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Digital Twin and Its Implementation in 3D Printing: A Research Review

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Abstract
The emergence of Additive Manufacturing (AM) has created a plethora of opportunities for different industries due to its application in 3D printing technology. Since its introduction back in 1980, 3D printing technology has overseen numerous developments and changes. A rarity back in the day, 3D printing has now become cheaper and available for everyone who wishes to learn and experiment with the technology. Although 3D printing technology can produce optimized and detailed printing at a cheaper rate than in earlier days, it can still be time-consuming and quite costly due to the technology's tendency to follow the trial-and-error method when printing. A proposed solution to such an issue is by implementing Digital Twin (DT), a virtual representation of an object that provides real-time reflection between the virtual and physical space and can interact and converge with the flow of data between both spaces. However, despite the need, Digital Twin is yet to achieve its fullest potential due to a gap in knowledge regarding its concept and development methods. This paper, therefore, intends to provide a brief review regarding the implementation, applications as well as challenges of DT for 3D printing, to provide an understanding of the current trends that can be utilized for further research regarding Digital Twin and its implementation in 3D printing.

Keywords: 3d printing; additive manufacturing; digital twin; internet of things

Introduction

Additive manufacturing (AM), also known as 3D printing technology or Digital Fabrication technology, is a revolutionary technology that creates objects in a physical form from geometrical representation through successive addition of materials [1]. According to the American Society for Testing and Materials (ASTM) Committee, additive manufacturing is defined as "a process of joining materials to make objects from 3D model data, usually layer upon layer, as opposed to subtractive manufacturing methodologies". Likewise, ASTM defines 3D printing as "the fabrication of objects through the deposition of a material using a print head, nozzle, or another printer technology, often used synonymously with additive manufacturing" [2, p. 2]. 3D printing has become an ever-growing technology that is currently widely used across the globe by the manufacturing industry to produce custom goods.

3D printing technology was first conceptualized by Charles Hull in the 1980s for commercialization purposes. [1]. Because AM has emerged as rapid tooling and manufacturing technology, it has since then rightly positioned itself at the cusp of introducing the Fourth Industrial Revolution [3]. Over the years, numerous technologies pertaining to AM have been developed such as Stereolithography (SLA), Fused Deposition Modeling (FDM), Selective Laser Sintering (SLS), Laser Engineered Net Shaping (LENS), and Laminated Object Manufacturing (LOM) [4]. With the help of AM, a computerized 3D solid model is converted into a standard AM file format such as the traditional Standard Tessellation Language (STL) format in order to transform it into a finished product [5]. As additional cutting tools or fixes are not required, AM also helps in the production of complicated objects that are tough to produce through other processes, mostly due to the complex geometry of such objects.

Before the introduction of 3D printing techniques, traditional methods that were employed by companies for industrial prototyping were not able to provide any competitive advantage in their industry. Eventually, in 1980, additive manufacturing was crucial in introducing a new automated fabrication technique of 3D solid objects that originated from a digital computer-aided design (CAD) file. During its early days, the 3D printing technology was riddled with inadequacies such as slow and expensive printing, substandard level of details and quality of finish, use of plastic as the only material, and so on [6]. Over time, the technology has evolved and has become more useful due to its increasing affordability and fine attention to detail [7]. Designers can now examine their designs in physical form and perform necessary changes for better optimization of their products.

While most of the pre-existing issues have been addressed innovatively, there are still a few drawbacks of AM. For instance, in the case of metal printing, fabricated items can have uncontrolled porosity as well as brittleness and become prone to shrinkage and brittleness. Similarly, the FDM can also undergo challenges related to the quality of the surface of the printer as well as the printed object's structural integrity due to the problems related to proper tuning of the numerous process parameters before printing. Additionally, failed 3d prints can also be the result of other issues such as motor stall, timing belt break, breaking failure, nozzle blockage, items getting detached from the 3d printer's bed, abnormal extrusion and so on. Oftentimes, such errors result in 19% of material waste on average whereas, in case of FDM 3D printers, almost 34% of total materials, including the material used for support structures are wasted [8]. As a result, there have been breakthroughs in fourth industrial revolution technologies, often characterized by big data, Machine Learning (ML) along with the Internet of Things (IoT) to solve such issues [9]. The development of technologies related to Artificial Intelligence (AI), ML, Deep Learning (DP) as well as big data has therefore become an essential step during data collection from different sensors that are able to provide most of the relevant data [10]. Such technologies enhance the efficiency of existing systems due to their tendency to work through complex problems.

Apart from the aforementioned technologies, another modern technology that is often considered the backbone of industry 4.0 is the Digital Twin (DT), often deemed as the doorway between imagination and the Cyber-Physical System. DT is the physical product’s virtual representation which consists of details about the physical product and can simulate the behavior after the cyber-physical fusion [11]. Digital Twin was first conceptualized by Michael Grieves while working at NASA with John Vickers [12]. During a lecture in 2003, Grieves attributed the origin of DT with respect to the product life-cycle management and explained the 3 components of Digital Twin: a physical product, the product’s virtual representation and the two-way connection of data that gathers and exchanges detailed information about the process from the existing physical product to the virtual representation and vice versa [13].

Glaessegen and Stargel proposed another definition of DT in 2012 as the combination of three different components, namely the physical object, the virtual product and finally, the interrelation between both of them [11]. DT is therefore a representation of the fabrication service or process in the digital virtual world that is often guided by preset properties as well as conditions. From a cyber-world context, DT enables a mechanism for the digital transfer of real-world items and processes together with their relevant surrounding environment. Thus, DT can help optimize items or processes by analyzing and understanding them without the need to allocate resources for trial and error methods [14].

The implementation of DT in AM technology has been crucial when overcoming issues related to additive manufacturing such as saving time as well as improving part quality [15]. Gaikwad et al. [16] has proposed three ways how DT can impact AM significantly. According to the study, it can be done by optimizing the process parameters such as scan speeds as well as laser power and by providing guidelines for build orientation, support placement and part design. Secondly, it can be done by identifying and observing process faults through the combination of theoretical predictions and real-time sensor data in order to provide a model-based feedforward control in AM. The final step is by reducing computational burden during multi-scale modeling along with storing and analyzing huge volumes of in-situ sensor data. Generally, implementation of DT consists of three steps. The first step in the implementation cycle is to create a digital twin prototype (DTP) that consists of data related to planning and analysis along with the ways to implement them into the physical system. This is followed by designing the digital twin instances (DTI) of each physical object and its properties. Finally, the systematic properties of all digital twins need to be integrated (digital twin aggregate - DTA) to ensure further predictions can be made by understanding the acquired data and information [14]. Likewise, for smart manufacturing, the digital twin also has the possibility to assist when performing the monitoring as well as troubleshooting tasks of machine tools in an autonomous manner. This can be achieved by developing a special type of signal-based sensor twin and adapting the sensor twin into the cyber-physical systems [17]. Moreover, the use of innovative technologies - the pillars of industry 4.0, would enhance the effectiveness of DT and its application in the cyber-physical system. If implemented effectively, DT can represent its physical twin with accuracy, realism and fidelity.

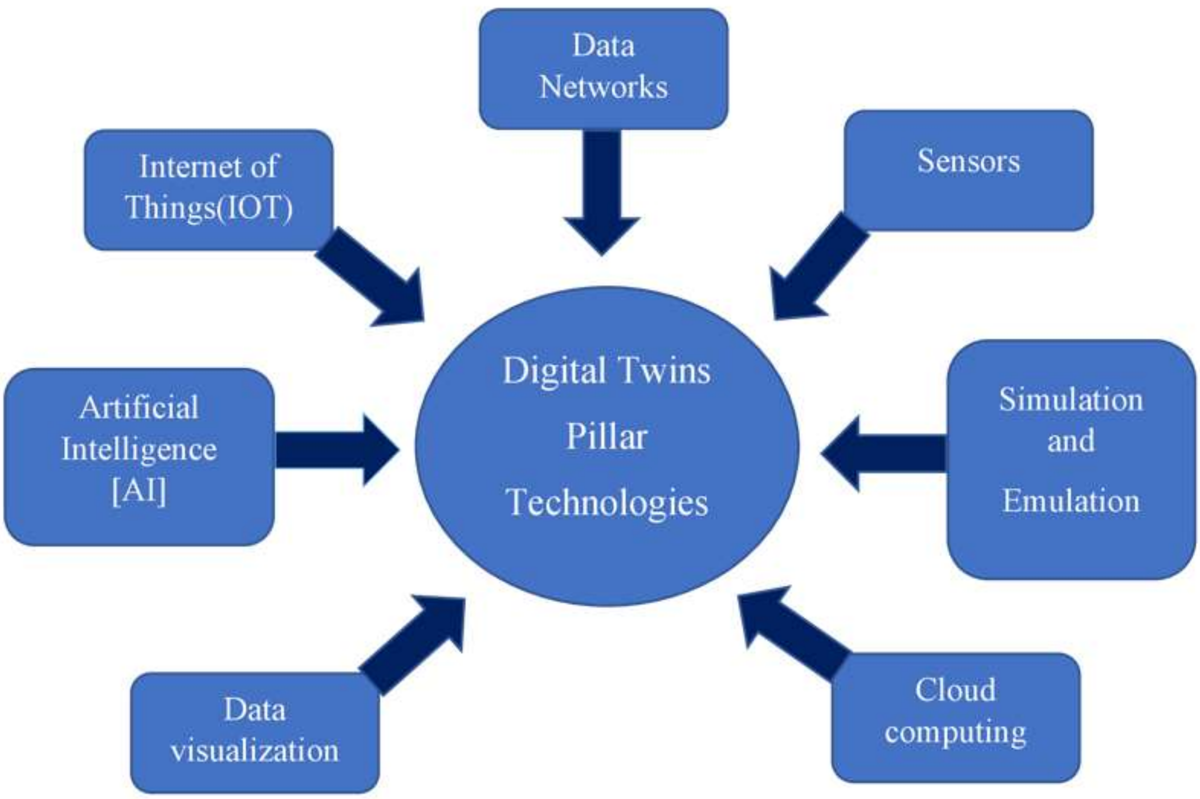

Figure 1: Pillar Technologies of Digital Twin [14]

Implementation of DT in different fields:

Due to the increasing interest shown in DT since its conceptualization in 2003, it has made its way into some of the global industries over the past couple of years [18]. Together with IoT, DT has enabled individuals and companies to optimize and provide better results by detecting issues sooner and predicting outcomes more efficiently and accurately to build better products. As digital Twin can also be used during product redesign, it can be immensely helpful in the process of product improvement. Such implementation of DT in the redesign process can also foster innovation and improve the quality of physical products [19]. DT's characteristics and potential has therefore been significantly useful in multiple industries. Some of the fields that have been impacted by digital twins are:

1. **Smart Cities:**

The use of DT has been hugely effective within smart cities due to the integration of IoT and the subsequent development in connectivity [12]. Integrating IoT with cloud computing along with the implementation of DT is essential when building smart cities. DT has become more influential while offering smart solutions in construction, energy sectors and transportation - all of which are crucial during city planning [20]. Advancement in DT is bound to happen with the increase in the number of smart cities. It can be further helpful when assessing test scenarios and allowing DT to analyze the environment through the changes in collected data. Its ability to detect the actual and possible future scenario can be effective towards traffic management [21], renewable energy [22] and livestock management [23].

2. **Health Care:**

AI algorithms along with DT have the potential to oversee how certain changes in a person's lifestyle can affect their health. Recommendations can also be made if any issues can be found related to such lifestyle using both DT and AI [12]. A study [24] has demonstrated how AI and IoT can be used to create DT avatars of people, giving them the ability to envision changes that can happen with their physical self through such avatars [12]. Another study discusses the potential of creating a patient's DT with the help of Industry 4.0 connectivity and an autonomous surgery harnessing IoT. A working prototype in the form of a remote surgery application that can be accessed through 4G mobile network and uses virtual reality is also proposed by the authors to deliver precision surgery [25].

3. **Manufacturing**

As manufacturing companies often track products and processes in order to become more efficient and cost-effective, implementing DT can be highly beneficial for manufacturers [26]. When it comes to manufacturing, DT can help predict issues sooner as it can give real-time data on machine performances and production lines [27]. In the case of the automotive industry, the DT of the car engine or other parts can be used for simulation while data analytics can be used to predict the component's present as well as future capabilities [28], [29]. Such use of DT has most famously been implemented by Tesla [12]. Likewise, in the construction industry, DT as well as data analytics can aid during the development stage of a building when predicting and maintaining structures by comparing virtual and physical structures with greater accuracy [30]. Adopting DT-based technologies such as BIM, also known as Building Information Modeling, has also been influential when it comes to changes within the construction industry [31].

3D printing

Basically, it is the process of printing layers on top of one another in order to produce three-dimensional objects by extracting details about the item from its digital file. While David E. H. Jones is credited for the introduction of 3D printing in 1974, Chuck Hull of 3D System Corporation followed through on the notion and filed his own patent in 1984. 3D printing has since surpassed the standardization as well as printing of smaller tools and objects and has continued its development in material application [3]. The evolution of 3D printing technology over the past couple of decades has also resulted in a reduced cost when purchasing 3D printers, which has created a surge in its commercial use [32]. Nowadays, more than one hundred types of raw materials are used to manufacture numerous items such as bio constructs, singular parts, spare parts, micromachines, electronica and even jewelry. This has created a breakthrough in the 3D printing industry as policy makers, entrepreneurs, academicians, and society are certain to encounter numerous opportunities as well as challenges in the coming future [33].

3D printer consists of basic parts such as print bed, which is the flat surface that is used to print the object; extruder, which feeds the filament onto the nozzle for heating; filament, which is the material that enters the extruder as well as the nozzle and is used to print and finally the motherboard, which is the control board of the printer [34]. Referencing to a computer aided design (CAD) model, 3D printing uses a layer-by-layer additive manufacturing method to create an object from various materials such as polymers, ceramics, metals, composites, resins and other smart materials such as nickel-titanium as well as special materials such as food items such as chocolate, meat, sauce, candy and so on [2]. Regarding applications of 3D printing, food layered manufacture or 3D food printing can be used to produce various food products for those who need a strictly controlled diet [35]. Similarly, 3D printing is also one of the leading technologies that is prevalent in the manufacturing process for pharmaceutical as well as healthcare technology due to its cost-efficient economical process and high productivity. [36]

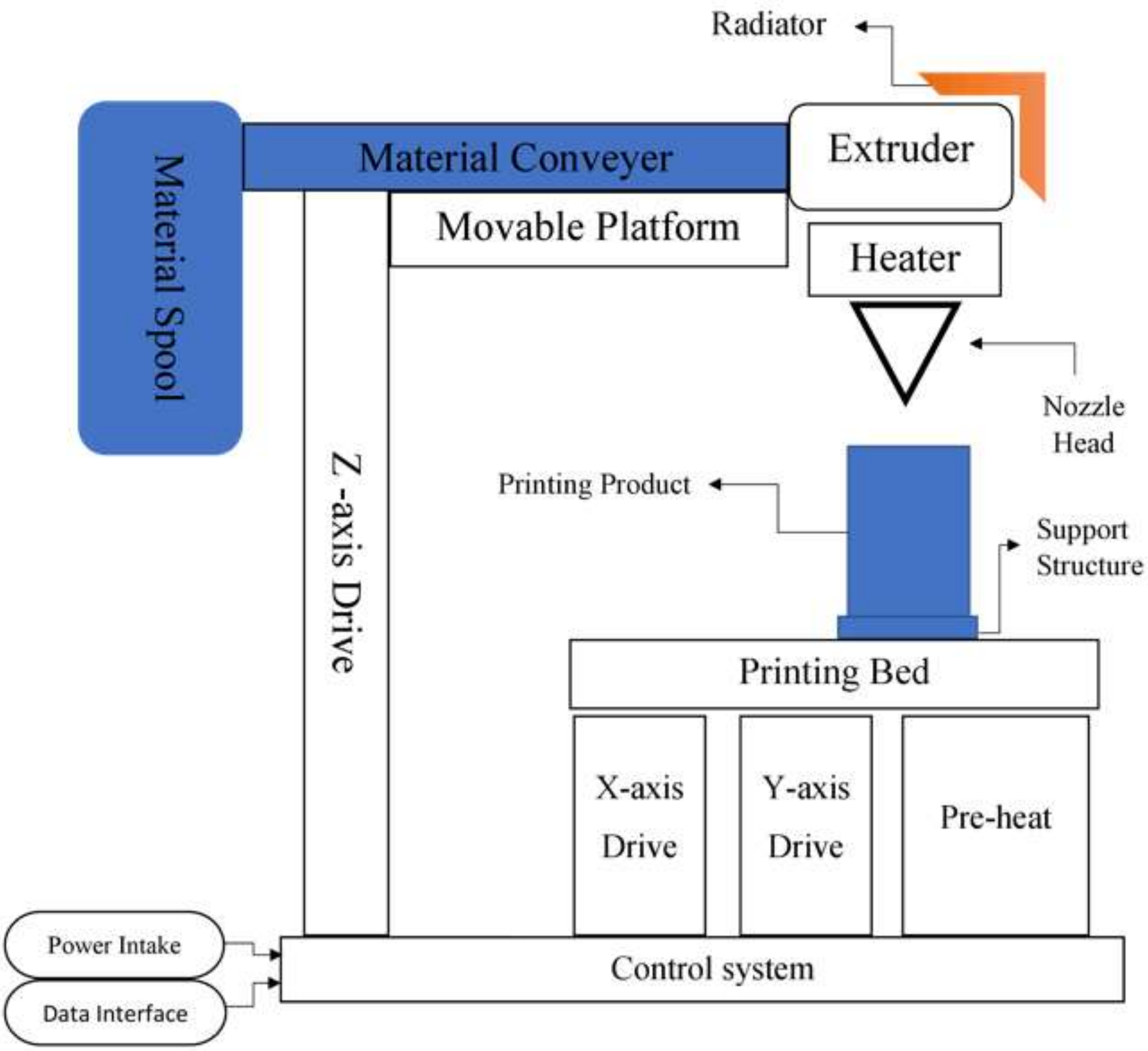

Figure 2: Schematic Diagram of a 3D printer [2]

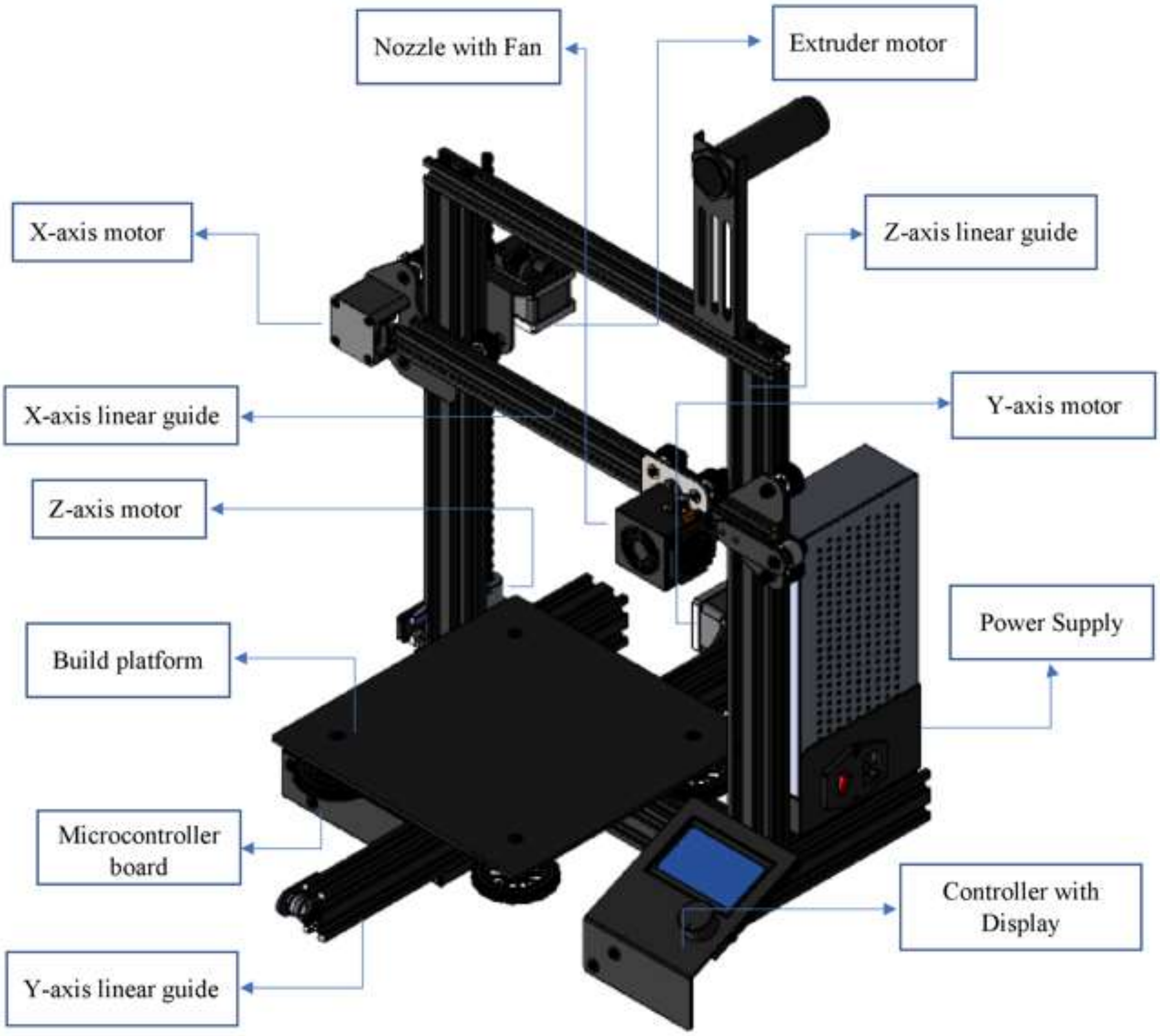

Figure 3: Ender 3 Pro Printer along with its parts

DT Application for 3D Printing

It is fair to say that the current impact of DT when it comes to 3D printing technology has been influenced by the implementation of DT in numerous sectors. Currently, numerous applications of 3D printing are found depending on the type of 3D printing technology. In a study by Mourtzis et al. [37], DT for Fused Deposition Modeling (FDM) is designed and developed to integrate quality assessment modules. Similarly, a database has also been modeled in order to monitor the results of experiments conducted in the study. The DT will also be used to provide remote control and monitoring capabilities and to compensate for existing errors. Furthermore, implementation of Augmented Reality (AR) interface is also proposed. AR-based DT technologies for AM enables a more convenient interaction between human and machine [38]. The research for AR is mostly focused on reducing production cost of AM products. This can be done either by detecting a process that has completely failed and stopping the process or by making sure to prevent low-quality and defective 3D prints with the help of results based on simulation as well as references from previous prints.

The study [37] also talks about how DT is involved in the overall 3D printing method. In order to achieve the rapid prototyping effect, the object's 3D CAD is sliced into a layer-by-layer section before 3D printing. A dataset is then created with the help of the slicing algorithm that corresponds to the slices of the item, which includes the details about the size, shape and so on. This is followed by creation of G-code instructions, which are transferred to the 3D printer for the manufacturing process [39]. For an FDM 3D printer, the DT will be designed as a form of attachment to the conventional setup. As some commercial 3D printers operate processes remotely, cloud databases are included in the workflow to ensure DT has access to the stored information. The proposed DT will also utilize AR interfaces where processes are replicated [38]. Users will then be able to inspect simulation of the printer's previous prints and the stored results and adjust slicer settings by referencing previous prints.

The paper [38] also proposes using cumulated small cylinders to estimate the component's geometry called 'Volume Approximation by Cumulated Cylinders (VACCY). VACCY technique is more pragmatic when simulating the virtual component's printing process in the digital twin. For mobile AR-platforms, implementing AR based DT needs a huge amount of calculation power. DT ensures consistent delivery of details in a summarized way so that end-users can make critical decisions in a short period of time. The paper [40] talks about the implementation of desktop 3D printer's DT that can be used to display the printer's parameters and related alerts in real-time and facilitates control of the printer's crucial functions with the help of a lightweight AR model which helps maintain bi-directional information exchange. The paper concludes that DT was exported as an Android application where the model is displayed right after the image target is scanned. The DT correctly displayed the 3D printer's parameters and successfully transferred the control instructions while the corresponding changes were also reflected in the 3D printer. The implemented DT can achieve its objective of data abstraction and enables faster understanding and seamless control of its respective processes. Additionally, the paper also showcases that 11 respondents out of 18, who had never used a 3D printer before, are also more likely to utilize the DT interface. The following figures (4 and5) shows the screenshot of DT as can be seen in the Android device and the DT displaying a notification alert when the temperature for the print bed exceeds a specified threshold.

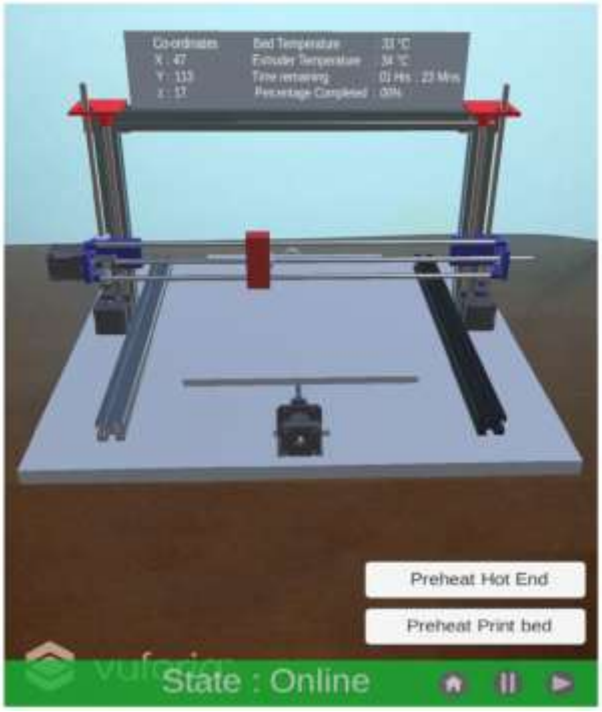

Figure 4: Output of AR Device

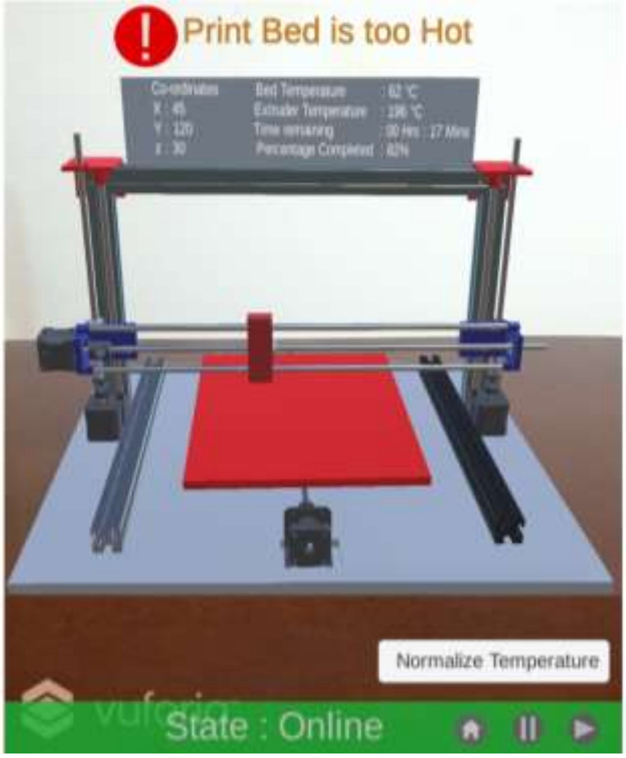

Figure 5: Alert for High Print Bed Temperature

Odada et al. [41] presented in their paper the design and use of FDM 3D printer's data-driven DT that monitored the 3D printer's motion in real time. The system consists of FDM 3D printer's virtual model, which is connected with the physical printer. The linked virtual model followed the motions of the physical 3D printer's main parts with less than half a second lag. With the help of this, the user could extract information related to the virtual printer's printing process such as the vibrations in different parts of the printer and compare the link with the observed motions. With the help of MS Excel as well as Kepserverex's DDE driver along with a data logger, the authors were able to develop a history tracking platform that can run simulations of part printing operations, which enabled the comparison of datasets generated at different times. Likewise, the paper [42] presents a DT architecture that caters to performance monitoring as well as anomaly detection in additive manufacturing processes. The DT proposed in this paper consists of a hybrid automation model at its core, which is capable of capturing both functional as well as the continuous dynamics of the AM processes along with a flexible function block which can be used for numerous objectives like performance monitoring and anomaly detection. The authors also inform on the nature of their future work, which will mostly focus on developing efficient ways for real-time data processing and STL monitoring along with efficient schemes for system monitoring as well as control for multiple AM machines.

Paper [43] discusses the need to have a more efficient and cost-effective DT driven virtual verification process for 3D printers and its designs. According to authors, the application of a Digital Twin driven virtual verification addresses the gap between physical simulations and virtual simulations of 3D printed design and geometrical CAD design as CAD software is not able to analyze the functionality as well as the performance of 3D printers together with its designs. The DT approach can measure physical designs to maintain accuracy and track the historical database of previous models for future comparison. Similarly, the DT also allows simulation as per the changes in the real environment such as differences in humidity as well as temperature. The increasing use of sensors and IoT technology along with the advanced form of machine learning technologies as well as big data analytics enables uploading of real-time data and updating the virtual world continually. Finally, authors highlight the need to develop DT that focuses on the analysis of current as well as future technologies in order to develop a DT driven virtual verification. With DT, it is also easier for designers to forecast behavior of the product through virtual verification as designers do not need to wait until the product is completely manufactured in order to alter the product's design [44]. Virtual verification through DT also helps in reducing inconsistencies between the existing behavior and the expected behavior while also minimizing costs and design cycles.

Another paper by Stavropoulos et al. [45] talks about the design as well as the implementation of DT for Additive Manufacturing processes. According to the paper, AM procedures are often optimized through offline monitoring and modeling tools due to the lack of proper real-time decision support as well as adaptiveness that are offered by DT. The paper proposes a DT supporting platform that gathers current details and provides optimization to networked AM producers by taking into consideration cycle time, connectivity to production planning and energy consumption. The proposed model details the users to improve their product quality and reduce the material waste for products which do not fulfill the requirements. By providing adaptivity and control, the usability of the model in a DT aims to improve the accuracy of production planning by optimizing the selection of values for process parameters and positively affecting the build time. Build time is the amount of time taken to print an object, without including the design time, conversion of the CAD file to STL file or the creation of G-Code [46]. The software then collects all the details and offers secure storage so that it can be easily accessed by other authorized users. The quality of product can be improved whereas the energy consumption is decreased with the help of the methodology outlined in the paper for different FDM printers.

Knapp et al. [47] proposes a recourse to rigorously validate a DT of AM process that showcases accurate projections of the temporal as well as spatial variations of metallic parameters which influences the component’s properties and structure. Digital twin and its key building blocks use a transient, 3 dimensional model which calculates solidification parameters, temperature and velocity fields, cooling rates and deposit geometry [48]. Such a DT model is presented and validated along with experimental information of single-pass, single-layer deposits. The proposed DT model was able to correctly determine 3D curved surface deposit geometry for single-pass deposits, velocity distributions and transient temperature, solidification parameters, cooling rates, micro harness and secondary dendrite arm spacing in a computationally efficient manner. Additionally, the given framework was also able to reduce the required time for costly empirical tests in order to assess the influence that process variables have on single-layer deposit geometry, cooling rates and some structural features.

In the paper by Moretti et al. [49], an original form of optical imaging solution that can be used for identification and stacking of layer contour is proposed. The proposed solution addresses the current challenge related to image and range/resolution interpretation, based on the prevalent manufacturing process parameters through DT. DT also ensured the vision system uses a high resolution image only when necessary by tracing the layer contour’s predicted positions when obtaining a sequence of images. Similarly, with the help of DT, the vision system is also able to algorithmically interpret images by focusing solely on relevant areas indicated by simulated prediction, which reduces the possibility for false positives. Likewise, it can also monitor the quality of contour through a detailed differentiation between the reference contour and the measurement acquired through simulation that replicates the actual fingerprint of the process, instead of relying on the CAD model's slicing edge. Furthermore, issues related to fabrication can be detected by the system, which causes the alarms to be triggered, thus providing an option to terminate the build during its early stages or initiate necessary actions to correct them.

Sieber et al. [50] present the formulation of DT through the integration of geometrical measurement data by enhancing an optical model. This technique aids in strengthening the high precision process in 3D printing in order to fulfill conditions pertaining to optical precision requirements. In the simulation model, a process flow between fabrication by inkjet printing, design of freeform components, fabricated optical suface's geometrical measurement and the measurement data's feedback was developed and their interfaces have been defined. By assessing the measurements, the printing process was able to adapt in order to compensate for the process errors and tolerances. Additionally, the manufactured component's performance was simulated and compared with the nominal performance, and the enhanced model could be used for sensitivity analysis. In this paper, a mathematical software called Mathematica was used to calculate the arbitrary freeform optical surface. Likewise, OcticStudio - an optical simulation tool was introduced to conduct an optical analysis of the whole system model. The communication between both tools - Mathematica and OpticStudio was made possible through Wolfram Symbolic Transfer Protocol (WSTP) to carry out an automatic analysis of the optical properties of different variants.

In a paper by Gidwani et al. [51], a DT additive reconstruction tool is implemented to create an explicit characterization of layer by layer 3D printed parts in CAD software. This approach outlines the principle of DT reconstruction which can be applied to numerous CAD software while keeping a distinct universal G-Code Parser module that is written in a Python script. The method aims to maintain a simple workflow without loss of information. Additionally, the computational time can also be minimized by excluding Boolean Union operation if needed and selectively reconstructing and unioning the specific layers after specifying the algorithm's layer numbers. Another paper by Weinand and Rosengerger [52] refers to software solutions for creating DT. In the paper, the DT of 3D printers are developed through creation and validation of the requirements within the tested programs. Instead of utilizing DT to simulate a production line, the goal of the paper is to use the tested program to simulate the 3D printer.

Mukherjee and DebRoy [53] explain in their paper that the DT of a printing machine can minimize the number of tests related to trial and error and help acquire the required attributes of the product as well as to become time-efficient for part qualification in order to ensure the numerous printed components remain economical. With the help of a comprehensive DT for 3D printing machine that includes mechanistic, statistical and control models of 3D printing, ML as well as big data can minimize counts for trial and error testing as well as the time that is normally taken between the product’s design and production, all the while reducing defects. The schematic representation of the DT and the mechanistic model is shown in the figure below:

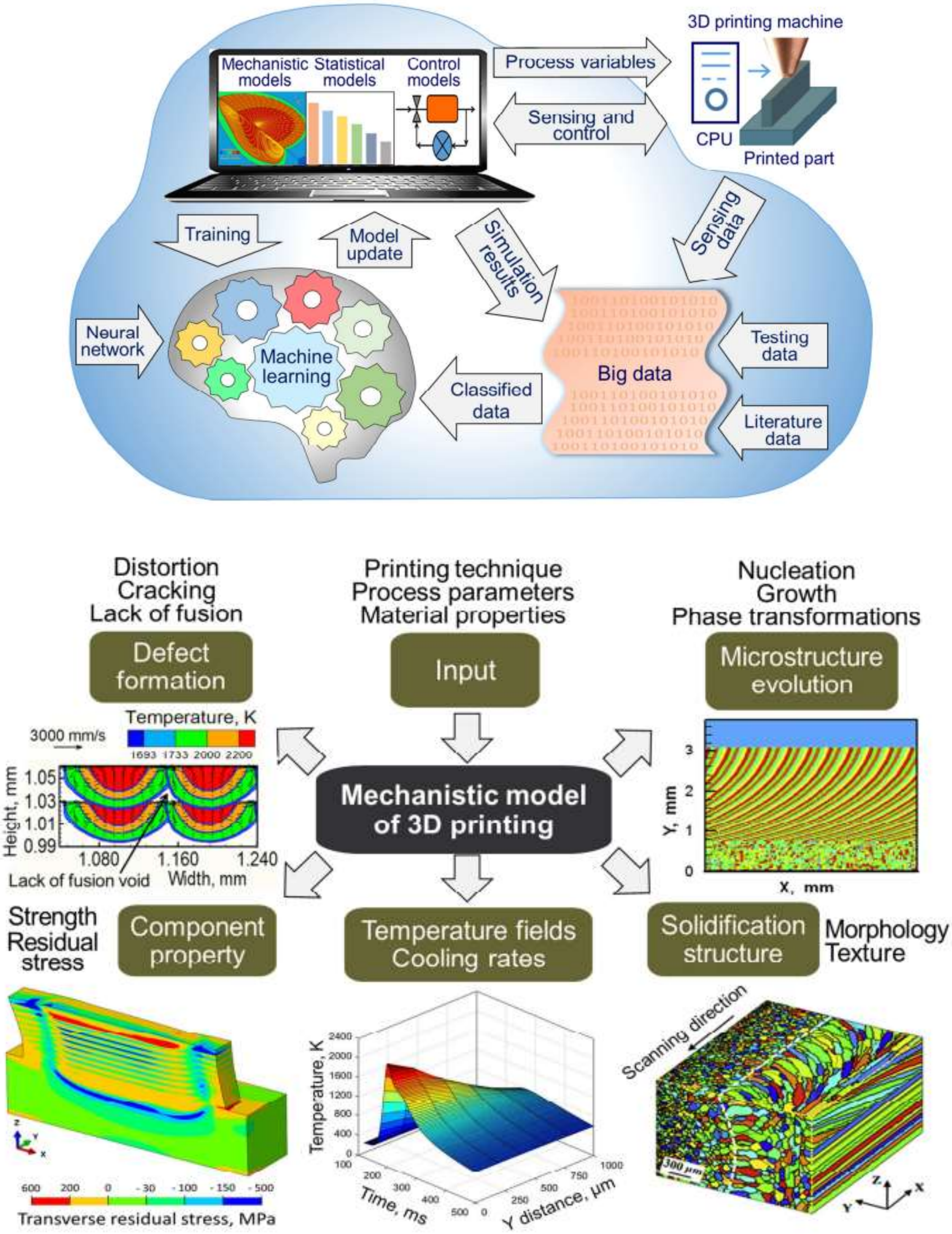

Figure 6: Schematic representation of the Digital Twin (above) and a mechanistic model (below) [53]

Machado et al. [54] iterates the influence of DT in the AM industry and how IoT and DT are the way to move forward for the said industry. IoT has been hugely influential for manufacturing technologies when it comes to being able to produce faster, in a more dynamic way by ensuring quality standards are maintained. The fundamental aspects when developing a DT of the optical system of a powder bed fusion (PBF) machine is analyzed along with the concept of DT to the laser source as well as to the galvanometric scanner. The process proposed in the paper is fundamental for the integration of IoT information modeling towards the additive manufacturing solutions. Furthermore, the paper also analyzes how technical details can be generated during the process and how the data can be used to develop a DT that can connect IoT devices into an AM system. As per Chhetri & Faruque [55], in order to highlight and implement the benefits of digitalization to legacy manufacturing systems, Internet of Things (IoT) is used so that it can address previously unresolved issues pertaining to DT. IoT is used to build DT with the help of an indirect medium such as side-channels, that can help localize irregular faults and understand the manufactured product's quality while also keeping itself updated.

In this paper [56], a DT-based cloud-edge collaboration architecture for 3D printers is proposed for the cloudification of manufacturing equipment in the cloud manufacturing environment. In order to resolve the lack of network availability by traditional cloudification, time-sensitive services are deployed at the edge, realizing the local extensive of cloud services. This process aids in defining the DT information model of FDM AM, which enables real-time controlling and monitoring based on the DT. The development of edge computing and its integration with DT and IoT can solve numerous issues and improve performance [57]. As mentioned in the paper [56], edge computing can mediate issues related to the large amount of generated data, time delay and security concerns. Through cloud-edge collaboration, verification of the effectiveness of the process is made possible by implementing an application case, which in turn provides a reference solution for other manufacturing equipment's cloudification in the cloud manufacturing environment.

The paper [58] talks about a novel DT ecosystem which can be implemented in order to perform process monitoring, testing along with remote management of AM - FDM machines in a simulated virtual environment. The DT system proposed in the paper consists of two approaches: a data driven approach by OctoPrint - an open-source 3D printer web controller application that can capture its key parameters as well as status. The second method is using externally mounted sensors to perform a data-driven approach in order to estimate the 3D printer's actual behavior and attain precise synchronization between the virtual 3D and the physical printers. The DT system can capture the whole operation as well as capability of the FDM machine and hence can be useful during optimization as well as in-process analysis. Furthermore, a DTE architecture was applied to the system which consists of two key components: the data acquisition-processing-distribution component (APDC) as well as the virtual-representation component (VRC). Both components are used to interconnect and coordinate elements that incorporate the Digital Twin Ecosystem (DTE) system and can achieve continuous synchronization between the digital system and the physical asset, with a mean response time of 265.94 ms.

Octoprint integrates 3D printer control software with a web interface so that the printer can be controlled and its progress can be monitored over the connected network. It is a free and open source software that sends Gcode to the remotely connected 3D printer, which allows to perform and observe every aspect of the printer with the help of a Raspberry Pi [59]. The server for Octoprint and its web interface also provides 24/7 network access. With a 24/7 network access, total control of the printer, its axis movements, extruder behavior, tools temperature and numerous other real time features such as launch, pause, resume, cancel along with serial communication with the 3D printer, managing G-code commands, time lapse generation to locate and resolve printing errors are possible [60].

As per the study conducted by Henson et al. [61], part distortion during AM can lead to significant waste of resources and catastrophic failure. Current research is more focused on identifying and detecting specific causes that might cause part failures such as extruder clogging. Integration of early warnings and fast detection systems for print failures has always been a top priority to minimize errors [62]. However, as print failures can also be the outcome of numerous errors - which can be both known and unknown, relying on identifying individual root causes may not be the best idea. The authors therefore propose adoption of DT strategy to differentiate model predictions to parameters that are obtained from the in-situ sensing data. The paper also focuses on DT strategy to detect distortion by generating a multi-view optical sensing system for movable print beds and failure detection methods by analyzing multi-view of part images layer by layer. This methodology performs real-time comparisons of pre-print simulation of ground truth images and print images that are acquired throughout the printing process in order to determine whether the print should be continued or terminated.

3D Printer Challenges for Digital Twin

When it comes to the manufacturing environment, mostly physical objects are used for engineering. Converting a digital design towards a working prototype was not only costly with fewer margin of errors, but the price to pay for having to go back to redesign was similarly time-consuming and expensive. DT, with its capability to model as well as simulate digitally, has advantages such as reducing time and money for trial and error optimization, reducing defects and minimizing product qualification procedures, has been revolutionary in the manufacturing industry due to its potential [63]. However, implementation of DT still has a few drawbacks and challenges as DT models still need other conceptual details, maturity as well as integration across the fast iterations and lifecycle in order to close the gap between the limitations of the current system engineering models [64]. DT keeps in check information related to the products and its performance that are based IoT-based smart connected systems and products. There is however a definitive lack of IoT's standards and its integration as well as alignment on a global scale. Due to the ties between DT and IoT, standardization of IoT is an essential step to achieve maximum benefits. Therefore, standardization of IoT and its supporting technologies has become essential to realize a smart society through various technological services [65].

Similarly, integration of a cyber-physical closed-loop system is crucial for optimization through Digital Twin. An efficient DT can integrate all the manufacturing processes through a closed-loop system and can be used for optimization of manufacturing, product design, maintenance and so on [66]. The importance of closed-loop systems is further highlighted in a study [67] where the authors have noted that a closed-loop DT for manufacturing can be introduced by integrating DT with digital thread on the software platform through the product manufacturing life cycle. Integration of both IoT and DT can form a closed-loop DT system that can collect processing information and provide its details as a feedback to the manufacturing system throughout the design and manufacturing process. By doing this, product issues or adjustments can be updated at the same time it has been noted, thus making the manufacturing system an autonomous, self-optimizing and intelligent production system through the integrated smart algorithm. As a result, DT cannot only describe the behaviors related to the real system, but can also propose solutions to resolve such issues [68]. However, there is a deficiency of a closed-loop data feedback system that can converge the data between physical and virtual space. Developing a closed-loop DT system is therefore integral, as it can alleviate numerous problems that occur during the printing process.

DT's scope can range from a small manufacturing product or process to a complicated and highly sophisticated production system which provides the required accuracy with the help of smart data analytics. Hence, system architectures must be scalable in nature in problem size function, IT profile as well as the range of viable models with desired capabilities. Although there are basic ideas and components regarding what Digital Twin should do, there is a lack of universal and standardized characteristics of DT [69]. Full potential of DT is yet to be realized due to the lack of standard practices and terminologies which indicates a lack of widely accepted Digital twin framework. This shows that there is a need to have a more scalable and efficient system architecture for the design and development along with the application of DT [70].

Similarly, information sharing is also one of the hurdles in the modern manufacturing industry due to various factors such as culture, company policy, data ownership and so on. Both internal as well as external sharing of data can become a major challenge outside of the DT's engineering and technological complexities. Moreover, the consistency when it comes to sharing data and necessary information between relevant stakeholders among the company's supply chain is also crucial to the validity of DT. Hence, one of the key functionality of DT is also the digitization of the supply chain within a company. However, supply chain's digitization is a complex process due to the considerable amount of effort and time it takes for adequate technological advancement and financial investments [64]. Furthermore, issues related to costs of implementing technologies such as sensors and computational resources along with the necessity of catering to the long term and large scale requirements of big data analytics and AI also poses a hindrance for effective DT development and integration [69].

Wagner et al. proposes that the key future challenge for digital twin will be to define and develop a compatible structure for a comprehensive use of DT across the complete product engineering process due to its need to incorporate production planner concepts and product designers [71]. As different technologies need to be merged together to create a single system DT that meets the specified framework, Odada et al. [41] talks about the need to identify the ideal level of detail for the DT early in the process. Similarly, numerous other challenges such as the price of using different technologies during the design and development phase for the finalized systems as well as the lengthy time period during development are also mentioned in the paper. Also, some other challenges as specified by Bevilacqua et al. are data privacy issues, security related issues and connectivity between the virtual and real system [72]. Along with that, proper management of the real-time data in order to ensure the system is more understandable and the accuracy level of the DT are also some of the challenges. Moreover, integration between the virtual entities involved in the process, ownership of the involved data, technical implementation and the accuracy level of the DT depending on factors such as computational processing power, network speeds and so on are also some of the challenges that implementation of DT for 3D printers may face [13]

Conclusion

3D printing technology along with its implementation in additive manufacturing has established itself as one of the pioneering technologies in the world today. Over the years, the application of 3D printing has successfully contributed towards a collaboration of digitally designed products and a final manufactured product. The 3D printed products are now being manufactured in numerous fields as outlined earlier such as to create models for smart cities, manufacturing industries, healthcare sectors and so on. Together with other fourth industrial revolution concepts such as Internet of Things (IoT), cyber-physical systems, cloud computing and data analytics, 3D printing has been widely adopted for research as well as industrial and business purposes in order to better optimize their product and services.

However, the additive manufacturing industry is still susceptible to imperfect implementation due to an absence of machine driven simulations that can process closed-loop interactions with the printer and produce details on a real time basis when printing. Users are still likely to go through a trial and error method to optimize the printed parts, which often results in a wastage of resources. Any prevalent reasons that may cause printing failure should be addressed beforehand to ensure the process is completed efficiently. While anticipating problems can provide better output, it is not always ideal as issues may arise during the printing process such as changes in temperature resulting in nozzle clogging and warping of printed products.

With the help of Digital Twin, numerous issues that are faced in 3D printing technologies can be resolved. Complications pertaining to printing processes can be understood and solved through DT due to its real-time transfer of data between both virtual as well as physical processes. While the application of Digital Twin has exponentially increased in other industries, in case of 3D printing, DT is still in its infancy. Mostly because for 3D printing, the concept of DT is still abstract as there are no standardizations regarding the notion and application of digital twin in 3D printing. Research is still underway on how to develop a DT that can perform efficiently. For better optimization, sensors and other web based applications such as OctoPrint are currently being used to create a more robust DT platform. Future research should focus on creating an easy-to-use DT for 3D printing that can increase efficiency when printing and provide a real-time closed-loop feedback system between physical and virtual space in order to resolve any errors that arise during the printing process.

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