Digital Twin: Enabling Technology, Challenges and Open Research

Aidan Fuller[a,*], Zhong Fan[a], Charles Day[a] and Chris Barlow[b]

[a]School of Computing and Mathematics, Keele University Staffordshire, ST5 5BG
[b]Astec IT Solutions Limited, Rugeley Staffordshire, WS15 1UW

ARTICLE INFO

Keywords:
Digital Twin
Data Analytics
Enabling Technologies
Industrial Internet of Things (IIoT)
Internet of Things (IoT)
Literature Review

Abstract

Digital Twin technology is an emerging concept that has recently become the centre of attention for industry and in more recent year's academia. The advancements in industry 4.0 concepts have facilitated its growth, particularly in the manufacturing industry. The Digital Twin is defined extensively but is best described as the effortless integration of data between a physical and virtual machine in either direction. The challenges, applications, and enabling technologies for Artificial Intelligence, Internet of Things (IoT) and Digital Twins are presented. A review of publications relating to Digital Twins is performed, producing a categorical review of recent papers. The review has categorised them by research area; Manufacturing, Healthcare and Smart cities, discussing a range of papers that reflect these areas and the current state of research. The paper provides an assessment of the enabling technology, challenges and open Research for Digital Twins.

1. Introduction

Digital Twin is at the forefront of the Industry 4.0 revolution facilitated through advanced data analytics and the Internet of Things (IoT) connectivity. IoT has increased the volume of data usable from manufacturing, healthcare, and smart city environments. This IoT rich environment, coupled with data analytics, provides an essential resource for predictive maintenance, fault detection to name a couple and also the future health of manufacturing processes and smarty city developments [6], while also aiding anomaly detection in patient care, fault detection and traffic management in a smart city [51][55]. The Digital Twin can break down the challenge of seamless integration between IoT and data analytics through the creation of a connected physical and virtual twin (Digital Twin). A Digital Twin environment allows for rapid analysis and real-time decisions made through accurate analytics. Since the centre of gravity of the literature relates to manufacturing application, the review has tried to capture relevant publication from 2015 across three area; manufacturing, healthcare and Smart cities. The papers use a range of academic sources found through keywords related to IoT and data analytics, but with an overall aim of identifying papers relating to Digital Twin.

1.1. Research Questions

RQ1. What is a Digital Twin and some of its misconceptions with current and previous definitions?

RQ2. What are the applications, challenges, and enabling technologies associated with IoT/IIoT, data analytics and Digital Twins?

RQ3. Is there a link between IoT, IIoT and data analytics with Digital Twin technology?

RQ4. What are the open research and challenges with Digital Twins?

*Corresponding author
a.fuller@keele.ac.uk (A. Fuller); z.fan@keele.ac.uk (Z. Fan); c.r.day@keele.ac.uk (C. Day); cbarlow@astecsolutions.com (C. Barlow)
ORCID(s): 0000-0002-3391-2407 (A. Fuller)

This paper focusses on the status of Digital Twins as the IoT/IIoT and data analytics identify as enabling technologies. The rest of the paper is as follows: Section II will define a Digital Twin, identiying similar concepts and applications, while highlighting the misconceptions seen when defining a Digital Twin. Section III discusses the challenges found. Section IV investigates the key enabling technologies for Digital Twins while giving a brief history of each key enabling technologies. Section V relates to current research, split into three subsections. The first being subsection A and B, is setting out the methodology for producing the categorical review table, subsections C presents a concise analysis of a range of papers on Digital Twins across a plethora of disciplines, with a concluding section giving insight from an industry perspective. Section VI presents open research, with overall challenges and findings for Digital Twin research. Section VII concludes the paper.

2. Digital Twin

2.1. What is a Digital Twin?

The origins of the Digital Twin are set out in this section. The review sets out clear definitions while also looking at the some of the misconceptions found with wrongly identified Digital Twins.

Formal ideas around Digital Twins have been around since the early 2000s [25]. That said, it may have been possible to define Digital Twins earlier owing to the ever changing definitions.

2.1.1. Definitions

The first terminology was given by Grieves in a 2003 presentation and later documented in a white paper setting a foundation for the developments of Digital Twins [25]. National Aeronautical Space Administration (NASA) released a paper in 2012 entitled "The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles."

Nasa 2012 [24] "A Digital Twin is an integrated multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin." [24]

Chen 2017 [13] "A digital twin is a computerized model of a physical device or system that represents all functional features and links with the working elements."

Liu et al. 2018 [45] "The digital twin is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart."

Zheng et al. 2018 [94] "A Digital Twin is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level."

Vrabic et al. 2018 [90] "A digital twin is a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualised in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making."

Mandi 2019 [49] "A Digital Twin is a virtual instance of a physical system (twin) that is continually updated with the latter's performance, maintenance, and health status data throughout the physical system's life cycle." [49]

Definition a) is an ambiguous definition specific forNASA's interplanetary vehicle development. [24] is one of the early papers that defines Digital Twins. Despite there being over six years between a) and f) publication the consensus remains that there is not a fundamental or significant change. Academia and industry alike have not helped in distinguishing DT's from general computing models and simulations. Future work requires a more definitive definition for a Digital Twin.This research aims to aid in the development of an updated definition, while also helping in analysing related work and pointing out wrongly identified Digital Twins.

2.2. Digital Twin Misconceptions

2.2.1. Digital Model

"A Digital Model is a digital representation of an existing or a planned physical object that does not use any form of automated data exchange between the physical object and the digital object. The digital representation might include a more or less comprehensive description of the physical object. These models might include but are not limited to simulation models of planned factories, mathematical models of new products, or any other models of a physical object, which do not use any form of automatic data integration. Digital data of existing physical systems might still be in use for the development of such models, but all data exchange is done in a manual way. A change in the state of the physical object has no direct effect on the digital object and vice versa." [37] Fig. 1. illustrates a Digital Model.

2.2.2. Digital Shadow

"Based on the definition of a Digital Model, if there further exists an automated one-way data flow between the state of an existing physical object and a digital object, one might refer to such a combination as Digital Shadow. A change in state of the physical object leads to a change of state in the digital object, but not vice versa." Fig. 2. illustrates a Digital Twin. [37]

2.2.3. Digital Twin

"If further, the data flows between an existing physical object and a digital object are fully integrated into both directions, one might refer to it as Digital Twin. In such a combination, the digital object might also act as controlling instance of the physical object. There might also be other objects, physical or digital, which induce changes of state in the digital object. A change in state of the physical object directly leads to a change in state of the digital object and vice versa." [37] Fig. 3. illustrates a Digital Twin.

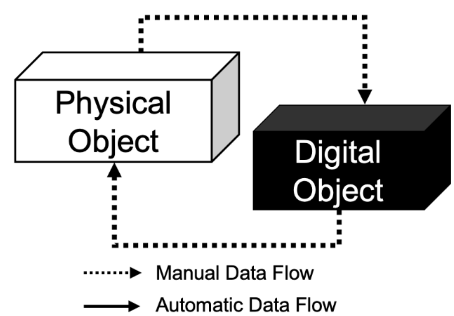

Figure 1: Digital Model [37].

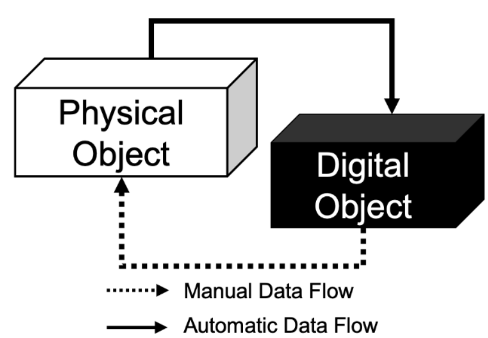

Figure 2: Digital Shadow [37].

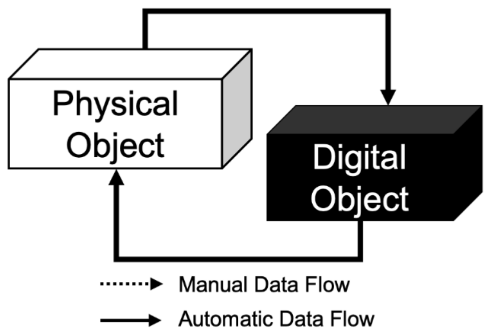

Figure 3: Digital Twin [37].

Figure one to three and their definitions present the different levels of integration for a Digital Twin. Table IV in section V of this review presents a range of publications, highlighting the claimed level of integration against the actual integration based on the above definition. The definitions and figures should help in the development and identification of future Digital Twins.

2.3. Digital Twin Applications

The next subsection of this review focusses on the areas discussed above - IoT, data analytics and Digital Twins, firstly, looking at the potential applications of each topic, the review will look at some of the current challenges. The last part of the section will look at the key enabling technologies associated with each and how they help the Digital Twins. This section identifies some of the potential applications for this technology. For the moment the term and concept of a Digital Twin is growing across academia, and the advancements in IoT and AI are enabling this growth to increase [28][15][17][19][31][34]. At this stage, the main areas of interest are samart cities and manufacturing with some healthcare related applications of Digital Twin technology found. Section V discusses papers relating to current work in this field.

2.3.1. Smart cities

The use and the potential for Digital Twins to be dramatically effective within a smart city is increasing year on year because of the fast developments in connectivity through IoT.

With an increasing number of smart cities developed, the more connected communities are, with this comes more Digital Twins use. Not only this, the more data we gather from IoT sensors embedded into our core services within a city, it will pave the way for research aimed at the creation of advanced AI algorithms. As we know, a benefit of a smart city is the elements of advanced connectivity [55][74][62]. This greater connectivity affects some of the core services within a city that would normally be unused dormant data. These could be data on demand data of building, the data might be achieved but no actual AI analysis carried out. The same conclusion can be made for traffic management systems, traffic cameras that are just recording, these could be used to create traffic management models to reduce for example congestion and overall emission within a road network.

- Buildings
- Roads
- Logistics
- Public Services
- Power Grid
- People

The ability for these services and infrastructures to have sensors and to be monitored with IoT devices is of great value for all kinds of future proofing. It can be used to help in the planning and development of current smart cities and help with the ongoing developments of other smart cities. As well as the benefits of planning, there are also benefits within the energy saving world. This data gives excellent insight into how our utilities are being distributed and used. Advancement for the smart city is the potential to utilise Digital Twin technology. It can facilitate growth by being able to create a living testbed with a virtual twin to one test scenarios, two it allows for the Digital Twin to learn from its environment analysing changes in data collected. The data collected can be used for data analytics and monitoring. The scope for Digital Twins is becoming more viable as the development of smart cities increases connectivity and the amount of usable data [9][8][75][12].

2.3.2. Manufacturing

The next identified application and most popular setting for Digital Twin is within a manufacturing setting. The biggest reason for this is that manufacturers are always looking for a way in which products can be tracked and monitored in an attempt to save time and money, a key driver and motivation for any manufacturer hence why Digital Twins look to be making the most significant impact within this setting. Likewise, with the development of a smart city, connectivity is one of the biggest drivers for manufacturing to utilise Digital Twins. The current growth is in line with the Industry 4.0 concept, as seen in Fig. 6. The 4th industrial revolution, this harness the connectivity of devices to make this concept of Digital Twin a reality for manufacturing processes [92][6][64][38][88].

The Digital Twin has the potential to give real-time status on machines performance as well as production line feedback. It is giving the manufacturer the ability to predict issues sooner. Greater connectivity ensures machine performance. AI algorithms and the Digital Twin has the potential for greater accuracy as the machine can hold large amounts of data, needed for performance and prediction analysis. The Digital Twin is creating an environment to test products as well as a system that acts on real-time data, within a manufacturing setting this has the potential to be a hugely valuable asset [52][26][51][10].

Another application of Digital Twins is in the automotive industry, most notably demonstrated by Tesla. The ability to have a Digital Twin of an engine or car part can be valuable in terms of using the twin for simulation and data analytics [47][46]. AI improves the accuracy of testing as it can perform data analytics on live vehicle data to predict the current and future performance of components.

The construction industry is another sector that hosts a range of applications for Digital Twin use. The development stage of a building or structure is a potential application for a Digital Twin. The technology cannot only be applied in the development of smart city buildings or structures but also as an ongoing real-time prediction and monitoring tool. The use of the Digital Twin and data analytics will potentially provide greater accuracy when predicting and maintaining buildings and structures with any changes made virtually then applied physically. The Digital Twin gives construction teams greater accuracy when carrying out simulations as the algorithms can be applied in-time within the Digital Twin before the physical building.

A common goal seen so far across the field of Digital Twins is this idea of real-time simulation as opposed to low detailed static blueprint models. The use of these models serve a purpose, but they are not using real-time parameters which limits the predictability and learnability. The Digital Twin can be learning and monitoring simultaneously, as well as applying machine and deep learning algorithms [41][93][70][53].

2.3.3. Healthcare

Similarly, with the smart city and manufacturing concept for Digital Twin applications. The growth and development enabling technology are having on healthcare is unprecedented as the once impossible is becoming possible. On an IoT front the devices are cheaper and easier to implement, hence the rise in connectivity [32][44].The increased connectivity is only growing the potential application of Digital Twins use within the healthcare sector. One future application being a Digital Twin of a human, giving a real-time analysis of the body. A more realistic current application is a Digital Twin used for simulating the effects of certain drugs. Another application sees the use of a Digital Twin for planning and performing surgical procedures [77].

Likewise with other applications within a healthcare setting the use of a Digital Twin gives researchers, doctors, hospitals or healthcare providers the ability to simulate environments specific to their needs whether it be real-time or looking to future developments and uses. As well as this, the Digital Twin can be used simultaneously with AI algorithms to make smarter predictions and decisions. Just as many applications within healthcare do not directly include the patient but are beneficial for the ongoing care and treatment. Digital Twin for healthcare is in its infancy, but the potential is vast from using it for bed management to large scale wards and hospital management.

Having the ability to simulate and act in real-time is even more paramount within healthcare as it can be the difference between life or death. The Digital Twin could also assist with predictive maintenance and ongoing repair of medical equipment. The Digital Twin within the medical environment has the potential along with AI to make life saving decisions based on real-time and historical data. The real potential is to be discussed more in section V, discussing current research within a healthcare setting [21][67].

Some applications of a Digital Twin are identified here, showing some of the cross overs in the intended use demonstrating how predictive maintenance is adaptable from manufacturing plant machines to healthcare patient care. It also shows some of the applications where they do not cross over, and Digital Twin use is specific to its intended use. The advancements in AI, IoT and Industry 4.0 have facilitated the growth in Digital Twin applications. Section V will look at identifying the current research within the areas of Industrial IoT and data analytics with a view to how they could be used to aid a Digital Twin. This insight from academia will aid other researchers, enabling them to find gaps within the research and moves towards a more comprehensive definition of a Digital Twin.

2.4. Digital Twin in Industry

General Electric (GE) first documented its use of a Digital Twin in a patent application. From the concept set out in the patent, they developed an application called the "Predix" platform [50] which is a tool for creating Digital Twins. Predix [50] is be used to run data analytics and monitoring. In recent years, GE has scaled back their plans for Digital Twin citing plans to focus on their heritage as an industrial multinational rather than a software company. Siemens, however, has developed a platform called "MindSphere" [63] which has embraced the Industrial 4.0 concept with a cloud based system that connects machines and physical infrastructure to a Digital Twin. It uses all the connected devices and billions of data streams with the hope of transforming businesses and providing Digital Twin solutions [63].

An Alternative platform for developing Digital Twin and AI technology is "ThingWorx" [12]. This platform created by PTC is an Industrial Innovation Platform with the main focus harvesting IIoT/IoT data and presenting via an intuitive, role-based user interface that delivers valuable insight to users. The platform facilitates the smooth development of data analytics while also developing an environment for a Digital Twin solution [12].

IBM, another large scale technology company developed a platform called "Watson IoT Platform" [40] marketed as an all round IoT data tool that can be used to manage large scale systems, real-time through data collected from millions of IoT devices. The platform has several add on features; cloud based services, data analytics, edge capabilities and blockchain services. All of which makes this a possible platform for a Digital Twin system [40].

From an open source viewpoint, there are two big projects to highlight. The first is the "Ditto" project by Eclipse [16]. A ready to use a platform that can manage the states of a Digital Twin, giving access and control to physical and Digital Twins. The platform lies in a back-end role providing support for already connected devices and simplifying the connection and management of Digital Twins [16]. Another open source project called "imodel.js" developed by Bentley Systems [3] is a platform for creating, accessing and building Digital Twins.

3. Challenges

It is becoming more evident that Digital Twin runs in parallel with AI and IoT technology resulting in shared challenges. The first step in tackling the challenges is to identify them. Some of the common challenges are found with both data analytics and the Internet of Things, the end aim is to identify shared challenges for Digital Twins.

3.1. Data Analytic Challenges

Some of the challenges within the field of machine and deep learning are listed below.

3.1.1. IT Infrastructure

The first big challenge is the general IT infrastructure. The rapid growth of AI needs to be met with high-performance infrastructure in the form of up to date hardware and software, to help execute the algorithms. The challenge with the infrastructure currently is down to the cost of installing and running these systems. For instance, the costs of the high-performance GPUs that can perform the machine and deep learning algorithms are in the thousands, anything from $1,000 to $10,000. As well as this, the infrastructure needs updated software and hardware to run such systems successfully. Overcoming this challenge is seen through the use of GPUs "as a service" providing on-demand GPUs at cost through the cloud. Amazon, Google, Microsoft and NVIDIA, to name a few, are offering unique on-demand services similar to traditional cloud based applications, breaking the barrier to demand, but the poor infrastructure and high cost is still challenging for data analytics. Using the cloud for data analytics and Digital Twins still pose challenges in ensuring the cloud infrastructure offers robust security.

3.1.2. Data

From a data point of view, it is a two-fold problem. Firstly the big challenge is to get high quality data for the AI algorithms to perform to high accuracy. However, secondly with the growth of big data and IoTs increasing the volume of data that we have, the increase also leads to collecting poor quality data. To ensure the data is not poor quality, it needs to be sorted and cleaned. Ensuring the highest quality data is fed into the AI algorithms.

3.1.3. Privacy and Security

Privacy and security is an important topic for anyone concerned with the computing industry and is no different when performing data analytics. Laws and regulation are yet to be established fully because of the infancy of AI. The challenge is more scrutiny, regulation and measures concerning AI in the future as the technology grows. Despite being a challenge, it is a necessity as the privacy and security of user data is paramount. Future regulation ensures the development of algorithms that take steps to protect user data. The General Data Protection Regulation (GDPR) is a new regulation that ensures the privacy and security personal data across the UK and throughout Europe. Despite being an umbrella regulation concerning data and security, this highlights the concerns with handling data when developing AI algorithms.

Regulation is one step to ensure personal data is protected. Another method is Federated learning, a framework for training models that is decentralised. It allows user's data in a learning model to stay centralised without sharing any data, addressing privacy and security issues when implementing data analytics within a Digital Twin.

3.1.4. Trust

Trust is another challenge that concerns much of the field of AI, the first being because it is relatively new and secondly because unless the developer is familiar with the complexity, the use of AI can be daunting. The anxiety that robots and AI will become a dominant force on Earth, taking control of key infrastructure from humans is a barrier to trust.

The issue of trust can be a barrier because the portrayal of the technology mostly focusses on the negative effects that could hypothetically occur. Positive media stories in the field of artificial intelligence are becoming more common, but the challenge is evident, and the need for wider exposure of AI and the positive uses would help overcome challenges with trust. Privacy and security challenges contribute to these trust issues, but more comprehensive privacy and security regulation in AI builds trust.

3.1.5. Expectations

The last challenge for data analytics is the expectation that it can be used to solve all our problems. Careful consideration is vital for AI use. Investing time in AI use identifies the correct application, ensuring standard models could not produce the same results. The same as other new technologies, they have the potential to work hand in hand with strengthening things like manufacturing and smart city developments.

The potential user only sees the benefit and believe it will instantly save time and money, hence the high expectations. In reality, the field is still in its infancy, and the challenges need to be kept in mind when applying data analytics. Evident through the number of scenarios that use "AI" for processes that do not need it, in contrast to other situations where AI is needed. Greater exposure and understanding of AI is needed to allow people to gain basic knowledge of the area, thus learning how it can and can be applied.

3.2. IIoT Challenges

Listed below are the challenges found in the field of the Industrial Internet of Things:

3.2.1. Data, Privacy, Security and Trust

With the huge growth of IoT devices both in the home and industrial setting comes the challenge of collecting large amounts of data. The challenge is trying to control the flow of data, ensuring it can be organised and used effectively. The challenge becomes a bigger problem with the advent of big data. The use of IoT increases the large volumes of unstructured data. For IoT to handle the amount of data, sorting and organisation of data is a necessity and will result in more data being usable and providing value. Otherwise, the data collected through IoT will be lost or it will be too cost-prohibitive to extract the value from the enormous volumes of data..

As this data could be sensitive, it could be of value to a criminal increasing the threat. The threat is significantly increased for businesses when they could be dealing with sensitive customer data. Cyber attacks pose more challenges with criminals targeting systems and taking them offline, in an attempt to cripple an organisation's infrastructure. Some organisations have thousands of connected IoT devices posing a risk that cyber-criminals may target them to take control and use the devices for their services. An example of this is the Mirai botnet scandal were nearly 15 million IoT devices worldwide were compromised and used to launch a Denial of service attack [89]. The risk of DDoS attacks increases because of the rapid growth of IoT. As well as this, the lag in priorities around privacy and security solutions pose a further risk of attack. When installing the devices, the most up to date security features and protection is needed, if not this is a vulnerability which offers a back door into a larger connected IoT environment.

3.2.2. Infrastructure

The IT infrastructure currently in place is behind purely because of the rapid growth seen in IoT technology compared with the older systems currently in place. The updating of old infrastructure and integration of new technology helps facilitate IoT growth.

Updated IoT infrastructure provides an opportunity to benefit from the latest technology and leverage the applications and services available in the cloud without expensive refreshing of existing systems and technology.

Another challenge for IoT systems is connecting old machines to the IoT environment. One of the ways to combat this is retrofitting IoT sensors to legacy machines, ensuring data is not wasted and old machines can have some form of analytics.

3.2.3. Connectivity

Despite this growth in IoT use, the challenges of connectivity still exist. Prevalent when trying to achieve the goal of real-time monitoring. A large number of sensors within one manufacturing process poses a significant challenge when trying to connect all of them simultaneously.

Challenges with attributes like power outages, software errors or ongoing deployment errors are impacting this overall goal of connectivity. Just having one sensor not fully connected could dramatically affect the overall goal of a given process. For example, IoT devices are one source of feeding data to AI algorithms; this can become a major challenge as all the data is required for it to perform accurately, missing IoT data could detrimentally affect the running of the system. Retrofitting machine and harvesting the data already served up by the machine is a methods of ensuring all data is collected. Imputation methods is a process of finding replacement values for missing IoT sensor data, a concept used to ensure full connectivity and facilitates the running of AI models with high accuracy with little to no missing data.

3.2.4. Expectations

Likewise with AI, the expectations associated with IoT are a challenge. Due to organisation and end users not fully understanding what to expect from IoT solutions or how to best use them. A promising aspect is the rapid growth in IoT indicates the end users and organisations recognise the value in IoT and how a smarter connected world can benefit us all.

The expectation that IoT can just be used infinitely without prior knowledge can be damaging. With the knock on effect, posing more pressure on privacy and security concerns further putting the burden on challenges with trust. Similarly to AI, the background knowledge of IoT is needed to ensure it is used to its full potential.

3.3. Digital Twin Challenges

This section draws primarily on the challenges associated with Digital Twins. However, as the research progresses, it is clear to see challenges found in data analytics, IoT and IIoT are shared challenges for Digital Twins with some discussed below:

3.3.1. IT Infrastructure

Likewise, with both analytics and IoT, the challenge is with current IT infrastructure. The Digital Twin needs an infrastructure that allows for the success of IoT and data analytics; these will facilitate the effective running of a Digital Twin. Without a connected and well thought through IT infrastructure, the Digital Twin will fail to be effective at achieving its set out goals.

3.3.2. Useful Data

The next challenge is around the data needed for a Digital Twin. It needs to be quality data that is noise free with a constant, uninterrupted data stream. If the data is poor and inconsistent, it runs the risk of the Digital Twin under performing as it's acting on poor and missing data. The quality and number of IoT signals is an essential factor for Digital Twin data. Planning and analysis of device use is needed to identify the right data is collected and used for efficient use of a Digital Twin.

3.3.3. Privacy and Security

Within an industry setting, it is clear that the privacy and security associated with Digital Twins is a challenge, firstly because of the vast amount of data they use and secondly the risk this poses to sensitive system data. To overcome this challenge, the key enabling technologies for Digital Twins - data analytics and IoT - must follow the current practices and updates in security and privacy regulations. Security and privacy consideration for Digital Twins data contribute to tackling trust issues with Digital Twins.

3.3.4. Trust

The challenges associated with trust are both from a organisations point of view and user. Digital Twin technology needs to be discussed further and explained at a foundation level to ensure the end users and organisations know the benefit of a Digital Twin, which will aim to overcome the challenge of trust.

With more understanding, trust in Digital Twins prevails. The enabling technology will give more insight into the steps that ensures privacy and security practices are followed through development, in turn, overcoming challenges with trust.

3.3.5. Expectations

Despite Digital Twin adoption being accelerated by industry leaders Siemens and GE, caution is needed to highlight the challenges that exist for the expectations of Digital Twins and the need for more understanding. The need for solid foundations for IoT infrastructure and a greater understanding of data required to perform analytics will ensure the organisations will make use of Digital Twin technology. It is also a challenge to combat the thoughts that the Digital Twin should be used solely because of the current trends. The positives and negatives for the expectation of Digital Twins need to be discussed to ensure appropriate action when developing Digital Twin systems.

It is clear to see the different challenges for both the Industrial IoT/IoT and data analytics but shared challenges for the application of a Digital Twin. These are important to moving forward to ensure they are taken into account in the future development of Digital Twins as well as when using IIoT/IoT and data analytics. Table I below shows a summary of challenges for both data analytics and I/IoT while showing the combined challenges for a Digital Twin.

Table 1
Shared Challenges

Digital Twin	
Data Analytics	*Industrial IoT/IoT*
IT Infrastructure	IT Infrastructure
Data	Data
Privacy	Privacy
Security	Security
Trust	Trust
Expectations	Expectations
	Connectivity

4. Enabling Technologies For Digital Twins

This section discusses the enabling technologies for Digital Twins.

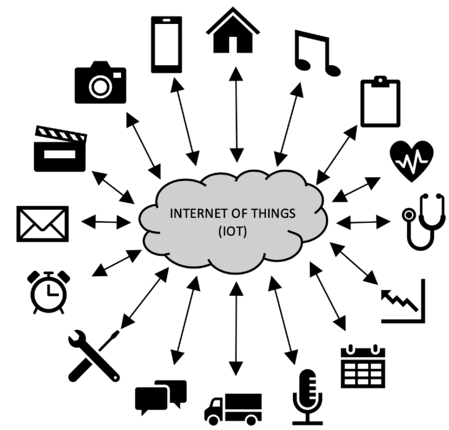

Figure 4: Internet of Things Diagram

4.1. Brief history of the Internet of Things

The Internet of Things is the term given to devices connected to the internet. It is giving so called “things” a sense of intelligence and the ability to collect information on their environment. The term first published in the late 1990s with Kevin Ashton setting out his vision for IoT [2]. The idea that all devices that are interconnected giving the developer the ability to track and monitor everything we do, thus leading to a smarter world. An example of this is found many years earlier at Carnegie Mellon University in Pittsburgh. This programme would connect a Coca-Cola machine via the Internet to see if the drink was ready and cooled enough for a user to buy and consume [61], a simple but effective use case for Ashton’s vision.

The number of IoT devices recorded year on year shows the considerable growth of this technology. In 2018 the figure was over 17 billion [35]. By the year 2025, [81]predicts that there will be over 75 billion devices with the industry predicted to be worth over \$5 trillion [18].Fig. 5. shows the growth in IoT devices since 2016. These figures show the enormous impact these devices are having and further adds to the vision set out by Ashton. The significant number of connected devices aids the visions of a fully connected world, Fig. 4. illustrates this idea of connected services through IoT. The proliferation of IoT devices is universally beneficial, impacting the core of daily life, the communication sector, healthcare, building and transport, smart cities and manufacturing [18, 20].

4.2. Brief history of the Industrial Internet of Things

The concept of Industrial Internet of Things(IIoT) has come from the term IoT, drafted by Ashton [2]. The definitions of IoT varies across academia, and the same goes for defining IIoT. The term is similar in characteristics to IoT but with an added emphasis on industrial processes. Boyes et al. present a range of definitions for IIoT, but the main focus outlined is improving productivity for industry [7]. Within manufacturing and industrial settings the original systems are Industrial Control Systems (ICS). These are well docu-

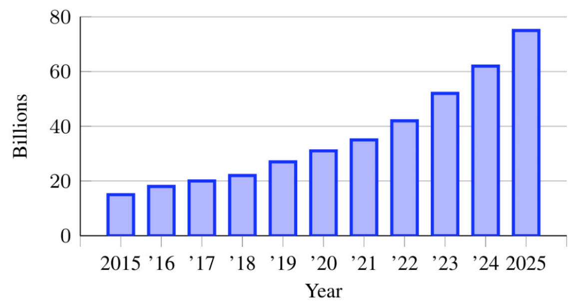

Figure 5: IoT Device Growth [81]

mented and used, but the benefits of these systems becoming autonomous and smart is desirable potentially seen through IIoT. Another technology closely linked to both IoT and IIoT is Cyber Physical Systems (CPS) [36] [23]. Both ICS and CPS are similar to IIoT but not the same. The main difference being IIoT devices require a connection to the internet as opposed to being closed in an ICS architecture [42].

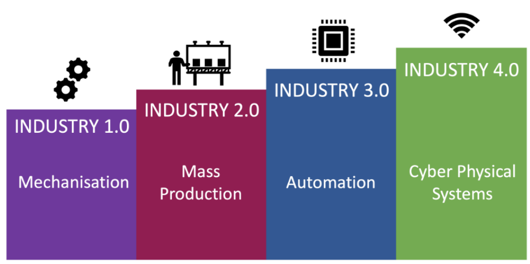

Figure 6: Industrial Revolution

Like IoT, IIoT can have a huge impact on improving manufacturing processes. IIoT allows for tasks to be evaluated with greater knowledge and real-time responses through connected devices. Thus improving the performance, production rate, costs, waste and many other critical deliverables within the industry setting [69]. The IIoT does not only affect manufacturing but agriculture, oil, gas and other large scale processes. Likewise, with IoT, Industrial IoT is having a significant impact within industry. Especially seen with Morgan Stanley predicting the market size to reach $110 billion by 2021 [79]. [59] reports that IIoT could add $14.5 trillion to the global economy by 2030 Fig. 6. shows the development of Industry 4.0, which is the introduction of IIoT within the industrial revolution timeline [59].

4.3. I/IoT Enabling Technologies and Functional Blocks

Both IoT and IIoT have a wide range of essential areas that ensure the running of connected systems. These enabling technologies are classified into four main functional domains, as described by [95]. These domains cover the individual enabling technologies from network communication, hardware and software to data processing, power and energy storage — all with specific goals to enable the full development of an IoT system facilitating an Industry 4.0

Table 2
Enabling Technologies and Functional Blocks: I/IoT

Domain	Enabling Technology
D1) Application Domain	I/IoT Application
	Architecture
	Software and APIs
D2) Middleware Domain	Cloud Platforms
	Data Processing Mechanism
	Data Storage
D3) Networking Domain	Communication Protocol
	Network Interface
	Adoption Mechanism
D4) Object Domain	Hardware Platform
	Embedded Objects
	Mechanical and Electrical Parts

architecture.

The four enabling technology domains for I/IoT comprises of: D1) Application domain, D2) Middle-ware domain, D3) Network domain and D4) Object domain as seen below in Table II.

D1 is made up of three layers. The first is the application layer, which is the I/IoT applications; Smart home, Smart cities to Smart farms. Next is the architecture layer; this can be enabling software architectures; SOA (Service-oriented architecture) or REST (Representational State Transfer) both examples of what makes up the architecture layer. The third layer; Software and APIs bridges the application domain to the middleware domain. It maintains the operating systems and software. For instance, Android and custom made OS's used to operate an IoT system. It could also be made up of custom built APIs for the deployment of an IoT system, both of which are a key technology for bridging D1 to D2.

The middleware domain is made up of three more layers. The first being the cloud platform, which is made up of services that provide on-demand computing resources through the cloud. Microsoft, Amazon and Google are leaders providers in cloud services.

The second layer is data processing; enabled through the use of data mining and example services developed by BigQuery, Apache and Storm. The third enabling layer in D2 is data storage. Essential in an I/IoT infrastructure, an example is MongoDB that offer large storage engines.

The third part of the IoT system is D3 the networking domain, which is made up of three enabling layers. The first is the communication protocol layer; this comprises of the application, transport and network protocols for a given system, enabling seamless communication. The second enabling layer is the network interface. Located here are essential technology standards (for example RFID) used throughout the IoT system again for enabling the seamless integration of IoT. The final layer of D3 the networking domain is the adoption mechanisms. Consisting of the adoption layer which includes standards like 6TiSCH and IEEE 1095 which enable more reliable wireless communication, likewise with the connectivity interface and the gateway layer, all of which are key enabling technology standards for the development of an I/IoT system.

D4 is the final block in the IoT system illustrated in Table II. The object domain is made up of three enabling layers. The first is the hardware platforms, consisting of the hardware solutions, examples being Raspberry Pi or Arduino. This domain brings together the last three layers; examples being sensors, radio tags, displays and firmware. Vital in connecting the system. The last layer is the mechanical and electrical parts, made up of the batteries and the processing units needed to run the device.

The splitting up of the domain into four functional blocks is easier for understanding the twelve enabling sections of this given IoT system; this provides an integrated framework that is interconnected.

4.4. Brief History of Data Analytics

The term data analytics is an umbrella term that groups analytic concepts, seen throughout the paper and academia. Hence why an understanding and analysis of other papers is needed. The term data analytics stems from the field of "Data Science", a multidisciplinary subject that covers a range of concepts, with an emphasis on collecting and presenting data for analysis to gain greater insight. The subsection below presents an in depth analysis of the field of data analytics. The identification and highlighting of these topics will help in analysing other papers and seeing where this research fits in [57].

4.4.1. Data

To perform data analysis, the need for raw data is paramount. There are several actions needed to turn this data into usable information, ready for use in algorithms and statistical analysis. These being the Requirements, Collection, Processing and Cleaning. The requirements set out the necessary needs of the data and how it is used, ensuring that specific requirements are outlined, taking into account the intended use of the data. The second stage acts on the requirement of collecting the relevant data, identifying physically where and how the data will be collected. The collected will then go through a processing phase in which data is sorted according to the requirements. The final phase and arguably the most important, is the cleaning of data. Despite the data being collected and sorted, it may have significant gaps or erroneous data. This cleaning phase uses the imputation methods, previously identified as challenges to data analytics. These methods ensure that no missing data exists [82][64].

4.4.2. Statistics

Statistics is the overarching term for the collection, classification, analysis, and interpretation of data. Briefly relevant in this case for data analysis as statistical models underpin machine learning algorithms. Statically inference and descriptive statistics are another way in which data analytics are used to describe observations in collected data. AI and the following topics below show the growth of advanced data analytics [65][82].

4.4.3. Artificial Intelligence

Artificial Intelligence (AI) is the first topic of interest in data analytics. The overall definition of AI dates back to the late 50s with this concept of creating "intelligent systems" [78]. These are categorised below into topics of potential importance for this project [22][71].

4.4.4. Machine Learning

A subsection of AI, machine learning is the creation of algorithms that can give the computer the ability to learn and act for the user without being directly programmed to do so. Machine learning is used to create programmes that use sophisticated algorithms to collect and analyse data autonomously. For more general analysis, machine learning can fit into two types of learning: [73][23].

Supervised Learning This is the most popular form of machine learning. The algorithms use large amounts of labelled data to analyse and learn. The algorithm is tasked with learning and analysing the labelled data to identify a given task correctly; image classification is one example [56]. The algorithms learn from training data and are then given test data to see how well it is accurately predicting what an image is showing, presented through an accuracy percentage. The user then analyses these answers and any errors are corrected and relearned, helping train the model and increasing the accuracy of a given algorithm [73].

Unsupervised Learning A supervised learning algorithm collects large amounts of data, where an unsupervised learning algorithm does not. Simply, because the algorithm does not have the task of analysing user input [56]. Unsupervised learning algorithms learns on their own methods to categorising and highlighting patterns within data instead of relying on user feedback. Clustering is one method of categorising data. Algorithms learn to cluster unlabelled data sets together, potentially showing hidden patterns that were not explicitly identifiable [56].

4.4.5. Deep Learning

Deep learning is another part of the field of data analytics and a subsection of machine learning. Deep Learning algorithms learn unstructured and unlabelled data using complex neural networks with autonomous feature extraction as opposed to manual extraction [54]. These networks utilise machine learning to create deeper learning algorithms that can take longer to train because of the much larger neural networks, but this allows for greater accuracy. Another type of learning is semi-supervised learning, defined as having some labelled data, but more data is unlabelled to see how the algorithms can learn to be more accurate [54]. Many more algorithms appear throughout the field of data science, but these are the most common.

4.4.6. Data Visualisation

The final subtopic within data analytics is visualisation, defined as a graphical representation or visualisation of data or results. The type of data affects the way its visualised. The most common being multidimensional data which can be presented using graphs and charts, taking multiple variables, for instance, bar or pie charts. Another data type is geospatial; this involves data collected from the earth through location data, visualised through distribution maps, cluster maps and more commonly contour maps [4].

4.5. Enabling Technologies and Functional Blocks for Data Analytics

The next section concerns data analytics within the field of Artificial Intelligence, Machine and Deep learning. Using [5] descriptions of enabling technologies for data analytics and using the classification used by [95], the section creates Table III. The enabling technologies are similar to IoT in many ways but have slightly different layers around visualisation and the algorithms side of analytics. An overview is seen below, with the domains labelled D5, D6, D7 and D8.

Table 3
Enabling Technologies and Functional Blocks: Data Analytics

Domain	Enabling Technology
D5) Object	Data Collection and Prepossessing
	Data Repositories
D6) Middleware	Storage Facilities
	Data Processing
	Analysis Techniques and Algorithms
D7) Networking	Wireless Network Technology
D8) Application	Hardware & Data Visualisation
	Data Analytic Applications

Table III is produced, as a result of analysing Table II by Bibriand Krogstie [5], however, is slightly different in presentation. The table starts with D5 the object domain followed by D6 the middleware domain, D7 the network domain and lastly D8 the application domain. In each of the domains are a list of enabling technologies associated with data analytics.

D5 is the object domain which has three layers. The first enabling layer is the data collection, which deals with the preprocessing of data for the analytic solutions. The use of data sensing tools and methods enables the collection of data. Digital signal processing units also ensure the harvesting of data. The second layer is the data repository which facilitates the storage and use of databases. The final layer of D5, linking to D6 is the storage facilities which enable the storage of large amounts of data through the use of server storage enabling on-demand data. This layer also is the connection to the processing of the storage data to the middleware domain.

D7 is the middleware domain, consisting of three enabling layers. The first linking with D6 which relates to storage processing. The second layer in D6 is data processing which is the main layer for enabling data analytics, cloud services and the main middleware architectures, including software and database systems.

The third layer in D6, not seen in Table II is the analysis and algorithms. This layer facilitates the task of data mining, machine learning, statistics and querying of the collected data. As well as the enabling models within data analytics; supervised and unsupervised learning.

D7 is the networking domain, showing enabling technology for the connectivity protocols looking at wireless and communication and how they enable efficient collection and processing of data from previous layers and domains. D7 also concerns the enabling standards relating to the privacy and security mechanisms.

The final domain discussed is D8, entitled Application. D8 has two enabling technology layers. The first being the hardware and visualisation layers. This layer enables tangible technology to record the data and carry out machine and deep learning or statistical analysis. The visualisation side of the layer easily enables the display of useful information regarding user tasks.

Finally, the application layer highlights the applications relating to data analytics such as self-driving cars, image recognition or virtual personal assistants (Amazon's Alexa). Table II presents the functional domains for enabling technologies associated with IoT/IIoT. Table III presents the functional domains for enabling technologies for data analytics. The above section provides future work for creating another table on functional domains for enabling technologies of a Digital Twin.

5. Current Research

This next section identifies related work for IoT/IIoT and data analytics with a focus on Digital Twins publications. Discussing a range of publications and identifying gaps in the field.

5.1. Categorical Review Methodology

The first part of this section performs a categorical review. This first section aims to follow the same methodology as Kritzinger et al, [37] to reproduce a categorical review table of selected publications. The main elements of the review draw on the three levels of integration of a Digital Twin, as described in section II, subsection B of this paper and, by Kritzinger et al. [37].

The basis of the methodology is to draw on work done by Kritzinger et al. [37] The authors have categorised forty-three papers regarding Digital Twins ranging from 2001 to 2017, from looking at Google Scholar and other publishers to gather papers. For this search the authors used Google Scholar with specific searches targeting ACM, IEEE and Science Direct repositories. Of the research found there were 177 paper to look at from 2015 to present (June 2019), only 42 were pre 2017. The search terms include variations of Digital Twin (Digital-Twin, Digital Twins). As well as the term Digital Twin, the search included adding terms relating to the broad research areas (Industrial Digital Twin, Healthcare Digital Twin, Smart Cities Digital Twin). Table IV is the reproduced table which uses twenty six key sources from three areas, Manufacturing, Healthcare and Smart Cities.

5.2. Table IV Design

The following sections discuss the columns used in Table IV:

5.2.1. *Paper*

The first column provides the authors and year of each publication.

5.2.2. *Type*

The second column identifies each paper by the type of research carried out; review paper or a case study. It could also be a new concept relating to Digital Twins or a definition, each is categorised accordingly.

5.2.3. *Defined Twin*

The next two columns are the definition relating to levels of integration. The first identifying what the author is referring to; Digital Model, Shadow or Twin.

5.2.4. *Actual Twin*

The second column identifies if the paper accurately describes a Digital Twin, Model or Shadow. The definitions from section II are used to classify the publication, giving insight into the misconceptions in definitions.

5.2.5. *Broad Area*

A fifth column identifies the broad areas of research: this being Manufacturing, Healthcare and Smart Cities.

5.2.6. *Specific Area*

The sixth column elaborates on the broad area narrowing down to a specific area. For instance, in manufacturing, this would be narrowed down to a Smart Factory or Fault Diagnosis area of interest. For Smart Cities, this is narrowed down to Traffic or Infrastructure.

5.2.7. *Technology*

The final column identifies the technology used, for example; simulation, data analytics, IoT.

The paper is ordered alphabetically in three broad areas, Manufacturing, Healthcare and Smart Cities shown in Table IV.

5.3. Paper Reviews

The following sections draw on the papers reviewed in the categorical review. The sections are not limited to but will include the main areas of paper collected relating to Healthcare, Smart Cities and Manufacturing. The order of the areas present, reflect the level of current research in terms of the number of papers found. With healthcare, the number of papers found is limited, but the potential life changing benefits Digital Twins can have on the healthcare industry are prevalent [43][41][21][67].

Followed closely is the smart city area with a small number of papers found. Most research falls within the manufacturing setting. Fig. 7. shows the share of papers in terms of the area of research they fit in to; Healthcare, Manufacturing or Smart Cities.

All three areas are discussed below with example papers.

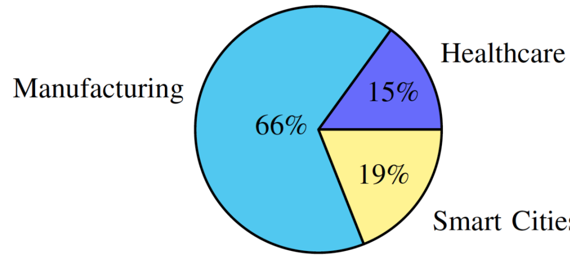

Figure 7: Percentage Share of Research Areas

5.3.1. *Healthcare*

An element to take from the several definitions of Digital Twins is the concept as described by He [27], the "digital replications" of a physical thing. El Saddik redefined this with the inclusion of Digital Twin replications of living things as well as non-living entities [21]. Showing potential use of the Digital Twin for the healthcare sector shows it is not limited to manufacturing.

Ross [67] presents work with Hewlett-Packard using AI and IoT to create Digital Twin avatars of people in several ways. From a health perspective, the Digital Twin technology, combined with AI algorithms, can be used to see the effects specific lifestyle changes could have on a person's health. recommending specific changes from AI and Digital Twin analysis. This use emphasises the full integration of data from both the physical twin (The Human) and the Digital Twin (The Replica). Giving the human the ability to see what impact their actions are having on the physical twin while also showing the effect some lifestyle changes could have on them [67].

In another more recent setting, Laaki et al. [41] present a working prototype of autonomous surgery harnessing IoT and Industry 4.0 connectivity to create a Digital Twin of a patient. The authors propose a remote surgery application through a mobile network. The prototype uses a robotic arm, VR with a 4G environment to deliver precision surgery. The paper presents the complexity with multidisciplinary research, citing this as one of the reasons why the work used simulation as opposed to a physical prototype. Laaki et al. also discusses problems with integrating the prototype with a Digital Twin. The author explores some of the advancement in AI and Industry 4.0 and how they ease the challenges of connectivity, integration and multidisciplinary research [41].

Liu et al. [44] present a novel approach for the future delivery of healthcare combining cloud technology with Digital Twins to create a framework that helps to monitor, diagnose and predict the health of a patient. Liu et al. achieve this through the advancement and use of IoT devices through wearable technology and in home sensors with an emphasis on use for the elderly. Not only a framework, but the author also presents a number of applicable applications citing the feasibility of each. Liu et al. main contributions of the paper being the ability to predict a problem with patients more accurately, through the combined use of IoT, Cloud and Digital

Table 4
Categorical Review

Paper	Type	Defined Twin	Actual Twin	Broad Area	Specific Area	Technology
Bilberg, Malik (2019) [6]	Case Study	DT	DS	Manufacturing	Smart Factory	Simulation
Chhetri et al. (2019) [14]	Case Study	DT	DT	Manufacturing	Assembly Line	AI, Sensors, Simulation
He et al. (2018) [27]	Review	DT	DS	Manufacturing	Power System	Simulation, AI, Analytics
Howard (2019) [28]	Concept	DT	DM	Manufacturing	Product Development	EDA, Visualisation
Jain et al. (2019) [30]	Concept	DT	DT	Manufacturing	Fault Diagnosis	Industry 4.0
Karadeniz et al. (2019) [33]	Case Study	DT	DS	Manufacturing	Ice Cream Machines	AR, VR, Industry 4.0, AI, CPS
Kuehn (2019) [39]	Concept	DT	DS	Manufacturing	Smart Factory	Simulation
Lu (2019) [48]	Review	DT	No Example	Manufacturing	Smart Factory	Cloud, CPS, Industry 4.0
Mandolla et al. (2019) [51]	Case Study	DT	No Example	Manufacturing	Aircraft	Blockchain, Visualisation
Mawson, Hughes (2019) [52]	Case Study	DT	DT	Manufacturing	Energy Modelling	Industry 4.0
Min et al. (2019) [53]	Case Study	DT	DS	Manufacturing	Petrochemical Factory	AI, Optimisation
Qi, Tao (2018) [64]	Review	DT	DT	Manufacturing	Smart Factory	Industry 4.0 , AI, Cloud, Big Data
Shangguan et al. (2019) [72]	Case Study	DT	DM	Manufacturing	Wind Turbine	CPS
Sivalingam et al. (2018) [74]	Review	DT	DS	Manufacturing	Wind Turbine	CPS, Simulation
Tao et al. (2019) [84]	Review	DT	DT	Manufacturing	Smart Factory	CPS, Industry 4.0, AI
Tao et al. (2018) [87]	Review	DT	DT	Manufacturing	Assembly Line	CPS, Industry 4.0, AI
Xu et al. (2018) [92]	Concept	DT	DS	Manufacturing	Fault Diagnosis	CPS, Industry 4.0, AI, Transfer Learning
El Saddik (2018) [21]	Definition	DT	DT	Healthcare	Patient Monitoring	VR, AI
Laaki et al. (2019) [41]	Concept	Undefined	DS	Healthcare	Surgery Robotics	Industry 4.0, AI, VR
Liu et al (2019)[44]	Concept	DT	DT	Healthcare	Health Management, Elderly Health	Cloud, CPS
Ross (2016) [67]	Review	DT	DT	Healthcare	Predictive Health & Well-being	VR, 3D Modelling
Chen et al. (2018) [12]	Review	Undefined	DS	Smart City	Driving	Simulation, AI
Jo (2018) [31]	Review	DT	DT	Smart City	Livestock Farms	Industry 4.0
Mohammadi, Taylor (2017) [55]	Concept	DT	DT	Smart City	Infrastructure Analysis	Simulation, VR
Pargmann et al. (2018) [62]	Review	DT	DS	Smart City	Wind Farm	AR, AI, Cloud
Ruohomäki et al. (2018) [68]	Case Study	DT	DS	Smart City	3D Energy Mapping	Visualisation, Sensors Ontology

Twin technology [44].

5.3.2. Smart Cities

The next part of the paper is on current research in Smart Cities for Digital Twins. Research in recent years has seen substantial growth in urbanisation combined with the rise of IoT and data analytics [55]. Mohammadi et al. [55] cite this as one of the motivations for the work. Mohammadi et al. identify the varying states in spatiotemporal flux emphasising these need to be understood to maintain growth. The concept they present does this through the use of Digital Twin and Virtual Reality headsets, allowing them to monitor fluctuations while making predictions thought real-time analytics [55].

Ruohomäki et al. [68] also present a framework, "mySMARTlife" which makes use of advancements in IoT across cities to create a smart city Digital Twin. The paper presents proposals for helping in urban planning and built environments, but has particular uses in the energy consumption field with the ability to use the Digital Twin for monitoring and comparing of energy consumption based on the environment and human impact. Both used for real time and future developments [68]. Both Mohammadi et al. [55] and Ruohomki et al. cite the need for the uptake of Industry 4.0 concepts to ensure the level of data exchange is high enough for the twin to perform accurately.

Fuelling the energy grid along with implementing the integration of renewable energy methods, is a challenge. With this comes the need for accurate delivery within a smart city. Wind power is an example of a renewable energy source which needs to be delivered, monitored and analysed. Pargmann et al. [62] present a cloud based Digital Twin monitoring system used for the development and monitoring of wind farms. The author presents a working prototype that uses data feeds, and parameters set out both from a technical and business context. Allowing for the creation of a working twin of a wind farm development [62].

Sivalingam et al. [74] reviews and produces a case study that investigates wind farm use and energy consumption for a smart grid. The paper cites some of the challenges with the reliability of power consumption and the general maintenance of wind turbines. The authors propose a working methodology that makes use of IoT sensors combined with data analytics within a Digital Twin environment to accurately perform and predict maintenance of the wind turbines [74].

In terms of supplying a smart city Jo et al. [31] and Chen et al. [12] both presents work that is related to smart cities. Jo and Chen both utilise the use of Digital Twins. The first presented by Jo et al.[31], a paper that produces a feasibility study on the potential uses of a Digital Twin for a smart farm. The author notes the importance of industry 4.0 for the realisation of this project as it makes the deployment of Digital Twin a challenge in complex environments. The authors highlight three applications, GE's Predix, Eclipse's Ditto and IBM's Watson as contenders for the deployment of Digital Twin technology along with some guidelines on how the monitoring of livestock can be smarter through the use of a Digital Twin [31].

Chen et al. [12] present Digital Twins for cars and traffic management. The paper explores the challenges with driving, showing there needs to be more data flow within the vehicle used and a connection to other vehicles in the vicinity. Chen et al. [12] present a framework that uses a Digital Twin combined with learning algorithms that monitor and analyse feedback based on user behaviour. The algorithms facilitate a real time digital behavioural twin of a driver, providing warnings and instructions on how to drive more safely to minimise risk [12].Both Jo et al. and Chen et al. share the need and challenge of data exchange both citing the need for greater connectivity, which is needed to achieve the optimum result and accuracy for each of the Digital Twins.

5.3.3. Manufacturing

The last section concerns an area that has the most amount of research relating to Digital Twins. It is also an area that has many subfields, from large smart factories to smaller machines and tools. For this reason, the section splits into the following sub sections.

Smart Manufacturing Reviews Reviews in this field are limited, but the first to note is presented by Qi and Tao [64] which give a comprehensive "360" view on Digital Twins for big data in a manufacturing and industrial setting. It gives a comparison of enabling technologies for Digital Twins as well as arguing the importance of emerging technologies for the development of smart manufacturing [64].

Tao presents two review papers,[87] and [84], the first [87] compares Digital Twins and Cyber-Physical systems within a smart manufacturing environment. The latter by Tao [84], a state of the art paper for Digital Twins combined with industry. Both papers share enabling technologies; IoT, Cloud, Big Data, and Artificial Intelligence showing how the technology use Digital Twins. Tao [85] also elaborates on some of the main application uses; Digital Twin Simulation, Digital Twin as a Service, Data Fusion and Interaction and Collaboration. Both cite the increased development of Industry 4.0 technologies with an emphasis on data analytics and IoT as a factor in the growth and use of Digital Twins.[87] [84][85].

Simulation and Artificial Intelligence The above papers have touched on some key areas relating to using Digital Twins combined with simulation and AI approaches for manufacturing. Kuehn [39] describes a concept that cites "virtual clones" of a system combined with machine learning algorithms to enhance the manufacturing process. The author categories key areas in a manufacturing process to highlight their specific goals and concept for applying a Digital Twin to the manufacturing process, giving enterprises the ability to test, simulate and optimise manufacturing processes in a virtual environment ensuring increased quality and efficiency.

Min et al. [53] similarly to Kuehn [39] presents a paper that exhausts the key enabling technologies with an emphasis on digital twin solutions using AI, specifically machine learning giving comprehensive evaluations. The work evaluates the pros and cons of using machine learning and Digital Twins for the petro-chemical industry, applying each to an industrial IoT petrochemical factory [39]. A limitation is that the Digital Twin and algorithms are unique to a petrochemical plant. Transfer learning could be used to find commonalities in algorithms to help create solutions transferable to other manufacturing processes.

A subsection of manufacturing is fault diagnosing with two papers of interest found. The first being presented by Jain et al. [30], this focuses more on simulation as opposed to an AI based paper. The authors present a simulation study which discusses a Digital Twin approach to fault diagnosis for distributed photovoltaic systems (PV). The advancements in Digital Twin technology allows the team to develop a Digital Twin that can estimate accurately faults relating to PV energy units in real-time [30].

Similar work by Xu et al. [92] proposes a more AI focused solution for fault diagnosis in a smart manufacturing environment. Xu et al. highlight challenges in the amount of training data available for creating accurate AI algorithms for new manufacturing processes, something also needed to create accurate Digital Twins. To ensure any challenges are mitigated, the front running of the model is using Digital Twin which learn and diagnoses faults while producing training data. The second phase can then make use of transfer learning using the collected training data from phase one of the algorithm. A more accurate fault diagnosing system is achieved with the help of a Digital Twin and transfer learning. The authors present a workable case study with a car manufacturing environment testing and evaluating the effectiveness of the concept [92].

System Design and Development Another key area for embracing Digital Twin use is through the design and development stage of manufacturing processes and system. Shangguan et al. [72] discuss an approach that draws on Digital Twin use but also introduces the Cyber Physical System (CPS) trend. The authors present a Hierarchical Digital Twin Framework (HDTM) for the design and development of dynamic CPSs in a smart manufacturing environment. The Digital Twin is used throughout the levels of CPS design, harnessing the ability to reuse and test against physical data on a virtual twin. The benefits of a Digital Twin are best seen here as it gives the authors the ability to use the twin in a real-time predictive design setting as well as learning for large scale system changes. The framework is an application for industrial robot design [72].

Howard [28] presents a paper that is an insight into the trend of Digital Twin, evaluating its uses and suitability for the ever-evolving smart manufacturing world. The main goal achieved is the design and development of manufacturing electronic hardware through "virtual validation" utilising a Digital Twin [28]. Both papers cite challenges identified by leaders and visionaries in the world of Digital Twins, analytics and smart manufacturing.

Aside from high level system design Karadeniz et al. [33] and Chhetri et al. [14] produces a contextual paper on the development of Digital Twin systems for manufacturing processes. The first by Karadeniz et al. [33] a paper that discusses the advancements in Industry 4.0 and IoT. Exploring how this growth is facilitating the trends of AR (Augmented Reality) and VR (Virtual Reality). The authors set out a concept that creates a Digital Twin of gastronomic things (devices and processes relating to food and cooking), the paper presents this as "eGastronomic things" similar to the Internet of Things. The gastronomical processes have physical IoT sensors collecting data to create a Digital Twin. The authors use an ice cream machine as a case study to show how a Digital Twin can help in monitoring and maintaining the performance of "eGastronomic" processes. In this case, an ice cream machine [33].

The latter by Chhetri et al. [14] also cites the advancements in digitalisation for the growth in smart manufacturing design and developments. The authors propose a methodology that takes advantage of the growth in IoT to build a Digital Twin of a manufacturing process. In this concept, the IoT sensors help collect and store data streams that are used to indirectly highlight side channel states; acoustics, power and magnetic output of a process. These can be used to localise a fault and identify problems with the manufacturing processes. The team validates the work with a case study of Fused-Deposition Modelling system (FDM) which produces high accuracy anomaly detection, the first of its kind in this format [14].

Mandolla et al. [51]discuss another trend adapted for the smart manufacturing industry, Blockchain. A growing list of blocks within a decentralised ledger can be used to record data across a number of computers. The previous blocks are linked using a cryptography hash, a method of protecting data using the use of codes. These hashes are unique to each block and contain attributes such as timestamp and transaction data. Blockchain growth is facilitating its increased use in processes other than its original intended use; cryptocurrency [29, 60, 66].

Mandolla et al. [51] present an example, in a case study on how they have created a Digital Twin that exploits the use of blockchain and Digital Twins combined. The authors focus on aerospace manufacturing concerning the metal additive process. Mandolla et al. create a Digital Twin of this process while providing a conceptual answer to securing the process through blockchain, and monitoring through a Digital Twin [51].

Similarly Bilberg and Malik [6] are using robotics, exploring how to adapt them for the manufacturing process. Bilberg and Malik present an event driven Digital Twin that works in parallel with a robot to perform tasks on an assembly line. The other combines the physical task and the virtual task to create a real-time, skills-based robotic production line accurately allocating a task to the human or robot based on the optimum production they could respectively achieve [6]. Both papers highlight the benefits of digitalisation, but both also cite the challenges with seamless integration, something needed for the effective running of an assembly line and Digital Twins [51] [6].

Energy Efficient Manufacturing In line with national and international targets, the energy used need to be monitored and reduced, hence the need and growth of potential solutions for energy efficient manufacturing. Both Lua et al. [48] and Mawson [52] present systems and architecture for energy efficient manufacturing. A driver for this is the benefit for the environment. However, more efficient manufacturing will also reduce cost, increase profits and future investments. Lu et al. present a paper that focuses on developing an architecture that implements an energy aware Digital Twin model with a platform called MCLoud. Both of which facilities an Industry 4.0 environment where manufacturing processes are monitored continuously and self-configured through CPSs and Digital Twins with energy efficiency the overall goal.

Mawson et al. [52] also draw on the advancement in Industry 4.0, citing a review on their effectiveness for increased automation, connectivity and flexibility for manufacturing processes. The main contributions of the paper is a holistic review of methodologies and frameworks delivered for the analysis of energy compulsion at the machine process level. Mawson et al. cite various simulation tools, but they lack multi-level integration.

In order to produce a high accuracy model, all aspects of the manufacturing from the materials to resource flows are needed to analyse energy consumption accurately. These are challenges showing how Digital Twins, VR and AR will facilitate future research [52].

6. Open Research

The penultimate section in this review briefly discusses open research for Digital Twins. Also looking at literature reviewed for challenges facing future research.

6.1. Digital Twin in Manufacturing

Across the manufacturing industry, fully integrated Digital Twin use is minimal, with varies publications on smaller parts concerning the development of a Digital Twin. With none of the literature covering all aspects of a Digital Twin from the physical and virtual modelling to the data, connection and service parts of modelling a Digital Twin. Modelling and scaling are needed to create generic Digital Twins. [94] [70] Both present sensor-based modelling of different stages of a Digital Twin with [72] only focusing on the hierarchy modelling of the virtual and physical modelling of a Digital Twin, the need for a generic model for a complete DT is needed.

Data Fusion is another area of literature that is heavily researched across all areas of science but is less researched when applying data fusion and Digital Twins in an industrial setting. Likewise, with DT modelling, another avenue is to incorporate data fusion when developing generic models. The literature looks at how predictive maintenance can incorporate Digital Twins with data fusion which is a promising area of research[11] [45].

Data fusion is also talked about under the term "Cyber-Physical" fusion for Digital Twins. Again the modelling being limited to researching Digital Twin that use virtual and physical data fusion. The need is for standardised approaches when modelling data fusion with Digital Twins. [11][45][86], explore some of the ways data fusion can be used for Digital Twins in industry, while also highlighting some of the potential challenges with implementing data fusion from connection problems to security threats.

Prognostics and Health Management (PHM) is another term used primarily in an industrial setting as it can be applied to the health and manufacturing processes from small to large scale plants [58][1][92]. Digital Twin technology promotes PHM as the potential for research in areas of fault diagnosis and predictive maintenance for industrial processes are tangible with the development of Digital Twins [49][80].The Digital Twin allows for the potential interaction and collaboration of machines, giving the ability for simulation of processes, facilitating the goal of more accurate manufacturing [91] [83][87].

6.2. Digital Twin in Healthcare

This next section discusses the open research for Digital Twins in a healthcare setting. Some of the research cites the potential for adapting Digital Twin technology for humans. An example is a Digital Twin of a person to monitor day-to-day health and well-being. It also has the potential to act as a human twin for simulating what positive and negative lifestyle changes could have on the physical human. The significant open research comes in the form of modelling and breaking down the barriers to modelling a human body to a Digital Twin. Again down to the issue of having no standardised Digital Twin modelling methods [86], Needed to make generic Digital Twins of a human.

Similar to PHM in manufacturing this concept is an exciting area of research with the Digital Twin being used to monitor and maintain the health of people. From day to day health care to ongoing health conditions the Digital Twin can be used in a similar way to PHM, combining data analytics to ensure patients are healthy. [41] presents open research relating to surgery; using historical data with current real time data for Digital Twin simulations of surgery and overall healthcare. The aim is to spot risks before they arise using the virtual Twin of the patient.

An area of research is in the field of data fusion. With [41][44] citing the need for research in accurately dealing with data collected and processed for a Digital Twin, mainly as it deals with sensitive patient data over the virtual and physical Digital Twin, adequate interaction and convergence is needed for greater trust and use, hence the need for more research.

Remote surgery and healthcare is another exciting area of research. The ability of a doctor being able to perform pre-surgery checks remotely through a Digital Twin is a promising way to minimise risk to life. Another concept presented by Lakki et al. [41] is the open research in network supported remote surgery, this comes in line with the developments of 5G for mobile networked surgery, another area of future research for Digital Twins in healthcare [41] [67].

With data fusion, modelling, remote surgery and the implementation of Digital Twins for healthcare facilitate more specific areas of research. [67][21][41][44] All cite the ongoing concern with the security of collection and processing of data for a Digital Twins, more importantly when dealing with sensitive data from a healthcare setting. The goal of future work to ensure the privacy of the data used for a Digital Twin.

6.3. Digital Twin in Smart Cities

The final area of interest is the open research for Digital Twins for a smart city. The review shows that this area is similar to healthcare in terms of limited academic research. The papers currently cover large parts of this broader vision of a smart city. Anything from city-wide Digital Twins for smart cities to more specific areas like traffic management Digital Twins [12][76], livestock management [31] to renewable energy [62]. The area smart cities covers and its smaller projects help towards the bigger picture of how the large scale Digital Twin can be used for a fully connected Digital Twin for a large town or city.

An exciting opportunity is the combination of Digital Twin with local infrastructure as explored by [55] and [68] making use of 3D modelling for smart city development and maintenance. Open areas to be researched come in the form of applying data analytics. Examples being predictive analytics applied to Digital Twin for developing smart cities Digital Twin.

A standardised Digital Twin for a smart city is a must. However, this brings further research in areas for the interactions of data fusion for the physical and virtual interchange of data for a Digital Twin. The need for modelling in a smart city is emphasised by [12] and [76] with the call for more generic models that take into account all components of a smart city. Chen [12], presents a traffic management concept integrated without the need for further developments or more generic modelling, setting a standard for compatibility between smart buildings to smart traffic. With the rise and development of Digital Twins for manufacturing, it is clear to see the opportunities for smart cities is on the rise [55][68][12].

6.4. Specific Findings

6.4.1. Data Models

The first set of findings relate to the Digital Twin model and its architecture. There is a lack of unified models or a generic Digital Twin architecture in the literature,with no consensus on how to build a Digital Twin system. Developing a design paradigm for building a Digital Twin could be a generic way of implementing a basic Digital Twin system.

6.4.2. Heterogeneous Systems

As the Digital Twin environment is heterogeneous, while also being connected to large distributed networks. It is an ongoing goal seen throughout the area for researchers to gain a deeper understanding of how to deal with such systems, achieved through evaluating and comparing current Digital Twin systems with each other seeing how they differ in handling smaller and larger heterogeneous Digital Twin environments.

6.4.3. Artificial Intelligence (AI)

With the advancement in digitalisation, AI is one of the leaders and facilitators for growth and adaptability for enabling Digital Twins. With the open areas of research evaluating the impact of AI, machine and deep learning algorithms could potentially have on the advancements and uses of Digital Twin technology. These advancements in Industry 4.0 concepts have enriched the way we live, work and communicate, in turn, opening more research opportunities as the demand for Digital Twin technology increases.

6.4.4. Security

With the advancements in technology like blockchain, comes several opportunities to ensure security with the main focus on looking for solutions that help secure Digital Twins.

6.4.5. Data Exchange

Like security and AI, with more connectivity comes the rise in Digital Twin systems and its enabling technologies. More research will ensure the Digital Twin can thrive when sharing data between devices. An open area is looking for solutions in achieving seamless integration of data for small IoT systems and large heterogeneous systems. The development of small Digital Twins needs to be scaled up, taking into account weak data exchange.

6.4.6. IoT

Most of the open research is from an IoT point of view when thinking of a Digital Twins. There needs to be a way to retrofit sensors to ensure the data exchange is accurate and performing to its best ability. Edge computing is another open area of research for IoT Technology.

6.5. Challenges to Open Research

There are a number of challenges found when trying to overcome the open research for Digital Twins, as seen below.

6.5.1. Multidisciplinary

One significant challenge comes from the multidisciplinary environments used for designing and developing. The challenges come because of the many different fields of research involved in collaborating, which can be helpful for breakthroughs but also a hindrance as visionaries for the field have different directions for the research, ultimately leading to slower results.

6.5.2. Standardisation

As highlighted in the extensive research and seen in many new and emerging technologies, a challenge is with the lack of standardisation. This resultis in differences in what a Digital Twin is from one project to the next. A contributing factor to this is the variety of definitions seen, this coupled with no standardisation is a challenge and slowing the progress of the digital twin technology.

6.5.3. Global Advancements

With the vast advancements in Digital Twins and their enabling technologies come many benefits but also challenges. Futuristic and unrealistic goals lead to slower uptake and development of newly adapted technologies and opinions. With the breakthrough of Industry 4.0 and the rapid growth of digitalisation comes the growth of technologies at different rates. The accelerated growth leads to a range of challenges with connectivity and data exchange. The supporting systems or IoT devices may not be compatible with Digital Twin. This growth at different rates can also pose new challenges for security in terms of exposing vulnerabilities.

7. Conclusion

The growth in Digital Twin use has seen a shift in recent years, facilitated by an increase in the number of published papers and industry leaders investing heavily in developing Digital Twin technology. It would not be possible without the same growth in the AI and IIoT fields which are becoming a key enabler. It is clear to see that the majority of the Digital Twin research is in the manufacturing field, as evidenced through the large proportion of papers presented in this area. The number of papers found in manufacturing is noticeably different to papers discussing Digital Twins for smart cities and healthcare. The big gap seen is the potential for combining AI with Digital Twins and exploring where these algorithms can be applied. The effects of AI combined with Digital Twin is amongst the publications but on a small scale. The exciting and inevitable future research will look at scaling up of smaller successful Digital Twins. An important finding is the lack of standardisation and definition for Digital Twins. Addressing the challenges with standardisation, ensures future development are actually of Digital Twins and not wrongly defined concepts.

The paper highlights two other areas of growing interest, Digital twins for healthcare and smart cities. Thus the reason why the paper contributes a categorical review that includes not only manufacturing but healthcare and smart cities. The paper discusses each area, discussing how researchers are developing Digital Twins, while also identifying challenges and key enabling technologies, thus aiding future work. As a result of the categorical review, it is evident that papers are wrongly identifying Digital Twins. The paper also identifies the lack of clear definitions for a Digital Twin, showing how there is no real difference in definition since initially coined in 2012. The lack of clear definitions, coupled with wrongly identified Digital Twins, is a reason for more concepts rather than full proof Digital Twin publications because of the definition and ambiguity.

Despite the field of Digital Twin being in its infancy and dominated by manufacturing, this paper paves the way for further work. The paper provides a foundation for other researchers to investigate the field further. Papers concerning Digital Twin use in manufacturing, identify a range of publications with particular growth in the health of the machine and predictive maintenance. Digital twins for Healthcare draws on similar themes investigating papers that use Digital Twin for predictive analytics of the human body. The paper also highlights the advancements in remote surgery and the importance of researching data fusion, mainly due to the nature of sensitive data used in healthcare. Research for smart cities is limited, but the potential to investigates Digital Twins for traffic management systems and smart city developments is on the rise.

Acknowledgement

This work is partly supported by the SEND project (grant ref. 32R16P00706) funded by ERDF and BEIS. We would also like to thank Astec IT Solution Ltd as an industry partner to conduct this research.

References

[1] Alam, K.M., El Saddik, A., 2017. C2ps: A Digital Twin Architecture Reference Model for the Cloud-Based Cyber-Physical Systems. IEEE Access 5, 2050–2062. URL: http://ieeexplore.ieee.org/document/7829368/, doi:10.1109/ACCESS.2017.2657006.

[2] Ashton, K., 2009. That 'Internet of Things' Thing - 2009-06-22 - Page 1 - RFID Journal. RFID Journal URL: https://www.rfidjournal.com/articles/view?4986.

[3] Automation, 2018. Bentley Systems releases iModel.js open-source library. URL: https://www.automation.com/library/resources/bentley-systems-releases-imodeljs-open-source-library.

[4] Barkwell, K.E., Cuzzocrea, A., Leung, C.K., Ocran, A.A., Sanderson, J.M., Stewart, J.A., Wodi, B.H., 2018. Big Data Visualisation and Visual Analytics for Music Data Mining, in: 2018 22nd International Conference Information Visualisation (IV), pp. 235–240. doi:10.1109/iV.2018.00048.

[5] Bibri, S.E., Krogstie, J., 2017. The core enabling technologies of big data analytics and context-aware computing for smart sustainable cities: a review and synthesis. Journal of Big Data 4. URL: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-017-0091-6, doi:10.1186/s40537-017-0091-6.

[6] Bilberg, A., Malik, A.A., 2019. Digital twin driven human–robot collaborative assembly. CIRP Annals URL: https://linkinghub.elsevier.com/retrieve/pii/S000785061930037X, doi:10.1016/j.cirp.2019.04.011.

[7] Boyes, H., Hallaq, B., Cunningham, J., Watson, T., 2018. The industrial internet of things (IIoT): An analysis framework. Computers in Industry 101, 1–12. URL: https://linkinghub.elsevier.com/retrieve/pii/S0166361517307285, doi:10.1016/j.compind.2018.04.015.

[8] Brandtstaedter, H., Ludwig, C., Hubner, L., Tsouchnika, E., Jungiewicz, A., Wever, U., 2018. DIGITAL TWINS FOR LARGE ELECTRIC DRIVE TRAINS, in: 2018 Petroleum and Chemical Industry Conference Europe (PCIC Europe), IEEE, Antwerp. pp. 1–5. URL: https://ieeexplore.ieee.org/document/8491413/, doi:10.23919/PCICEurope.2018.8491413.

[9] Brosinsky, C., Westermann, D., Krebs, R., 2018. Recent and prospective developments in power system control centers: Adapting the digital twin technology for application in power system control centers, in: 2018 IEEE International Energy Conference (ENERGYCON), IEEE, Limassol. pp. 1–6. URL: https://ieeexplore.ieee.org/document/8398846/, doi:10.1109/ENERGYCON.2018.8398846.

[10] Burnett, D., Thorp, J., Richards, D., Gorkovenko, K., Murray-Rust, D., 2019. Digital twins as a resource for design research, in: Proceedings of the 8th ACM International Symposium on Pervasive Displays - PerDis '19, ACM Press, Palermo, Italy. pp. 1–2. URL: http://dl.acm.org/citation.cfm?doid=3321335.3329685, doi:10.1145/3321335.3329685.

[11] Cai, Y., Starly, B., Cohen, P., Lee, Y.S., 2017. Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing. Procedia Manufacturing 10, 1031–1042. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351978917302767, doi:10.1016/j.promfg.2017.07.094.

[12] Chen, X., Kang, E., Shiraishi, S., Preciado, V.M., Jiang, Z., 2018. Digital Behavioral Twins for Safe Connected Cars, in: Proceedings of the 21th ACM/IEEE International Conference on Model Driven Engineering Languages and Systems - MODELS '18, ACM Press, Copenhagen, Denmark. pp. 144–153. URL: http://dl.acm.org/citation.cfm?doid=3239372.3239401, doi:10.1145/3239372.3239401.

[13] Chen, Y., 2017. Integrated and Intelligent Manufacturing: Perspectives and Enablers. Engineering 3, 588–595. URL: https://linkinghub.elsevier.com/retrieve/pii/S2095809917307105, doi:10.1016/J.ENG.2017.04.009.

[14] Chhetri, S.R., Faezi, S., Canedo, A., Faruque, M.A.A., 2019. QUILT: quality inference from living digital twins in IoT-enabled manufacturing systems, in: Proceedings of the International Conference on Internet of Things Design and Implementation - IoTDI '19, ACM Press, Montreal, Quebec, Canada. pp. 237–248. URL: http://dl.acm.org/citation.cfm?doid=3302505.3310085, doi:10.1145/3302505.3310085.

[15] Coraddu, A., Oneto, L., Baldi, F., Cipollini, F., Atlar, M., Savio, S., 2019. Data-driven ship digital twin for estimating the speed loss caused by the marine fouling. Ocean Engineering 186, 106063. URL: https://linkinghub.elsevier.com/retrieve/pii/S0029801819302616, doi:10.1016/j.oceaneng.2019.05.045.

[16] Damjanovic-Behrendt, V., 2018. A Digital Twin-based Privacy Enhancement Mechanism for the Automotive Industry, in: 2018 International Conference on Intelligent Systems (IS), pp. 272–279. doi:10.1109/IS.2018.8710526.

[17] David, J., Lobov, A., Lanz, M., 2018. Leveraging Digital Twins for Assisted Learning of Flexible Manufacturing Systems, in: 2018

IEEE 16th International Conference on Industrial Informatics (INDIN), IEEE, Porto. pp. 529–535. URL: https://ieeexplore.ieee.org/document/8472083/, doi:10.1109/INDIN.2018.8472083.

[18] David Curry, 2017. ARM: One trillion IoT devices by 2035, $5 trillion in market value. URL: https://readwrite.com/2017/07/26/arm-iot-2035-dl1/.

[19] DebRoy, T., Zhang, W., Turner, J., Babu, S., 2017. Building digital twins of 3d printing machines. Scripta Materialia 135, 119–124. URL: https://linkinghub.elsevier.com/retrieve/pii/S1359646216305991, doi:10.1016/j.scriptamat.2016.12.005.

[20] Din, I.U., Guizani, M., Rodrigues, J.J., Hassan, S., Korotaev, V.V., 2019. Machine learning in the Internet of Things: Designed techniques for smart cities. Future Generation Computer Systems 100, 826–843. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167739X19304030, doi:10.1016/j.future.2019.04.017.

[21] El Saddik, A., 2018. Digital Twins: The Convergence of Multimedia Technologies. IEEE MultiMedia 25, 87–92. URL: https://ieeexplore.ieee.org/document/8424832/, doi:10.1109/MMUL.2018.023121167.

[22] Elijah, O., Rahman, T.A., Orikumhi, I., Leow, C.Y., Hindia, M.N., 2018. An Overview of Internet of Things (IoT) and Data Analytics in Agriculture: Benefits and Challenges. IEEE Internet of Things Journal 5, 3758–3773. doi:10.1109/JIOT.2018.2844296.

[23] Fei, X., Shah, N., Verba, N., Chao, K.M., Sanchez-Anguix, V., Lewandowski, J., James, A., Usman, Z., 2019. CPS data streams analytics based on machine learning for Cloud and Fog Computing: A survey. Future Generation Computer Systems 90, 435–450. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167739X17330613, doi:10.1016/j.future.2018.06.042.

[24] Glaessgen, E., Stargel, D., 2012. The Digital Twin Paradigm for Future NASA and U.S. Air Force Vehicles, in: 53rd Structural Dynamics and Materials Conference, American Institute of Aeronautics and Astronautics, Honolulu, Hawaii. URL: http://arc.aiaa.org/doi/abs/10.2514/6.2012-1818, doi:10.2514/6.2012-1818.

[25] Grieves, M., 2014. Digital Twin: Manufacturing Excellence through Virtual Factory Replication. White Paper. NASA. URL: http://www.apriso.com/library/Whitepaper_Dr_Grieves_DigitalTwin_ManufacturingExcellence.php.

[26] He, R., Chen, G., Dong, C., Sun, S., Shen, X., 2019. Data-driven digital twin technology for optimized control in process systems. ISA Transactions URL: https://linkinghub.elsevier.com/retrieve/pii/S0019057819302332, doi:10.1016/j.isatra.2019.05.011.

[27] He, Y., Guo, J., Zheng, X., 2018. From Surveillance to Digital Twin: Challenges and Recent Advances of Signal Processing for Industrial Internet of Things. IEEE Signal Processing Magazine 35, 120–129. URL: https://ieeexplore.ieee.org/document/8454907/, doi:10.1109/MSP.2018.2842228.

[28] Howard, D., 2019. The Digital Twin: Virtual Validation In Electronics Development And Design, in: 2019 Pan Pacific Microelectronics Symposium (Pan Pacific), IEEE, Kauai, HI, USA. pp. 1–9. URL: https://ieeexplore.ieee.org/document/8696712/, doi:10.23919/PanPacific.2019.8696712.

[29] Huh, S., Cho, S., Kim, S., 2017. Managing IoT devices using blockchain platform, in: 2017 19th International Conference on Advanced Communication Technology (ICACT), pp. 464–467. doi:10.23919/ICACT.2017.7890132.

[30] Jain, P., Poon, J., Singh, J.P., Spanos, C., Sanders, S., Panda, S.K., 2019. A Digital Twin Approach for Fault Diagnosis in Distributed Photovoltaic System. IEEE Transactions on Power Electronics , 1–1URL: https://ieeexplore.ieee.org/document/8692656/, doi:10.1109/TPEL.2019.2911594.

[31] Jo, S.K., Park, D.H., Park, H., Kim, S.H., 2018. Smart Livestock Farms Using Digital Twin: Feasibility Study, in: 2018 International Conference on Information and Communication Technology Convergence (ICTC), IEEE, Jeju. pp. 1461–1463. URL: https://ieeexplore.ieee.org/document/8539516/, doi:10.1109/ICTC.2018.8539516.

[32] Joordens, M., Jamshidi, M., 2018. On The Development of Robot Fish Swarms in Virtual Reality with Digital Twins, in: 2018 13th Annual Conference on System of Systems Engineering (SoSE), IEEE, Paris. pp. 411–416. URL: https://ieeexplore.ieee.org/document/8428748/, doi:10.1109/SYSOSE.2018.8428748.

[33] Karadeniz, A.M., Arif, I., Kanak, A., Ergun, S., 2019. Digital Twin of eGastronomic Things: A Case Study for Ice Cream Machines, in: 2019 IEEE International Symposium on Circuits and Systems (ISCAS), IEEE, Sapporo, Japan. pp. 1–4. URL: https://ieeexplore.ieee.org/document/8702679/, doi:10.1109/ISCAS.2019.8702679.

[34] Knapp, G., Mukherjee, T., Zuback, J., Wei, H., Palmer, T., De, A., DebRoy, T., 2017. Building blocks for a digital twin of additive manufacturing. Acta Materialia 135, 390–399. URL: https://linkinghub.elsevier.com/retrieve/pii/S1359645417305141, doi:10.1016/j.actamat.2017.06.039.

[35] Knud Lasse Lueth, . State of the IoT 2018: Number of IoT devices now at 7b – Market accelerating. URL: https://iot-analytics.com/state-of-the-iot-update-q1-q2-2018-number-of-iot-devices-now-7b/.

[36] Kobara, K., 2016. Cyber Physical Security for Industrial Control Systems and IoT. IEICE Transactions on Information and Systems E99.D, 787–795. URL: https://www.jstage.jst.go.jp/article/transinf/E99.D/4/E99.D_2015ICI0001/_article, doi:10.1587/transinf.2015ICI0001.

[37] Kritzinger, W., Karner, M., Traar, G., Henjes, J., Sihn, W., 2018. Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine 51, 1016–1022. URL: https://linkinghub.elsevier.com/retrieve/pii/S2405896318316021, doi:10.1016/j.ifacol.2018.08.474.

[38] Kritzler, M., Hodges, J., Yu, D., Garcia, K., Shukla, H., Michahelles, F., 2019. Digital Companion for Industry, in: Companion Proceedings of The 2019 World Wide Web Conference on - WWW '19, ACM Press, San Francisco, USA. pp. 663–667. URL: http://dl.acm.org/citation.cfm?doid=3308560.3316510, doi:10.1145/3308560.3316510.

[39] Kuehn, W., 2019. Simulation in Digital Enterprises, in: Proceedings of the 11th International Conference on Computer Modeling and Simulation - ICCMS 2019, ACM Press, North Rockhampton, QLD, Australia. pp. 55–59. URL: http://dl.acm.org/citation.cfm?doid=3307363.3307370, doi:10.1145/3307363.3307370.

[40] Kumar, S., Jasuja, A., 2017. Air quality monitoring system based on IoT using Raspberry Pi, in: 2017 International Conference on Computing, Communication and Automation (ICCCA), pp. 1341–1346. doi:10.1109/CCAA.2017.8230005.

[41] Laaki, H., Miche, Y., Tammi, K., 2019. Prototyping a Digital Twin for Real Time Remote Control Over Mobile Networks: Application of Remote Surgery. IEEE Access 7, 20325–20336. URL: https://ieeexplore.ieee.org/document/8632888/, doi:10.1109/ACCESS.2019.2897018.

[42] Liao, Y., Loures, E.d.F.R., Deschamps, F., 2018. Industrial Internet of Things: A Systematic Literature Review and Insights. IEEE Internet of Things Journal 5, 4515–4525. doi:10.1109/JIOT.2018.2834151.

[43] Liu, J., Du, X., Zhou, H., Liu, X., ei Li, L., Feng, F., 2019a. A digital twin-based approach for dynamic clamping and positioning of the flexible tooling system. Procedia CIRP 80, 746–749. URL: https://linkinghub.elsevier.com/retrieve/pii/S2212827119300654, doi:10.1016/j.procir.2019.01.063.

[44] Liu, Y., Zhang, L., Yang, Y., Zhou, L., Ren, L., Wang, F., Liu, R., Pang, Z., Deen, M.J., 2019b. A Novel Cloud-Based Framework for the Elderly Healthcare Services Using Digital Twin. IEEE Access 7, 49088–49101. URL: https://ieeexplore.ieee.org/document/8686260/, doi:10.1109/ACCESS.2019.2909828.

[45] Liu, Z., Meyendorf, N., Mrad, N., 2018. The role of data fusion in predictive maintenance using digital twin, in: Annual Review Of Progress In Quantitative Nondestructive Evaluation, Provo, Utah, USA. p. 020023. URL: http://aip.scitation.org/doi/abs/10.1063/1.5031520, doi:10.1063/1.5031520.

[46] Lohtander, M., Ahonen, N., Lanz, M., Ratava, J., Kaakkunen, J., 2018. Micro Manufacturing Unit and the Corresponding 3d-Model for the Digital Twin. Procedia Manufacturing 25, 55–61. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351978918305766, doi:10.1016/j.promfg.2018.06.057.

[47] Longo, F., Nicoletti, L., Padovano, A., 2019. Ubiquitous knowledge empowers the Smart Factory: The impacts of a Service-oriented Digital Twin on enterprises' performance. Annual Reviews in Control 47, 221–236. URL: https://linkinghub.elsevier.com/retrieve/pii/S1367578818301299, doi:10.1016/j.arcontrol.2019.01.001.

[48] Lu, Y., Peng, T., Xu, X., 2019. Energy-efficient cyber-physical production network: Architecture and technologies. Computers & Industrial Engineering 129, 56–66. URL: https://linkinghub.elsevier.com/retrieve/pii/S0360835219300324, doi:10.1016/j.cie.2019.01.025.

[49] Madni, A., Madni, C., Lucero, S., 2019. Leveraging Digital Twin Technology in Model-Based Systems Engineering. Systems 7, 2019. URL: http://www.mdpi.com/2079-8954/7/1/7, doi:10.3390/systems7010007.

[50] Magargle, R., Johnson, L., Mandloi, P., Davoudabadi, P., Kesarkar, O., Krishnaswamy, S., Batteh, J., Pitchaikani, A., 2017. A Simulation-Based Digital Twin for Model-Driven Health Monitoring and Predictive Maintenance of an Automotive Braking System, in: International Modelica Conference, pp. 35–46. URL: http://www.ep.liu.se/ecp/article.asp?issue=132%26article=3, doi:10.3384/ecp1713235.

[51] Mandolla, C., Petruzzelli, A.M., Percoco, G., Urbinati, A., 2019. Building a digital twin for additive manufacturing through the exploitation of blockchain: A case analysis of the aircraft industry. Computers in Industry 109, 134–152. URL: https://linkinghub.elsevier.com/retrieve/pii/S0166361518308741, doi:10.1016/j.compind.2019.04.011.

[52] Mawson, V.J., Hughes, B.R., 2019. The development of modelling tools to improve energy efficiency in manufacturing processes and systems. Journal of Manufacturing Systems 51, 95–105. URL: https://linkinghub.elsevier.com/retrieve/pii/S0278612518304151, doi:10.1016/j.jmsy.2019.04.008.

[53] Min, Q., Lu, Y., Liu, Z., Su, C., Wang, B., 2019. Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. International Journal of Information Management URL: https://linkinghub.elsevier.com/retrieve/pii/S0268401218311484, doi:10.1016/j.ijinfomgt.2019.05.020.

[54] Modi, A.S., 2018. Review Article on Deep Learning Approaches, in: 2018 Second International Conference on Intelligent Computing and Control Systems (ICICCS), pp. 1635–1639. doi:10.1109/ICCONS.2018.8663057.

[55] Mohammadi, N., Taylor, J.E., 2017. Smart city digital twins, in: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), IEEE, Honolulu, HI. pp. 1–5. URL: http://ieeexplore.ieee.org/document/8285439/, doi:10.1109/SSCI.2017.8285439.

[56] Moujahid, A., Tantaoui, M.E., Hina, M.D., Soukane, A., Ortalda, A., ElKhadimi, A., Ramdane-Cherif, A., 2018. Machine Learning Techniques in ADAS: A Review, in: 2018 International Conference on Advances in Computing and Communication Engineering (ICACCE), pp. 235–242. doi:10.1109/ICACCE.2018.8441758.

[57] Najafabadi, M.M., Villanustre, F., Khoshgoftaar, T.M., Seliya, N., Wald, R., Muharemagic, E., 2015. Deep learning applications and challenges in big data analytics. Journal of Big Data 2. URL: http://www.journalofbigdata.com/content/2/1/1, doi:10.1186/s40537-014-0007-7.

[58] Negri, E., Fumagalli, L., Macchi, M., 2017. A Review of the Roles of Digital Twin in CPS-based Production Systems. Procedia Manufacturing 11, 939–948. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351978917304067, doi:10.1016/j.promfg.2017.07.198.

[59] NetObjex, 2018. Industrial Revolution. URL: https://www.netobjex.com/how-humans-are-empowering-digital-transformation-in-industry-4-0/.

[60] Novo, O., 2018. Blockchain Meets IoT: An Architecture for Scalable Access Management in IoT. IEEE Internet of Things Journal 5, 1184–1195. doi:10.1109/JIOT.2018.2812239.

[61] Ornes, S., 2016. Core Concept: The Internet of Things and the explosion of interconnectivity. Proceedings of the National Academy of Sciences 113, 11059–11060. URL: http://www.pnas.org/lookup/doi/10.1073/pnas.1613921113, doi:10.1073/pnas.1613921113.

[62] Pargmann, H., Euhausen, D., Faber, R., 2018. Intelligent big data processing for wind farm monitoring and analysis based on cloud-technologies and digital twins: A quantitative approach, in: 2018 IEEE 3rd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), IEEE, Chengdu. pp. 233–237. URL: https://ieeexplore.ieee.org/document/8386518/, doi:10.1109/ICCCBDA.2018.8386518.

[63] Petrik, D., Herzwurm, G., 2019. iIoT ecosystem development through boundary resources: a Siemens MindSphere case study, in: Proceedings of the 2nd ACM SIGSOFT International Workshop on Software-Intensive Business: Start-ups, Platforms, and Ecosystems - IWSiB 2019, ACM Press, Tallinn, Estonia. pp. 1–6. URL: http://dl.acm.org/citation.cfm?doid=3340481.3342730, doi:10.1145/3340481.3342730.

[64] Qi, Q., Tao, F., 2018. Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison. IEEE Access 6, 3585–3593. URL: http://ieeexplore.ieee.org/document/8258937/, doi:10.1109/ACCESS.2018.2793265.

[65] Qi, Q., Tao, F., Zuo, Y., Zhao, D., 2018. Digital Twin Service towards Smart Manufacturing. Procedia CIRP 72, 237–242. URL: https://linkinghub.elsevier.com/retrieve/pii/S2212827118302580, doi:10.1016/j.procir.2018.03.103.

[66] Reyna, A., Martín, C., Chen, J., Soler, E., Díaz, M., 2018. On blockchain and its integration with IoT. Challenges and opportunities. Future Generation Computer Systems 88, 173–190. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167739X17329205, doi:10.1016/j.future.2018.05.046.

[67] Ross, D., 2016. Digital twinning [Information Technology Virtual Reality]. Engineering Technology 11, 44–45. doi:10.1049/et.2016.0403.

[68] Ruohomäki, T., Airaksinen, E., Huuska, P., Kesäniemi, O., Martikka, M., Suomisto, J., 2018. Smart City Platform Enabling Digital Twin, in: 2018 International Conference on Intelligent Systems (IS), pp. 155–161. doi:10.1109/IS.2018.8710517.

[69] S V Engineering College, Tirupati, India, B, R.R., 2018. A Comprehensive Literature Review on Data Analytics in IIoT (Industrial Internet of Things). HELIX 8, 2757–2764. URL: http://www.helix.dnares.in/wp-content/uploads/2017/12/2757-2764.AP_.22.pdf, doi:10.29042/2018-2757-2764.

[70] Schleich, B., Anwer, N., Mathieu, L., Wartzack, S., 2017. Shaping the digital twin for design and production engineering. CIRP Annals 66, 141–144. URL: https://linkinghub.elsevier.com/retrieve/pii/S0007850617300409, doi:10.1016/j.cirp.2017.04.040.

[71] Sezer, O.B., Dogdu, E., Ozbayoglu, A.M., 2018. Context-Aware Computing, Learning, and Big Data in Internet of Things: A Survey. IEEE Internet of Things Journal 5, 1–27. doi:10.1109/JIOT.2017.2773600.

[72] Shangguan, D., Chen, L., Ding, J., 2019. A Hierarchical Digital Twin Model Framework for Dynamic Cyber-Physical System Design, in: Proceedings of the 5th International Conference on Mechatronics and Robotics Engineering - ICMRE'19, ACM Press, Rome, Italy. pp. 123–129. URL: http://dl.acm.org/citation.cfm?doid=3314493.3314504, doi:10.1145/3314493.3314504.

[73] Shinde, P.P., Shah, S., 2018. A Review of Machine Learning and Deep Learning Applications, in: 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1–6. doi:10.1109/ICCUBEA.2018.8697857.

[74] Sivalingam, K., Sepulveda, M., Spring, M., Davies, P., 2018. A Review and Methodology Development for Remaining Useful Life Prediction of Offshore Fixed and Floating Wind turbine Power Converter with Digital Twin Technology Perspective, in: 2018 2nd International Conference on Green Energy and Applications (ICGEA), IEEE, Singapore. pp. 197–204. URL: https://ieeexplore.ieee.org/document/8356292/, doi:10.1109/ICGEA.2018.8356292.

[75] Soe, R.M., 2017a. FINEST Twins: platform for cross-border smart city solutions, in: Proceedings of the 18th Annual International Conference on Digital Government Research - dg.o '17, ACM Press, Staten Island, NY, USA. pp. 352–357. URL: http://dl.acm.org/

citation.cfm?doid=3085228.3085287, doi:10.1145/3085228.3085287.

[76] Soe, R.M., 2017b. Smart Twin Cities via Urban Operating System, in: Proceedings of the 10th International Conference on Theory and Practice of Electronic Governance - ICEGOV '17, ACM Press, New Delhi AA, India. pp. 391–400. URL: http://dl.acm.org/citation.cfm?doid=3047273.3047322, doi:10.1145/3047273.3047322.

[77] Sonal, Reddy, S., Kumar, D., 2018. Review of Smart Health Monitoring Approaches with Survey Analysis and Proposed Framework. IEEE Internet of Things Journal , 1–1doi:10.1109/JIOT.2018.2872389.

[78] Srivastava, S., Bisht, A., Narayan, N., 2017. Safety and security in smart cities using artificial intelligence — A review, in: 2017 7th International Conference on Cloud Computing, Data Science Engineering - Confluence, pp. 130–133. doi:10.1109/CONFLUENCE.2017.7943136.

[79] Stanley, M., 2016. IIoT & the New Industrial Revolution. URL: https://www.morganstanley.com/ideas/industrial-internet-of-things-and-automation-robotics.

[80] Stark, R., Fresemann, C., Lindow, K., 2019. Development and operation of Digital Twins for technical systems and services. CIRP Annals URL: https://linkinghub.elsevier.com/retrieve/pii/S0007850619300502, doi:10.1016/j.cirp.2019.04.024.

[81] Statista, . IoT: number of connected devices worldwide 2012-2025. URL: https://www.statista.com/statistics/471264/iot-number-of-connected-devices-worldwide/.

[82] Taleb, I., Dssouli, R., Serhani, M.A., 2015. Big Data Pre-processing: A Quality Framework, in: 2015 IEEE International Congress on Big Data, pp. 191–198. doi:10.1109/BigDataCongress.2015.35. iSSN: 2379-7703.

[83] Tao, F., Cheng, J., Qi, Q., 2018a. IIHub: An Industrial Internet-of-Things Hub Toward Smart Manufacturing Based on Cyber-Physical System. IEEE Transactions on Industrial Informatics 14, 2271–2280. doi:10.1109/TII.2017.2759178.

[84] Tao, F., Qi, Q., Wang, L., Nee, A., 2019a. Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison. Engineering 5, 653–661. URL: https://linkinghub.elsevier.com/retrieve/pii/S209580991830612X, doi:10.1016/j.eng.2019.01.014.

[85] Tao, F., Zhang, H., Liu, A., Nee, A.Y.C., 2019b. Digital Twin in Industry: State-of-the-Art. IEEE Transactions on Industrial Informatics 15, 2405–2415. URL: https://ieeexplore.ieee.org/document/8477101/, doi:10.1109/TII.2018.2873186.

[86] Tao, F., Zhang, M., 2017. Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing. IEEE Access 5, 20418–20427. URL: http://ieeexplore.ieee.org/document/8049520/, doi:10.1109/ACCESS.2017.2756069.

[87] Tao, F., Zhang, M., Liu, Y., Nee, A., 2018b. Digital twin driven prognostics and health management for complex equipment. CIRP Annals 67, 169–172. URL: https://linkinghub.elsevier.com/retrieve/pii/S0007850618300799, doi:10.1016/j.cirp.2018.04.055.

[88] Umeda, Y., Ota, J., Kojima, F., Saito, M., Matsuzawa, H., Sukekawa, T., Takeuchi, A., Makida, K., Shirafuji, S., 2019. Development of an education program for digital manufacturing system engineers based on 'Digital Triplet' concept. Procedia Manufacturing 31, 363–369. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351978919304214, doi:10.1016/j.promfg.2019.03.057.

[89] Vishwakarma, R., Jain, A.K., 2019. A survey of DDoS attacking techniques and defence mechanisms in the IoT network. Telecommunication Systems URL: http://link.springer.com/10.1007/s11235-019-00599-z, doi:10.1007/s11235-019-00599-z.

[90] Vrabič, R., Erkoyuncu, J.A., Butala, P., Roy, R., 2018. Digital twins: Understanding the added value of integrated models for through-life engineering services. Procedia Manufacturing 16, 139–146. URL: https://linkinghub.elsevier.com/retrieve/pii/S2351978918312897, doi:10.1016/j.promfg.2018.10.167.

[91] Wu, D., Jennings, C., Terpenny, J., Kumara, S., 2016. Cloud-based machine learning for predictive analytics: Tool wear prediction in milling, in: 2016 IEEE International Conference on Big Data (Big Data), pp. 2062–2069. doi:10.1109/BigData.2016.7840831.

[92] Xu, Y., Sun, Y., Liu, X., Zheng, Y., 2019. A Digital-Twin-Assisted Fault Diagnosis Using Deep Transfer Learning. IEEE Access 7, 19990–19999. doi:10.1109/ACCESS.2018.2890566.

[93] Zhang, H., Liu, Q., Chen, X., Zhang, D., Leng, J., 2017. A Digital Twin-Based Approach for Designing and Multi-Objective Optimization of Hollow Glass Production Line. IEEE Access 5, 26901–26911. URL: http://ieeexplore.ieee.org/document/8082476/, doi:10.1109/ACCESS.2017.2766453.

[94] Zheng, Y., Yang, S., Cheng, H., 2018. An application framework of digital twin and its case study. Journal of Ambient Intelligence and Humanized Computing 10, 1141–1153. URL: http://link.springer.com/10.1007/s12652-018-0911-3, doi:10.1007/s12652-018-0911-3.

[95] Čolaković, A., Hadžialić, M., 2018. Internet of Things (IoT): A review of enabling technologies, challenges, and open research issues. Computer Networks 144, 17–39. URL: https://linkinghub.elsevier.com/retrieve/pii/S1389128618305243, doi:10.1016/j.comnet.2018.07.017.