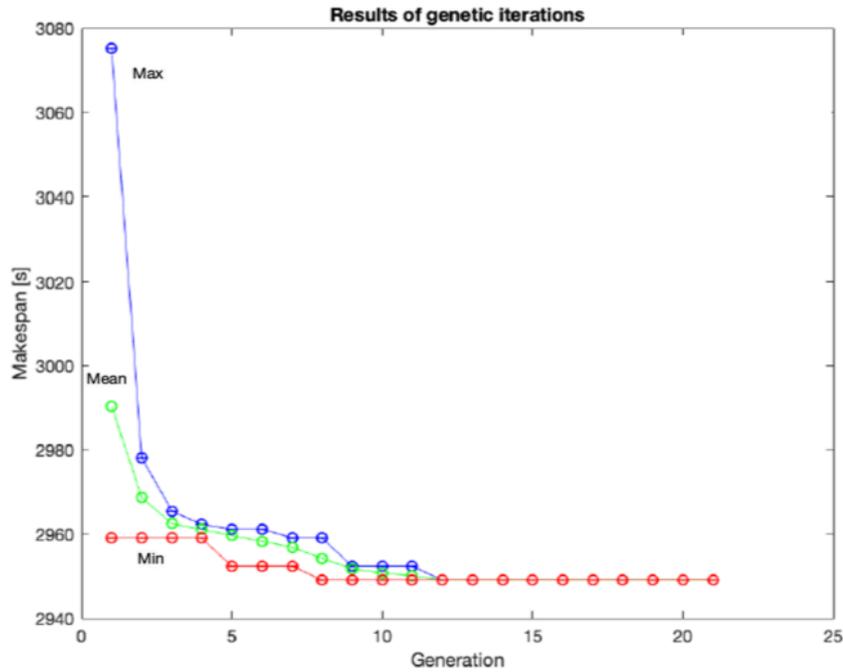


Figure 35: Application Case result (without EHI model)

## 11. Structural life prediction using Digital Twin

The operation of the Digital Twin for life prediction would proceed as diagrammed in Figure below. The Digital Twin is represented in the figure as a single entity, but it may consist of several components that are intimately linked, such as a thermal/heat transfer model, a dynamics model, a stress analysis model, and a fatigue model. The CFD model of that specific aircraft is then “flown” virtually through those flights to estimate the loads and environments the aircraft will experience.

The **CFD and FEM** models are closely coupled so that the effect of aeroelastic vibrations and structural deflections on the aerodynamic flow, if any, can be captured, and vice versa. Traditionally, any effect between structural deflections and aerodynamic flows has been discounted, but for a realistic high fidelity model, the possible interactions between physical phenomena should not be ignored from the start.

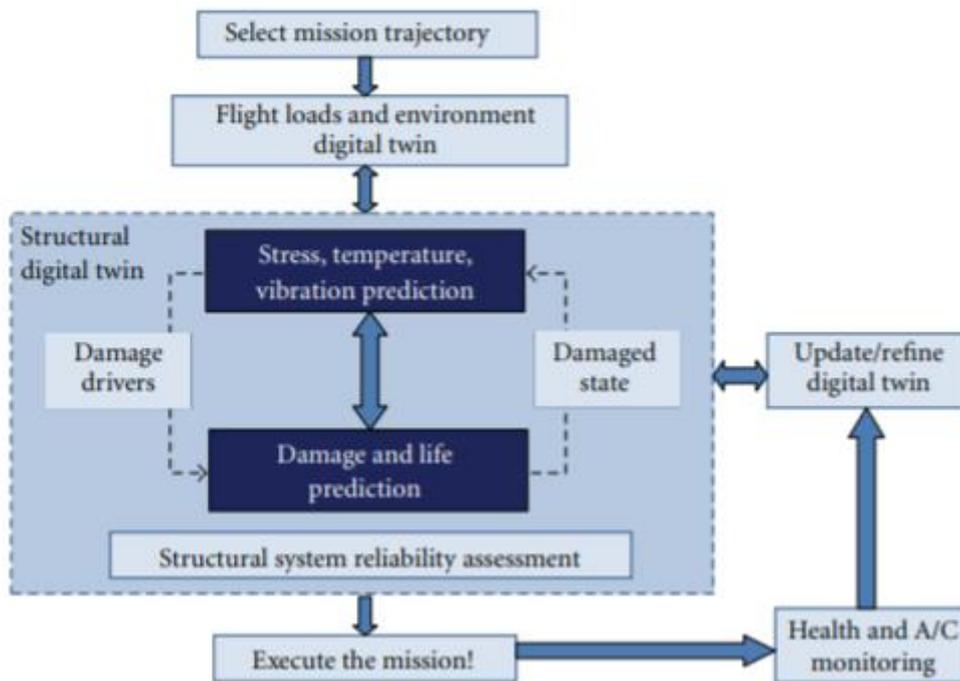


Figure 36: Digital twin life prediction concept

Many of the physical phenomena discussed above are nonlinear. As a result, the structural FEM must perform nonlinear analysis. Since the evolution of the material state and the development of damage affect the stiffness of structural components, the coefficient of thermal expansion, and the load at which inelastic deformations begin, among other properties, the material state evolution and damage models must pass information back to the “stiffness matrix” of the FEM so that the thermal and stress fields are accurately determined.

In addition to having sensors for damage detection at critical locations, the SHm system also senses and records strain histories at select locations during the flight. The strains in the Digital Twin at the selected locations are compared to the strains recorded on the physical aircraft. The damage state at locations in the Digital Twin corresponding to aircraft locations with SHm sensors is compared to the condition detected by the SHm system. Differences between the Digital Twin and the condition of the aircraft are resolved with a formal mathematical process such as Bayesian updating. In this way, the Digital Twin undergoes continuous improvement and becomes more reliable the longer the aircraft is in service

The use of the Digital Twin is not limited to decisions about a single flight. The usage for a particular aircraft can be projected forward for any desired length of time.

## 11.1 E3 Application

The Digital Twin is typical of what is called an “E3 Application”, a complex system in high-dimensional spaces. The HPC community has identified certain application characteristics and math and algorithms needs which have already been discussed for the Digital Twin. Within the context of the Digital Twin, there is a need to solve coupled PDEs, quantify uncertainty, design and optimize the structure, while handling large and noisy data.

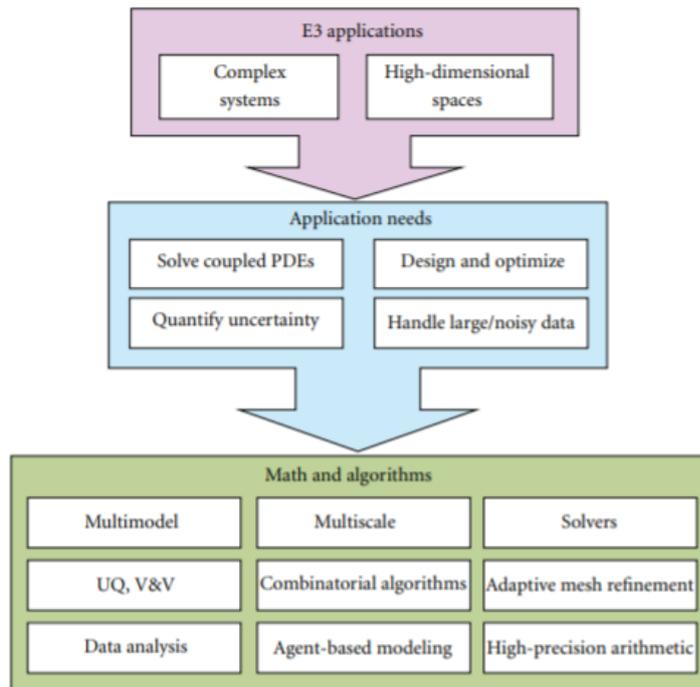


Figure 37: Common application characteristics E3 application

The HPC community has accurately described the computational problems of the Digital Twin. Solving very large systems of PDE’s with uncertainty everywhere is at the core of the Digital Twin concept.

Kestrel integrates multiple single executable modules. The most significant for the purposes of the Digital Twin are a CFD solver and a linear modal representation of the aircraft along with fluid-structure interfacing operations. Aerodynamic loads are applied directly to the structure. However, the stresses in the structural components still need to be determined to enable life prediction.

## Conclusion

The concept of Digital Twin is not old as other industrial revolutions, Anyhow research in this are keeping going and researchers and working hard to find the final are reliable solution to implement this concept to industrial and other activities. There are several research and publications on Concept of digital twin but none of them give you the exact answer how to you can directly implement this concept.

We as a team of Engineers and researchers from State university of Campinas at department of Mechanical and Manufacturing engineering try to implement this concept to an industrial application. We development and prototype (physical) which is a Truck loader toy who work and a production line on the other hand we developed a CAD model using software Solidworks. And try to integrated these two with the help of plant simulation software to monitor the simulation environment of this system.

As, I mentioned this concept is not fully matured and research is keep going so we were not able to get final results from this research but a satisfying outcome has been achieved by integrating different environments.

## Appendix

Research paper (Under review will published until end of July 2021)

### Steps for Data Exchange between Real Environment and Virtual Simulation Environment

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#### ABSTRACT

Recently the technological evolution resulting from the fourth industrial revolution, especially with the advancement of the internet of things and bigdata, coupled with the change in consumer behavior, are forcing companies to improve the efficiency of production systems. Now, companies must mass produce to keep costs low, but they must also be flexible and offer a wide variety of products. Thus, companies are increasingly using computational tools to improve decision making, especially with the application of simulation and digitization of production systems. However, online data collection is presenting itself as a solution to decrease the time for the development of simulation models and, thus, speed up decision making. In this way, this work shows the steps required for online data exchange between a real system and a virtual production system. For this, a prototype will be used that demonstrates these basic concepts.

**CCS CONCEPTS:** Computing methodologies – Modeling and simulation

**Additional Keywords and Phrases:** Discrete Event Simulation; Industry 4.0; Digital Twin.

#### ACM Reference Format:

First Author's Name, Initials, and Last Name, Second Author's Name, Initials, and Last Name, and Third Author's Name, Initials, and Last Name. 2018. The Title of the Paper: ACM Conference Proceedings Manuscript Submission Template: This is the subtitle of the paper, this document both explains and embodies the submission format for authors using Word. In Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY. ACM, New York, NY, USA, 10 pages. NOTE: This block will be automatically generated when manuscripts are processed after acceptance.

## References

- Negri, E., L. Fumagalli, and M. Macchi. 2017. "A Review of the Roles of Digital Twin in CPS-Based production Systems." *Procedia Manufacturing* 11 (June). The Author(s): 939–48.
- R. Rosen, G. Von Wichert, G. Lo, and K. D. Bettenhausen, "About The Importance of Autonomy and Digital Twins for the Future of Manufacturing," in *IFAC-PapersOnLine*, 2015, vol. 48, no. 3, pp. 567–572 .
- N. Jazdi, *Cyber Physical Systems in the Context of Industry 4.0*, in: *Autom. Qual. Testing, Robot. 2014 IEEE Int. Conf.*, 2014: pp. 1–4. doi:10.1109/AQTR.2014.6857843
- Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., ... Nee, A. Y. C. (2018). Digital twin-driven product design framework. *International Journal of Production Research*, 1–19. doi:10.1080/00207543.2018.1443229
- Schroeder, G. N., Steinmetz, C., Pereira, C. E., & Espindola, D. B. (2016). Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange. *IFAC-PapersOnLine*, 49(30), 12–17. doi:10.1016/j.ifacol.2016.11.115
- Catarinucci, L., D. D. Donno, L. Mainetti, L. Palano, L. Patrono, M. L. Stefanizzi, and L. Tarricone. 2015. "An IoT-Aware Architecture for Smart Healthcare Systems." *IEEE Internet of Things Journal* 2 (6): 515–526
- Goswami, M., Y. Daultani, and M. K. Tiwari. 2017. "An Integrated Framework for Product Line Design for Modular Products: Product Attribute and Functionality-driven Perspective." *International Journal of Production Research* 55 (13): 3862–3885
- Knapp, G. L., T. Mukherjee, J. S. Zuback, H. L. Wei, T. A. Palmer, A. De, and T. DebRoy. 2017. "Building Blocks for a Digital Twin of Additive Manufacturing." *Acta Materialia* 135: 390–399.
- Lee, J., B. Bagheri, and H. A. Kao. 2014. "Recent Advances and Trends of Cyber-physical Systems and Big Data Analytics in Industrial Informatics." *International Proceeding of Int Conference on Industrial Informatics (INDIN)* 1–6
- Liu, C., and X. Xu. 2017. "Cyber-physical Machine Tool-the Era of Machine Tool 4.0." *Procedia CIRP* 63: 70–75
- Liu, Y., J. Jin, P. Ji, A. Harding, and R. Y. Fung. 2013. "Identifying Helpful Online Reviews: A Product Designer's Perspective." *Computer-Aided Design* 45 (2): 180–194
- Tuegel, E. J., A. R. Ingraffea, T. G. Eason, and S. M. Spottswood. 2011. "Reengineering Aircraft Structural Life Prediction Using a Digital Twin." *International Journal of Aerospace Engineering* 1–14. doi: 10.1155/2011/154798

- Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. *Int. J. Adv. Manuf. Technol.* 2018, 94, 3563–3576
- Barricelli, B.R.; Casiraghi, E.; Fogli, D. A Survey on Digital Twin: Definitions, Characteristics, Applications, and Design Implications. *IEEE Access* 2019, 7, 167653–167671
- Terkaj, W.; Gaboardi, P.; Trevisan, C.; Tolio, T.; Urgo, M. A digital factory platform for the design of roll shop plants. *CIRP J. Manuf. Sci. Technol.* 2019, 26, 88–93.
- Siemens. MindSphere. 2020. Available online: <https://siemens.mindsphere.io/en> (accessed on 18 November 2020)
- Hietala, J.; Ala-Laurinaho, R.; Autiosalo, J.; Laaki, H. GraphQL Interface for OPC UA. In *Proceedings of the 2020 IEEE International Conference on Industrial Cyber Physical Systems (ICPS)*, Tampere, Finland, 10–12 June 2020.
- Lehto, M. Scalability of Digital Twins: Challenges and Possibilities for Efficient Implementation. Seminar Presentation. 2019. Available online: <https://youtu.be/ZsG1KLiBvqk>; <https://www.aalto.fi/en/industrial-internet-campus/digitwin-demo-day22112019> (accessed on 2 October 2020).
- Liu, M.; Fang, S.; Dong, H.; Xu, C. Review of digital twin about concepts, technologies, and industrial applications. *J. Manuf. Syst.* 2020
- Schroeder, G. N., Steinmetz, C., Pereira, C. E., & Espindola, D. B. (2016). Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange. *IFAC-PapersOnLine*, 49(30), 12–17. doi:10.1016/j.ifacol.2016.11.115.
- Bazilevs, Y., Deng, X., Korobenko, A., Lanza di Scalea, F., Todd, M. D., & Taylor, S. G. (2015). Isogeometric Fatigue Damage Prediction in Large-Scale Composite Structures Driven by Dynamic Sensor Data. *Journal of Applied Mechanics*, 82(9), 091008. doi:10.1115/1.4030795
- Davis, J., Edgar, T., Porter, J., Bernaden, J., & Sarli, M. (2012). Smart manufacturing, manufacturing intelligence and demand-dynamic performance. *Computers & Chemical Engineering*, 47, 145–156. doi:10.1016/j.compchemeng.2012.06.037
- Tuegel, E. (2012). The Airframe Digital Twin: Some Challenges to Realization. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference<BR>20th AIAA/ASME/AHS Adaptive Structures Conference<BR>14th AIAA. doi:10.2514/6.2012-1812
- Sacco, M., Pedrazzoli, P., & Terkaj, W. (2010). VFF: Virtual Factory Framework. 2010 IEEE International Technology Management Conference (ICE). doi:10.1109/ice.2010.7477041

- Garetti, M., Rosa, P., & Terzi, S. (2012). Life Cycle Simulation for the design of Product–Service Systems. *Computers in Industry*, 63(4), 361–369. doi:10.1016/j.compind.2012.02.007
- Canedo, A. (2016). Industrial IoT lifecycle via digital twins. *Proceedings of the Eleventh IEEE/ACM/IFIP International Conference on Hardware/Software Codesign and System Synthesis - CODES '16*. doi:10.1145/2968456.2974007
- Glaessgen, E., & Stargel, D. (2012). The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles. 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference<BR>20th AIAA/ASME/AHS Adaptive Structures Conference<BR>14th AIAA. doi:10.2514/6.2012-1818
- Lee, J., Kao, H.-A., & Yang, S. (2014). Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment. *Procedia CIRP*, 16, 3–8. doi:10.1016/j.procir.2014.02.001
- Lee, J., Bagheri, B., & Kao, H.-A. (2015). A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23. doi:10.1016/j.mfglet.2014.12.001