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A Systematic Literature Review on Adoption of Digital Twins in Manufacturing

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ABSTRACT
Digital Twins are virtual representations of assets and processes that are used to understand, predict and optimize performance. Manufacturing sector is still being run with traditional and conventional methods. The introduction of Industry 4.0 paved the way for automation and enhancement in manufacturing processes. Digital Twins utilize the enabling technologies of Industry 4.0 for monitoring, tracking and optimization of a process. Industries require newer technologies to sustain in this competitive market. In this paper, a detailed literature review is done to study the existing applications of Digital Twins in Manufacturing sector. Barriers which exist for implementation of Digital Twins in Manufacturing are also discussed.

KEYWORDS: *Digital Twins, Manufacturing sector, Industry 4.0, Automation, Optimization*

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I. INTRODUCTION

Digital twin is the digital replica of physical assets, processes and devices. According to Tao et al. (2018a), Dr. Michael Grieves first originated the Digital Twin concept in 2003[1]. The first article about Digital Twins was published in 2011 which conceived Digital Twins as method for predicting structural life of aircraft. According to Lu et al. (2020), NASA defined Digital Twins as 'an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, and so forth, to mirror the life of its flying twin'[2]. Digital Twins can also be defined as a dynamic virtual representation of a physical object which uses real time data. It consists of three parts: the physical product, the digital product and connections between the two products. Barricelli et al. (2019) reports applications of Digital Twins in Manufacturing, Aviation sector and Healthcare sector[3]. According to Qi et al. (2019), application areas of Digital Twins are cargo shipping, aerospace, automobile[4]. With the introduction of Industry 4.0 and easy availability of sensors, many researches are being done which will assist manufacturing sector. Digital Twins is one such concept which is new and less explored in manufacturing.

Manufacturers require systems which are interactive in nature. Digital Twins in manufacturing can be seen in Kannan and Arunachalam (2019) where hardware implementation of Digital Twins is carried out on grinding wheel[5]. In Qi and Tao (2018), fusion of Big Data in manufacturing and Digital Twins is presented for application in smart manufacturing[6]. Large amount of data is generated while using sensors, so BDA can be applied for extracting useful information. Today, majority of the people use smartphones. Application of smartphones for implementing Digital Twins is done in Coronado et al. (2018) where using an android application, the machining process is tracked[7]. In Zhang et al. (2018), manufacturing of blisk, which is a part of aircraft engine is done by application of Digital Twins[8]. Digital Twins can also be used for simulation based optimization of manufacturing processes which is performed in Guo et al. (2019)[9]. In Luo et al. (2019), using Digital Twins, life of ballscrew which is used in CNC milling m/c is predicted[10]. Thus from above studies, it can be said that Digital Twins can be used to monitor, track, simulate, predict and optimize the manufacturing process.

The Research questions which are formulated for the study are as follows:
RQ1: What is the current literature on the application of Digital Twins in Manufacturing?
RQ2: What are the future trends in Digital Twins adoption and implementation in Manufacturing sector?

II. LITERATURE REVIEW

A systematic way was followed for reviewing the literature on applications of Digital Twins in Manufacturing. Keywords used for searching the papers include 'Digital Twins', 'Digital Twins in Manufacturing', 'Digital Twins in Production'. These keywords are provided to open source database where the papers are collected. There are some criteria which were selected for inclusion and exclusion of papers. Only peer reviewed journal papers were selected for study. Other papers like Conference papers, Proceedings papers are excluded from this study. For shortlisting of the papers, 'TAK' (Title, Abstract, Keyword) principle is used which provides a clear idea about the contents of the paper. Papers which are relevant to this study are selected. Recent papers which were published from past 5-6 years were considered. Based on these criteria, 35 papers were selected for the study. Figure 1 depicts the methodology of Literature survey.

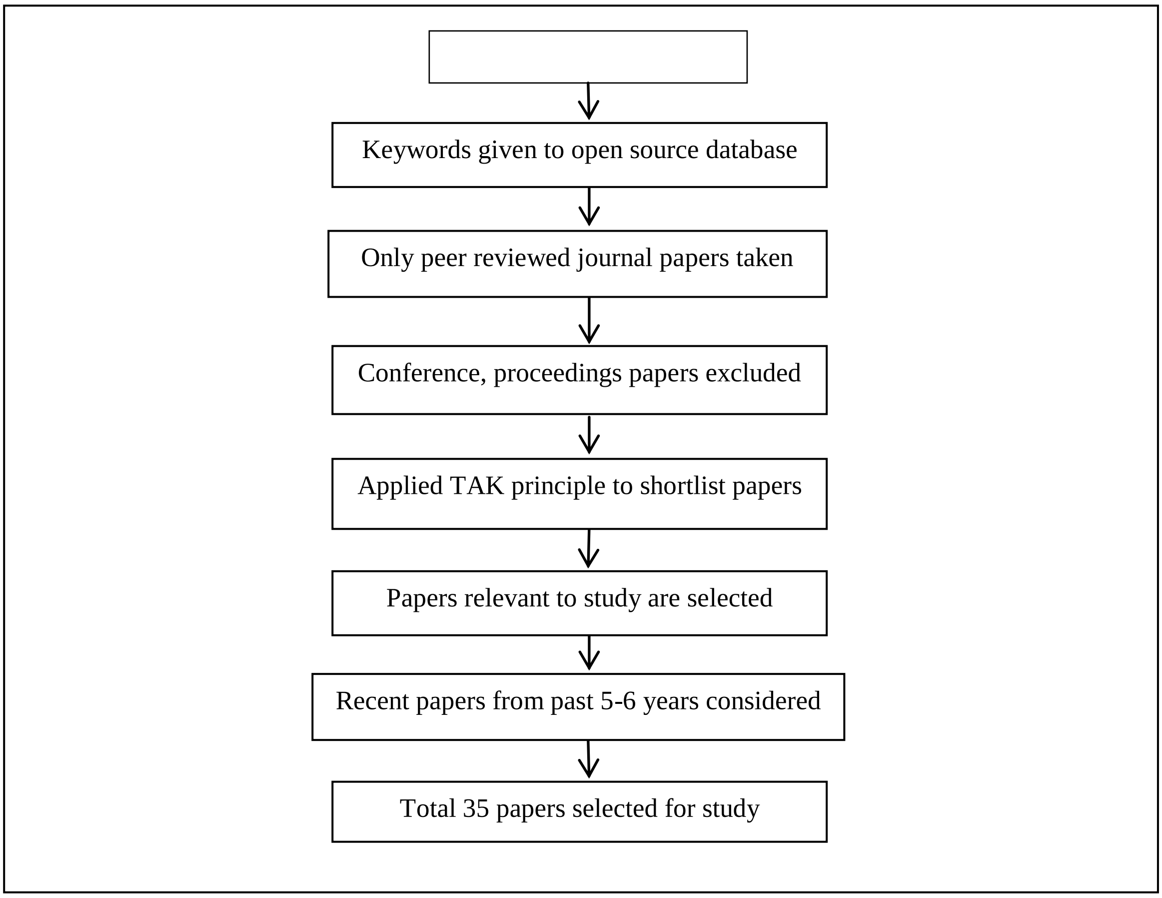

Figure 1: Methodology of Literature Survey

2.1 Distribution of Papers based on year of publication

From Figure 2 it can be clearly seen that most of the papers are published in past 3 years. It indicates that Digital Twins concept for manufacturing is still in early stages and more work is being done on it. It is also due to the fact that manufacturing units are in constant search for technologies which will assist them in efficient production runs. Year 2019 has the most papers published with 17 papers. This is followed by Year 2018 with 9 papers and Year 2020 with 8 papers.

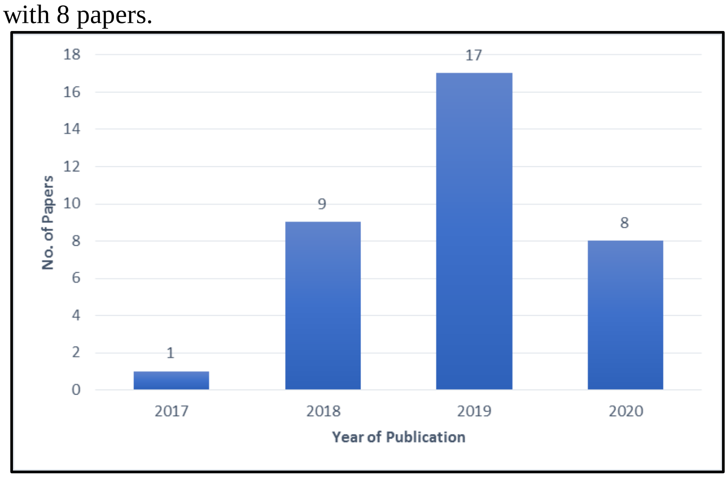

Figure 2: Year wise distribution of papers

2.2 Distribution of papers based on country of origin

According to Figure 3, China is leading with most research papers published on Digital Twins at 23 papers. China is followed by Germany, Italy and South Korea with 2 papers each.

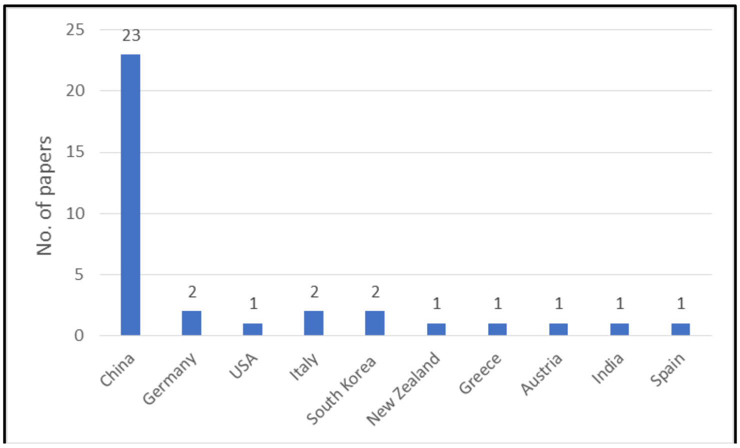

Figure 3: Country wise distribution of papers

III. RESEARCH METHODOLOGY

The papers are classified into 5 broad categories. These include Theoretical papers, Conceptual framework papers, Simulation papers, Prototype (Hardware Implementation) papers and Case study based papers. 8.57% papers are Theoretical papers from total 35 papers, 17.14% are Conceptual Framework papers, 11.43% are Simulation papers, 40% are Prototype papers and 22.86% are Case Study based papers.

3.1 Theoretical Papers

There are total 3 papers in this category. In Qi and Tao (2018), integration of digital twin (DT) & big data are discussed[6]. The big data concept is explained and manufacturing applications are listed. Digital twin concept is discussed and applications in product design, monitoring are discussed. DT and big data are compared based on application in manufacturing. Creation of digital twins for factory production assisted by big data is then discussed. In Qi et al. (2019), various enabling technologies are listed for different DT operations[4]. First a brief introduction and description about Digital Twins is presented. Further a 5 dimensional model for digital twins is presented which forms the base for implementing Digital Twins. Enabling technologies are then discussed for DT modeling, management of data, services and connections. Tools are listed which can be used for performing the above operations. In Lu et al. (2020), an overview of Digital Twins is presented[2]. Researches done by industries like General Electric, Siemens, Microsoft are listed. A timeline of various information sharing standards is presented based on the year in which they were introduced. Various communication protocols are also listed.

3.2 Conceptual Framework Papers

There are total 6 papers in this category. In Cheng et al. (2018), integration of CPS with digital factory is discussed[11]. The elements of physical factory are connected with IoT devices through which DT of factory is prepared. This data is tracked, historical data is analyzed and predictions can be made about production process. Services to be provided by the process are integrated with the DT and a closed loop framework is developed for intelligent demand and supply of products. In Damjanovic-Behrendt, V. and Behrendt, W. (2019), approach based on open source is used for implementing DT[12]. In the DT, there are various models like data models, computational models and service oriented models. Data models acquire the data and do the required processing. Computational models consist of analytics and using learning algorithms to identify patterns and anomalies in data. Services model consists of interaction between system and customers. In Ding et al. (2019), DT-CPPS framework is presented[13]. Product lifecycle data is acquired and integrated by the DT. This virtual part then keeps a track on resources required for production like raw materials, tools. Also it performs scheduling of jobs, monitors the operation for proper supply of finished goods. In Leng et al. (2019), Digital twin for manufacturing system is presented[14]. In this, virtual modeling of physical part is done. A decentralized mechanism is developed for implementing the tasks. Parallel control of manufacturing is done so as to cope up with changing demands of customers and also due to ease of control. In Tao et al. (2018b), framework of product design which is based on DT is presented[15]. In Tao et al. (2018c), concept of DT is applied to PLM stages[16].

3.3 Simulation Papers

There are total 4 papers in this category. In Delbugger and Rossmann (2019), to increase variability in systems, a new model is proposed[17]. A part or process whose digital twins are to be made, they are reconfigurable in nature. These DTs contain 'capabilities' that are entities that describe the actions which the part or process is going to perform. Such capabilities are coupled together to form an EDT. In Guo et al. (2019), modular approach has been used in digital twins[9]. This study is done in a paper cup factory which requires redesigning due to increased demand. Building modules are formed according to modular approach and digital twin of entire plant is made. Simulation of the digital twin is done in Siemens software. In Lu Y. et al. (2019), implementation of EVA model is done for remanufacturing of engine plant[18]. Simulation is done using IoT data on production line. During simulation, timestamps are generated for change in state of elements in the model. EVA model proves useful in remanufacturing as planning of process is reduced to 30 days from 70 days. In Schluse et al. (2018), experimentable DTs are implemented[19]. The system used is a ReconCell consisting of 2 UR10 robots. Using Digital Twins modeling of SysML blocks is done. Virtual Test beds are used for carrying out virtual operations.

3.4 Prototype (Hardware Implementation) Papers

There are 14 papers in this category. In Ardanza et al. (2019), HMI (Human Machine Interface) is introduced for various applications[20]. First, HMI is introduced for 3D printer. A more customized HMI is provided which displays printing process information. At a time, many 3D printers can be controlled using this HMI. HMI is also developed for UR 10 robotic arm by developing a DT for it. In Cheng J et al. (2020), Industrial internet framework is applied to steam turbine production plant[21]. The entire lifecycle of steam turbine is identified. Parameters concerning functioning of plant, requirements of customers are identified. Based on this, simulation of the plant is done. All parts are not produced in a single factory so collaboration is required. For this, common platform is made for enterprise collaboration. In Cimino et al. (2019), DT is implemented in the I4.0 lab[22]. OPC UA is used for acquisition of data. Modeling of DT is done in MATLAB. PLCs are present in all modules of the lab which assist in connecting physical part to DT of it. Different states are created for modeling the DT. GUI is created on MATLAB. Using MATLAB functions, data is analyzed. Real time information is acquired and stored. In Coronado et al. (2018), android application based MES was executed in a facility where there are many CNC machine tools[7]. All the raw material present in inventory was registered and was stored in cloud along with the details of it like material, supplier, length, diameter. Cutting tool information is also stored in database. By storing the raw material and cutting tool data, their usage is tracked using an Android application. Timestamps are recorded for each activity which is done. In Guo et al. (2020), DT-GiMS is implemented on lathe m/c assembly[23]. Using pool management technique, operator performs tasks on machine according to orders. If there is any abnormality, then operator reports to the supervisor. There is a hierarchy which consists of users, planners, supervisors, operators and logistics operator. In Huang et al. (2020), implementation of blockchain is done in DT[24]. Design of turbine is done in Solidworks. Preparation of DT of turbine starts with manufacture of it. After delivery of turbine to customer, DT tracks the usage of turbine and uses the data collected for maintenance. To process and store data, blockchain is used for data management. Data is stored in blocks which can be accessed by mobiles.

In Kannan and Arunachalam (2019), using IoT devices, prediction of end life of grinding wheel is done[5]. For predicting wheel life, Auto Regression Moving Average prediction model has been developed. This model requires historical data from the sensor. In Liu C et al. (2020), control of CPPS is done based on web[25]. 3D printing application is presented for this study. In Luo et al. (2019), life of ballscrew which is used in CNC milling m/c is predicted[10]. The ball screw is an important part as it will ensure machining accuracy. In Nikolakis et al. (2019), the ergonomic constraints while performing pick & place operations in factory warehouse are determined[26]. In Wang and Wang (2018), WEEE management is executed using Digital Twins[27]. The entire process from product designing to manufacturing to service and till retirement of product is monitored. Cloud based system is designed where all the data and resources allocated for the product can be viewed from mobile or computers. In Zhang et al. (2018), PMDT method is used for manufacturing of blisk, which is a part of aircraft engine[8]. Real time data mapping is done between the machines and DT. Job scheduling is done which is selected as example. In Zhou et al. (2019), using sensors real time data is collected with which simulations can be done[28]. The virtual process is then combined with knowledge base. In Zhuang et al. (2018), application of DT is done on a complex shop floor[29]. Using IoT devices, physical shop floor is mapped into virtual part. In the virtual part, iterative optimization is done to increase productivity by running simulations.

3.5 Case Studies Papers

There are 8 papers in this category. In Caputo et al. (2019), a test case has been presented in FCA plant for creation and validation of numerical model for evaluation of ergonomic indexes[30]. In Chen et al. (2020), an example of smart factory is given[31]. This factory has a CNC machine, 3D printing machine, AGVs. Parts are sent to different stations for operations, which are done automatically and are controlled. Energy consumption of the plant is analyzed. In Leng J et al. (2020), reconfiguration of assembly line needs to be done[32]. For this, details about the operations to be performed are stored. A framework of all the machines that are needed for manufacturing is made. Next, decision engine provides reconfigurations that can be done using knowledge base models. Simulations are done based on the new recommendations. The reconfigured assembly line is compared with conventional one. In Min et al. (2019), machine learning is used in a petrochemical plant where catalytic cracking unit is selected for study[33]. Increasing yield of light oil is set as a target. In Park et al. (2019), a micro smart factory is depicted and digital twin is applied to it[34]. Here, 3D printed parts are produced and post processing is done on it. Further the parts are inspected, packed and assembled. This work is done using robots. The DT of it reflects the entire process and monitors it. In Park et al. (2020), digital twin is prepared for the entire MSF[35]. Optimization algorithms are made for production scheduling. They are then simulated within the digital twin to check their effectiveness. If there is any occurrence of abnormality, dynamic response will be derived. In Zhang et al. (2017), rapid individualized design of production line of hollow glass is done using DT[36]. This is done based on decoupling algorithm. The entire production line is simulated and optimized using optimization algorithm. According to performance evaluation, design changes are suggested. In Zheng et al. (2019), a digital twin of the production line of welding is prepared[37]. Real time mapping and interaction between physical part and virtual part is done consistently. Robotic arm of industrial robot is modeled to track the translation and rotation movements of it.

IV. RESULTS AND DISCUSSION

This paper reviews literature based on Digital Twins in Manufacturing. Total 35 articles are selected to be reviewed. These articles are then classified into 5 categories. Out of all the categories, Prototype (Hardware Implementation) based papers are more in number. There are 8 papers based on Case Studies which are second highest amongst the categories. This implies that the studies conducted are limited only to prototypes and case studies.

In Kannan and Arunachalam (2019), the prediction model used gave accuracy of 75% in predicting redress life[5]. Cost estimation was done to find out manufacturing costs, which resulted in an increase of resource and energy efficiency by 14.4% using DT than that of using traditional approach. In Zhang et al. (2018), job scheduling was done and Gantt charts were prepared for same and this was possible due to machine status updation to the DT[8]. This proved beneficial in enhancing production efficiency. In Park et al. (2019), by implementing DT in MSF, interoperability is achieved[34]. Personalized production is materialized as every machine is interconnected and process is tracked continuously. In Delbugger and Rossmann (2019), Digital Twins was used to build a model based system that will assist in better tracking of the system and can also help in monitoring every action being performed within the system[17]. In most of the papers, Digital Twins are successfully used for monitoring and tracking the process. As large amount of data is generated, there is a need to extract the useful data for processing. Big Data Analytics can be used to analyze the data. Prediction models and algorithms can be used to predict future performance of system based on historical data available with the Digital Twin.

There are various barriers regarding implementation of Digital Twins in Manufacturing. From above papers we have seen that there is very less actual implementation of Digital Twins in industries. Digital Twins is a fairly new concept in manufacturing. For a complex physical system, maintaining a DT of it becomes difficult as number of sensors and data related to it increases. Proper synchronization mechanism needs to be established between Digital Twins and physical entities. Accuracy of the Digital Twins needs to be maintained and any change in physical entity needs to be recorded.

V. CONCLUSION

Digital Twins is an emerging technology that can be very beneficial for industries. This technology has the capability to transform a conventional manufacturing unit into a smart manufacturing one. A systematic literature survey is done to study current applications of Digital Twins in Manufacturing. Further, barriers are identified in implementing Digital Twins in Manufacturing.

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