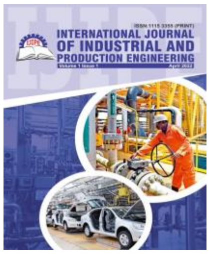

Vol. 1 No. 1 (2022): VOLUME 1

INTERNATIONAL JOURNAL OF INDUSTRIAL AND PRODUCTION ENGINEERING (IJIPE)

JOURNAL HOMEPAGE: https://journals.unizik.edu.ng/index.php/ijipe/

A SYSTEMATIC REVIEW OF DIGITAL TWIN SYSTEMS FOR IMPROVED PREDICTIVE MAINTENANCE OF EQUIPMENT IN SMART FACTORIES

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Abstract
The deployment of intelligent systems in the management and monitoring of the components of production systems have led to improved quality and enhanced productivity on the manufacturing shop floor. This paper presents a systematic review of the digital twin and other intelligent systems for use in the predictive maintenance of equipment on the shop floor. Many databases, such as the Google Scholar, Scopus, IEEE Xplore, Research Gate, and Science Direct were used for data collection. The study revealed that intelligent systems such as the digital twin are effective tools for predictive maintenance of equipment in production systems. This has been found to improve productivity and reduce downtime in production systems. The study highlights the current trends, benefits and limitations in the deployment of intelligent systems such as the Digital Twin, for use in the predictive maintenance of equipment in smart factories.
Keywords: *Intelligent systems, manufacturing Equipment, Industry 4.0, Smart Factory, Maintenance.*

1. Introduction

Production system of an organization is that part, which produces products of an organization. It involves man, machines and processes. The use of intelligent systems in managing and monitoring the components of a production system have brought ease and accuracy in dealing with the system (Mgbemena, 2020; Mgbemena, Onuoha, Okpala, & Mgbemena, 2020; Mgbemena et al., 2017; Mgbemena, Oyekan, Hutabarat, Xu, & Tiwari, 2018; Mgbemena et al., 2016; Mgbemena, Tiwari, Xu, Prabhu, & Hutabarat, 2020). A Digital Twin (DT) system can capture and monitor the whole of a production system in real-time, a major breakthrough discovery in technological advancement using industry 4.0 technologies. DT is a digital model of a particular physical element or a process with data connections that enable convergence between the physical and virtual states at an appropriate rate of synchronization (ISO, 2019). The DT concept was first seen in a presentation by the University of Michigan in 2002, for the formation of a Product Lifecycle Management

(PLM) Center (Grieves & Vickers, 2016). The presentation has all elements of the DT: real asset, virtual copy, the link for data flow from real to virtual spaces, the link for data flow from virtual to real space. DT can be used for interrogative and predictive purposes. Other areas of application include cyber security, virtual commissioning, fast error detection, data analysis, simulation etc. DT can also be used for forecasting and optimization of production systems at each life cycle phase in real time (Shafto et al., 2010). In construction, digital technologies such as data analytics and artificial intelligence, robotics and automation, building information management, smart wearable technologies, digital twins and industrial connectivity are applied in pursuit of operational and productivity gains in the sector (Turner, Oyekan, Stergioulas, & Griffin, 2020).

Major area where DT is applied in production system is in predicting maintenance of equipment. Production equipment will always be liable to wear and thus require maintenance. The mode of maintenance has improved over the centuries with the industrial revolutions, first was the industry 1.0 and reactive maintenance witnessed in 18th century, where repairs are done only after equipment breakdown. Reactive maintenance leads to shorter asset life, downtime etc. Industry 2.0 and preventive maintenance used in the 19th century, during this era maintenance were done periodically especially when deviations start to show up in the equipment procedure. Industry 3.0 and proactive maintenance, this was the birth of automation as was seen during and after the World War II. Industry 4.0 and Predictive Maintenance, has been found to be an effective form of maintenance (Pech, Vrchota, & Bednář, 2021). By analyzing equipment data, it identifies pattern and predict failures before they occur. This has been in existence since the innovation of the internet but was commercialized in 1994. The fourth revolution is still happening, it distinguishes itself from other generations through fast transferring of data and information with the help of internet.

Digital Twin solutions integrate artificial intelligence, machine learning and software analytics with data collected in production plants to create digital simulation models that are updated when production process parameters or working conditions change (Bevilacqua et al., 2016). The real-time data from the intelligent sensors are used to foretell when the asset will need maintenance and prevent equipment breakdown. When industrial machines break down, the end point is not the cost of changing that equipment but rather the resulting downtime. A stagnated production line may mean thousands of dollars lost every minute, predictive maintenance using digital twin system can avoid all these anomalies. Questions like, what if machine could tell when one of its parts was about to fail? What if the machine could even tell you which part needs to be replaced? Will unplanned downtime reduce considerably? In the literature, Digital Twin solutions have been developed to affect a consistent improvement in production efficiency (Tao & Zhang, 2017), and increase business opportunities (Tao et al., 2018). The applications of Digital Twin in maintenance ensure the safety of process plant operators and maintainers, even if it is a resilience engineering challenge for research (Patriarca et al., 2018).

This paper presents a systematic literature review of the current trends in the application of intelligent systems for improved predictive maintenance of equipment. The paper dwelt on digital twin, and how the intelligent systems aid in predicting maintenance of production equipment in smart factories.

2. Methodology

This paper presents the different facets of the DT and other intelligent systems in a production system, with a special focus on their application in predictive maintenance of equipment. The research strategy adopted is presented and the results analyzed.

2.1 Search strategy

An ordered and planned search was carried out to identify papers with focus on digital twin and other intelligent systems, especially papers that applied these systems in predicting maintenance and general monitoring of a production system. The materials were gathered through web searches, different databases were accessed such as, Science Direct, Scopus, Springer, Google Scholar, IEEE Xplore, and Research Gate.

Materials written only in English Language with related literature published from 2010 to 2021, were selected, so as to capture the recent trends and applications of the systems under review, and its impacts in modern engineering practice. Another important consideration for eligibility was the selection of papers that answered any of the following questions:

- Does the paper focus on industry 4.0 technologies?
- Does the paper have a digital twin system?
- Does the paper have an intelligent system?
- Does it discuss the application of these intelligent systems for predictive maintenance and general production system monitoring?

All papers not published before 2010 and not written in English Language were not selected for this study.

2.2 Search Results

Materials were initially sorted out based on the title and abstract. Papers that did not contain information on digital twin and intelligent systems and any form of application of the system in a production system, especially in predictive maintenance were dropped. Only online publications written in English language and published within the period under study were used. At last, a total of 50 papers were gathered, these papers were thoroughly studied to extract its case studies and experimental descriptions.

2.3 Analysis

The entire papers studied in this review are presented in the table 1 below.

Table 1: Analysis of 2010 – 2021papers

S/N	**Article**	**Author, Country and year**	**Journal**	**Objective of the paper**	**Number of papers studied**	**Duration**
1	The concept of Industry 4.0	Bartodziej (2017) Germany	Springer	Industry 4.0 is described in detail, with the drivers of the concept explained. The potential, similar and international approaches to the concept are described.	22	2018-2021
2	The digital shadow of production – A concept for the effective and efficient information supply in dynamic enviroments.	Bauernhansl et al. (2018) Germany	ScienceDirect	A roadmap for the digital shadow of production is presented, the digital shadow with all its subsystems is designed to allow a more efficient operation of value creation systems.	16	1982-2017

3	CyberFactory#1 – Securing the industry 4.0 with cyber-ranges and digital twins.	Becue et al. (2018) France	14th IEEE International Workshop on Factory Communication Systems (WFCS)	It aims at solving the problem between productivity and security through the design, development and demonstration of a system of systems that embraces the technical, economical, human and the societal dimensions of future factories.	14	2017-2017
4	The facets of digital twins in production and the automotive industry	Biesinger (2019) Germany	2019 23rd Int. Conf. Mechatronics Technol. (ResearchGate)	The paper presents the different facets of digital twin in automotive industry and evaluates their practical benefits.	20	2010-2019
5	A case study for a digital twin of body-in-white production systems general concept for automated updating of planning projects in the digital factory	Biesinger (2018) Germany	2018 IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA)	The paper describes a concept for creating a digital twin of a body-in-white production system for the concept and rough planning projects.	27	2003-2018
6	Predictive maintenance using tree-based classification techniques: A case of railway switches	Burhsh et al. (2019) Netherlands	ScienceDirect	To develop predictive models that utilize existing data from a railway agency and yield interpretable results.	43	1986-2018
7	Smart factory of industry 4.0: Key technologies, application case, and challenges	Chen et al. (2018) China	IEEE Access	A hierarchical architecture of the smart factory was proposed, key technologies were analysed from the aspects of the physical resource layer, the network layer, and the data application layer.	96	2010-2017
8	Current and future requirements to industrial analytical infrastructure – part 2: smart sensors	Eifert et al. (2020) Germany	Springer	To present a combined view on the future of PAT (process analytical technology), which is projected in smart labs and smart sensors.	29	1998-2019
9	A data-driven predictive maintenance approach for spinning cyber-physical production system	Farooq et al. (2020) China	Journal of shanghai jiaotong university (ResearchGate)	A new data-driven predictive maintenance and an architectural impulse, based on a regularized deep neural network using predictive analytics, are proposed for ring spinning technology.	20	2012-2019
10	Literature review: framework of prognostic health management for airline predictive maintenance	Fei et al. (2020) China	IEEE 2020 chinese control and decision conference (CCDC)	To present a literature review of prognostic health management techniques and the framework of prognostic and health management in order to predict aircraft maintenance.	48	1989-2020

11	Review on smart gas sensing technology	Feng et al. (2020) China	MDPI proceedings journal (sensor)	Smart gas sensing methods was introduced to adress gas sensor defects by adding sensor arrays, signal processing, and machine learning techniques to traditional gas sensing technologies.	151	2002-2019
12	Review on exploration of graphene in the design and engineering of smart sensors, actuators and soft robotics	Jin et al. (2020) China	Chemical engineering journal advances, also available in ScienceDirect	Mechanisms, design and engineering, and development of different graphene-based sensors actuators and robotics were summarised.	197	2001-2020
13	The role of smart sensors in production processes and the implementation of industry 4.0	Karabegovic et al. (2019) Ukraine	Journal of engineering sciences	To outline the motives for the implementation of smart sensors and applications of smart sensors in production processes.	18	1994-2019
14	Recent advances and trends in predictive manufacturing systems in big data environment	Lee et al. (2013) USA	ScienceDirect	To develop an approach and tools to convert data into useful, actionable information.	9	2006-2013
15	Machine health management in smart factory: A review	Lee et al. (2018) Korea	Springer	To review machine health management of machines, classifying the references by the monitoring components, types of measurements, as well as PHM tools and algorithms.	157	1989-2017
16	The quality management ecosystem for predictive maintenance in the industry 4.0 era	Lee et al. (2019) USA	Springer	The paper presents new ideas for predictive quality management based on an extensive review of the literature on quality management based on new technologies.	31	2002-2018
17	Human-centered dissemination of data, information and knowledge in industry 4.0	Li et al. (2019) Sweden	ScienceDirect	The paper examines the relationship between the existing literature on dissemination of data, information and knowledge within the manufacturing industry with state-of-the-art research on industry 4.0	43	1994-2019
18	Predictive maintenance for pump systems and thermal power plants: state-of-the-art-review, trends and challenges	Olesen & Shaker (2020) Denmark	MDPI proceedings journal (sensor)	A systematic overview of literature in regard to application for Predictive maintenance (PdM), is presented, before delving into the domain of thermal power plants and pump systems.	96	1997-2020
19	Smart parking sensors, technologies and applications	Paidi et al. (2018) Sweden	The institution of engineering and	The study suggests a combination of machine vision, convolutional neural	51	1993-2018

	for open parking lots: A review		technology journals	network or multi-agent systems suitable for open parking lots due to less expenditure and resistance to varied enviromental conditions.		
20	Predictive maintenance and intelligent sensors in smart factory: Review	Pech & Vrchota (2021) Czech Republic	MDPI proceedings journal (sensor)	The study summarizes the current trends in intelligent sensors used for predictive maintenance in smart factories.	177	1997-2021
21	Shaping the digital twin for design and production engineering	Schleich et al. (2017) Germany	ScienceDirect	The paper proposed a comprehensive reference model based on the concept of skin model shapes, which serves as a digital twin of the physical product in design and manufacturing	17	1997-2017
22	Predictive maintenance, its implementation and latest trends	Selcuk (2017) Turkey	Sage journals	The paper presents new trends and techniques in the field of predictive maintenance. It also presents suggestions for how to implement a predictive maintenance programme in a factory.	72	1995-2015
23	A review of rock bolt monitoring using smart sensors	Song et al. (2017) USA	MDPI proceedings journal (sensor)	The paper presents a brief introduction on the types of rock bolts followed by a comprehensive review of of rock bolt monitoring using smart sensors.	76	1984-2017
24	Industry 4.0 and lean manufacturing: a proposed integration model and research propositions	Sony (2018) Namibia	Tarlor & Francis	A novel model is proposed in this paper, that integrates framework of lean manufacturing with industry 4.0	86	1981-2018
25	Ten lessons for managers while implementing industry 4.0	Sony & Naik (2019) Namibia	IEEE engineering management review	The paper answers question what are the important lessons for managers while implementing industry 4.0?	31	2009-2019
26	Teaching management system with applications of RFID and IoT technology	Tan et al. (2018) China	MDPI proceedings journal (Education sciences)	A kind of WiFi supported RFID reader is implemented using open source hardware platforms.	23	2009-2018
27	An empirical analysis of total quality management and total productive maintenance in industry 4.0	Tortorella et al. (2018) South Africa	In Proceedings of the International Conference on Industrial Engineering and Operations Management (IEOM), 2018	The investigated the impact of industry 4.0 adoption and operational performance improvement due to apply total quality management and total productive maintenance.	55	1977-2018

28	TagScan: Simultaneous target imaging and material identification with commodity RFID devices.	Wang et al. (2017) USA	In Proceedings of the 23rd Annual International Conference on Mobile Computing and Networking	TagScan was introduced, a system that can identify the material type and the horinzontal cut of a target simultaneously with cheap commercial off-the-shelf RFID devices.	50	1974-2017
29	Visualization of the digital twin data in manufacturing by using augmented reality	Zhu et al. (2019) New Zealand	ScienceDirect	This paper proposes a method to visualize the digital twin data by using AR technology in a real manufacturing enviroment.	23	2006-2018
30	Future Modeling and Simulation of CPS-based Factories: An Example from the Automotive Industry.	Weyer et al. (2016) Germany	ScienceDirect	An appropraite framework for modeling and simulation of CPS-based factories in an automotive industry, was presented.	20	2007-2016
31	Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing	Tao & Zhang (2017) China	IEEE Access	A novel concept of digital twin shop-floor (DTS) based on digital twin is explored and its four key components are discussed.	41	2011-2017
32	Digital twin-driven product design, manufacturing and service with big data.	Tao et al. (2017) China	International journal of advanced manufacturing technology	The paper proposed a new method for product design, manufacturing, and service.	53	2009-2017
33	Smart home-based IoT for real-time and secure remote health monitoring of triage and priority system using body sensors: Multi-driven systematic review.	Talal et al. (2019) Malaysia	Journal of medical systems	The aims to establish IoT-based smart home security solutions for real-time health monitoring technologies in telemedicine architecture.	198	2008-2018
34	Literature review on the ‘Smart Factory’ concept using bibliometric tools.	Strozzi et al. (2017) United Kingdom	International journal of product research (Taylor & Francis)	To depict a landscape of the scientific literature on the concept of the ‘Smart Factory’ due to its significant innovation in the production systems within the manufacturing sector.	47	1991-2014
35	Innovation trends for smart factories: A literature review	Sousa et al. (2019) Portugal	World conference on information systems and technologies	To analyze the different dimensions of innovation in order to create a smart factory.	39	1986-2018
36	Draft modelling, Simulation, Information - Technology and Processing Roadmap	Shafto et al. (2010) USA	National aeronautics and space administration (NASA)	NASA developed this draft space technology roadmap for use by the national research council as an initial point of departure.	24	2000-2010
37	A conceptual framework for industry 4.0. In Industry 4.0: Managing The Digital Transformation	Salkin et al. (2018) Turkey	Springer	A conceptual framework for industry 4.0 is proposed concerning fundamentals of smart products and smart processes development.	46	2004-2017

38	Challenges and opportunities of condition-based predictive maintenance: A review	Sakib & Wuest (2018) USA	ScienceDirect	The paper presents an overview of condition-based predictive maintenance solutions to avoid unplanned failures during operational process-based on advanced data analytics.	35	2005-2018
39	Digital twin: Mitigating unpredictable, undesirable emergent behaviour in complex systems	Grieves & Vickers (2016) USA	Transdisciplinary perspectives on complex systems	The paper described the digital twin concept and its development, how it applies across the product lifecycle in defining and understanding system behaviour.	28	1933-2015
40	Cognitive Maps Tool for Developing a RBI & M Model.	Bevilacqua et al. (2016) Italy	Quality and reliability engineering international	The paper analysed the proposed RBI & M model through a case study of an Italian refinery.	32	2001-2016
41	Digital Twin-The Simulation Aspect.	Boschert & Rosen (2016) Germany	Springer	The paper focused on the simulation aspects of the Digital Twin.	13	2004-2015
42	Control from the cloud: Edge computing, services and digital shadow for automation technologies.	Brecher et al. (2019) Germany	2019 IEEE international conference on robotics and automation (ICRA)	An architecture based on edge computing as an enabling technology for an adaptive production together with the digital shadow are presented.	29	2011-2018
43	IBM Watson Studio: A Platform to Transform Data to Intelligence.	Cecil & Soares (2019) Portugal	Springer	The paper discussed the transformation of raw data to intelligence through a systematic process of data understanding and model building.	38	1959-2018
44	ViTrack: Efficient Tracking on the Edge for Commodity Video Surveillance Systems.	Cheng & Wang (2018) China	IEEE Transactions on parallel and distributed systems (TPDS)	The paper presents ViTrack, a framework for efficient multi-video tracking using computation resource on the edge for commodity video surveillance systems.	32	1997-2020
45	Manufacturing upgrading in industry 4.0 era.	Chen et al. (2020) China	Systems research and behavioural science	The paper conducts an analysis of intelligent manufacturing in small and medium-sized enterprises (SMEs), and provides insight on upgrading manufacturing SMEs in industry 4.0 era.	48	2000-2020
46	Pangu: Towards a software-defined architecture for multi-function wireless sensor networks.	Guo et al. (2018) China	2017 IEEE 23rd international conference on parallel and distributed systems (ICPADS)	The paper present a study towards a software-defined architecture for multi-function wireless sensor networks.	24	2003-2016
47	Dynamic network surgery for efficient DNNs.	Guo et al. (2016) China	arXiv	The paper proposed a network compression method	22	1989-2016

				called dynamic network surgery, which can remarkably reduce network complexity by making on-the-fly connection pruning.		
48	Case study: WIRELESSHART vs ZIGBEE network.	Habib et al. (2015) Lebanon	2015 IEEE 3rd international conference on technological advances in electrical, electronics and computer engineering (TAEECE)	The paper showed by simulations and literature that wirelessHart technology fits better than Zigbee technology for industrial requirements.	10	2007-2013
49	IoT devices and applications based on LoRa/LoRaWAN	Khutsoane et al. (2017) South Africa	2017 IEEE 43rd annual conference of industrial electronics society	The paper surveyed IoT devices and different applications based on LoRa and LoRaWAN in order to understand the current stream of devices used.	31	2012-2017
50	A smart manufacturing use case: Furnace temperature balancing in steam methane reforming process via kepler workflows.	Korambath et al. (2016) USA	The international conference on computational science (ICCS 2016).	The paper presents a system that regulates the flow rate of fuel gases which in turn optimizes the temperature distribution across a furnace.	12	2001-2016
51	Applying a 6 Dof robotic arm and digital twin to automate Fan-based reconditioning for aerospace maintenance, repair, and overhaul	Oyekan, Farnsworth, Hutabarat, Miller & Tiwari (2020) United Kingdom	Sensors (MDPI)	The paper presents an investigation to create an automation cell for the fan-blade reconditioning component of Maintainence,Repair, Overhaul (MRO).	33	2003-2019
52	A digital maintenance practice framework for circular production of automotive parts	Turner, Okorie, Emmanouilidis & Oyekan (2020) United Kingdom	4th IFAC workshop on advanced maintenance engineering, service and technology	The paper acts as a primer for digital maintenance practice within the circular economy and the utilisation of industry 4.0 technologies.	47	2001-2020
53	Utilization industry 4.0 on the construction site: Challenges and opportunities	Turner, Oyekan, Stergioulas & Griffin (2020).	IEEE transactions on industrial informatics	The paper discussed the relevance of industry 4.0 technologies in construction, such as data analytics and artificial intelligence, robotics and automation, building information management, smart wearable technologies, digital twins and industrial connectivity	56	2007-2020

3. Results and Discussions

There are many facets of the digital twin in different variations of digital models in today's production settings. Table 2, provides a summary of digital twin in the production of leading multinational companies and their applications. Many companies are working on similar digital twins, including General Electric, Hirotec Corporation, Rockwell Automation, ABB, Siemens, Cenit AG and EKS InTec Gmbh. Some are working on a real-time coupling of the digital models with the physical production plant like Cenit AG and EKS InTec Gmbh. There are also new applications for digital twins, such as integration planning for production facilities at Daimler AG and cyber security at Airbus AG.

These various applications of DT offer great benefits in production. These benefits include "increased productivity", "reduced complexity", "time savings" reduced cost, improved quality and identification of new business opportunities (Biesinger, 2019). Big data analyses are the next stop in digital twin, which will aid in identification of new business opportunities. Due to lack of data quality, real production data is not suitable for big data analysis and artificial intelligence algorithm. Also, increased cyber security, increased efficiency and reduced risk are key benefits of digital twins. However, in a production system, a digital twin can also be used to develop and optimize new and existing products. Table 3, summarizes the benefits of digital twin in production.

Table 2: Digital twin applications in production systems (Biesinger, 2019)

Manufacturer:	**Digital twin and fields of application:**
Daimler AG (GER) (Biesinger, 2018), (Biesinger, 2019)	**Digital twins:** Integration twin (planning facet of production); virtual commissioning and maintenance twin in production; various twins in the vehicle design phase. **Applications:** Integration planning; virtual commissioning; maintenance; virtual prototyping and testing
Airbus AG (FRA) (Becue et al., 2018)	**Digital twin**: Digital model **Application:** Cyber security
Cenit AG (GER) (Bartevyan, 2019)	**Digital twin:** Engineering twin, simulation **Application:** Coupling of the physical plant with a digital model; testing of the plant in the project planning phase, design for function and operability
Honeywell (USA) (Bonner, 2019)	**Digital twins**: Digital image of a refinery **Applications:** Unifies existing data silos into a virtual entity; federates data across different applications to drive end -to-end integration; leverages process simulation technology beyond the current scope of process design; federates data across different applications to drive end-to-end integration; utilizes the cloud to overcome maintainability issues and enables 3rd party expertise
Hirotec Corporation (JPN) (Bartevyan, 2019)	**Digital twin:** Digital model production cell **Applications:** Testing; PLC validation and virtual commissioning
ABB (CHE) (ABB review)	**Digital twins:** PLM simulation; design models and manufacturing data **Applications:** Design; simulation and visualization; simulation of behavior, advanced services – pre-configuration; diagnostics - observation; predictive maintenance; 3D visualization

Rockwell Automation (USA) (Schmitke, 2019), (Vasko, 2019)	**Digital twins:** Digital model; a virtual model-based representation of the physical system **Applications:** Test of PLC code; virtual commissioning; online diagnostics; virtual sensors; predictive maintenance; sales tool; design
EKS InTec GmBH (GER) (Haas, 2019)	**Digital twin:** Virtual commissioning, coupling robots of a plant with robots in a digital model **Application:** Fast error detection and data analytics
Siemens AG (GER) (Siemens online)	**Digital twins:** PLM simulation; digital model of products **Applications:** Forecast and optimization of the product, production, and performance
General Electric (USA) (GE Digital)	**Digital twins:** component twin; asset twin; process twin; system/unit twin **Applications:** Predict the future; monitor; simulate, control and optimize lifecycles

TABLE 3: Benefits of digital twin in a production system (Biesinger, 2019)

S/N	Benefits	Sources
1	Increased productivity due to improved maintenance structure	(GE Digital)
2	Increased quality	(Bauernhansl et al., 2018)
3	Lower costs	(Schmitke, 2019)
4	Increased efficiency	(Siemens online)
5	Reduction of risk with the aid of hard wares through real-time machine monitoring	(Haas, 2019)
6	Identification of new business fields	(Bonner, 2019)
7	Time savings due to reduced downtime	(Bartevyan, 2019)
8	Reduced complexity	(Biesinger, 2019)
9	Increased cyber security	(Becue et al., 2018)

3.1 Digital Twin Life Cycle of a Production System

A digital twin is always created to correspond to the physical production line. To monitor and track changes in a production line is always a hectic task, especially for a longer production period. However, to achieve this, a new current system image must be fully synchronized with an existing system image (figure 1). With the synchronization, major changes are not lost during the production life cycle. A method for synchronizing a current digital twin with existing data was developed to enable digital tracking of changes in a production line, the data are versioned for clarity. Each equipment component is saved with one instance as well as one or more instance revisions. An instance with the corresponding instance revisions represents an asset component during the production lifecycle.

The instance contains plant information that constitutes the device that cannot be changed, such as the manufacturer and serial number. The instance of the system component includes one or more instance revisions. Instance revisions store information that can change e.g. the position of the device in the production plant or the device description. This information is stored via the instance revision.

The instance revision is always valid for a certain period of time, changes in the production plant can be traced by the validity of the different instance revisions.

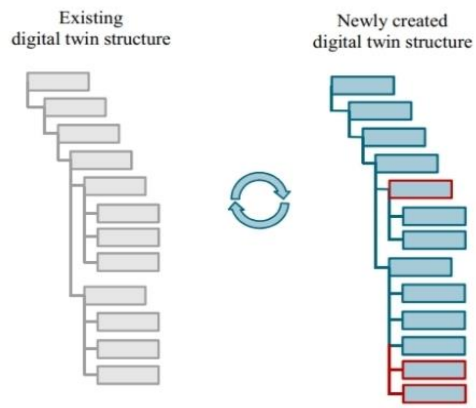


Fig 1: Synchronization of a new created twin with an existing twin (Biesinger, 2019)

The instance contains plant information that constitutes the device that cannot be changed, such as the manufacturer and serial number. The instance of the system component includes one or more instance revisions. Instance revisions store information that can change e.g. the position of the device in the production plant or the device description. This information is stored via the instance revision.

The instance revision is always valid for a certain period of time, changes in the production plant can be traced by the validity of the different instance revisions.

3.2 Intelligent Systems and Predictive Maintenance in a Production System

The next step in sophistication involves using real-time condition monitoring, where sensors continuously collect data about the state of an asset and send alerts based on pre-established rules or when critical levels are exceeded. One thing that has changed over the years is the amount of data that goes into making these predictions. The enhanced use of data corresponds with increasing levels of maturity, and these are accompanied by improvements in maintenance performance. By collecting more and more data, maintenance staff are able to make better informed decisions that lead to increased reliability, higher uptime, fewer accidents and failures, as well as lower costs. Much work has not been done in reviewing literature with focus on sensors for maintenance; the few available discussed the systems separately with no link to any known technology.

However, most of the reviewed literature involve smart sensors and smart factories, a focal aspect of the industry 4.0 concept. Leading the reviews is Talal et al. (2019), they described suitable sensors for application in health monitoring; but Strozzi et al. (2017) expands the literature review, gave more insight on implementation and transmission of big smart factories. Sousa et al. (2019) and Lee et al. (2017) addressed the execution process about managing organizational and technological changes. Pereira & Romero (2017) and Bahena-Alvarez et al. (2019) also addressed the implementation of the principles of an intelligent factory and emphasized that the method of

implementation determine how effective the value creation will be. In the area of maintenance of digital factories, there are many literature reviews with focus on predictive maintenance. Sakib & Wuest (2018) analyzed the diversion from service activities to predictive, proactive maintenance and areas (Zonta et al., 2020) in the context of industry 4.0. Fei et al. (2020) explained the application of sensors in the field of aircraft systems. Olesen and Shaker (2020) describe its practical application in thermal power plants. The automotive industry is also moving towards looking at the whole lifecycle aspects of the components used in vehicles, integrating digital maintenance within its production and formulating a digital maintenance framework for automotive manufacturing (Turner, Okorie, & Emmanouilidis, 2020). In the aerospace industry, digital twin is applied during the Maintenance, Repair and Overhaul (MRO) of aircraft engine's fan blade for reduced fuel burn and increased operational efficiency (Oyekan, Farnsworth, Hutabarat, Miller, & Tiwari, 2020).

3.2.1 Hard Wares Used in Building Intelligent Systems for Equipment Maintenance

The major function of hardware is to detect and identify the location of resources across the facility, which involves logistics such as transportation and warehousing. Hardware can connect the expert with production unit in real time, especially when the experts are not present in the facility. Thus, machines can be monitored and repairs performed from anywhere covered by internet. They process data from equipment and processes in real time (Salkin et al., 2018; Bartoziej, 2017), the data is now used to monitor the equipment. The most available of the sensor (wireless) work on radio frequency identification (RFID), Bluetooth technology, and ZigBee (Chen et al., 2018). As defined by Eifert et al. (2020), intelligent sensor is a multi-component measuring and monitoring device that is self-optimized, self-calibrating, and easy to integrate into the environment for high connectivity.

The intelligent sensors in production aid in enabling predictive maintenance and control (Tan et al., 2018). This can be achieved through adequate facility management which involves monitoring of equipment and raising alarm when the equipment deviates from the specified standard parameters (Chen et al., 2020). The parameters such as product cycle time, temperature and pressure are converted into signals by the sensors, and can be measured electronically (Karabegovic et al., 2019). The focal thing here is the knowledge of the state of the system under normal condition so as to program the hardware to react to any deviation from normalcy. The components of the machines can also be traced such as screws, seals etc – to allow tolerance measurement and general monitoring of the condition of machines and other equipment. The summary of different hardware (sensors), its measurable parameters as applied in predictive maintenance and monitoring of production processes are shown in Tables 5. The hardware are portable and durable. They are wireless and robust in terms of data transmission; they are also cheap and economical. Their characteristics are summarized in the Fig.3 below.

Table 5: Sensors' characteristics (Pech & Vrchota, 2021)

S/N	Sensor Type	Sensor Description
1	Virtual	Software sensor, B&R X20CM4800X, Beckhoff
2	Vibration	EL3632, SiemensS7-1200 PLC, bearing testbed
3	Position Tracking	RFID for traceability
4	Multiple (Temperature, Pressure, flow, Position, Power)	Silane (SiH4) flow sensor, radio frequency plasma generation sensor, peak-to-peak voltage radio frequency sensors
5	Torque	Torque three-axis sensor for torque signals, chuck-mounted sensor
6	Torque, Force	Kistler 9257B piezodynamometer (sampled at 250 Hz)
7	Multiple (flow, Temperature, Volatility, Energy, Volume, Gas, Chemical)	Sensors and actuators in chemical process
8	Accelerometer	Integrated Electronics Piezo-Electric (IEPE) sensor
9	Multiple (Temperature, Vibration)	Tmote sky (wireless sensors module) and Z1 mote (ADXL345 accelerometer and TMP102 temperature sensor)
10	Light, Temperature	LED sensors architecture
11	Vibration, Temperature	Micro-Electro-Mechanical System (MEMS) of vibration sensors (LIS3DH)
12	Multiple (Vibration, Optical, Acoustical, Power)	3D scanner (Microscope OLS3000), power meters type CW240
13	Energy	Smart meter (Schneider PM5350)

Fig. 2: Main characteristics of intelligent sensors (Pech et al., 2021)

3.2.2 How Predictive Maintenance Compares to other Options.

Predictive Maintenance is the most advanced type of maintenance currently available with time-based maintenance. Factories run the risk of performing too much maintenance or not doing enough. PdM predicts equipment failures to optimize maintenance efforts (Selcuk, 2017; Tortorella, 2018). The technology is based on real time monitoring of equipment and processes, by this, maintenance is carried out only when needed. According to Carvalho et al. (2019) and Bukhsh et al. (2019), Predictive Maintenance is a technology used to determine when maintenance is needed. With reactive maintenance, maintenance is performed when needed, but at the cost of unscheduled downtime. PdM solves these issues, maintenance is only scheduled when specific conditions are met and before the equipment breakdown. It relies on internet of things (IoT) devices that monitor conditions of assets. A secondary but not less crucial function of PdM is its ability to detect fault earlier using historical data, machine learning, and visual aspects of faults, color and wear, through which maintenance can be carried out by experts virtually. As a part of Industry 4.0 concept, PdM minimizes maintenance cost, enables zero-waste production, and reduces the number of major equipment failures (Li et al., 2019).

Zonta et al. (2020), developed three approaches: The first approach is based on a physical model, characterized by mathematical model requiring the timeliness of the state and statistical methods of evaluation. The second is the knowledge-based approach, the complexity in the physical approach is reduced by this approach, and the last approach is the data-driven approach, mostly common in the current PdM development. Data-driven approach is based on artificial intelligence such as; machine learning, statistical modelling and is best suited in conditions of Industry 4.0 (Lee et al., 2019). Experience-driven and data-driven maintenance were distinguished by (Farooq et al., 2020). Experience-driven maintenance is based on gathering knowledge about production equipment which is then used to plan future maintenance, while data-driven preventive maintenance is based on analyzing a large volume of data.

3.3 Big Data Analytics

The application of big data analytics in maintenance represents the fourth level of maturity in predictive maintenance, as shown in the PdM maturity growth model in Figure 3(a & b). It is called the fourth level Predictive Maintenance 4.0, (PdM 4.0).

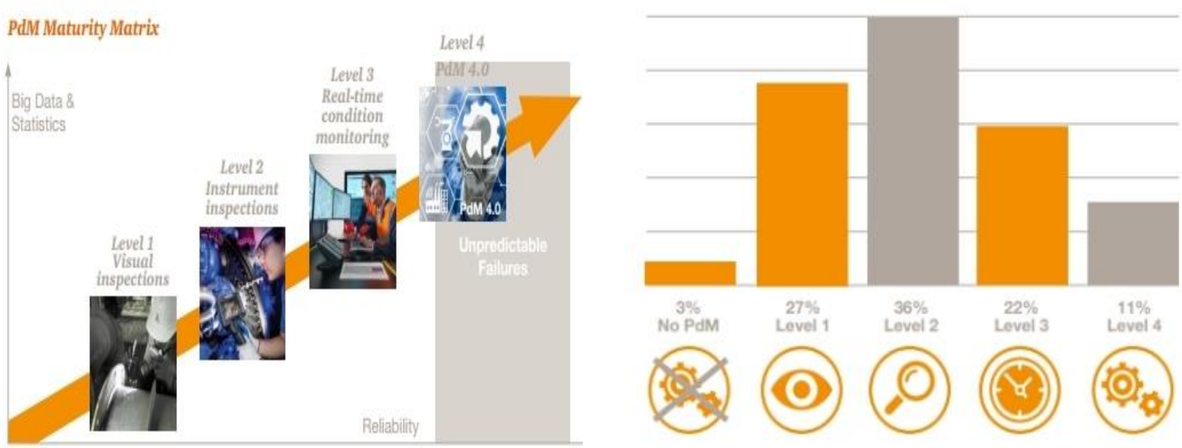
PdM 4.0 is about predicting future failures in assets and ultimately prescribing the most effective preventive measure by applying advanced analytic techniques on big data about technical condition, usage, environment, maintenance history, and similar equipment elsewhere and in fact anything that may correlate with the performance of an asset.

Level 1. Visual inspections: periodic physical inspections; conclusions are based solely on inspector's expertise.

Level 2. Instrument inspections: periodic inspections; conclusions are based on a combination of inspector's expertise and instrument read-outs.

Level 3. Real-time condition monitoring: continuous real-time monitoring of assets, with alerts given based on pre-established rules or critical levels.

Level 4. PdM 4.0: continuous real-time monitoring of assets, with alerts sent based on predictive techniques, such as regression analysis



(a) **(b)**

Fig. 3 (a & b): PdM maturity growth model (Pech et al., 2021)

4. Conclusion

Digital twin is a group of complex systems composed of mathematical models, computational methods, hardware and software devices, which permit the real-time synchronization between a virtual system and real process. This is evidenced in the articles reviewed in this paper; different DT technologies such as data analytics, machine learning, Internet of things (IoT), hardware (sensors) and many others were used to create virtual replicate of existing equipment and productions systems. The hardware in the system supports the real-time monitoring, which makes DT a sophisticated tool in tracking and predicting equipment failure. Due to the large volume of data that are captured and processed by DT over a period, it has the capability of giving maintenance instructions to avert imminent equipment breakdown. DT technology works perfectly in factories that have the necessary facilities that enable digital twin (smart factory). No doubt, is expensive to set and maintain, but the long-term benefits outweigh the cost; these includes effective time management, increased general productivity, less complexity in the system and reduces maintenance cost drastically. The special aspect about the new methods for digital twins is that they make it possible for the digital models to update themselves partially or even fully automatically.

This study also x-rays other intelligent systems built with industry 4.0 technologies for use in predictive maintenance. Different types of sensors, which form integral part of a digital twin system and the parameters they monitor, were presented and analyzed.

Further fields of research of DT and intelligent systems can be the increase in cyber security. Since Digital Twins are based in the cloud and do not require physical infrastructure, the associated security tend to be lower than other types of systems. Every time a new connection is made and more data flows between devices and the cloud, the potential risk for compromise increases. Therefore, manufacturing industries considering digital twin technology must be careful not to rush into adoption without assessing and updating current security protocols.

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