Chapter 6
Digital Twins and Intelligent Decision Making

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6.1 Introduction

Twin (noun): something containing or consisting of two matching or corresponding parts.

- Oxford University Press

Chapter 5 discussed ways of simulating and modelling manufacturing systems an offline manner. Offline in this context means the simulation is running disconnected from the real system and is reliant on the user to update parameters and data to maintain the accuracy of the model. In contrast, this chapter details online simulations, where the model is connected directly to the physical system and is automatically updated as the system changes. This approach is common called a *digital twin*. In addition, this chapter will discuss decision support systems, which are software packages intended to enhance the decision making process discussed in Chapter 4, and to make complex problems solvable.

A digital twin is a simulated replica of a complex system. Unlike more

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J.C. Chaplin et al. (eds), *Digital Manufacturing for SMEs*
DOI: https://doi.org/10.17639/91WZ-CP62

conventional simulation, the digital twin is connected in real-time to the physical equivalent and collects generated data. This allows the digital twin to improve its accuracy based on the real system, and for the digital twin to analyse the system or perform tests which would be too costly or time consuming to run on the real thing. Digital twins are used to model complex systems and have their origins in the modelling of air and spacecraft.

The first definition of a digital twin (then just a nameless concept) was coined by Michael Grieves in 2002 [1] as a concept for product-lifecycle management. After many different names including Mirrored-Spaces Model, Information Mirroring Model, and Virtual Twin, the now established name "digital twin" was subsequently introduced by John Vickers in a NASA report published in 2010 [2] and has become the standard terminology. A review of literature published between 2012 and 2016 by Negri and colleagues [3] as part of the MAYA project found 16 different definitions for digital twins across four research fields: aeronautics and space, robotics, manufacturing, and informatics. Some of the proposed definitions can be found in Table 6.1-1.

Year	Definition
2010	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 [4].
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 [5].
2015	Very realistic models of the process current state and its behaviour in interaction with the environment in the real world [6].
2016	The simulation of the physical object itself to predict future states of the system [7].
2018	Digital twins are realistic digital representations of physical things [8].

Table 6.1-1 Definitions of digital twins in chronological order.

Grieves described the digital twin model at its most basic with the diagram seen in Figure 6.1-1. A digital twin always corresponds to a *physical twin* – the actual physical in stance of the product that is being simulated with the digital twin.

The physical twin and digital twin are connected. This is what distinguishes a digital twin from a more conventional simulation. Data is collected from the physical twin in real-time with sensors and used to improve and optimise the digital twin. The digital twin can run analysis methods, and multiple possible scenarios can be tested digitally. The processed information gained from these can be fed back to the physical twin to optimise the real-world performance.

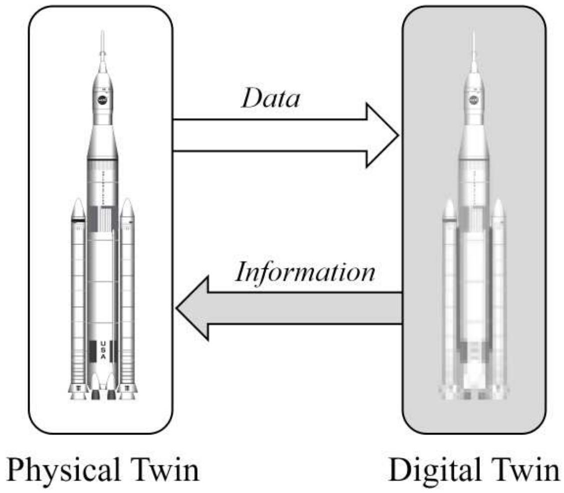

Figure 6.1-1 The digital twin is the virtual counterpart to the physical twin, and is used to better understand complex systems such as manufacturing lines or rockets. Data collected with sensors in the physical twin inform the digital twin and improve accuracy, and insight gained by analysing the digital twin can be used to control the physical twin. Image rights: Author, adapted from [1].

Simple systems can be simulated to a sufficient level of detail that the added complexity of a real-time connect may not be required. Digital twins are typically reserved for complex systems where creating an adequate simulation offline is not possible, and the simulation must be improved over time.

"Airplanes, rockets, manufacturing floor equipment, and even automobiles have or will have [digital twin instances]. Paper clips will not".

- Michael Grieves

The key differentiating factor between a conventional model and a digital twin is that the physical system is feeding real-time data into the digital twin to update the model. Though significant structural changes to the physical system may require manual intervention, data such as manufacturing throughput, buffer sizes, up/down times etc. can be automatically collected and used to keep the digital twin updated. Any simulations that run on the digital twin's model use the latest, most accurate information.

Before digital twins are discussed further, it is important to understand how it is possible to connect a digital twin simulation to the physical twin – the online aspect which differentiates the approach from the offline approaches in Chapter 5. This is achieved using sensors to monitor the physical twin, and report back its state, and section 6.2 will introduce sensors and the modern development of smart sensors.

6.2 Sensors

6.2.1 Introduction to Sensors

The manufacturing industry must achieve sustainable growth and increases in productivity to remain competitive on the global stage. Increasingly, access and exploitation of manufacturing data is contributing to these aims, enabling quicker, more effective decision-making.

One of the key technologies for data exploitation is the *Internet of Things* (IoT), which embeds sensors and communication equipment in manufacturing machineries and lines, each collecting and transmitting data to the manufacturing enterprise's network. The application of these techniques to manufacturing is also sometimes called the Industrial Internet of Things (IIoT).

IoT is a recent development and is a broad term for a set of technologies, systems, and design principles associated with using Internet-connected things that monitor and manipulate the physical environment. IoT connects sensors and actuators, to information and communication technologies (ICT) systems via wired or wireless networks. The most important technology at the device or hardware level in this network infrastructure is the *sensor* technology, as it is the most basic means for collecting and controlling data in real time.

A sensor is a device that observes and measures a physical property of a natural phenomenon or man-made process, and converts that measurement into a signal. That signal can then be reported to a worker, used to trigger an actuator, or collected for analysis. Sensors have played a role in manufacturing since their invention. They provide a means for gathering information on manufacturing operations and processes as they are performed. Typically, this means some property of the process (temperature, speed, location etc.) is converted into an electrical signal and collected by the process controller, often a programmable logic controller (PLC). The controller may use the sensor reading to modify the process, or the signal may just be logged for later inspection.

Process data are records of the processing performed to create products, including details such as the program performed (for a CNC machine), the user-set process parameters, and recorded data from sensors such as vibration, temperature, or cutting force (depending on the process). Correlating this with the individual product ID allows for analysing this data relative to the quality outcomes or service life of the specific product. Most traditional sensors convert their measured property into electricity, and hence require a wire or cable to connect with the external instruments that record this value. The cable can be copper wire, twisted pair or fibre optic.

The data from sensors must somehow be sent to a computer for interpretation or storage. Often this will be a local PLC or data capture device where the sensor data can immediately be acted upon. It may be a remote server where data can be logged in a database or simple spreadsheet. *Fieldbus* is the term used for industrial computer networks. Many standards exist including Ethernet, Industrial Ethernet, Controller Area Network (CAN), Process Field Bus (Profibus) and a wide variety of vendor specific technologies. Use of these will depend on equipment compatibility and the requirements for process control.

Wireless sensors offer flexibility of installation, resulting in improved process monitoring and control while simultaneously offering reduced installation and maintenance costs. Industrial applications offer a broad scope for growth in wireless sensor use, but this growth cannot be achieved without overcoming some of the key challenges facing the market:

- *Evolving standards*: New wireless communication technologies are still under research and development. Some of these standards might not be compatible with others, limiting the interoperability of the network.
- *Network size*: The application or use case scenario will determine the size of the network. Some wireless approaches are better for smaller or larger scales of deployment, and if the application demands a change in location, number of nodes or adjustments to topology the approach may have to be changed.
- *Open wireless frequency bands*: With the propagation of wireless technologies such as mobile phones and Wi-Fi, there is a lack of open frequency bands. Currently, most wireless sensor network devices operate in unlicensed bands such as 915 MHz and 2.4 GHz, and reliable communication can be affected by interference from other devices operating in the same frequency band.
- *Industrial safety*: Making a wireless sensor system fail-safe depends heavily on the type of application in which the wireless sensor is used.

On top of these networks, many higher level *machine to machine communication protocols* exist for exchanging process data (rather than control data) in industrial automation settings. These include Open Platform Communications – Unified Architecture (OPC UA), MTConnect, Data Distribution Services (DDS), and MQ Telemetry Transport (MQTT). The standards will significantly simplify the acquisition of process data by handling many networking aspects and providing a common standard for data.

6.2.2 Types of Sensors

Sensors convert physical phenomena into signals, and are an example of a primary data source (see section 5.2.2). Almost any physical phenomena can be measured with a sensor, but the most common types used are listed below.

- *Temperature*: This sensor gives temperature measurements as an electrical signal (e.g. voltage) proportional to the temperature measurement. There are various electrical temperature sensors such as the thermistor, thermocouple, resistance thermometer and the silicon band gap temperature sensor, and each have different properties which make them better or worse for certain situations.

- *Force, pressure:* There are devices that convert variations in applied force or pressure into an electrical signal. There are two principles that have become dominant in force measurement; strain gauge-based sensors and piezoelectric force sensors. Strain gauge sensors contain an electrically conductive foil which deforms as force is applied. This deformation changes the electrical resistance of the spring, and this property is converted to an electrical signal. Piezoelectric sensors contain two crystal disks with an electrode foil mounted in between. When applying force, this generates electrical charge that can be amplified and used as a signal. Piezoelectric sensors are first choice for fast measurements of small forces while strain gauge-based sensors are superior when larger forces are involved [9].
- *Level*: These sensors detect the level of liquids and other fluids and fluidised solids such as powders, and are common in industrial process control. Examples include hydrostatic sensors (which measure water pressure to deduce water level), and optical level sensors which use the attenuation of light to measure fluid depth.
- *Acceleration, vibration*: Motion can also be detected with sensors. Accelerometers measure acceleration in a single direction, and are often combined into units with two (bi-axial) or three (tri-axial) accelerometers at right angles to detect the direction of acceleration. Accelerometers can also be used to detect vibration. Accelerometers are often Micro-electro-mechanical Systems (MEMS) that converts the motion of a small mass into an electrical signal with piezoelectric crystals. These crystals generate small electrical signals when subjected to mechanical stress.
- *Orientation*: Gyroscopic sensors detect rotation around a single axis, and like accelerometers are often combined into bi-axial and tri-axial sensors. Tri-axial accelerometers can in fact detect the orientation of a stationary object as they detect Earth’s gravity. However, accelerometers cannot do this while the object is moving. Tri-axial accelerometers and tri-axial gyroscopes can be combined into Inertial Measurement Units (IMUs). IMUs are used to determine the orientation of mobile phones, adjustment of suspension in cars, and control of aircraft.
- *Proximity*: Proximity sensors detect if an object is physically close to the sensor, and effectively detect the presence or absence of objects. They can be implemented with a variety of technologies including optical, inductive, magnetic and capacitive methods. They are widely used in industrial automation like conveyor lines for counting and jam detection, and in machine tools for safety interlock and sequencing.
- *Position*: Position sensors detect the mechanical position of objects. They often use similar technologies to proximity sensors, but can determine if an object is present, but also how far the object is from the sensor. They can measure absolute distance, angular rotation, and tilt angles depending on the technology used and application. These are commonly used to control the motion of robots and actuators, rotation of valves, and angles of actuators.

- Other sensors include *humidity*, *gas*, *biosensor*, *photoelectric*, *flow*, and many others, far more than can be described in this book.

A discussion of sensors with additional detail on their applications in robotics can be found in Chapter 8.

6.2.3 Smart Sensors

At their core, sensors are often very simple mechanical or electronic devices to convert physical stimuli into electrical signals. However, the progress and miniaturisation of technology, combined with the move towards the Internet of Things means many sensors (and a particularly high percentage of wireless sensors) have more features than just signal transducing.

Smart sensors are microprocessor driven and include features such as communication capability and on-board diagnostics that provide information to a monitoring system and/or operator to increase operational efficiency and reduce maintenance costs. They can perform some computation locally, reducing the amount of information that must be transmitted. This is particularly important for wireless sensors which have less bandwidth available than wired sensors. Common characteristics of smart sensors include:

- *Signal conditioning* that preserves integrity and ensures isolation in harsh industrial environments, smoothing out noise and amplifying weak signals.
- Using *local computing power* to process and interpret data locally; make decisions based on the physical parameters measured, adjust parameters autonomously, and be selective about what data is transmitted.
- *Built-in diagnostics* for simplified troubleshooting and maintenance.
- Complying with a *variety of communication standards* such as Wi-Fi, Bluetooth and Zigbee, rather than being constrained to a single technology.

Sensors have been utilised in manufacturing for decades, but smart sensors offer new and diverse benefits that can potentially lead to greater profitability and productivity. Principally, smart sensors offer richer data – the context and relevance of the data is recorded in addition to the signal itself, and smart sensors can be selective about the data which is sent and where it is sent. Applications of smart sensors to manufacturing include:

- *Aggregation and collection of big data*: Big data and data mining uses extremely large quantities of data to “mine” for insights. Smart sensors facilitate this in three ways;
  - Firstly, smart sensors are often simpler to implement than conventional sensors, as they include all the necessary equipment and wireless communication protocols to connect to existing manufacturing execution systems in a single package without running lots of cables.

  - Secondly, the ability for smart sensors to pre-process data allows them to aggregate larger quantities of data and transmit them effectively. Big data and data mining typically relies on very large quantities of data to achieve the best insights, and simple sensors may not be able to gather and share the required data volumes.
  - Thirdly, smart sensors can often communicate with one another, allowing data from sensors to be correlated to each other, facilitating the analysis of data from multiple sources.
- *Quality control:* Quality is critical to manufacturing competitiveness, and quality control must be an integral element of the manufacturing process. Identifying problems early reduces or removes the cost of scrapped parts of expensive re-work. Keeping processes in control requires monitoring, and this is traditionally done with conventional sensors to feed into control charts and statistical quality control methods. Smart sensors however are able to pre-process data to detect anomalies as they occur, and provide real-time alerts and flags when processes are deviating from nominal. The additional features of smart sensors allow them to send richer information than just a signal relative to the physical parameter, and to make decisions.
- *Improving and automating logistics and asset management:* Battery powered and communicating wirelessly, smart sensors can track the location of assets, vehicles, inventory, or people. The data can be used by manufacturers to track logistics and the supply chain, monitor the movement and utilisation of assets, and find lost parts and tools.
- *Regulatory compliance:* Many manufacturing sectors are highly regulated, with stringent rules on data collection and data storage to ensure compliance. Compiling the necessary reports from sensor data, logs, and records across multiple systems can be extremely time consuming and labour intensive. A well-managed data management system combined with smart sensors can dramatically simplify this process, with sensors able to collect environmental data such as temperature and humidity, as well as equipment utilisation data such as energy consumption, hours of operation, and maintenance information.

6.2.4 Product Tracking

The fundamental function of sensors is to detect physical phenomena and convert it to electronic signals, but sensors may not always be as simple as converting (for example) a temperature to a voltage. A carefully set up optical sensor can become are barcode reader, allowing for richer and more complex information about the world to be collected. *Product tracking* is the use of sensors to determine what specific item is at a location, allowing for unique products to be tracked and more granular information to be collected. This information could then be fed into a digital twin, giving it live data on the products being produced.

Product tracking requires three key features to be implemented:

1. A way of uniquely identifying the product (or part, or asset) being tracked.
2. A way of acquiring data about the product (such as measurement data or process data) that can be correlated to its identifier.
3. A way of storing the acquired data for future reference.

There is no inherent requirement for any of these three features to be automated. The identifier could be a number written on the part with a marker pen, the acquisition of data could be process parameters noted on a sheet of paper, and the data could be stored in a plastic folder for later reference. This may seem an exaggerated example, but this approach remains extremely common in modern manufacturing companies both large and small. Handwritten job cards are still the most common standard used, and can function extremely effectively. However, every instance of manual data entry raises the chances of a mistake being made. Manual data entry also represents a skilled worker performing a low skilled job, and their time could often be better spent.

Automated product tracking technologies can fit into each of these three categories. They enable the identification, acquisition, and storage of data with less worker effort or no effort at all. They also significantly reduce the probability of error, and make data recall and analysis easier by enforcing common data standards. Automated product identification, also referred to as *Automatic Identification and Data Capture* (AIDC) are technologies that allow data to be entered into a computer system with little to no human involvement. The most common example of AIDC is the use of barcodes in retail stores. The use of these codes shows the three critical stages of AIDC:

1. *Data encoding:* Human-readable characters or numbers are rarely the most efficient way for AIDC technologies to represent data. Instead, data (such as the product number) is encoded in some way, such as the width of the bars in a barcode.
2. *Data reader:* A device able to reliably read the encoded data, and convert into an appropriate data format for transmission. The barcode scanner is an example of a data reader.
3. *Data decoder:* The data decoder converts the signal from the data reader back into the original characters that were encoded. For example, this would give the barcode number representing the product. The Point of Sale (POS) software can then look up the number in a database and retrieve the name and price of the item.

AIDC uses many different technology types, with different advantages and disadvantages. These are detailed in the table below [10]:

Technique	Performance	Advantages	Disadvantages
Human Manual Entry	Sensor Type: *Manual* Entry Time: *Slow* Error Rate: *High* Cost: *Low*	Low initial cost. Simple to set up. Highly adaptable.	High ongoing cost (cost of a worker's time). Slow entry speeds. Prone to error or omission.
Biometric	Sensor Type: *Optical (typically)* Entry Time: *Medium* Error Rate: *Low* Cost: *Medium*	Intuitive. Rapid identification of people. Appropriate for security applications.	Niche applicability. Often unpopular. Initial setup requires physical presence of people.
OCR (Optical Character Recognition)	Sensor Type: *Optical* Entry Time: *Medium* Error Rate: *Medium* Cost: *Medium*	Data remains human readable.	Characters must be printed. Low data density. Error rate condition (e.g. lighting) dependant.
Machine Vision	Sensor Type: *Optical* Entry Time: *Fast* Error Rate: *Application Dependent* Cost: *High*	Versatile application. Equipment can be reused for different applications. High speed. Can read other forms of data encoding such as barcodes.	Success highly dependent on application and quality of implementation.
1D Barcode	Sensor Type: *Optical* Entry Time: *Medium* Error Rate: *Low* Cost: *Low*	Cheap to implement. Versatile. Easy to print and affix barcodes.	Lower data density than 2D barcodes.
2D Barcode	Sensor Type: *Optical* Entry Time: *Medium* Error Rate: *Low* Cost: *High*	High data densities. Reliable and versatile. Barcodes take up more space than 1D, but still easy to use.	Equipment cost higher than 1D barcodes, so consider if 2D is necessary.
RFID (Radio Frequency Identification Tags)	Sensor Type: *Electro-magnetic* Entry Time: *Fast* Error Rate: *Low* Cost: *Medium*	Functional without line of sight. Versatile: Read/write capable tags and battery powered tags exist. High data density (with more expensive tags).	More expensive per-use than optical methods. Tags with high data capacity or read/write capability are expensive. Quality and read range can degrade in metallic environments.
Smart Cards (subtype of RFID)	Sensor Type: *Electro-magnetic* Entry Time: *Fast* Error Rate: *Low* Cost: *Medium*	Identifies people without biometrics. Can be implemented without the person being present. Quick and simple to use.	Can get lost / stolen / abused in ways biometrics cannot.
Magnetic Stripe	Sensor Type: *Electro-magnetic* Entry Time: *Medium* Error Rate: *Low* Cost: *Medium*	High density of data. Read / write capability.	Physical contact required to read data. Damaged by electromagnetic fields.

Table 6.2-1 A summary of common AIDC technologies and their properties.

It is important to note that there is no “best” technology – these technologies are all in use because they offer unique advantages and disadvantages. These technologies may also be implemented in isolation or in combination for different results. When considering which AIDC to use, the encoding, reader, and decoder should all be considered. For example, what is the available area for the encoding? Does the encoding need to be human readable as well as machine readable? How much data must be encoded? In what conditions must the encoding be read – well illuminated, or irregular and dark? Can the encoding be seen, or is it hidden on the product?

It’s also important to note that though new and emerging technologies such as Machine Vision may offer significant new capabilities, tried and tested technologies such as 1D barcode remain in such broad use due to their efficient, reliable, and cost effective operation.

6.2.5 Sensors Conclusions

Sensors are of course important in manufacturing for the control of processes, and many are often built into equipment and integrated into the control systems. The positions of actuators, presence or absence of parts, rotational speeds of spindles or temperatures of chemical processes are all examples of process features that must be monitored for the process to be successful, and often you may not know the sensors are there at all.

However, a critical part of creating an effective and useful model or digital twin is access to accurate data about the system you are trying to model. Sensors integrated into processes can provide useful data for a model, but often the key missing data is external to processes. The movement of parts around a system, the use of tooling or materials, inventory management, and any processes that must collaborate can require additional sensors to be implemented to capture the performance and parameters.

Sensors can either be read directly (primary sources) or fed into a secondary control system such as a PLC or embedded computer (secondary source) depending on application. Data from these can be logged in a database, spreadsheet, bespoke monitoring software, even manually recorded, and then the data analysed with the data processing cycle discussed in section 5.2. The difference between the conventional modelling approaches from section 5.3 and digital twins, is that conventional modelling takes a snapshot of a system and builds a model that remains static, whereas a digital twin is connected to the data logging, and can constantly update the model.

6.3 Digital Twins

6.3.1 Categories of Digital Twins

"Digital Twin" is an increasingly common buzzword in manufacturing and is often misused to refer to offline modelling and simulation approaches. As an emerging area, there are few formal standards for digital twins. The ISO/IEC JTC1/AG 11 Digital Twin [11] working group and ISO/TC 184/SC Industrial Data [12] technical committee are working on standards such as ISO/DIS 23247-1 [13] Digital Twin Framework for Manufacturing, but they are currently not completed. The German Plattform Industrie 4.0 network also promoted their asset shell standards for digital twins, but this serves as a starting point rather than a complete reference architecture. Due to the lack of standardization, the concept of the digital twin is still diverse, and often understanding is driven by providers of digital twin software tools. However, some authoritative groups have proposed different classifications of digital twins. When evaluating software that claims to be a digital twin, it is worth considering where it falls under these classes.

According to Kritzinger *et al.* [14] from Fraunhofer Austria Research, the level of data integration between the physical and digital counterpart enables the classification of the approach:

1. A *Digital Model* uses no automatic data transfer between the real/physical asset and the virtual model, only manual data transfer. Most would not consider this a real digital twin as the manual data exchange prevents the digital object having access to real-time data.
2. A *Digital Shadow* includes a one-way automatic flow of data from the physical asset to the digital representation.
3. A *Digital Twin* has data automatically flowing in both directions between the physical asset and the virtual model. In this instance, the digital twin is able to control the physical object based on the decisions of digital twin.

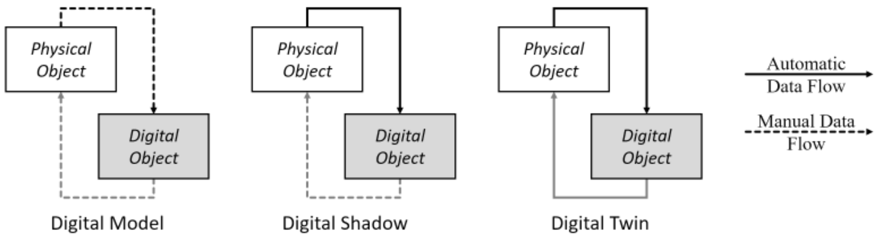

Figure 6.3-1 The classes of digital twins according to Kritzinger. The more automated the flow of information, the closer the result is to a "true" digital twin [14].

The Advanced Manufacturing Research Centre (AMRC) at the University of Sheffield in the UK has proposed classifying digital twins based on the capabilities and added value given by the digital twin [15]. The core functionality is presenting data in context, and the type of twin then depends on whether the optional added value features includes data analytics, control over the physical asset, and/or predictions via simulations. The three classes are:

- *Type 1 Supervisory Digital Twin*: A passive monitoring twin, where data is received from the physical system and combined into a single model. This model can be used to identify warning limits or thresholds on variables that indicate issues. Approximately equal to a Digital Shadow in Kritzinger's classification.
- *Type 2 Interactive Digital Twin*: The digital twin is able to influence the physical twin by setting parameters to improve key performance indicators with simple control algorithms. Control may be complete or partial. Approximately equal to the full digital twin in Kritzinger's classification.
- *Type 3 Predictive Digital Twin*: Integrates simulation and analysis methods to predict performance based on process data from the physical twin and use these to optimize processing parameters, and then proactively make these adjustments as needed in the physical twin.

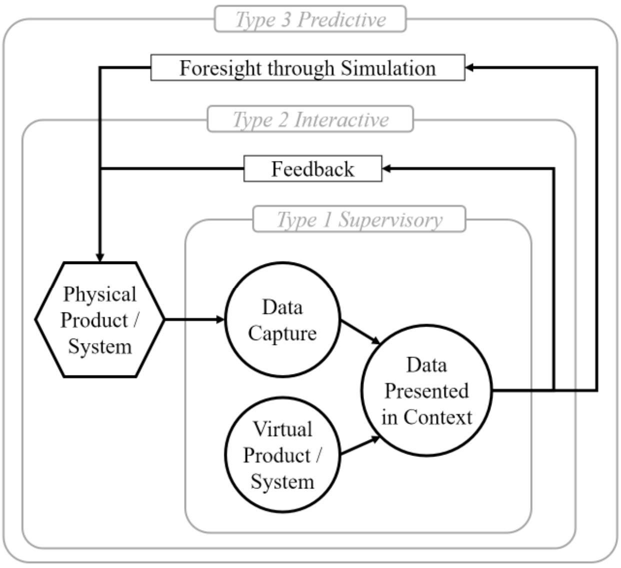

Figure 6.3-2 The types of digital twins are layered on top of one another, according to the AMRC classification [15].

6.3.2 Elements of Digital Twins

Due to the current lack of standards, the components and technical requirements of a digital twin vary with the type, classification, and supplier of the digital twin. However, some common elements are emerging.

- *Mandatory: Real-Time Connected Physical Twin.* Sometimes under considered, a digital twin requires a physical twin, typically a product or system. The physical twin can be a dumb and/or uncommunicative, or a smart product/system capable of machine-to-machine (M2M) communication or of communicating with humans. The digital twin will require sensors (either integrated into smart products / systems, or IoT solutions added afterwards), the communication standards to share the data with the digital twin, and the ability to do so in real-time. What qualifies as real-time is application dependant, but usually considered in the order of milliseconds.
- *Mandatory: Model.* The digital twin requires a virtual equivalent of the physical twin which gives context to the collected data, differentiating it from a database or data lake. Despite this difference, the digital twin still requires storage for collected data, and a database may be the underlying technical implementation of this. The model is one of the harder elements to define as it is highly application specific – a model of a factory may be implemented differently to a model of a jet engine for example. 3D models of the physical twin are a common consideration, but not mandatory.
- *Optional: Analytics and Simulation*. One of the most commonly envisaged use cases of digital twins is to use the twin to perform analysis and understand how better to control the physical twin. This is typically achieved through the use of simulation and analytics. It may seem strange that this is listed as optional – what is the point of a model if you never run simulations on it? However, as described by the AMRC classification [15], a digital twin can just be a way to present data in context without any analytics performed directly. Analytics and simulations remain a very common desirable feature of course but are not mandatory. Multiple different analytics and simulation techniques can be included in digital twins depending on the application, with the intention to identify problems or opportunities in advance based on the incoming data and state of the physical twin.
- *Optional: Control.* Giving a digital twin the ability to control the physical twin is not mandatory (see type 1 supervisory digital twins) but – like analytics and simulation – is a very common envisaged use. Sensors in the physical twin enable the data capture, but similarly actuators can enable the digital twin to change parameters or other elements of the physical twin's control system. This would typically be in conjunction with analytics or simulation tools to make the decisions to change parameters, which are then enacted in the physical twin.

6.3.3 Applications of Digital Twins

Digital twins can be used in a wide range of applications, including vehicle automation, power generation, traffic modelling and urban planning, healthcare, and more. Here however, we will focus on some applications specific to manufacturing [1].

- *Production line replication:* One of the most commonly envisioned applications of digital twins to manufacturing is the creation of a digital replica of a production line, or entire factory. Manufacturing simulations are not new but rely on a high degree of understanding of the process being simulated. The real-time connected nature of digital twins enables the live simulation to improve over time, to be monitored and optimised based on the real-time state of the system, and to respond to new and unexpected events. The digital twin serves two primary goals here. Firstly, the captured data for the production system is unified and kept in one place, simplifying monitoring and enabling historical snapshots of the system behaviour to be retrieved if a fault occurs. Secondly, the digital twin can run *front-running simulations*, using the faster-than-real time nature of simulations to "fast forward" and predict the state of the system in the future [16].
- *Product replication:* Even complex manufacturing systems may produce simple products that do not require a digital twin. However, when the product is as complex as the system that creates it, a product digital twin can offer some advantages. Similarly to production line replication, using a digital twin for a product aids in collecting all the data generated in its creation in one place, which is useful for highly regulated domains such as aerospace or pharmaceuticals. Digital twins can also be integrated with product lifecycle monitoring systems to ensure the expected processes are performed on the product, particularly when there are large sources of uncertainty in the manufacturing process or when configurations are changed as the product is being manufactured.
- *Preventative maintenance:* Preventative maintenance is a key technique for preventing costly breakdowns by scheduling maintenance during breaks in production to replace worn components before their expected failure. Preventative maintenance typically is regularly scheduled based on operator experience and the equipment manufacturer's guidance. Predictive maintenance monitors equipment condition with sensors to improve the estimation of when maintenance must be performed. This both helps determine if equipment will fail earlier than anticipated, or if the maintenance can be delayed – saving money.

  A digital twin of production equipment aids in the implementation of predictive maintenance by enabling the collection and analysis of sensor data from the equipment and running analysis to predict the optimum maintenance window. Data from previous breakdowns can be used to help identify imminent new breakdowns, and real-time data from the equipment can be compared to past "ideal" data to look for deviations.

- *Robotic planning / cobotics*: Industrial robotic path programming is often developed with offline simulations to plot and test proposed programs, using software packages such as ABB RobotStudio, KUKA.Sim or Dassault Systemes DELMIA. These are excellent tools for highly predictable, repetitive tasks. Where digital twins can aid this process is where the robotic process is variable or unpredictable. This can occur when the product is large, flexible, or of an unknown quality. Unpredictability can also occur when humans are involved in the process, and the increasing popularity of collaborative robotics or cobotics where robots and humans work together on.

  Safety is critical to the successful implementation of cobotics and digital twins allow the simulation used for motion planning to be updated in real time to ensure the position and motion of the human worker is accounted for. They could also allow for virtual or augmented reality techniques to enhance the human worker's interaction and control of the cobot.

6.3.4 Examples of Digital Twin Software

Digital twins are an emerging technology, and a rapidly changing field. Without clearly defined standards for digital twins, what does and does not qualify as a digital twin is ambiguous. Moreover, many offered digital twin packages are actually multiple pieces of software which work together to implement the digital twin. These packages often use an existing modelling and simulation package (such as those mentioned in section 5.3.5) with add-ons to gather data in real time. Due to the early-stage nature of the technologies, it is recommended you research solutions and developments before committing to a specific product or package, and pay particular attention to the types and elements of digital twins so you can be sure what you're purchasing does what you expect. However, here are some examples of solutions or packages on the market.

- *Siemens Digital Enterprise:* Siemens' digital twin offering is a holistic combination of a range of their software products rather than a single dedicated piece of software, but these come under the Digital Enterprise portfolio. Depending on the application area, different tools will be used. For example, in a pharmaceutical setting STAR-CCM+ is used as the model, HEEDS for analysis, and SIMATIC SIPAT is used for monitoring quality in real time. As Siemens also provides a wide range of industrial automation and sensing equipment, integrating this approach into a real-time digital twin is simplified.
- *GE Digital Predix:* Predix is a cloud-based data platform that can gather data from IoT sources, contextualise it with a model, and use analytics algorithms to predict future events. It has multiple stated applications including component, asset, system, and process modelling.
- *Dassault Systemes 3DEXPERIENCE:* Another large portfolio of software, 3DEXPERIENCE covers product design, process planning, simulation and analytics, and product data management. Calling digital twins

"3DEXPERIENCE Twins", the package covers the range of elements required for a digital twin. Other companies have also used 3DEXPERIENCE as a basis for their own digital twin products, such as *Veristar's AIM^{3D}* which is specialised for large vessels and gas/oil platform modelling.

- *Microsoft Azure Digital Twins:* Currently in a public testing phase, Azure Digital Twins is a forthcoming cloud-based digital twin solution with a domain-neutral "spatial intelligence graph" approach to modelling, and integration with Azure's existing IoT data ingress, machine learning and AI capabilities. Microsoft have also partnered with *Ansys Twin Builder* to add additional capabilities around predictive maintenance.

6.3.5 Implementation Challenges

As an emerging area, there are several challenges for digital twins to overcome to become mainstream. These are summarized here, and are aspects to be mindful of before adopting any specific digital twin solution.

- *Standards and Interoperability:* As discussed in section 6.3.1, there is currently a lack of industrial standards for digital twins, and even when they are finalized the adoption will take time. As a result, interoperability between different vendors of digital twin solutions or components of a solution may be limited. Many current tools are based on existing suites of manufacturing software, and mixing and matching these may be costly or not possible.
- *Trust*: A key part of digital twin sales pitch is for a system to self-optimize, with analytics and simulations being run on live data and the findings being used to tune and optimize the physical twin. However this requires a level of trust on behalf of the operators – a few incorrect decisions or wrong deductions could cause digital twin adopters to sever the automated control loop and instead use the digital twin as advisory rather than fully integrated.
- *Data Quantities:* A key aspect of digital twins is to collect real-time data in a single place and be able to present it in context (see Figure 6.3-2). This approach is not dissimilar to data lakes and data warehouses but unlike these approaches digital twins require the centralized data in real-time. Depending on the volumes of data, the distance of the data sources, and the method of data transmission, sending raw data may simply not be possible. Pre-processing data before transmission may go some way to alleviating.
- *Cybersecurity:* Any company innovating in Industry 4.0 is unfortunately a target for malicious entities, from individuals, organized gangs, to nation states. Irdeto found that 79% of surveyed companies implementing IoT has suffered some sort of cyber-attack against their IoT systems in the previous year [17]. The consequences of a cyber-attack on a digital twin could be significant, ranging from disruption of the physical twin, ransomware attacks, or theft of intellectual property due to the richness of data stored in the digital twin. Typical industrial security methods such as hardware security and air-gapping are no longer

sufficient. Instead, software-based protection should be implemented, a well-defined business process for software/firmware updates should be enacted, and data encrypted where possible.

- *Implementation:* Digital twins require the involvement of a wide range of equipment and people within a business to take maximum advantage of the approach. A common buzzword for digital twins is “holistic” i.e. something that is more than the sum of its parts, but in this case the word is appropriate. Digital twins can draw data from across a business, and if the data isn’t already organized or well understood the digital twin implementation process may be a painful one. Gartner [18] released a study conducted in 2017 among 202 companies, and described four best practices for implementing and maintaining digital twins:
  1. Investments in digital twin solutions could be driven by the product or process value chain, understanding why stakeholders need access to the data or control of the physical twin is key.
  2. Standardized documented procedures should be carried out during the creation to the digital twin to ensure this potentially highly complex system is well documented and understood, which will facilitate changes and upgrades.
  3. Use and access of data should be possible from multiple sources to allow interaction and evolution of the digital twin. This may require existing data silos to be broken down and standards implemented within the enterprise so that data can be accessed more widely.
  4. Proprietary software and non-standard formats should be avoided to ensure the company doesn’t get locked into an approach or is unable to integrate new software components.

6.4 Decision Support Systems

6.4.1 Introduction

Throughout this book the concept of decision making has been discussed, and its importance emphasised. The role of analysis in manufacturing is to enable better decisions to be made, and therefore for the business to be more productive and more profitable. All the tools and methods we have discussed exist to inform decisions. However, another classification of tools exists that can aid with decision making – the Decision Support System (DSS).

A DSS is a software system to support decision making in an enterprise, including but not limited to manufacturing. They typically have a constrained area of interest (the *domain*) in which they aid decisions. For example, DSSs are increasingly common in the medical field to aid with diagnosis and treatment plans where the problems are far from structured. There are three classes of DSS, representing the type of support they give:

- *Passive*: Offers information and analysis to aide a human in the decision making process, but doesn’t offer any direct suggestions or solutions.

- *Active*: Analyses available data to offer suggestions and solutions to the user.
- *Cooperative*: Offers suggestions and solutions to the user, but also takes feedback from the user to refine and improve the decisions and suggestions. These are rare outside of research however.

In addition, DSSs fall into four further classes based on the type of assistance they offer, and these are discussed in the following section.

6.4.2 Classes of Decision Support System

6.4.2.1 Communications-Driven

Perhaps the most common form of DSS, and one you may be using without realising that it is a decision support tool at all. *Communications-Driven DSS* (CD-DSS) facilitates decisions by allowing users to share information to collectively make a decision. They are often called Group Decision Support Systems for this reason. A CD-DSS does not generate or analyse data by itself, it makes it more available to users, including users who are distributed rather than co-located, and who are communicating asynchronously.

Examples include document sharing tools such as Google Docs or Microsoft SharePoint, and collaboration tools such as Slack or Microsoft Teams. Even teleconferencing solutions such as Skype or Zoom are sometimes described as CD-DSSs. These systems allow for users to make better decisions about unstructured and semi-structured problems by better pooling and sharing experience and knowledge, rather than the problem being tackled by a single individual. CD-DSSs are examples of passive DSSs.

6.4.2.2 Data-Driven

For semi-structured problems and even some structured ones, data may be available to inform the decision, but in a format which makes its use difficult or impossible for the decision maker to use effectively. Data-Driven DSSs (DD-DSS) take data (typically time-series data) and presents it to the user in a more informative manner, possibly after some initial analysis of the data. The data will be sourced from a company database or databases, and also sometimes include external data sources. Data is usually historical, but sometimes includes real-time data. The largest challenge with DD-DSS approaches is the integration of the data – how is machine-generated data captured and integrated with human-generated data.

A manufacturing dashboard is a common example of a DD-DSS in industry, displaying key data drawn from multiple sources to give a clear indication of the state of the shop floor, of the order book, or of productivity. Common examples include Microsoft Power BI, Dundas BI, and Tableau, but many companies also develop customised dashboards with visualisation libraries such as R Studio's Shiny or Grafana. Many approaches are directly integrated into the database such as SAP

HANA. Even a spreadsheet's reporting and graphing features can achieve these goals.

DD-DSSs are the second most common example of DSS, and the most common that people commonly consider as a DSS. They are often referred to as Business Intelligence packages, reflecting the increasing sophistication of the tools offered. They are usually passive, but increasingly have active decision support tools.

6.4.2.3 Model-Driven

Model-Driven DSSs (MD-DSS) use simulation models for decision support by offering predictions of the outcomes of changes to the existing circumstances. These can be numerical models build in spreadsheets, computer-aided design (CAD) models of products, all the way to multi-physics 3D simulations of manufacturing processes.

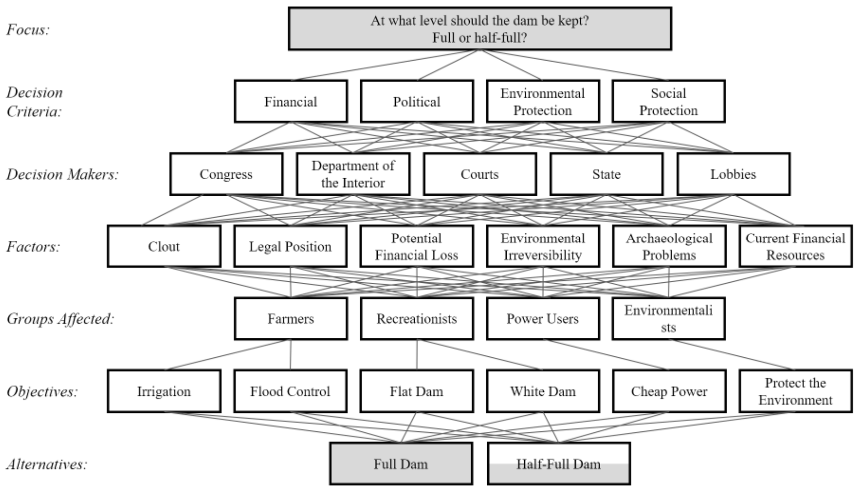

Figure 6.4-1 Analytical Hierarchy Processes are used to start deconstructing extremely complex and subjective problems to try to structure them into a model that allows alternatives to be tested.

Computer simulation offers the great advantage of studying and statistically analysing what-if scenarios, reducing the overall time and cost required for taking decisions. Monte Carlo simulation, discrete event simulation, agent and multi-agent simulation, system dynamics, and visual simulation are all in increasingly common use in manufacturing, and are discussed in section 5.3, The introduction of advanced simulation-based visualization of CAD designs with interaction and collaboration technologies such as augmented reality and virtual reality (AR/VR) is changing the product design process, enabling visual prototyping but also simpler collaboration between distributed teams, enabling CAD modelling to implement elements of

Communications-Driven DSS. Models and simulations are typically active DSS systems, giving the user the results of their proposed choices and in some cases running algorithms to show the optimal choice for a problem.

Also under the MD-DSS category are decision analysis models (DAM). DAMs are statistical tools and methods such as analytical hierarchy processes (AHP), decision tree analysis, multi-criteria decision analysis, and probabilistic forecasting to support decision making where multiple criteria needs to be considered and there is no single optimal answer.

6.4.3 Knowledge-Driven

Knowledge-Driven DSSs (KD-DSS) gather data, information, and knowledge from within the company and from external sources. They then use this database of past knowledge to make decisions with artificial intelligence (AI) techniques and recommends action. KD-DSS use AI techniques to combine large quantities of domain knowledge and past experiences to form new information. Expert Systems (which reached peak popularity in the 1980s and 90s) are a form of KD-DSS and used *if-then* rules and heuristics to solve problems. More modern KD-DSS use the latest developments in AI techniques such as neural networks, machine learning, fuzzy logic and genetic algorithms.

Reciprocal Learning-Based DSS (RL-DSS) are a sub-class of KD-DSS and can learn from common decisions and take over this decision making to reduce the human decision-making load. Routine decision tasks can be learned and programmed, and decision makers can update their knowledge and help create more intelligent decisions than previously possible for semi-structured problems.

In a manufacturing environment, capturing expert domain knowledge is a challenge. Instead, most modern manufacturing KD-DSS systems use data mining and machine learning to take large volumes of historical data and use this to determine the optimal course of action rather than relying on domain experts turning their knowledge into rules. Machine learning is proving extremely successful for classification problems such as defect classification, detecting problems with manufacturing processes so proactive and preventative maintenance can be performed, and creating models of manufacturing processes that were previously too complex for humans to fully understand

A famous example is IBM's Watson. Watson is a natural language question-answer computer system and is a form of KD-DSS, using a huge databank of knowledge and rules to rapidly answer questions. It used this approach to win first place in the game show Jeopardy!, beating the previous champions by a significant margin. Watson uses a complex method answering questions, but still shares the same approach as any other KD-DSS. How to answer the question is the decision, and it uses databases of information to propose possible solutions, and then a second database to determine which solution is most likely to be successful. This process takes milliseconds.

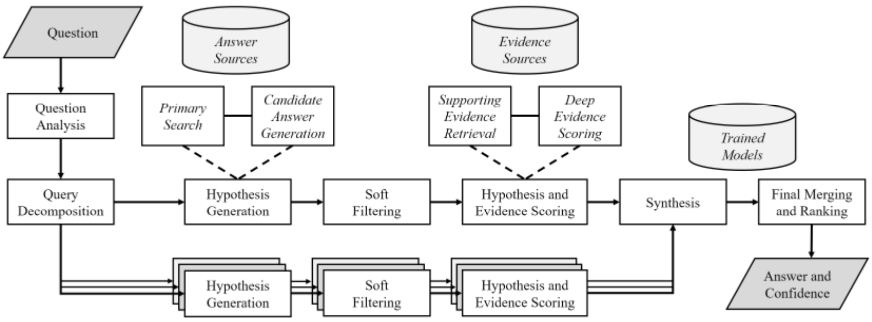

Figure 6.4-2 IBM's Watson used advanced natural language processing to analyse a question's meaning, and then draws upon a vast database of information to hypothesis answers and weigh them up with answers. Watson may be at the cutting edge of DSS systems, but the techniques used are increasingly common in commercial solutions.

6.5 Case Studies

6.5.1 Shop-Floor Monitoring – Rold

Rold are a medium-sized company in the domestic appliance components sector. The company has a high level of flexibility and responsibility due to being a family-run business, and have been able to combine this with the introduction of modern management approaches and novel technologies, constantly updating their standards in the search for the best performance to offer the market.

The company was experiencing the following issues in its production plant:

- Production machinery not connected to each other, thus not allowing, e.g., an efficient monitoring of the energy consumption as well as the analysis of the production data.
- Data not being available in real time and communicated in paper format, delaying the identification of problems and rectifying action.
- Widespread presence of subjective information and not objectified by the process, replying on operator expertise.
- Difficulty in having visibility of inter-plant processes, hindering identification of 'big picture' problems.
- Digital technologies not very common at the shop floor level.
- Need for operator empowerment in process control.

Many small to medium companies will look to external IT companies or solution vendors for assistance with digital twins or decision support systems. Due to Rold's size however, it possessed the in-house expertise to develop its own solution, which has since become a commercial product. Rold SmartFab is the result of Rold's research and development collaboration, which has put together internal company know-how and technologies to create a system for manufacturing SMEs that allows monitoring and analyzing information coming from the company's subsystem plants, and making them available on fixed, mobile and wearable devices. SmartFab is suited for companies in the mechatronic and manufacturing sectors, since it acquires the operating status of the machines and presents it in a user-friendly manner, in real-time and on smart devices anywhere. This allows for rapid identification of production issues, such as downtime and significant slowdowns. This digital manufacturing platform allows for:

- Real time monitoring of production lines.
- Real time data and alarms on touch screen devices and mobile devices, as well as wearable devices that are user-friendly (e.g. smartwatches).
- Using open standards and middleware, allowing modern machines to communicate with older ones.
- Cost reduction thorough a reduction of technical intervention and maintenance times.
- Empowerment of operators in the control of processes as they can now quickly access objective information.

A reduction of energy consumption and associated costs thanks to the possibility of measuring the energy usage of individual production resources in real time. Increasing the level of the operators' soft skills in terms of digitalization, paving the way for the future. The company mainly needed to overcome technological barriers related to the necessity of connecting heterogeneous machines, including legacy systems without standard interfaces. This shows the importance of open standards in manufacturing digitalization. If you are trying to gather data from multiple machines old and new, from multiple vendors with multiple communication protocols, you may have issues unless you are able to use common standards.

6.5.2 Remote Sensing - Alascom

Alascom are a medium IT-technology services company founded in 2001 and based in Milan, Italy. Alascom has developed extensive telecommunications and system integration expertise. For several years, it has implemented a solution-providing strategy combined with the development of new innovative solutions to integrate the production domain with the Information and Communication Technology (ICT) domain, broadening the approach to cover the Internet of Things (IoT), Industry 4.0 and data analytics. Alascom is expert in statistical analysis and programming tools, mathematical models, AI machine learning, and in memoryDB.

Alascom were tasked with implementing monitoring systems for a range of biogas plants to provide a comprehensive view of the entire plant network as well as individual plants. Biogas plants are complex systems that obtain “clean” energy.

Due to their complexity, maintaining correct functioning is fundamental to guarantee constant revenues flows as well as to avoid extra costs due to breakdowns, malfunctions, and downtimes. Furthermore, improving the efficiency and effectiveness of the electrical energy production of the plants is another fundamental objective which may be possible through better monitoring. The geographic dispersion of the plants and the inability to keep specialized maintenance personnel onsite and to improve the production performances means any monitoring solution must be remote, centralized, and granular.

Monitoring provides a comprehensive view of the entire plant and the details of the individual monitored systems. The objective is to improve the efficiency of the production process through the use of software that allows maximization of the revenue/cost ratio, to have a greater understanding of the process itself and to better understand the impact of different operating modes to reduce the complexity of network management.

The software, designed to be adaptable to different production plants, is able to normalize data coming from multiple sites enabling comparison between different plants in scope and size; the greater quantity of data can be analyzed to benefit each plant. The software architecture takes data from newly installed smart meter sensors and performs data analysis. The steps are as follows:

1. Smart energy meters installed in the biogas plant are used to monitor the electrical consumption of auxiliary systems.
2. "Concentrators" gather and combine data from the smart meters at a specified frequency and return the values in a standards-compliant manner on the physical Ethernet channel and the Modbus TCP protocol.
3. IoT gateways acquire data from multiple sources, normalize the data, and send it to the database of a digital platform, where the data is then then processed and presented. This architectural element is able to communicate with different systems, in particular with the concentrators for the acquisition of electrical measurements of the biogas auxiliary systems, and with the process controllers for the acquisition of data available from the existing control system.
4. Finally, a digital platform composed of a cloud database and web-based user interface. The first architectural level acquires normalized data, that is then stored and made available to the web service interface. The front-end is developed with web services technologies, it allows the visualization of plant data with appropriate indicators, dashboards and tables defined with the support of the domain experts of the client company. The filters available in the web interface allow the user to enter specific requests and obtain analysed information - graphical or numerical - in either descriptive or statistical-predictive form. The system, through the use of appropriate algorithms that operate on available data, automatically suggests what actions need to be carried out and when, also taking into account any constraints imposed by the user.

The sensor integration and software solution was a success – all the biogas plants can be monitored remotely from a single location, reducing costs and improving the efficiency of the plants. The project was not without challenges however, and the integration of the client company's biogas plant experts, consulting smart sensor experts, and Alascom's own software engineers was the single largest challenge they faced.

6.5.3 Connected Transport Systems – Bellini

Bellini is a small company specialized in the development, production, marketing, and technical assistance of lubricants and fluids. Due to the complexities of chemical manufacturing and the weight of the materials and products, Bellini wanted to review the production process with the integration of software for remote monitoring, as well as integration of automated guided vehicles (AGVs) for automated materials and product transport.

Shop-floor operators currently use stand-alone programmable logic controllers (PLCs) to control the production process: the information is not shared with the enterprise resource planning (ERP) software. It is necessary to improve the user interface in the silos and mixers area so that the information necessary for carrying out the activities within the process are more complete and shared with the ERP system. Additionally, the handling of materials and products between the production and the logistics department takes place manually. It is necessary to implement a transportation system for automated handling from the production department to the shipping bay.

Given the specified needs, the company decided to purchase a software program to monitor the progress of activities. In particular, the intervention envisaged the introduction of a software for remote control of the PLCs, the revamping of the sensors, and the replacement of the current LCD panels on the equipment with intuitive and larger touch screens. Improved access to information, allowing it to be viewed remotely or simply in a clear and unified manner is an example of a data-driven decision support system. Being able to clearly see the state of a system at a glance makes quick and effective decision making simpler and less prone to error. Thanks to the remote access of the PLC data, it will be possible to identify equipment failures and other losses quicker. The remote access of the PLC data avoids manual data entry giving a reduction of worker time and fewer introduced errors.

Control of AGVs often requires a digital twin approach for highly dynamic job routing typical of smaller dynamic companies – the live location of the AGVs needs to be controlled to ensure material can be routed where and when it is required in a safe manner. The new automated material handling system will allow the movement of material between the two departments in an automated way, thanks to the use of an AGV connected to positioning sensors, both on board and in the plant. The AGVs are more energy efficient than the current manual handling machines (forklifts mainly) saving costs. Manual material handling time is reduced thanks to the use of the AGV.

The main challenge was the search for the appropriate technological solution. One was eventually found after 4 months of design study. It was also an extensive investment to both acquire and to plan the integration of the system. As with any significant investment in digital manufacturing technologies, it is critically important to have a solid business case developed that shows the value of the proposed solution to the business.

6.6 Conclusions

This chapter discussed the latest advances in production analysis, including the use of online modelling and simulation (digital twins) and support tools for decision making (decision support systems), as well as detailing some use cases of examples of how access to data and the use of simulations can support businesses.

As these fields are new and/or rapidly evolving, it is important to understand both their strengths and limitations. There is a lot of hype surrounding digital twins, and the lack of standards mean many products may be labelled as digital twins without necessarily having the functionality you might expect. Though the potential advantages of online systems are significant, there are risks of investing in technology which may not be fully supported in the future, and which may not deliver on investment.

Critically before making any investment in a new modelling package of digital twin system is to develop a business case for it. What questions will this new approach enable us to answer that we could not before? How will we use the new information to improve productivity (or any other key performance indicator)? What changes will we need to make to our working processes, and how long will training and acclimatisation take? Particularly for digital twins where established standards have not been settled and buzzwords are frequently used, it is important to understand exactly what is being offered and the potential costs and benefits thereof.

If there is one critical lesson in this book, it is that mathematical formulae, digital modelling software, decision support systems and digital twins are all tools to assist in the decision-making process. All these tools have their strengths and weaknesses, and areas of applicability; the chapters in this book are not a scale from ‘bad’ tools to ‘good’ tools, only from manual, to offline digital, and then online digital. Understanding the decision-making process, the measurable key performance indicators, and why an analysis tool is required, and which is most useful is a critical skill for effective decision making in a manufacturing context. Without understanding exactly what questions are being asked and why, supporting tool will not be able to offer their full capacity in aiding the enterprise in answering those questions.

6.7 References

[1] M. Grieves, "Virtually intelligent product systems: digital and physical twins," *Complex Systems Engineering: Theory and Practice,* pp. 175-200, 2019.

[2] B. Piascik, J. Vickers, D. Lowry, S. Scotti, J. Stewart and A. and Calomino, "Materials, structures, mechanical systems, and manufacturing roadmap," *NASA Technology Area 12-2,* 2012.

[3] E. Negri, L. Fumagalli and M. and Macchi, "A review of the roles of digital twin in cps-based production systems," *Procedia Manufacturing,* vol. 11, pp. 939-948, 2017.

[4] M. Shafto, M. Conroy, R. Doyle, E. Glaessgen, C. Kemp, J. LeMoigne and L. and Wang, "Modeling, simulation, information technology & processing roadmap.," National Aeronautics and Space Administration, 2012.

[5] B. Gockel, A. Tudor, M. Brandyberry, R. Penmetsa and E. and Tuegel, "Challenges with structural life forecasting using realistic mission profiles," *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference,* p. 1813, 2012.

[6] R. Rosen, G. Von Wichert, G. Lo and K. and Bettenhausen, "About the importance of autonomy and digital twins for the future of manufacturing," *IFAC-PapersOnLine,* vol. 48, no. 3, pp. 567-572, 2015.

[7] T. Gabor, L. Belzner, M. Kiermeier, M. Beck and A. and Neitz, "A simulation-based architecture for smart cyber-physical systems," *2016 IEEE international conference on autonomic computing (ICAC),* pp. 374-379, 2016.

[8] A. Bolton, L. Butler, I. Dabson, M. Enzer, M. Evans, T. Fenemore, H. F. and e. al, "Gemini Principles," Centre for Digital Built Britain, 2018.

[9] HBM, "Piezoelectric or Strain Gauge Based Force Transducers?," [Online]. Available: https://www.hbm.com/en/3719/piezoelectric-or-strain-gauge-based-force-transducers/. [Accessed 2020 11 23].

[10] M. Groover, Automation, production systems, and computer-integrated manufacturing, Pearson Education, 2016.

[11] International Electrotechnical Commision, “ISO/IEC JTC 1 Information Technology - AG 11 Digital Twin,” [Online]. Available: https://www.iec.ch/dyn/www/f?p=103:14:3438570860908:::: FSP_ORG_ID,FSP_LANG_ID:25023,25. [Accessed 23 11 2020].

[12] International Organization for Standardization, “ISO/TC 184/SC 4 - Industrial Data,” [Online]. Available: https://www.iso.org/committee/54158.html. [Accessed 23 11 2020].

[13] International Organization for Standardization, “ISO/DIS 23247-1: Automation systems and integration — Digital Twin framework for manufacturing — Part 1: Overview and general principles,” [Online]. Available: https://www.iso.org/standard/75066.html. [Accessed 23 11 2020].

[14] W. Kritzinger, M. Karner, G. Traar, J. Henjes and W. and Sihn, “Digital Twin in manufacturing: A categorical literature review and classification.,” *IFAC-PapersOnLine,* vol. 51, no. 11, pp. 1016-1022, 2018.

[15] High Value Manufacturing Catapult, Visualisation and VR Forum, “Feasibility of an Immersive Digital Twin,” 2018.

[16] M. Grieves and J. and Vickers, “Digital twin: Mitigating unpredictable, undesirable emergent behavior in complex systems,” *Transdisciplinary perspectives on complex systems,* pp. 85-113, 2017.

[17] Irdeto, “Irdeto Global Connected Industries Cybersecurity Survey,” Amsterdam, 2019.

[18] R. Millman, “Gartner: Four best practices for managing digital twins,” 19 03 2018. [Online]. Available: https://internetofbusiness.com/half-of-businesses-with-iot-projects-planning-to-use-digital-twin/. [Accessed 23 11 2020].

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Digital Manufacturing Training System for SMEs (Digit-T)
Project ref: 2017-1-UK01-KA202-036807