INVESTIGATION OF DEVELOPING DIGITAL TWIN FOR ADDITIVE MANUFACTURING

Nursultan JYENISKHAN, B.S.

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School of Engineering and Digital Sciences
Department of Mechanical & Aerospace Engineering
Nazarbayev University

53 Kabanbay Batyr Avenue,
Astana, Kazakhstan, 010000

Supervisor: Professor Essam Shehab
Co-supervisor: Assistant Professor Md Hazrat Ali

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DECLARATION

I hereby, declare that this manuscript, entitled "*Investigation of Developing Digital Twin for Additive Manufacturing*", is the result of my own work except for quotations and citations, which have been duly acknowledged.

I also declare that, to the best of my knowledge and belief, it has not been previously or concurrently submitted, in whole or in part, for any other degree or diploma at Nazarbayev University or any other national or intentional institution.

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Name: Nursultan JYENISKHAN

Date: 03.05.2023

ABSTRACT

Additive manufacturing and digital twin concept are both important pillar technologies for fourth industrial revolution. The additive manufacturing method is being appealing by many high-performance industries owing to its ability to produce geometrically challenging parts with traditional manufacturing method. However, there are issues such as final product defects and requirement of human interventions and monitoring during printing processes to avoid time, material, and cost waste with additive manufacturing area.

The main aim of this research is to investigate the developments of digital twin technology for additive manufacturing specifically in fused deposition modeling 3D printers. The main objectives are to develop digital twin architecture and creating digital twin model for FDM printers. Digital twin is virtual model or digital representation of a physical entity, process, or component. Due to the challenges in additive manufacturing field, digital twin technology is considered as one of the possible solutions to fully digitize additive manufacturing processes and solve additive manufacturing problems such as real-time monitoring and controlling, predicting the faults and errors of printers and parts to avoid further waste on time and material, and increase manufacturing efficiency. After developing digital twin framework and architecture to implement, digital twin development is conducted. The main approach used to fulfill this research is to use Raspberry Pi 3B+ to connect FDM printer to OctoPrint, open-source software, to remotely control and monitor. In addition to this, extracting important data from OctoPrint and use them in modeling digital twin of FDM printer and its processes. The developed digital twin for the FDM printer meets its functional requirements such as bidirectional communication between physical and digital models, real-time remotely control and monitoring, and integration of machine learning for leveraging FDM printers to smart manufacturing.

The main key contributions of this study to knowledges are identification of benefits of digital twin implementation in different level, and implementation challenges. The development of the digital twin framework and architectural design are another important key contribution in addition to novel digital twin model of FDM printer with integration of some intelligence level.

Key words: *Additive manufacturing, 3D printing, digital twin, digitalization, real-time monitoring, error prediction, machine learning, digital manufacturing*

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List of Publications

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List of Abbreviations & Symbols

ABS	Acrylonitrile butadiene styrene
AM	Additive Manufacturing
AI	Artificial Intelligence
AR	Augmented Reality
DED	Direct Energy Deposition
DT	Digital Twin
EB-PBF	Electron Beam Powder Bed Fusion
FDM	Fused Deposition Modeling
FFF	Fused Filament Fabrication
GPIO	General Purpose Input/Output
GUI	Graphical User Interface
ICT	Information Communication Technology
IoT	Internet of Things
KPI	Key Performance Indicator
LOM	Laminated Object Manufacturing
L-PBF	Laser Powder Bed Fusion
ML	Machine Learning
PBF	Powder Bed Fusion
PC	Polycarbonate
PCABS	Polycarbonate Acrylonitrile butadiene styrene
PPSF	polyphenyl sulfone
REST API	Representational state transfer application programming interface
SLA	Stereolithography
UV	Ultraviolet
VACCY	Volume Approximation by Cumulated Cylinder
V&V	Verification and Validation
XR	Extended Reality

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1. INTRODUCTION

1.1 Research Background

The robust change and development of industry 4.0 technologies enable digital transformation and applying new business models in various industries [1]. Artificial Intelligence (AI), Internet of Things (IoT), data analytics, additive. Manufacturing (AM), information and communication technologies (ICT), digital twin (DT), and machine learning (ML) are leading technologies areas under the umbrella of industrial 4.0 revolution [2]. Especially additive manufacturing seems appealing and promising technology due to its ability to create highly complicated products that are difficult to construct using traditional manufacturing methods [1], [3].

The manufacturing process known as additive manufacturing, commonly referred to as 3D printing, is the manufacturing method that adds up raw materials by printing in a series of layers until reaching desired or final product from the given data of a model; this is different from traditional manufacturing, also known as subtractive manufacturing [1], [4], [5]. The aerospace industry initially adopted this technology for the rapid prototyping of time-consuming products [6]. The feasibility of 3D printers has been enhanced during the last decades, and industries have used them from aerospace to biomechanics [4]. One approach for digitizing additive manufacturing is using digital twin implementation.

A digital twin (DT) is a replica of an existing physical system that can be controlled and monitored real-time basis with the help of data from installed sensors to physical systems [3], [7]. Even though the digital twin is still in its early stages, its implementation could have advantages (such as improved decision-making process based on real-time data, prediction of the errors in the system and maintenance, and remote control) from implementing DT. However, the challenges and limitations of the technology should not be overlooked when designing DT [7].

1.2 Problem Statement

Digital Twin and additive manufacturing are developing areas within the scope of the fourth industrial revolution. However, there are challenges in both concepts on their own. Additive manufacturing faces challenges such as part defects, real-time monitoring, predictive errors, and process optimization. Moreover, it is overwhelming to control and monitor all printing processes by a human due to its slow and time-consuming manufacturing process. It requires close attention to avoid any cost, material, and time waste to stop the process as soon as the error occurs. Thus, it needs a more sophisticated system of monitoring and controlling, even an automated decision-making mechanism based on available real-time data. According to some researchers, employing the idea of a "digital twin," it is possible. However, it is challenging to implement DT due to its infancy stages in the industry, due to the lack of universally accepted implementation standards and guidance. Thus, this research paper investigates the development of DT implementation for AM and develops the DT framework and architecture to follow.

1.3 Motivation and Scope

The primary motivation of this study is to increase 3D printing efficiency and decrease time, cost, and material waste by digitizing 3D printers. DT implementation provides several benefits, such as real-time monitoring in and outside the manufacturing field, in which workers do not have to spend their whole time on the 3D printing site; instead, they can use their time more effectively on other works. In addition, a defect prediction mechanism of DT based on real-time data from 3D printers could save up a vast amount of resources and eliminate waste. Both industry and academia can benefit from it.

The main scope of this thesis work will be within the frame of a fused deposition modeling (FDM) printer and digital twin. Figure 1 illustrates the scope of this research, in and out of scope.

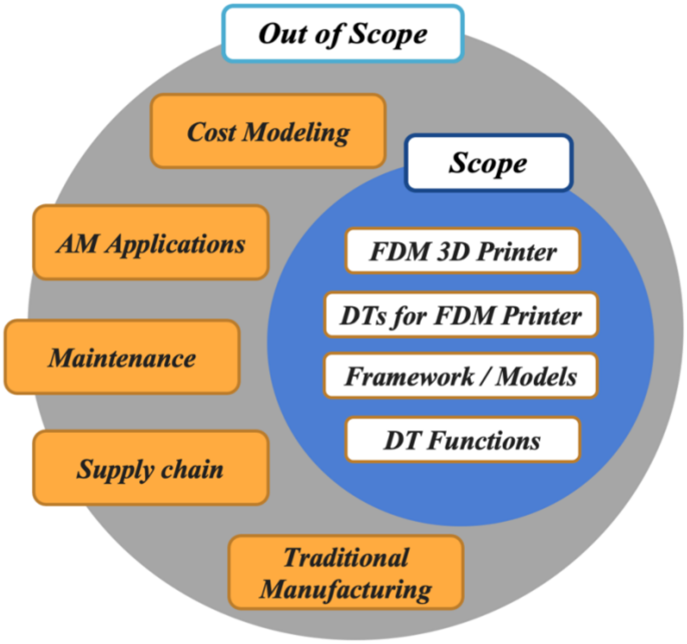


Figure 1. Research Scope

1.4 Aim and Objectives

This research project aims to investigate the development and create a digital twin for fused deposition modeling (FDM) 3D printers. There are four objectives of this study which are to.

1. Identify printing process parameters of FDM 3D printers and their effects on the final product in terms of defects;
2. Develop digital twin framework and implementation architecture for FDM 3D printers;
3. Create a digital twin model for FDM printers;
4. Validate the developed digital twin model.

1.5 Research Questions

The following are the research questions for this research work:

- What are the connections between process parameters and defects? (RQ1)
- What are the challenges and benefits of DT implementation in AM? (RQ2)
- What is the recent development of DT in FDM printers? (RQ3)
- What is the framework for DT development in AM? (RQ4)
- What are the methods and steps of creating DT for AM? (RQ5)

1.6 Thesis Structure

This thesis comprises five chapters. Chapter 2 presents a thorough assessment of the literature. The comprehensive literature is conducted in this chapter based on research questions. Chapter 2 includes a thorough understanding of additive manufacturing and narrowing down the context, understanding digital twins, its potential benefits and implementation challenges, and recent developments in FDM printers. Finally, research gap analysis and conclusion remarks are made.

The adopted research methodology is described in chapter 3, with equipment for the experimental setup. There are four phases in the methodology section of this thesis work. The first phase was the familiarization and understanding of context through literature review. In phase two, narrowed down the context and identified essential data for further development of design architecture. At the third phase, a digital twin was being developed in an FDM printer using an experimental arrangement. The created model was validated in the final phase using through a literature review and experts' judgment.

In chapter 4, development of a digital twin framework, implementation architectural design, and its implementation were presented based on the proposed architecture, and testing and validation of the developed model were conducted. The final chapter describes the discussion, conclusion, and future directions.

2. LITERATURE REVIEW

2.1 Introduction

This chapter presents conducted the literature review to discover recent efforts toward digital twin implementation for additive manufacturing and its implementation challenges. Due to the current rapid growth of digital technology, most industrial organizations now focus primarily on implementing digitalization products and trends in order to develop smart production systems. The industry 4.0 products, such as digital twin (DT), artificial intelligence (AI), data science, augmented reality (AR), blockchain, internet of things (IoT) are being implemented into the production, management, and business processes of organizations as a result of the explosive, quickly expanding, and massive changes.

The literature review areas and their flow of review are shown in Figure 2. Firstly, additive manufacturing field is explored and narrowed it down to fused deposition modeling 3D printing type. Then, important characteristics, process parameters, and defects are explored. After identification of 3D printer to work on, digital twin area is explored and its modeling types. Then, integration or synergies of digital twin and additive manufacturing area is explored and finally, current development in the area of digital twin for FDM 3D printers is explored.

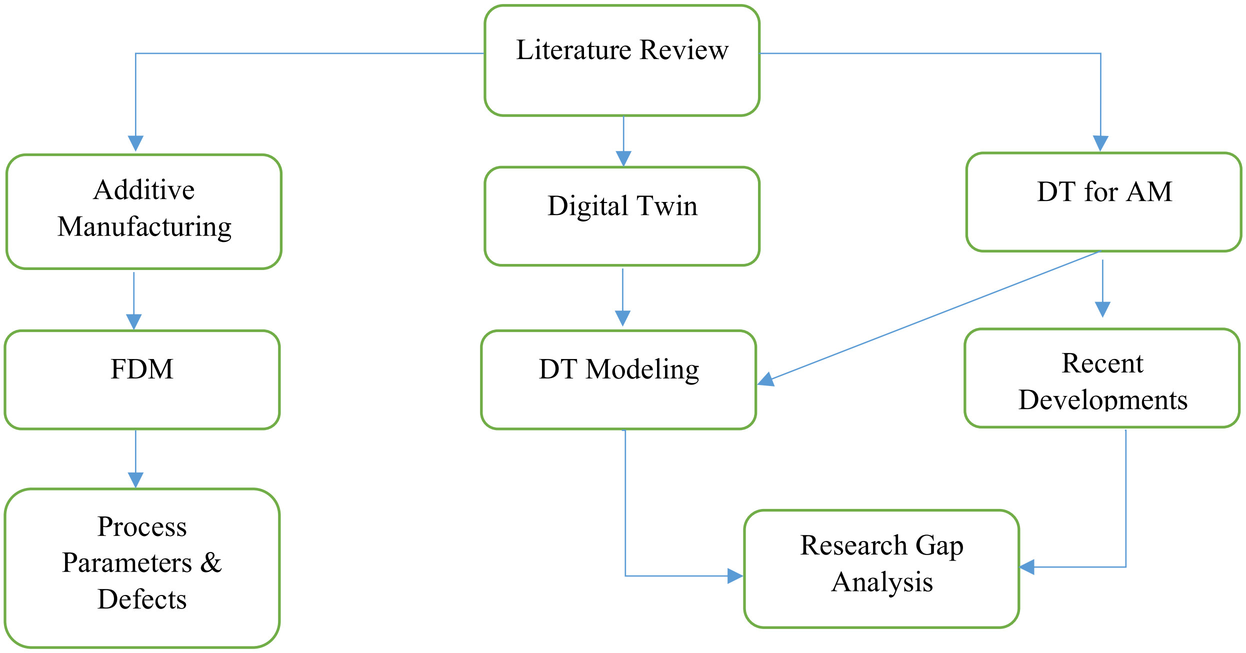


Figure 2. Literature Review Areas

2.2 Additive Manufacturing

2.2.1 Types of Additive Manufacturing

3D printers are categorized into seven common types which are listed below.

- Direct energy deposition (DED)
- Powder bed fusion (PBF)
- Binder jetting
- Stereolithography (SLA)
- Multi jet printing
- Laminated object manufacturing
- Fused filament fabrication (FFF)

Out of seven, there are three common types of 3D printers (PBF, DED, and binder jetting) are mainly used for metal-based component production [1], [8]. In addition to this, laser powder bed fusion (L-PBF) and electron beam powder bed fusion (EB-PBF) are popular types of 3D printers, in the family of powder bed fusion (PBF), and commonly used in the industry of aerospace for metal component production [1], [8].

2.2.1.1 Direct Energy Deposition

Direct energy deposition (DED) technology mostly used for metal-based component production as well as for metal alloys, sometimes it can be used for non-metal production [9], [10]. The working principle of this technology is building components impinging the powder to the melting pool layer by layer by melting powder or wire material (feedstock) from feeding nozzle using electron or laser beams, and arc [8],[9],[10]. The multiaxial flexibility provides creating more complex components with an ease and repair such as airfoils, blades of turbines, engine chambers, and compressors; thus, it is most commonly preferred by aerospace industries [8],[9]. The mechanical and thermophysical properties of produced components by DED technology are slightly differ from powder-fed or wire-fed types and directly affected by process parameters such as post heat treatment, cooling rates and load direction, especially wire-fed laser types [8],[9].

2.2.1.2 Powder Bed Fusion

One of the frequently employed 3D printers for metal-based production is powder bed fusion (PBF) 3D printing, in particularly PBF is commonly used by aerospace industries [8], [9]. Moreover, this technology can be compatible to use with engineering materials such as polymer and ceramics [11]. The working principle of PBF 3D printing is build-up components layer by layer basis by melting metal powder on the bed of the 3D printer [9],[12]. Remaining un-melted metal powder can be used in next layers and become support for structure [9],[12]. Due to its production capability of creating high quality and resolution components, this technology is becoming popular in the manufacturing industries and academia [8],[11]. Typical material for PBF process is the titanium alloys, and this technology has greater ability to create internal passages compared to DED technology [9].

2.2.1.3 Binder Jetting

Binder jetting technology is well-known technology for reliable and quick prototyping and tooling in the fabrication [9]. The mostly used materials in this technology are magnesium, ductile iron, aluminum, stainless steel, and copper alloys [9],[11]. In addition to this, binder jetting is also suitable for polymer and ceramic powders [9],[11]. The working principle of this technology is binding the powder material using binder adhesive between each layer until completing the final product layer by layer [9],[11]. In each layer, layer of powder material is spread over the build platform or previous layer on the platform [9].

2.2.1.4 Stereolithography

Stereolithography (SLA) or vat photopolymerization is one of the additive manufacturing methods of producing components using digital light processing or laser to harden liquid plastic (liquid photopolymer resin) layer by layer [11]. The benefits of this technology are creating 3D objects that is flexible, clear, castable, highly-detailed components, and good quality of surface smoothness [9],[11].

2.2.1.5 Multi Jet Printing

Multi jet printing is also known as polyjet printing and material jetting, that is using same method as inkjet printing technology [11],[13]. The working principle of this technology is curing the jetted liquid of photopolymer droplets into build platform by using UV lamp in layer-by-layer basis [9],[11],[13]. The benefit of this technology is creating very smooth surface, high accuracy components, and prototypes [9].

2.2.1.6 Laminated Object Manufacturing

The working method of laminated object manufacturing (LOM) is using adhesive coated sheet materials, from papers, composites, fabric materials, metallic materials, and synthetic materials, supplied by rolling mechanism [13]. Laser cuts desired shape onto sheet and conveys new un-cut sheet onto cut sheet to bond them together [13]. This process continues until acquire final shape of the component, which means creating component sheet by sheet [13].

2.2.1.7 Fused Deposition Modelling

Fused deposition modelling (FDM) is also known as fused filament fabrication (FFF), or material extrusion, is the most popular 3D printing type in additive manufacturing on the market [9]. The working principle of FDM 3D printer is, extrudes the filament by melting it through movable nozzle onto the build plate [13]. This cycle continues until printing the final shape of the component in layer-by-layer basis [13]. The illustration of working principle is depicted in Figure 3 [14]. Acrylonitrile butadiene styrene (ABS), medical-grade PC, polycarbonate (PC), polyphenyl sulfone (PPSF), PCABS blends, metals, ceramics, and wax are the commonly used materials in material extrusion technology [13].

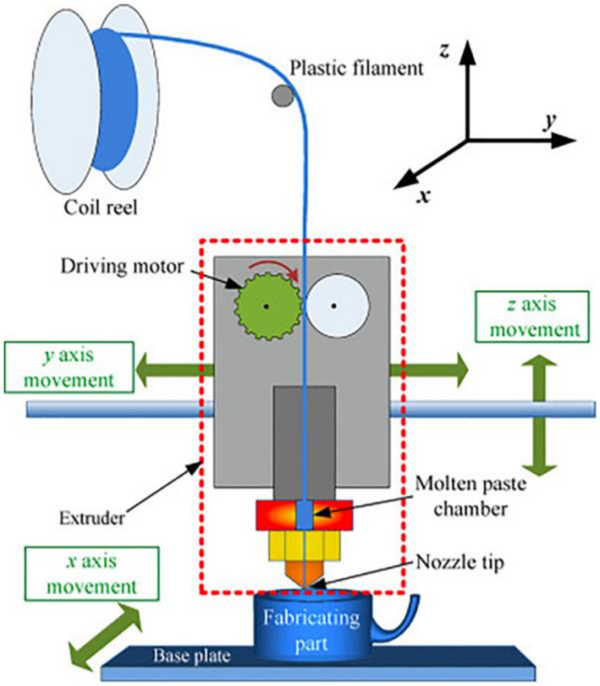


Figure 3. Diagrammatic representation of the principle of working of the FDM processes **[14]**

All seven types of 3D printers are briefly explained, and the illustrations are in Figure 4 [15].

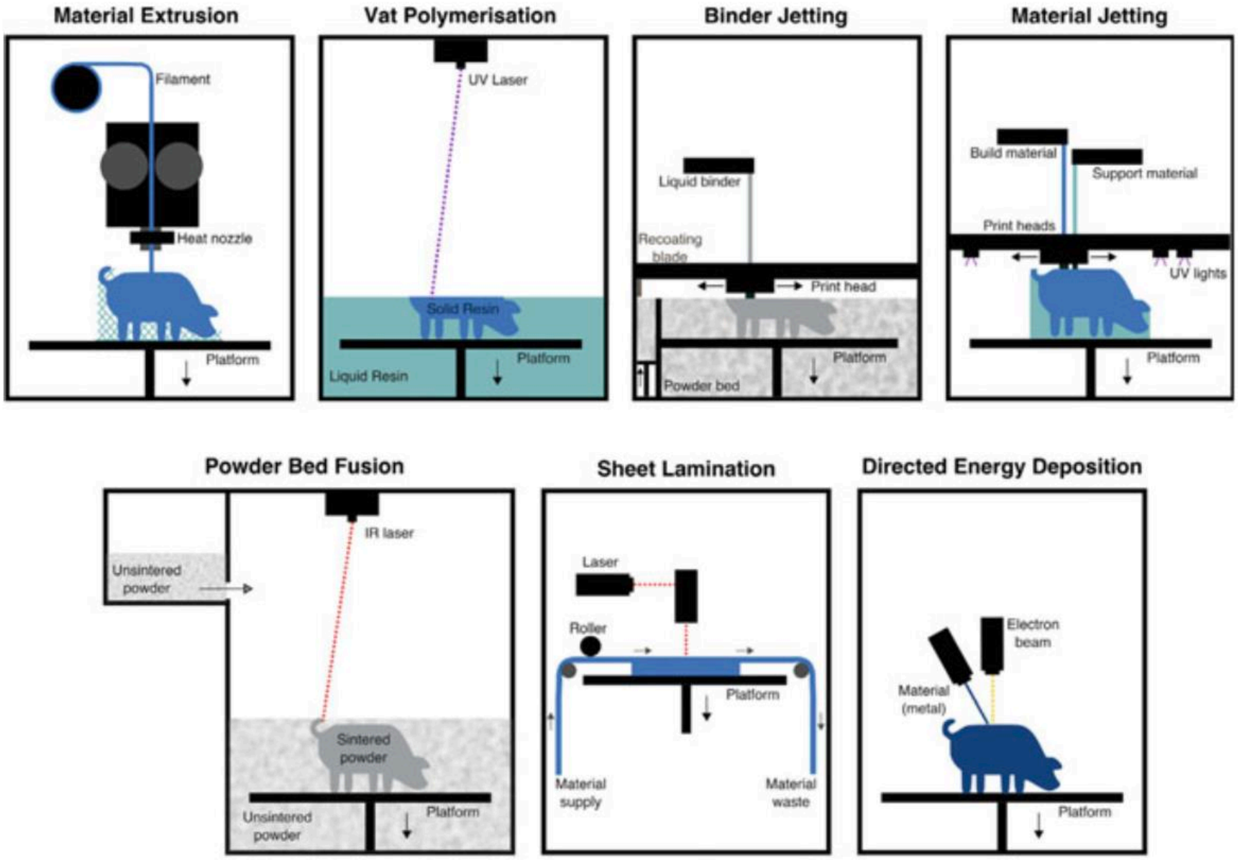


Figure 4. Illustrations of the seven categories of 3D printing Processes [15]

2.2.2 FDM printers: Important parameters and defects

Before discussing about DT, it is important to know and discuss further about FDM printers. 3D printers are being used extensively in wide spectrum in the industries. Among them, the most common type of printing technique is the FDM or FFF 3D printers due to their affordability and usability from consumer to industrial level. There are important process parameters that directly affect the quality of the final product [14], [15], thus it is essential to know effects of parameters to optimize printing processes. The parameters are machine parameters such as build platform temperature, deposition speed, extrusion temperature, build chamber temperature and slicing parameters such as air gap, raster width and orientation, layer thickness, infill shown in Figure 5 [15].

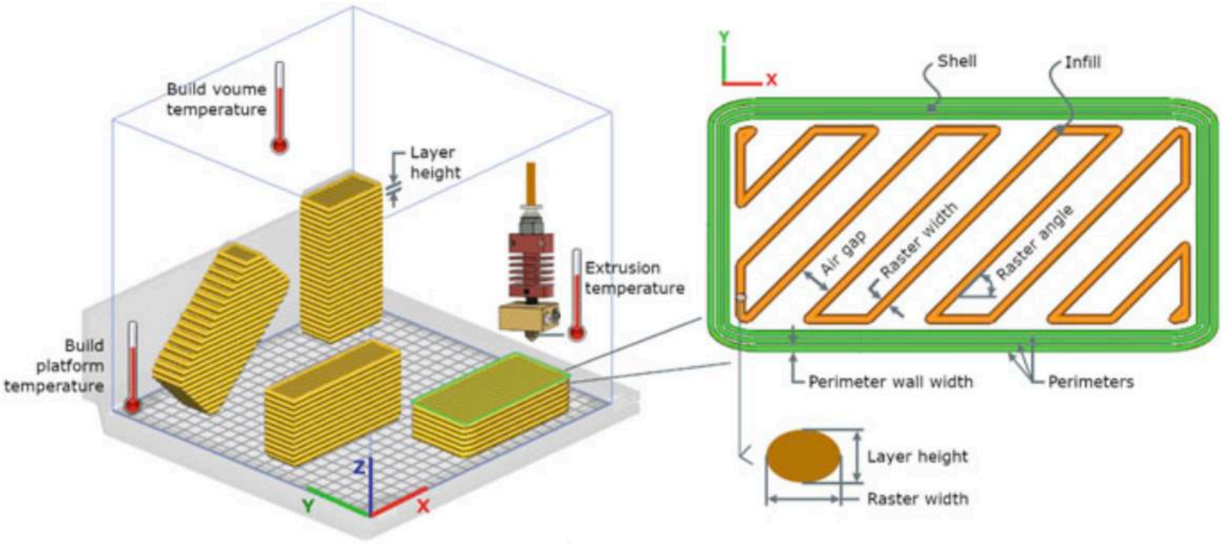


Figure 5. FDM process parameters **[15]**

The process parameters and their explanations are below with the effects on the final product [14], [15].

Extrusion temperature is the temperature of the extrusion which liquifies the filament or material feedstock by heating the extrusion according to the properties of filaments prior to extrude, also can be seen in Figure 5 [15]. The viscosity of the material feedstock is affected by the extrusion temperature which eventually affects the final product characteristics and properties. The temperature increase in extrusion affects the viscosity of the material flow through printer head, increase in mechanical properties as a result of connection strength between layers. Some polymers may leave residue in the printer head due to the degradation of polymers in higher temperature [14]–[16].

Nozzle diameter is the internal diameter of the nozzle which has considerable effects on printing time and proper flow of a semi-liquid filament. There is a positive ratio between diameter size and building time [14], [15]. In Figure 5 [15], it can be seen object orientations in the axis of X, Y, Z in color yellow. Build orientation is one of the main and important parameters for support structure volume and staircase effect which has effects of accuracy on object dimensions, build time, and surface finish on printed objects [15].

Layer thickness is the height of extruded layer depicted in Figure 5 [15], and it is smaller than the diameter of nozzle. Moreover, it is recommended that layer thickness should be 0.25 – 0.8 of a diameter of nozzle. It has effect on build time and surface quality of printed objects.

Decrease in layer thickness produces more precise and good surface quality parts, and enhances the tensile strength, however, increases build time [15], [16]. Unlike layer thickness, raster width is width of deposited layer from the nozzle, and it can also be seen in Figure 5 [15]. The print speed, nozzle diameter, and flow rate affect the raster width, and it has effect on build time in positive proportion [14], [15]. Raster angle is the angle between X-axis and the deposited raster, also shown in Figure 5 [15]. Moreover, same object can be printed with different raster angle and different orientation which create multiple combinations for the same object [14], [15].

In general, FDM 3D printer does not print objects in solid to save material and time, instead it prints inside of the object porously structured. There are many types of infill patterns such as rectilinear, hexagonal, concentric, grid, and triangles to name few. It has effects on strength, flexibility, and printing time [14]–[16]. Infill density is the volume of deposited material into objects to demonstrate how hollow is the printed object. It is shown by percentages by range from 0-100%, which 0% is completely hollow and 100% is solid [14]–[16].

Air gap is the gap between two joining beads, and the value can be zero (beads are in contact), positive (beads are not in contact, there is a gap between beads), and negative (beads are overlapped) for the gap. In the case of positive air gap, the build time decreases, and the object is less dense. In the case of negative air gap, increases printing time and the object is much dense which eventually increases the mechanical properties [14]–[16].

Print speed is the travel speed of nozzle while depositing filaments, and it has opposite correlation with building time. Higher print speed reduces build time and increases dynamic of the printer which could result deformation due to inappropriate motion during printing. On the other hand, lower printer speed increases build time despite fact that lower speed is good choice for greater precision and smoothness on final product [14], [15], [17].

Build platform is the printer bed which plays important role on adhesion of first layer on the platform. It is heated to increase adhesivity prior to printing [15]. As shown in Figure 6 [15], extra printed yellow part is brim in “a” and skirt “b”. Brim is extra area to provide better adhesion and avoid warping defect of printed objects. Unlike brim, skirt is extra thin layer outside the boundary to check the nozzle whether it is printing well or not [15]. These process parameters play crucial role on quality and characteristics of printed parts. It is important to note that there are numbers of desired properties expected from printed parts such as dimensional accuracy, surface roughness, mechanical properties, build time, part geometry, and others. The optimization can be made by using optimum degrees of process parameters. However, there are still issues on correlation and combination of process parameters [16].

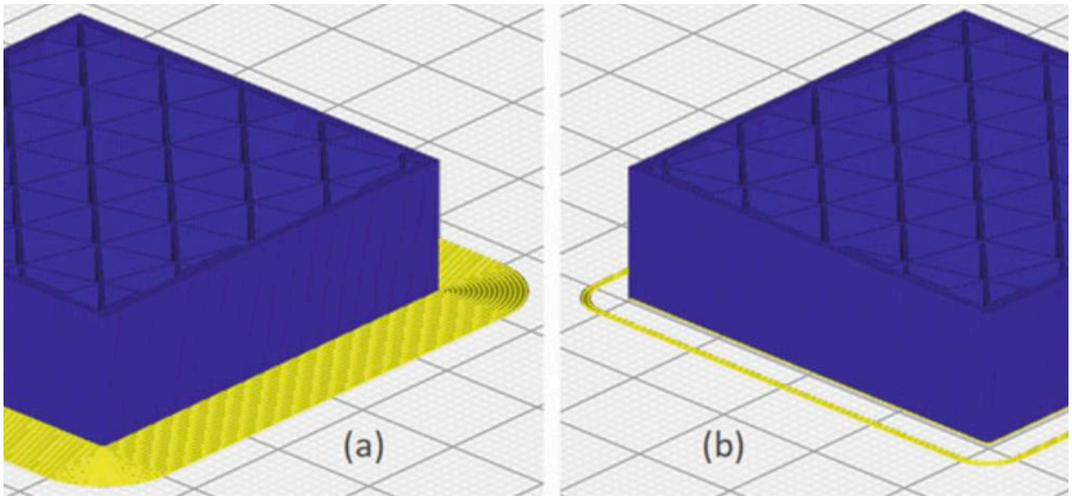


Figure 6. FDM printed part (blue) with a Brim (yellow) b skirt (yellow) **[15]**

In Figure 7 [15], depicted the most common defects in FDM printer. The reason for this defect varies from poor calibration of printers to process parameters. The most commonly encountered defect is warping which is caused by inappropriate cooling rates. Another defect is elephant foot which is caused by nozzle head distance to the printer bed. Layer shifting usually seen in open-loop system printers. Stringing can be solved by choosing appropriate extrusion temperature and proper feedstock retraction settings. Mechanical vibrations usually cause a defect called ringing. It can be minimized by reducing sudden direction change of printhead and reducing print speed. Due to the poor filament quality, mechanical properties, and temperature fluctuation, the z-woobie defect can be spotted. Curling defect is caused high temperature for melt filament to print. Layer separation defect can be seen due to the poor adhesive between layers and inappropriate temperature applied to print and cooling rates [15], [18].

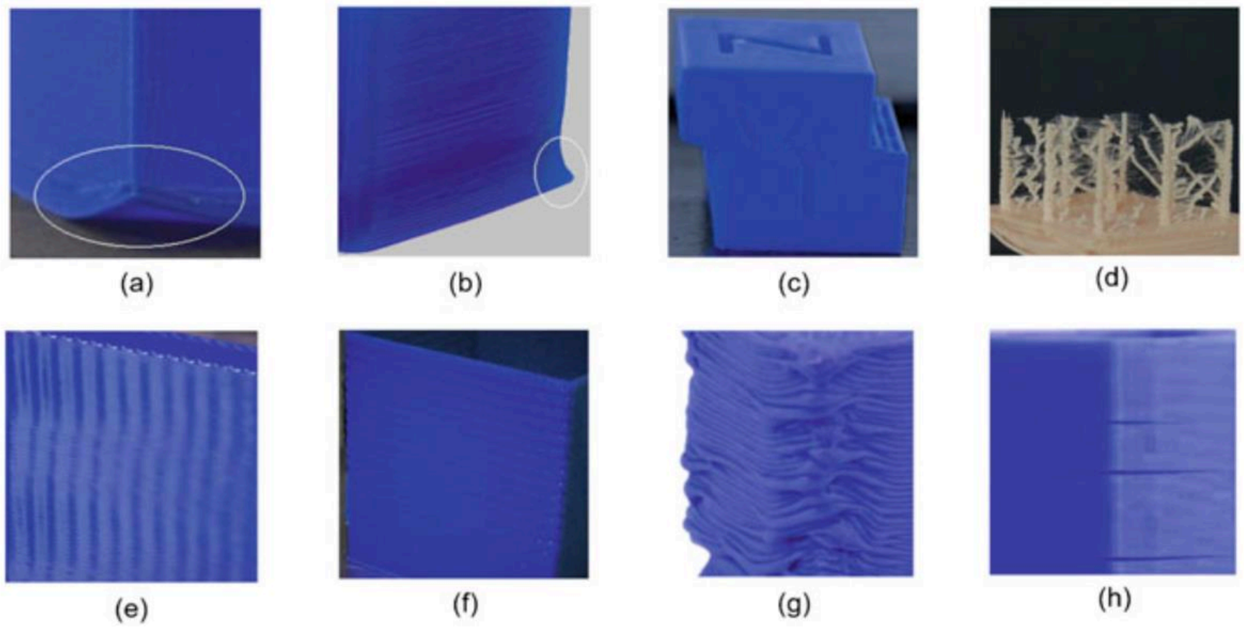


Figure 7. Defects in FDM printed parts, a warping, b elephant's foot, c layer shifting, d stringing, e ringing, f z-wobble, g curling, and h layer separation **[15]**

2.2.3 Benefits and Challenges of Additive Manufacturing

3D printers are appealing option to various industries, especially in aeronautical area due to its ability to produce highly complicated and lightweight products, time and cost-effective modules [19], [20]. Apart from these benefits, AM plays great role in design phase and experimental phase by rapid prototyping for testing cost and time effectively before mass production, as well as rapid tooling according to fabrication needs [4], [9]. On the other hand, most 3D printers are facing challenges such as inadequate mechanical properties of printed products, defects and fatigues of final products, and real-time production process monitoring and management [19], [21]. Researchers such as Scime [5], Wei [10], and Zhang [21] agree on that the use of digital twin may be able to address some of the issues with 3D printers regarding real-time monitoring, reducing or even neglecting trial and error testing process, defect detection of the final products before occurs.

2.3 Understanding Digital Twin

Before discussing about digital twin, it is important to address about digital model and digital shadow to make clear distinction between them. Digital model, shadow, and twin are a digital representation of a physical model. However, digital model is a low-level integration system which is data flow from physical to the digital and digital to the physical is not automated, but manually shown in Figure 8 (a). Digital shadow is one-way automatic and manual, data flow from physical to virtual is automatic, but opposite is manually which is data flow from digital model to physical model is manually shown in Figure 8 (b). A digital twin system is depicted in Figure 8 (c) as a bi-directional automated information transfer between virtual and physical models [22], [23].

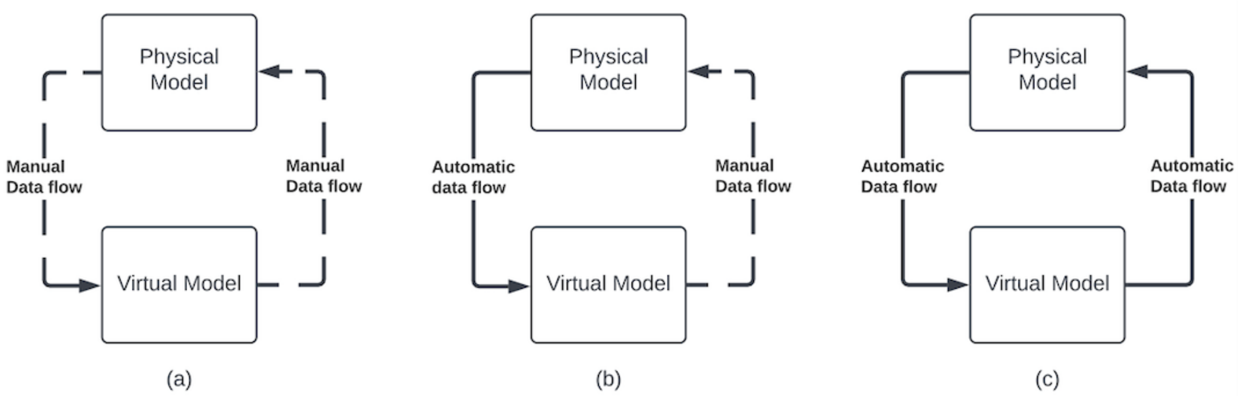


***Figure 8. Digital Model (a), Digital Shadow (b), Digital Twin (c)* [22], [23]**

2.3.1 Digital Twin application areas

It is interesting to note that, the use case of DT is potentially huge in real world starting from assets to factory level, even in entire product-life-cycle [24], [25]. Not only in manufacturing fields, but DT is also useful in health care, education, meteorology, smart cities, smart production and its process technology, energy, and transportation sectors [7]. From the systematic literature review done by Jones and his team [25], they addressed that the majority of the DT use cases are related to manufacturing. Moreover, by gathering big data form every phase of product life cycle provides opportunities to enhance and improve designing and production processes in later cycles [25]. Because DT provides two-way communication among real instance and the digital twin [24],[25].

2.3.2. Digital Twin potential benefits

According to the Oracle report, there are main eight potential benefits of DT, namely [7], [26]:

1. Real-time monitoring and controlling, remotely: DT will make it possible to remotely control using bidirectional communication and real-time monitoring using feedback mechanisms.

2. Increasing efficiency and safety: The full automation of the processes using DT will enable to control robots to use them on dangerous and dirty jobs instead of human with the help of real-time feedback system so humans can concentrate on more innovative and creative jobs.
3. Predictive maintenance and scheduling: Analyzing through big data from multiple sensors, DT will ensure the prediction of faults and smart maintenance scheduling.
4. Scenario and risk assessment: What if analysis through digital asset to make sure of reduction in risk assessment without jeopardizing physical asset.
5. Improved teamwork and collaboration amongst teams: Increased autonomy and DT platform can be accessible by different departments, to ensure better communication among departments and increase productivity on time-consuming collaborations.
6. Effective and well-informed decision support system: The availability of real-time big data will ensure and assist better and quicker decision-making process.
7. Individualization of goods and services: Increasing privatization and customization of the products in the market, DT will ensure smoother and quicker shifts for shifting needs.
8. Improved documentation and communication: Availability of real-time data and automated reporting mechanism will provide improved transparency for stakeholders.

2.3.3 Digital Twin potential challenges

There are numbers of challenges that should be addressed and studied to overcome challenges or issues in DT. One of the main parts of the DT is the big data, which huge amount of data are gathered from multiple sensors. Multi-source data could lead an issue of processing different types of data which leads to interoperability challenge, and data storage challenge due to the huge volume size which eventually leads to security and reliability challenges. Even though the large amount of data brings benefits across product life cycle, there is a still challenge because of silo effects. It leads to information sharing challenge in DT. The complexity of supply chain, level of parameters and required technology standards, and computational ability lead to scalability and indistinguishability challenge in DT technology [7], [27], [28].

2.4 Digital Twin for Additive Manufacturing

Digital twin and additive manufacturing are important technologies of intelligent manufacturing systems [29]. However, there is a lack or gap between additive manufacturing techniques and intelligent manufacturing [30]. This gap can be fulfilled by digital twin technology [31]. In addition to this, it is time and material consuming process to fabricate items with acceptable mechanical properties via 3D printers, and expensive due to the trial-and-error process of the 3D printers [32]. Moreover, structural integrity and quality of fabricated items' surface defects are controversial topics [17], [32]. In order to tackle these issues, some researchers agree on DT technology potentially solve 3D printers are facing [32] and even improvements in process performances [33]. In order to achieve this, there are pillar technologies for complete DT as shown in Figure 9 [32].

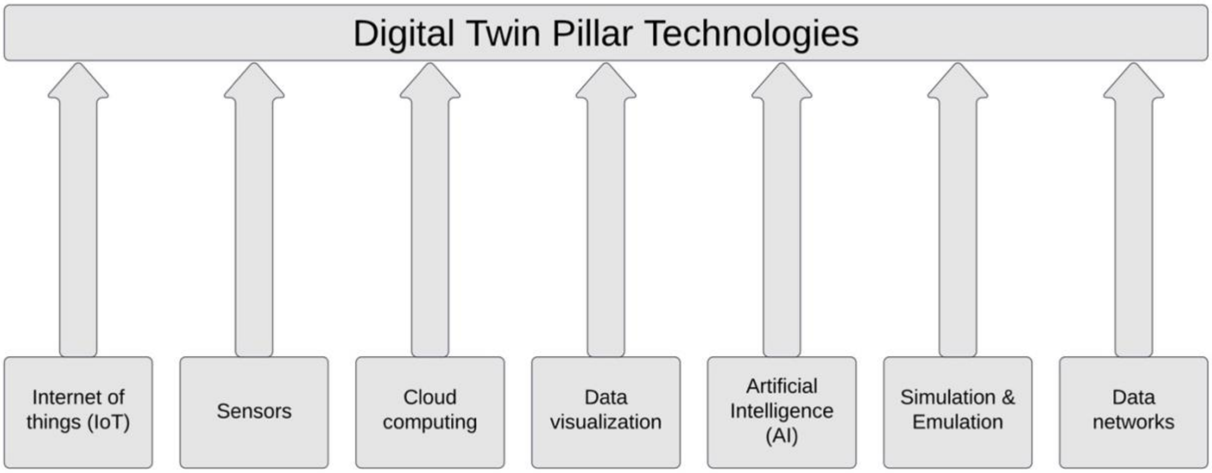


Figure 9. Digital twin pillar technologies **[32]**

2.4.1 Expected Solutions

DT has many benefits among all industries related to human activity such as automotive sector, shipping, industrial production, and in the livestock, etc. [32]. Potential benefits of this technology in additive manufacturing field are considered as reducing trial and error expenses, reducing defects, predicting possible outcomes of manufacturing processes, and real-time monitoring of manufacturing equipment and processes [17], [34]. On the other hand, potential challenges come along DT implementation challenges such as big data from multiple sources and sensors to be processed, software inputs, precise digital representations along entire processes, model complexity due to the elevated input sensors for machine learning, communication latency, human interaction and role in DT, lack of research outcomes on sustainability, and there is no universally accepted standardized model or reference model [24], [32].

2.4.2 Digital Twin Modeling Types

DT system is very complex and diverse topic in both industry and academia. There are some requirements to fully acquire digital twin, however it is challenging to do so. Despite the challenges, there are researchers and academicians trying to apply digital twin concept in every area.

The main and the most important requirement is having bidirectional communication between physical and digital object to make real-time decision for engineering management. Ideal DT should be indistinguishable from real part in terms of behavior and appearance. Moreover, it has ability to real-time monitoring, predicting future condition by analyzing real-time data, optimization in processes based on feedback and data, and predict the maintenance schedule based on machine data from sensors.

There are different types of models and approaches proposed for digital twin implementation. Kantaros et al. 2022 [32], discussed in their paper about grey box model using it for prediction [32]. Lu et al. 2020 [24] stated model that contains three main components which are information model for DT, two communication mechanism, and data processing [24]. In addition to this, Rasheed et al. 2020 [7], also stated about physic-based modeling (experimental modeling, three dimensional 3D modeling, high fidelity numerical simulators), data-driven modeling (data generation, data processing management and ownership, data privacy and ethical issues, machine learning and AI), and Big data cybernetics (data assimilation, reduced order modeling, hardware and software in the loop, other hybridization techniques, physics informed machine learning, and compressed sensing and symbolic regression) [7].

2.4.3 Digital Twin Implementation Methodology

Hyre et al., (2022) and Osho et al. (2022) propose the 4Rs methodology for digital twin implementation [35], [36].

1. Representation: Virtual representation of a model that is fed with real-time data, their visualization and analysis
2. Replication: Use data to create virtual system and ensure credibility of the system
3. Reality: Artificial Intelligence (AI), extended reality (XR) to enhance visualization of a model, using machine learning to predict

4. Relational: Decision making process based on implementation from Reality, and obtain bi-directional communication

Apart from modeling types and implementation methodology, it is important to identify which level of digital twin will be implemented. There are three levels of digital twin for additive manufacturing [37], [38].

1. Factory level digital twin: This type of DT is focused on modeling entire manufacturing process and machines including supply chain to monitor, control, and plan production tasks.
2. Machine level digital twin: This type of DT is focused on modeling single machine and its operation status to control and monitor build type and time, temperature, and others of one task
3. Process level digital twin: This type of DT is focused more on micro-scale of 3D printers to control, monitor, diagnosis, and predict process performance or final product failures.

The important level of DT is machine-level digital twin which is a key bridge between factory and process-level digital twin [37], [38].

2.4.4 Potential key benefits of implementing DT in FDM printers

Implementing digital twins brings key benefits to the industry and adds value to businesses. There are potential benefits of digital twin implementation at different levels, as shown in**Error! Reference source not found.**. The level of benefits varies from the micro-to macro-scale. For example, process monitoring in machine-level DT is a printing parameter in process-level product mechanical and thermal properties at the micro scale, but in factory-level DT, it is a production task at the macro scale.

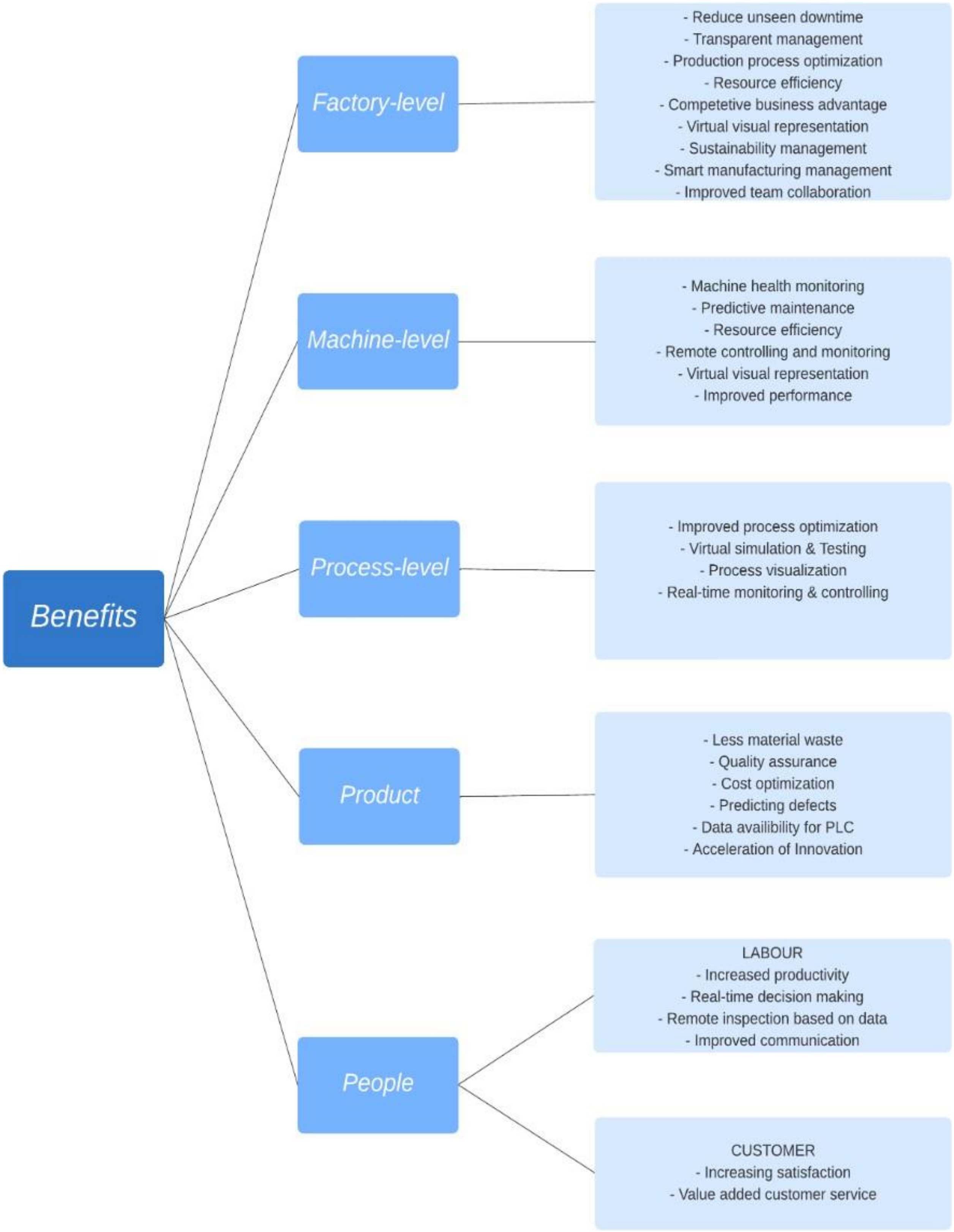


Figure 10. Benefits of Digital Twin in different levels

Implementing a digital twin enables smart manufacturing and can be accessed in real time by different departments. Thus, it improves team collaboration and business competitiveness in the industry. The main benefits of the digital twin at the factory level are the effective production processes management with the help of big data and predicting the maintenance of machines before errors occur that may result in downtime. In addition to this, as a result of analyzing big data, the digital twin can find the necessary parameters to be optimized and determine KPIs – key performance indicators to optimize and minimize energy usage so the system can operate in optimal conditions [7], [23], [26], [37], [39], [40].

Little research has been conducted on machine-level digital twins. However, the potential benefits include monitoring and improving the key performances and resources of 3D printers to allow the machine to operate efficiently. Moreover, the machine-level digital twin significantly links the factor-and process-level digital twins. Process-level digital twins allow monitoring and control of the mechanical and thermal properties of final products. The key benefits are resource efficiency, decreased waste, and prediction of defects that may occur in a final product by analyzing big data, improved documentation, and data availability for product lifecycle management. Digital twin technology provides increased productivity, a real-time decision-making process, and better communication among employers from different departments and administrators. Through the availability of big data, digital twin provides high-value customer services and increase customer satisfaction [7], [23], [26], [37], [39]–[41].

2.4.5 Digital twin implementation challenges in AM

The identification of these challenges was through a narrative literature review. Identifying and understanding these obstacles would contribute to the digitalization of the additive manufacturing industry. Identified challenges are crucial areas for further research, investigation, and recommendations to overcome and approach one step closer to fully operable digital twins and smart additive manufacturing. In Figure 11, eight key challenges categories of digital twin technology implementation are illustrated. In the following section, challenges will be discussed in a more detailed manner.

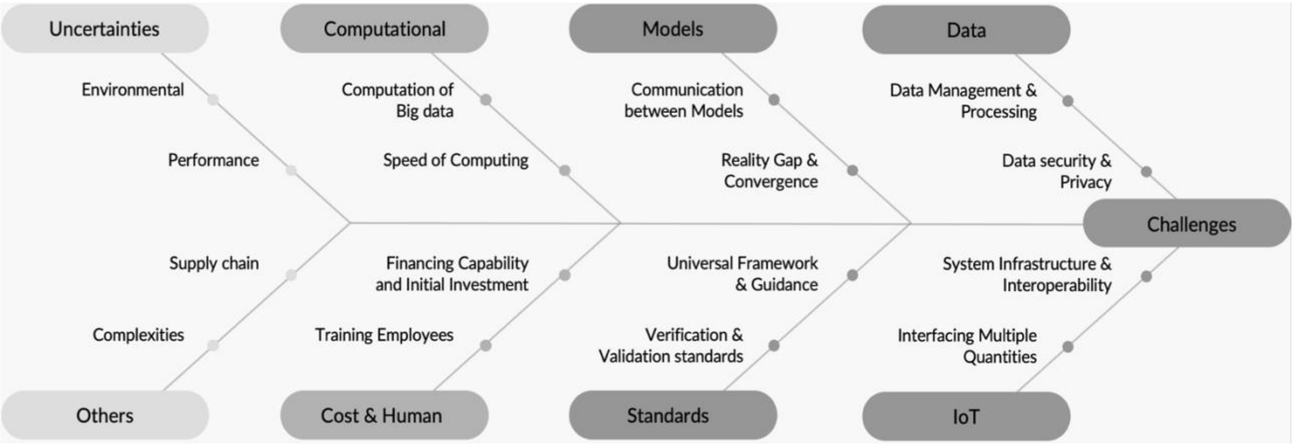


Figure 11. Challenges of Digital Twin implementation for AMs

There are eight categories of digital twin implementation challenges are identified as shown in Figure 11. In this section, detailed key challenges and sub-challenges will be explained in a detailed manner.

In Table 1, it can be seen data-related challenges. The fundamental need for complete digital twin implementation for additive manufacturing is big data. However, receiving and storing, processing and managing, and transferring these data between models are challenging. Feeding the system with real-time data, at the same time, processing and managing real-time data are also among data-related challenges due to different data formats from different sensors and low-quality data [22], [31], [32], [35], [37], [43], [44].

Table 1. Data-related challenges

Closed-loop data feedback deficient [31], [33]	Data sharing [31]
Data privacy [22], [31], [42]	Data security [22], [31]
Real-time data processing [31], [43]	Real-time data management [31], [43]
Data transfer [37]	Bidirectional data flow [33]
Big data [22], [32]	Data management [35]
IT infrastructure [22]	Data acquisition and storage [44]
Lack of material properties data [40]	Data quality [45]

Security and privacy of these data are also concerning aspects of data-related challenges. Thus, IT infrastructure plays a great role to manage these issues. It is costly to construct such a system, so cloud service is aa preferable option which comes with concerns of privacy and security [22], [31],

[42]. Two-way communication between physical and virtual models is an essential part of digital twin implementation. Due to the deficiency of closed-loop data feedback is still a challenging topic to solve the bidirectional communication challenge between additive manufacturing machines and mirrored twins in the digital environment [31], [33].

In Table 2, challenges regarding virtual and physical models are stated. As mentioned before, communication among models is significant to implement a fully functional digital twin. The main challenges are the communication among models, communication latency, reality gap, and integration of different technologies that work in a harmony [22], [24], [36], [37], [42], [45] More virtual and physical models converge, more digital twin model gets close to real-time monitoring with minimal data exchange latency [46].

Table 2. Models-related challenges

Reality gap [37]	Communication between models [22]
System integration [42], [45]	Interoperability [42]
Communication latency [24], [36]	Convergence between models [46]

In Table 3, digital twin implementation standardization challenges are listed. Lack of universally following guidance, framework, standardized characteristics and principles, and digital model make it more challenging to create a widely accepted digital twin to implement [31], [33], [35]. Moreover, it is also challenging to verify and validate the digital twin model with real-world experimental data and standards [35], [40].

***Table 3*. Standardization challenges**

Generic DT model [33]	Universal standardized DT characteristics [31]
Standardization principles [32]	Compatible structure for comprehensive use [31]
Universal guidance [35]	Widely accepted DT framework [31]
Experimental data for validation [40]	Verification & Validation standards [35]

In Table 4, challenges regarding IoTs are listed. IoT is one of the most important pillar technologies of digital twin implementation. However, challenges regarding IoTs are the lack of in-built sensors in some additive manufacturing machines, extra sensors required to gather data from physical instances, connectivity, IoT and cloud integration, merging of different technologies and their interoperability, and interfacing multiple quantities [22], [32], [33], [44], [47]. All those challenges can be partially solved by an appropriate IoT and IT infrastructure which can be costly.

Table 4. Internet of Things (IoT) - related challenges

IoT & Cloud platform integration [33], [43]	System interoperability[32]
Infrastructure [22]	Connectivity [22]
Lack of built-in sensors for historical data [47]	Difficulties in linking codes [40]
Non-intrusive sensor position [47]	Interfacing multiple quantities [44]

It is also a question of willingness to spend money on this technology, training employees according to need, and concerns of performance and return on investment. These are challenges concerning cost and human [22], [23], [31], [32], [43] shown in Table 5.

***Table 5*. Finance and Human related challenges**

Cost [31], [43]	Training [32]
Financing capabilities [32]	Expensive [23]

In addition to this, big data and complex infrastructure require high computational power, time, and speed for the digital twin model to operate in optimum conditions. Moreover, training machine learning and AI model needs high computational power and speed to process and analyze data to predict future behaviors of manufacturing processes and products to avoid time, cost, and material wastage [21], [33], [37], [40]. These are the computational challenges of digital twin implementation in additive layer manufacturing shown in Table 6.

***Table 6*. Computation challenges**

Computational power [37]	Computational time [33]
Computational errors [33]	Computation of Big data [21], [40]
Speed of computing [40]	AI model training computer power [21], [40]

Other than the previously mentioned challenges, there are other challenges and uncertainties, listed in Table 7, of digital twin implementation in the additive manufacturing industry. It is interesting that all listed challenges regarding digital twin implementation including uncertainties are important and interconnected with each other. Thus, it is crucial to overcome these challenges to acquire a more functional, operable, standardized, and affordable digital twin.

Table 7. **Computation challenges**

System integration & infrastructure [48]	Organizational [45]
Environmental [45]	Performance [45]
Supply chain [48]	Transition challenge [49]
Security [45]	Industry & academia partnership [40]
Uncertainties [23]	Complexities [35]

2.5 Recent Development of DT implementation in FDM printers

One of the big challenges for implementing digital twin for FDM 3D printers is the lack of universally accepted and applied implementation method [32]. Thus, there are different approaches for digital implementation. The following state-of-the-art studies are in least to most successful digital twin order.

Delli & Chang (2018) propose automated process of detecting defects of a printed parts based on a supervised machine learning algorithm which classifies all the printed parts into “good” and “defected”. They used single camera to take pictures (top view) of a part at certain stages during the printing process. Then applied image process technique to identify the part is defected or not [50].

Another interesting study by Henson et al. 2021, used digital twin strategy to spot part distortion while printing to avoid further material and time waste. They used three cameras to capture the pictures of printed objects (side views) while the part is printing. They faced challenges to shot pictures during printing process due to the continuously movement of printer bed. They developed an algorithm to shot pictures simultaneously from three different views from side when printer bed movement is stopped. They used this approach in certain stages during the printing process, and they used an algorithm to create 3D picture by using three pictures from different angels. Finally, the system automatically compares the 3D picture created from camera shots with 3D CAD models to identify whether there is a distortion or not as shown in Figure 12. Two out of three are successfully spotted the distortion in the experiment, and remaining one detected after short time [51].

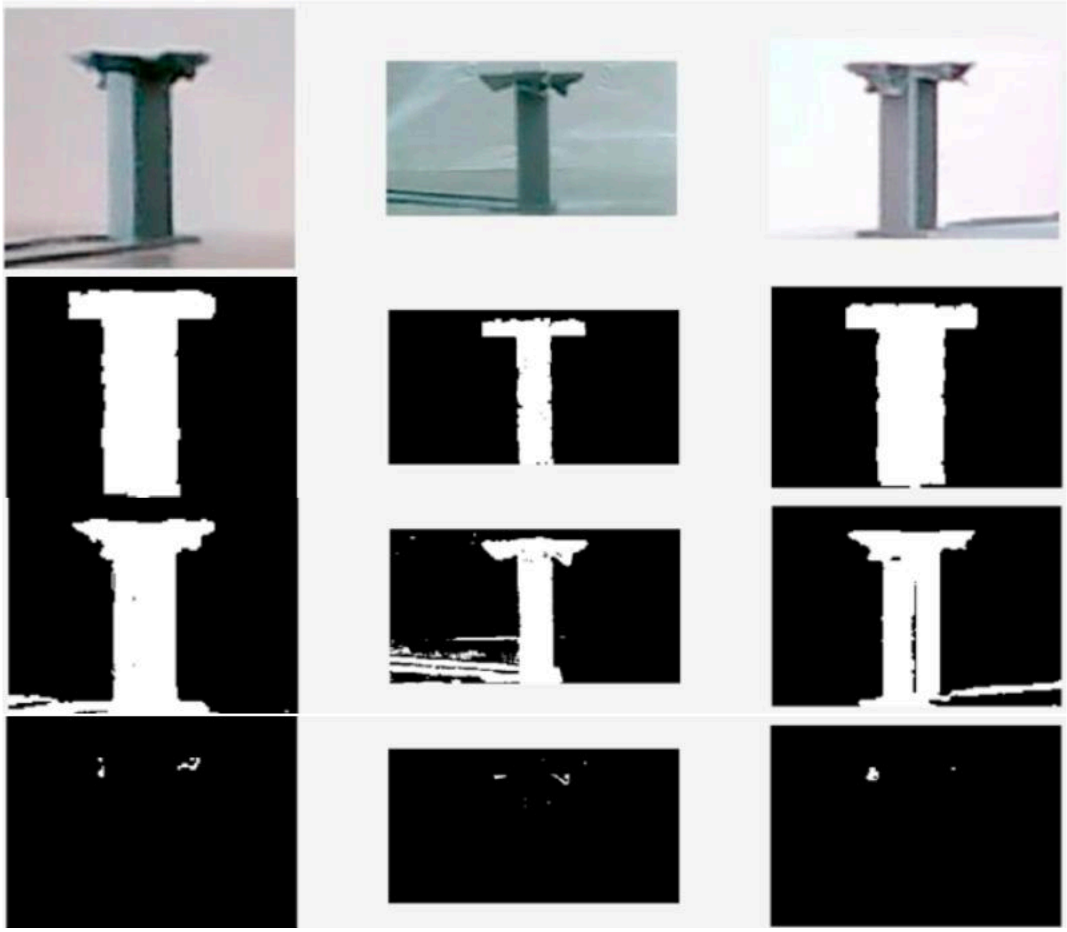
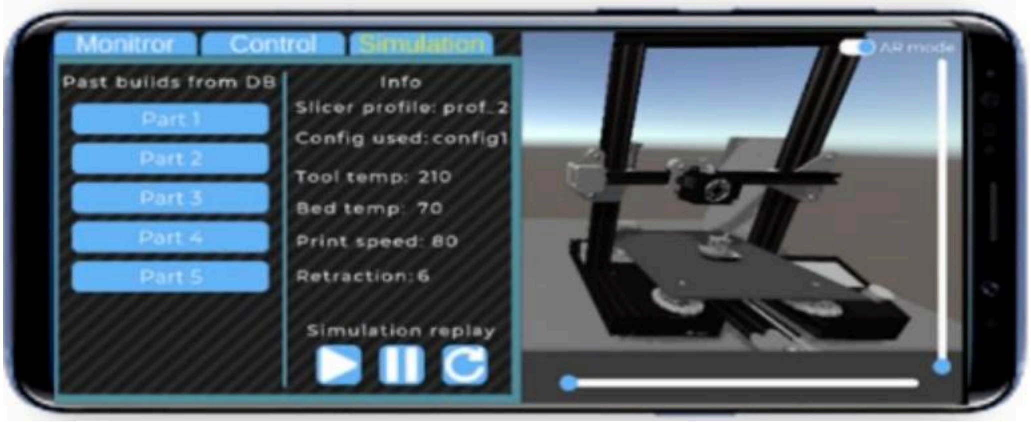


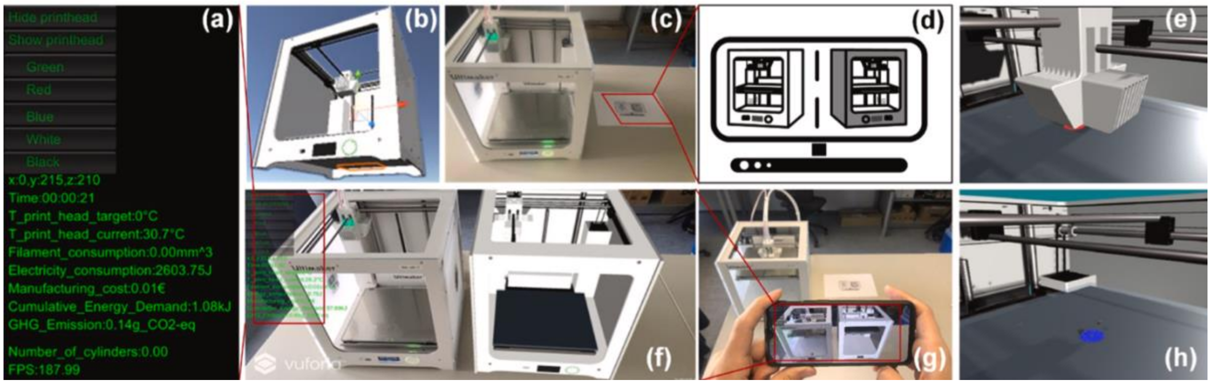
Figure 12. Top: Captured images 100th layer. Top-Middle: Ground-truth image 100th layer. Bottom-Middle: In-situ image 100th layer. Bottom: Comparison image 100th layer. [51]

Mourtzis et al., (2021), Yi et al., (2021), and Paripooranan et al., (2021) are used augmented reality (AR) in their digital twin implementation for FDM printers [17], [37], [52]. In the experiment done by Mourtzis et al., (2021), they used AR approach as shown in Figure 13, to have better idea on 3D printing processes and evaluating previous data and image that stored in cloud data base to minimize errors of printing. Without this approach, printer prints 4 faulty objects out of ten. After using this approach the faulty objects number fell to two from four out of ten [17]. Unlike Moutzis et al. (2021), Yi et al. (2021), proposed machine-level digital twin using augmented reality. They monitor electricity use, manufacturing cost, greenhouse gas emission, and energy consumption in addition to predicting printed part in digital environment as shown in Figure 14 (a). In terms of printed part, they used Volume Approximation by Cumulated Cylinder (VACCY) mathematical equation approach approximate the printed parts volume. For shape, they used current and target positions of nozzle or extruder to define its shape [37]. In the Paripooranan et al. 2020 [52] study, they successfully developed AR enabled DT for 3D printing. They used various types of software and microcontrollers to create virtual 3D printer with user friendly interface. Most of the machine parameters of the printer can be seen on the android device and can be controlled with limited functionality [52].



Slicer profile: prof_2
Config used: config1
Tool temp: 210
Bed temp: 70
Print speed: 80
Retraction: 6

Figure 13. Augmented Reality Graphical User Interface on smart device [17]



```
x:0,y:215,z:210
Time:00:00:21
T_print_head_target:0°C
T_print_head_current:30.7°C
Filament_consumption:0.00mm^3
Electricity_consumption:2603.75J
Manufacturing_cost:0.01€
Cumulative_Energy_Demand:1.08kJ
GHG_Emission:0.14g_CO2-eq

Number_of_cylinders:0.00
FPS:187.99
```

Figure 14 Overview of the developed AR-based digital twin: (a). Process parameters and indicators; (b). Digital twin in virtual environment; (c). Ultimaker 3 in the real environment; (d). Activation image; (e). Printing process with the printing head shown; (f). Ultimaker 3 and the digital twin in AR application; (g). AR application using mobile phone; (h). Printing process with printing head hidden **[37]**

Odada et al. (2021) and Pantelidakis et al. (2022) are developed same approach which is data-driven digital twin but used different components and approaches to create digital twin for FDM printers [43], [53]. Odada and the team (2021), used optical rotary encoders to detect and track the exact position of extruder and the printer bed in XYZ axis. For middleware, they used Modbus server for gathering position data reading from encoders installed to the physical printer through Arduino mega microcontroller. Then they created virtual 3D printer via Siemens NX software, and it receives position data through OPC-DA server which scans every 10miliseconds of Modbus server and send data to the Siemens NX to mimic physical movement of extruder and printer bed digitally. They concluded their study that it is possible to mimic 3D printer and its movements in a real-time manner, however there is a lag issue to be solved [43]. On the other hand, Pantelidakis and team (2022), developed digital twin ecosystem with two approaches and combination of them. First approach is by using web-controlled data driven digital twin. Second approach is by installing external sensors into physical FDM printer. The team digitalized the FDM printer and gathered data from sensors in the printer and external sensors. They used IR distance sensors for defining extruder and bed positions in XYZ axis. By using data from sensors, the virtual printer does almost exact same movement with physical printer. They concluded their study by stating that they achieved high accuracy, near real-time [53].

Guo et al. (2021) and team, used cloud-edge collaborative system to create digital twin for FDM printer. There are three layers in their system which are device layer, edge layer, and cloud layer. Device layers consist of FDM printers and additional sensors to gather additional data. Edge layer is consisting of edge application, edge data processing, and edge transmission which primary goal is to process data flow from device and send it to cloud edge. Cloud edge is consist of cloud data processing and cloud applications to visualize and show the current status of the FDM printers [54].

Stavropoulos et al. (2021) propose almost same approach or architecture with previously mentioned researchers for digital twin implementation on FDM printers, but used different devices, middleware, and sensors to collect data and process them. They used Dewesoft X software for data acquisition and monitoring, DAQ as a hardware as shown in Figure 15 [55]. In addition to this, Chhetri et al. (2019), added different types of machine learning algorithms to predict and detect the anomality on the printed product using data from IR, thermocouple, accelerometer and borescope sensors. Anomalities ranging from build failure detection to dimension of a printed parts. The experimental setup for this study is in Figure 16 [47].

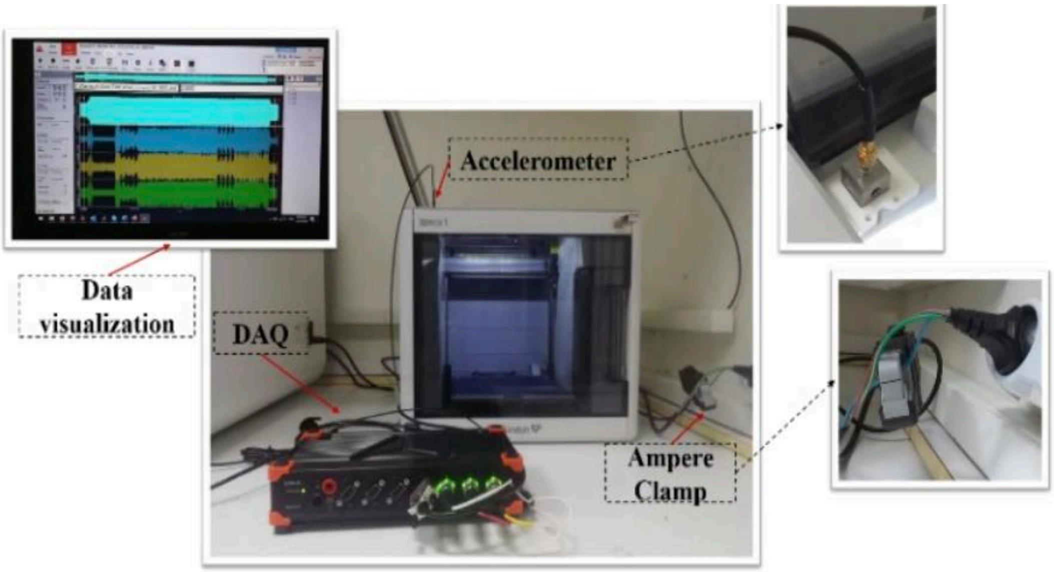


Figure 15. Test bench **[55]**

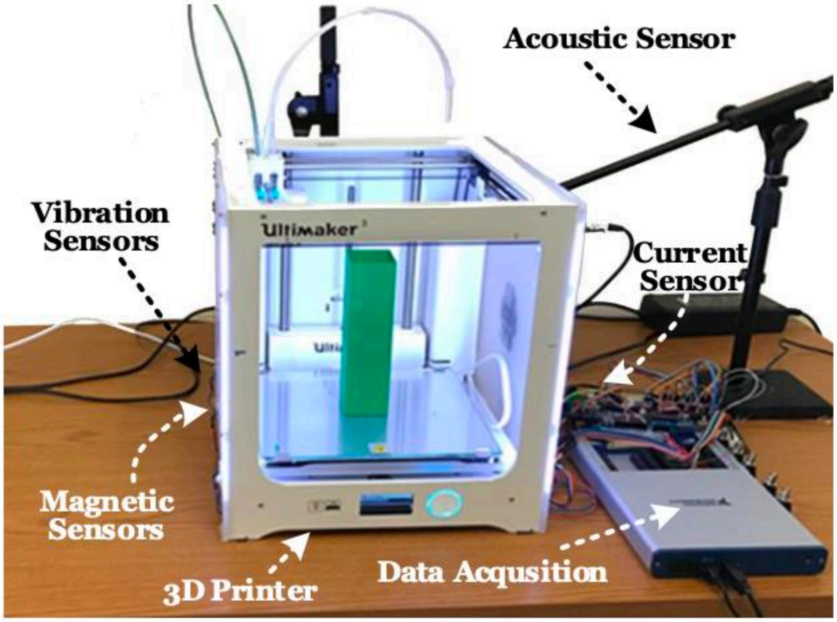


Figure 16. Experimental setup for modeling the digital twin **[47]**

Corradini & Sivestri (2022) are created more sophisticated and functional digital twin for a FDM printer using opensource software such as Octoprint to monitor and control the printing processes and status remotely. The main aim of their study is to digitally twin the printed part and compare it to understand whether there is error or defects on real part. CloudCompare opensource software to compare digital model with simulated model indicating the limits with color from blue to red. In addition to this, they used several sensors for detecting temperatures and positions of nozzle, printer bed, in XYZ and E0 (direct drive type extruder) axis [26].

2.6 Machine Learning

Machine learning (ML) is an integral part of the digital twin for making predictions based on data, explained in the “Reality” category of the 4Rs methodology mentioned in [35], [36]. ML is an unavoidable part of digital twin technology because of its ability to analyze what-ifs, make predictions, and reduce human interventions [36], [56]. The machine learning explanation is in [57] a “set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty.” ML has three areas: supervised, unsupervised, and reinforced learning [56], [57].

Supervised learning uses available labeled data to train machine learning models and uses these models to make predictions. Many algorithms are commonly used: decision trees, neural networks, logistic regression, and support vectors under two categories of regression and classification algorithms [56], [57]. Unlike supervised learning, unsupervised learning uses unlabeled data for training without human intervention, not for prediction, but for grouping and classification. Reinforcement learning is a method for training an ML model using trial-and-error processes. The ML model receives punishments or rewards based on its actions [56], [57].

In FDM processes, decision trees and other methods are used for surface roughness prediction in [58], which appears to have sufficiently high prediction. In the study conducted by Li et al. (2019), various supervised algorithms were used to predict surface roughness. Different ML algorithms have different accuracies [59]. Another study conducted by Jin et al. (2019) concluded that the ML model accurately predicted the part quality, and the feedback loop optimized the printing parameters of the FDM printer iteratively [60]. Another exciting study used experimental data to train an ML model, and as a result, the model performed with 95% accuracy in predicting the tensile strengths of a printed part [61]. In Sandhu et al. 2019 study, a pre-trained model with experimental data can detect the geometrical anomalies of a printed part with minimal error [62]. Even trained ML models can propose optimum printing parameters to increase the quality of a printed part based on the parameter settings, geometry, and location [63]. Finally, the study by Kadam et al. 2021 showed that pre-trained offline ML could be implemented for fault detection in real-time processes of FDM printers with minimal or affordable computing and experimental costs [64].

It can be seen from these studies that ML models play significant roles in predicting the errors, quality, and mechanical properties of printed parts. In addition, ML models can be trained offline using experimental data, and can be used as an online tool for real-time fault detection in FDM printers. This also reduces human intervention during printing. Thus, ML models are an indispensable part of digital twins, not only for FDM printers, but also for all manufacturing processes.

2.7 Research Gap Analysis

There are variety of studies regarding digital twin model, digital twin implementation, and digital twin for additive manufacturing in the literature. However, there is a lack of universal architecture to follow. There are different methods and approaches to achieve digital twin for additive manufacturing used by several researchers. The approaches are almost same, using different equipment. The main limitations in the literature are not addressing implementation challenges, very limited functional digital twin models, and excessive use of sensors, equipment and software. Some studies are focused on digital twin of additive manufacturing process, or digital twin of a machine, FDM printer. There is lack of sophisticated digital twin model and architecture for FDM printer. Additionally, there is a lack of universally guided methodology for creating a digital twin for additive manufacturing. Thus, recent research works by other researchers differ from each other. This research work concentrated on developing a practical digital twin implementation method for FDM printers.

3. RESEARCH METHODOLOGY

3.1 Introduction

This chapter provides a detailed research methodology, hardware and software requirements in order to develop the digital twin for FDM printers. The adopted research methodology for this research study has four main phases and the identification of required components and software are selected according to their accessibility, usability, performance, and cost.

3.2 Research Methodology

The detailed methodology of this research project comprises four phases, as shown in Figure 17. The first phase focused on literature review separately for AM, DT, and DT for AM to get familiarization regarding the context. After getting familiar with the context, the researcher selected an appropriate additive manufacturing type and reviewed it further to identify important process parameters and defect types.

The second phase of the methodology focused on identifying the challenges of a digital twin for additive manufacturing and capturing important elements and practices from the literature review. Then, develop a high-level architecture for digital twin implementation. At the same time, phases 1 and 2 covers objectives 1 and 2 of this research study.

The third phase of this study is to identify the required resources, such as hardware and software, for experimental setup for creating a digital twin for an FDM printer. For example, Linux, Octoprint open-source software, and more. In addition, identification of sensors for measuring essential parameters of the 3D printers and then training machine learning models for defect detection of particular geometry from printed parts. In this research case, the printing part is a hollow cube regardless of its dimensions.

The last phase is to create a minimum viable DT for AM by integrating all software into one platform and running the developed digital twin. After creating DT, it is crucial to observe how the digital twin works and how accurately the trained machine learning model predicts the defects of printing parts. Moreover, it is necessary to acquire bidirectional communication between digital and virtual models. Finally, validate the developed architecture and model through a literature review and expert judgments from academia. Phases 3 and 4 aimed to achieve objectives 3 and 4 of this research study.

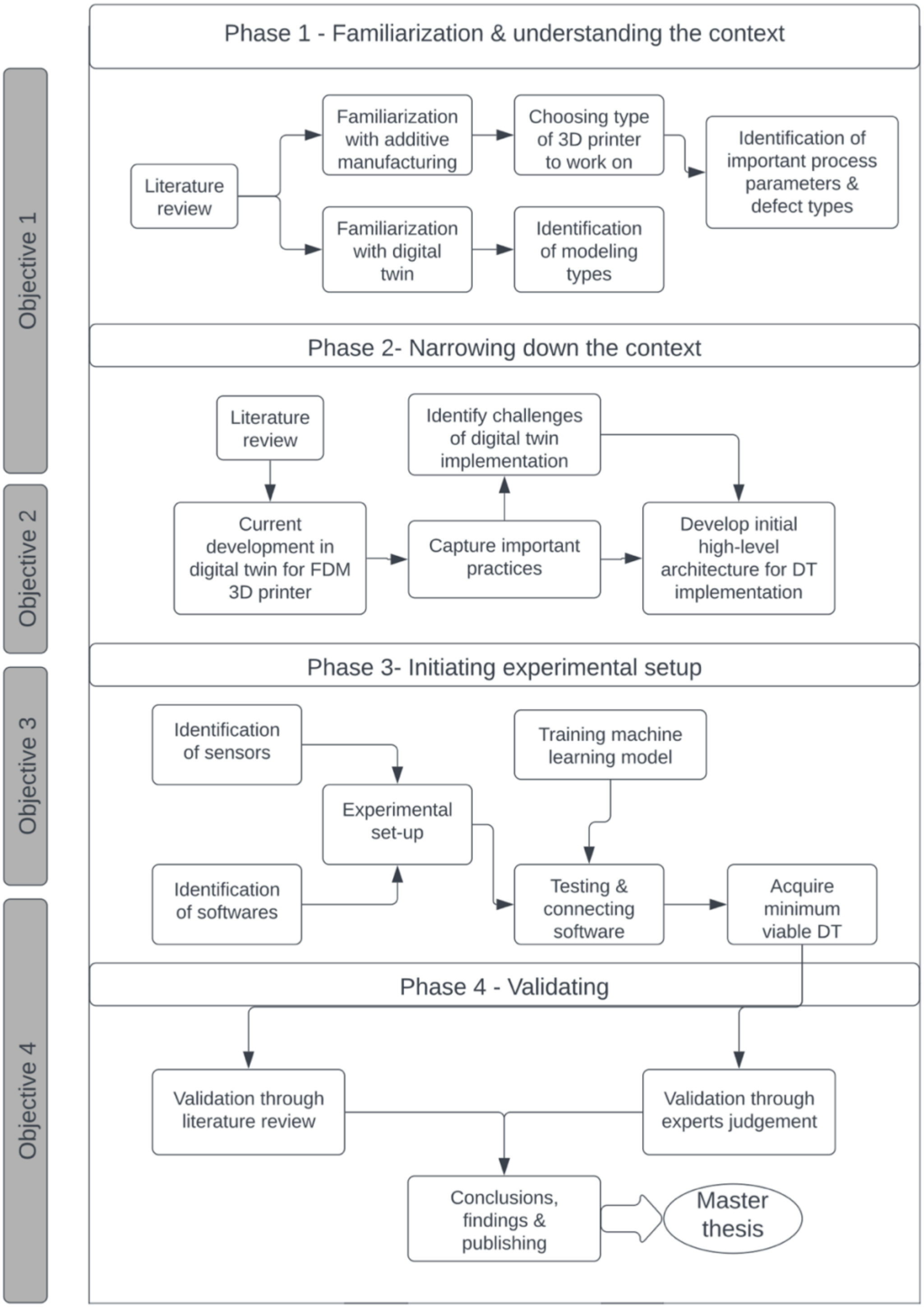


Figure 17. Research Methodology

3.3 Methodology for Digital Twin Implementation

There is a lack of universally accepted guideline for digital twin implementation for additive manufacturing. However, from the comprehensive literature review, it can be observed that most researchers' approaches were almost the same. They used various external sensors to gather data and feed the model with real-time data. Generally, the digital model was created in the unity client platform for visually appealing, and some other researchers have used data visualization on other platforms. Considering all these methods, the two different methods are developed for the data-gathering process in digital twin implementation.

1. Using various types of sensors for gathering data
2. Using in-built sensors for gathering data (use external sensors if necessary)

In this research study, option two was selected due to its benefits in reducing complexity and cost in the whole system. Because it is well-known that one of the challenges of digital twin implementation is system complexity and their interoperability. The list of required components for this research study is in the next section of this chapter, and design implementations will be explained in detail in chapter 4.

3.4 Hardware and Software

There are important hardware and software for the experimental setup to develop a digital twin for this research. The FDM printer is a physical object of the intended digital twin in this situation. The FDM printer's built-in sensors can be used to retrieve all of its data, which can then be sent to a digital twin via the data channel. The digital twin refers to a digital representation of a real-world FDM printer. It can take the form of a CAD file or data visualization that can be seen and operated via an augmented reality platform. Most crucially, a data route should be used to feed digital twins with real-time data from actual FDM printers. In order for physical and digital models to communicate with one another, middleware is by far the most important component. The key point is data channel needs to be trustworthy and effective. Because, there are distinct sorts of data from different sensors and protocols to be processed effectively. Moreover, middleware takes data from the physical model, delivers it to the digital model, and processes it concurrently. One of the most crucial roles of the digital twin is bidirectional communication mechanism between models. After evaluating the data, the digital twin then sends a command to the physical model in accordance with the decisions made based on the outcome of data processing. All the required hardware and software list is in Table 8.

Table 8. List of main components

Name	Description
InterPrint i3 FDM Printer	- It is a model of the Prusa i3 FDM-based 3D printer manufactured in Kazakhstan. - The working area is 200x200x200mm - The printing speed is 80mm/s - Printing materials are PLA, ABS, HIPS, and FLEX - OS is Repetier-Host, Cura - The nozzle diameter is 0.4mm
Raspberry Pi 3B+	- Microcomputer - 1GB RAM - 1.4GHz quad-core ARMv8 64bit processor - 32GB SD Card storage
Raspberry Pi 4B	- Microcomputer - 4GB RAM - 2.4 GHz quad-core 64bit - 32GB Storage SD Card
Monitor	HP desktop monitor
Keyboard	Fujitsu regular keyboard
Mouse	Regular mouse
Logitech Webcam Camera	Regular webcam camera
Chair Lamp	Regular chair lamp

In this research, InterPrint i3 FDM printer is selected, as shown in Figure 18, which hosts software for this particular 3D printer, the Repetier – Host. To make this FDM printer remotely accessible and controllable, an additional microcontroller is needed. Hence, the Raspberry Pi 3B is chosen as the microcontroller, as shown in Figure 19. Raspberry Pi is a single-chip computer with general-purpose input/output (GPIO) to explore the internet of things (IoT) and manipulate electronic components. A monitor, keyboard, and mouse are required apart from the microcontroller. A chair lamp and a Logitech camera are also chosen, as seen in Figure 20. In order to identify geometrical defects, the camera process the real-time video and image data with pre-trained machine-learning model. It is difficult to take high-quality photos because of the continuously moving printer bed and the inadequate lighting. Hence, it can be done more effective with the aid of additional light.

Octoprint, the open-source web-based software written in Python to remotely monitor and control the FDM 3D printers, is selected as the software. In terms of user customization, that is possible because it is an open-source platform. The Octopi image and Octoprint software were launched on the Raspberry Pi to make the 3D printer available for requests. Octoprint also has a REST.API is a set of guidelines that specify how to connect and interact between apps and devices. Octoprint is a simple-to-use web-based appication with a variety of useful plugins. Another Raspberry Pi is required to run machine learning algorithms. Due to the challenges mentioned in Chapter 2, such as system interoperability and computing challenges, two Raspberry Pi and two cameras are used in this research.

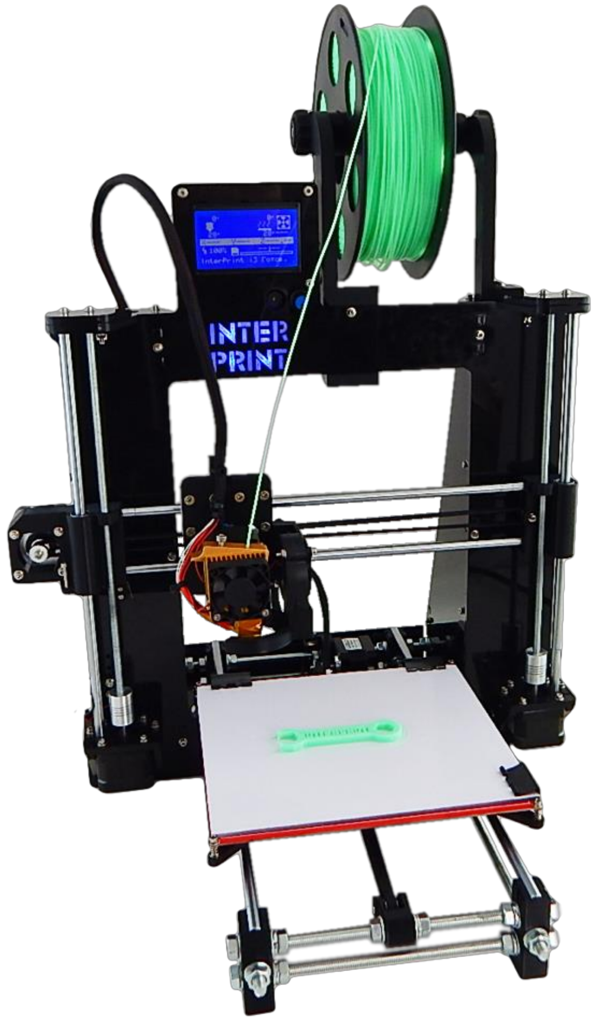


Figure 18. InterPrint i3 FDM Printer

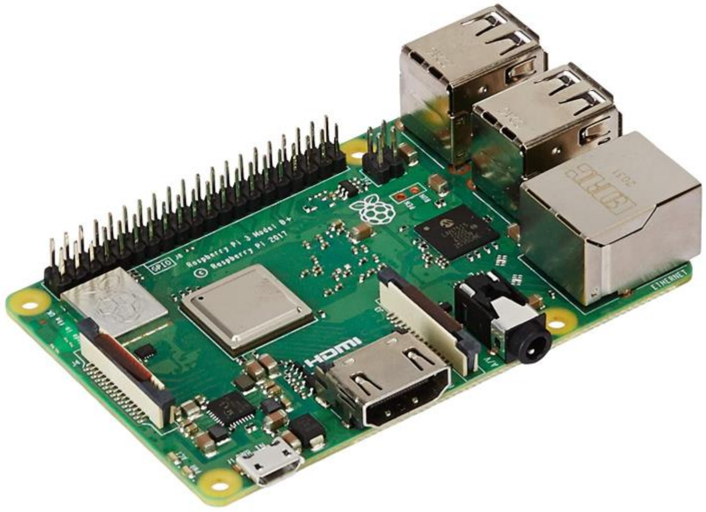


Figure 19. Raspberry Pi 3 Model B+

Figure 20. Logitech Web Camera

Finally, an additional thermocouple, as shown in Figure 21, and Arduino UNO, as shown in Figure 22 and Table 9, to measure bed and nozzle temperature to compare these data with data from the digital twin model so how much reality gap between physical and digital model.

Table 9. List of additional components

Name	Description
Arduino UNO	Microcontroller
MAX6675 Thermocouple	A temperature sensor that is compatible with sensing high temperature

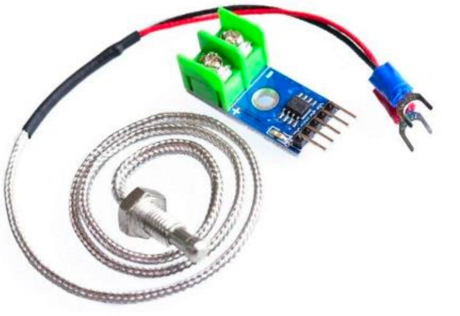


Figure 21. Thermocouple

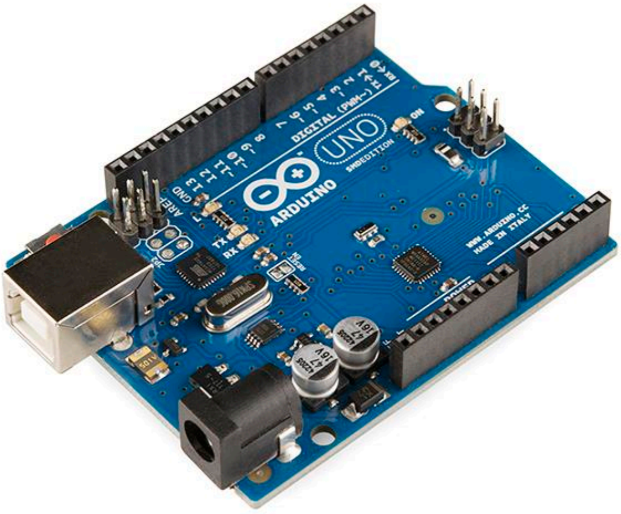


Figure 22. Arduino Uno

The printing part for this research case is the cube, regardless of its dimensions but limited to the working area of the printer, as shown in Figure 23. The infill for this cube is set to 10%.

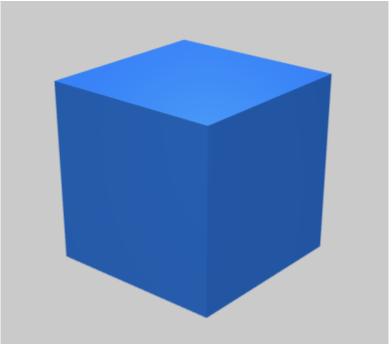


Figure 23. Cube for printing

4. DEVELOPMENT AND IMPLEMENTATION OF DIGITAL TWIN FRAMEWORK

4.1 Introduction

This chapter addresses the development stage of the digital twin and its design implementation stages in details. The design implementation stages consist of development of digital twin framework and its architectural design, and workflow of the digital twin model. Finally, the verification and validation of the developed digital twin model.

4.2 Digital Twin Development Stages

This research proposes a detailed process to design a digital twin through eight main steps, as shown in Figure 24. There are three groups in these eight steps of creating the digital twin. The first group (steps 1-4) develops base components for the digital twin. The second group (step 4&5) is for establishing a connection and upgrading the developed digital twin. The third group (step 6&7) is for acceptance of developed digital twin through verification and validation by literature review and Professors.

The first step is a significant step to understand what a digital twin is and define what functions of the digital twin will be used in the final product. In this research, three main functions are defined, such as real-time monitoring and controlling, a certain level of intelligence integration, and two-way communication between physical and digital models. As a second step, the development of architecture and framework based on the defined functions of the digital twin. The third step is the research and analysis of alternative hardware and software for creating the digital twin. After selecting appropriate components and software, building or creating a digital model for the digital twin in step four. It can be in the form of 3D, 2D, data visualization, and text form. The initial digital twin in this research work was in text form, and it can be upgraded to data visualization or 3D visualization for an appealing appearance to users. The connection between hardware and software is made in step five. Establishing a proper connection and satisfying bidirectional communication between physical and digital models is a significant step. Once step five is completed, we can achieve already minimum viable digital twin. In step six, the developed digital twin can be upgraded by adding machine learning models and can be upgraded to different visualization forms. However, it is important to remember that more systems and system integrations lead to more complexity, system interoperability, and computational burden challenges discussed in Chapter 2. The first six steps are enough to create a functional digital twin. After the first six steps, it is important to verify and validate the developed digital twin through literature review and Professors. An important question to be answered for verification is “Does this developed digital twin system work properly?” and for validation is “Does this developed digital twin system meet its requirements?”

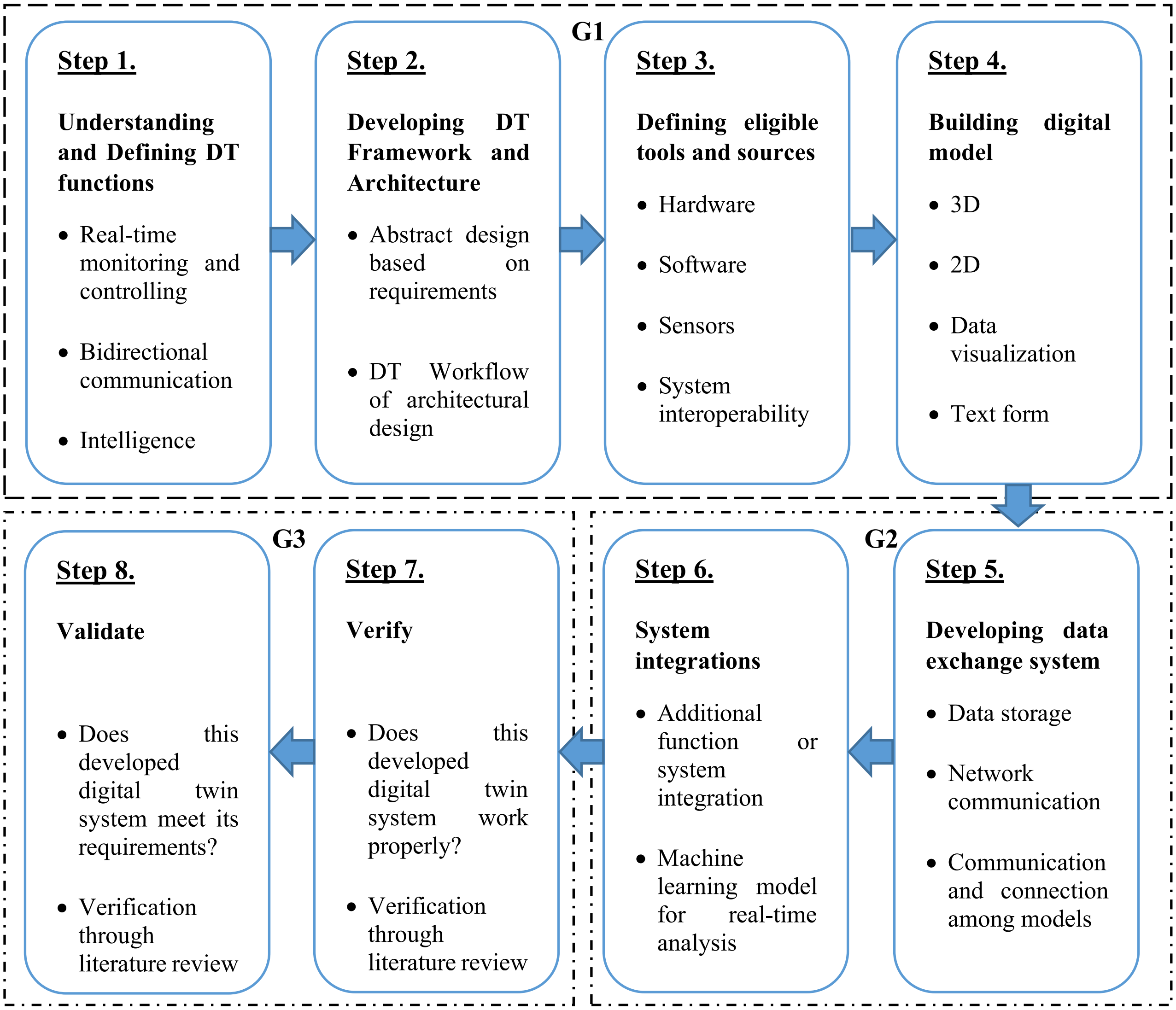


Figure 24. The proposed process to design a digital twin

4.3 Development of Digital Twin Framework for FDM Printers

Based on the requirements and functions of a digital twin, the following digital twin framework is developed, as shown in Figure 25. The framework consists of three main layers physical device layer, the data layer, and the digital model layer. In the physical layer, there are FDM printers, in-built sensors already within the printer, camera, and additional sensors. The camera is for visually monitoring the printing process remotely. Additional sensors gather data from the printer besides in-built sensors to measure the final outcomes and identify the reality gap.

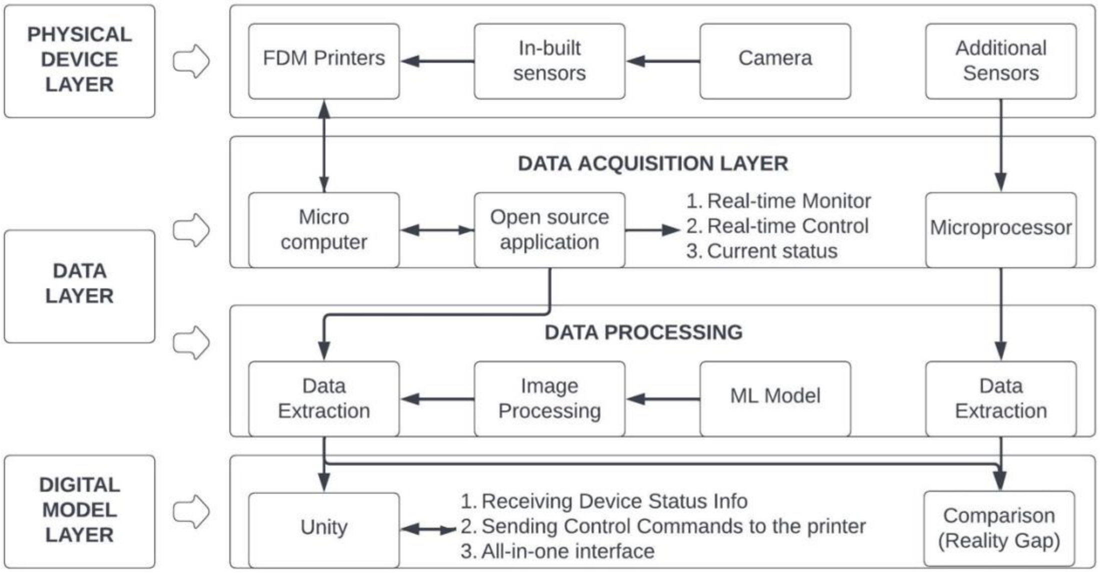


Figure 25. Digital Twin Framework for FDM printers

The second layer is the data layer, which consists of two sub-layers data acquisition layer and a data processing layer. The data acquisition layer is important for gathering data from the FDM printer's in-built sensors and attached camera. This process can be done using an open-source application compatible with the printer. The monitoring and controlling FDM printers through open-source applications are possible by using a microcomputer bridging between the physical printer and open-source application. After acquiring data, it is important to process them. All extracted data from the physical FDM printer should be sent to the digital model layer. Before sending them, the machine learning model plays a significant role in analyzing image data and identifying whether there are defects or not via image processing. If there is no defect, the machine learning model does not interfere with or notify the system. If there is a defect identification, it sends a signal to the digital model layer to inform there is a defect to avoid additional time, material, and cost waste. However, humans should interfere in this research case. Also, it can be done further coding and development to neglect human intervention in the entire system.

The unity client is an essential part of the digital model layer. Because all the real-time monitoring and controlling process of the 3D printer is in the unity client user interface, which makes it an intelligent additive manufacturing machine. One of the main requirements and functionalities of digital twins is intelligence. Thus, integrating remotely controlling and monitoring the printing process in real-time with machine learning provides a minimum viable digital twin model for FDM printers. Finally, the reality gap between the physical and digital models can be measured by comparing the outcomes of in-built and additional sensors.

4.4 Development of Digital Twin Implementation Architectural Design and its Workflow for FDM printers

Understanding and developing the architectural design for digital twin implementation in FDM printers is crucial, as shown in Figure 26 and its workflow in Figure 27. When designing the architecture of digital twin implementation for FDM printers, ideas and integrations from various studies in this area, industrial applications, and personal experience are adopted.

Considering all inputs from literature, the digital twin framework, and recent developments, the following architecture in Figure 26 is designed to implement the digital twin in FDM printers.

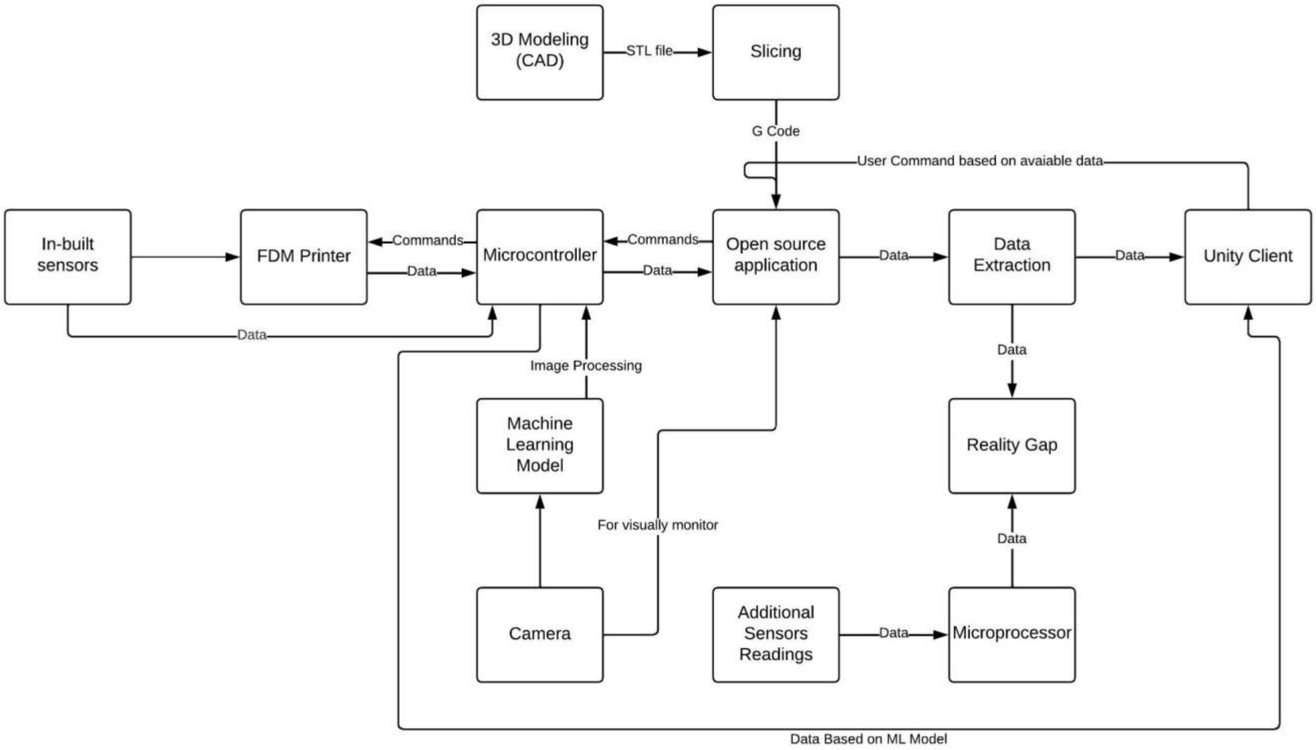


Figure 26. DT Architecture for FDM printers

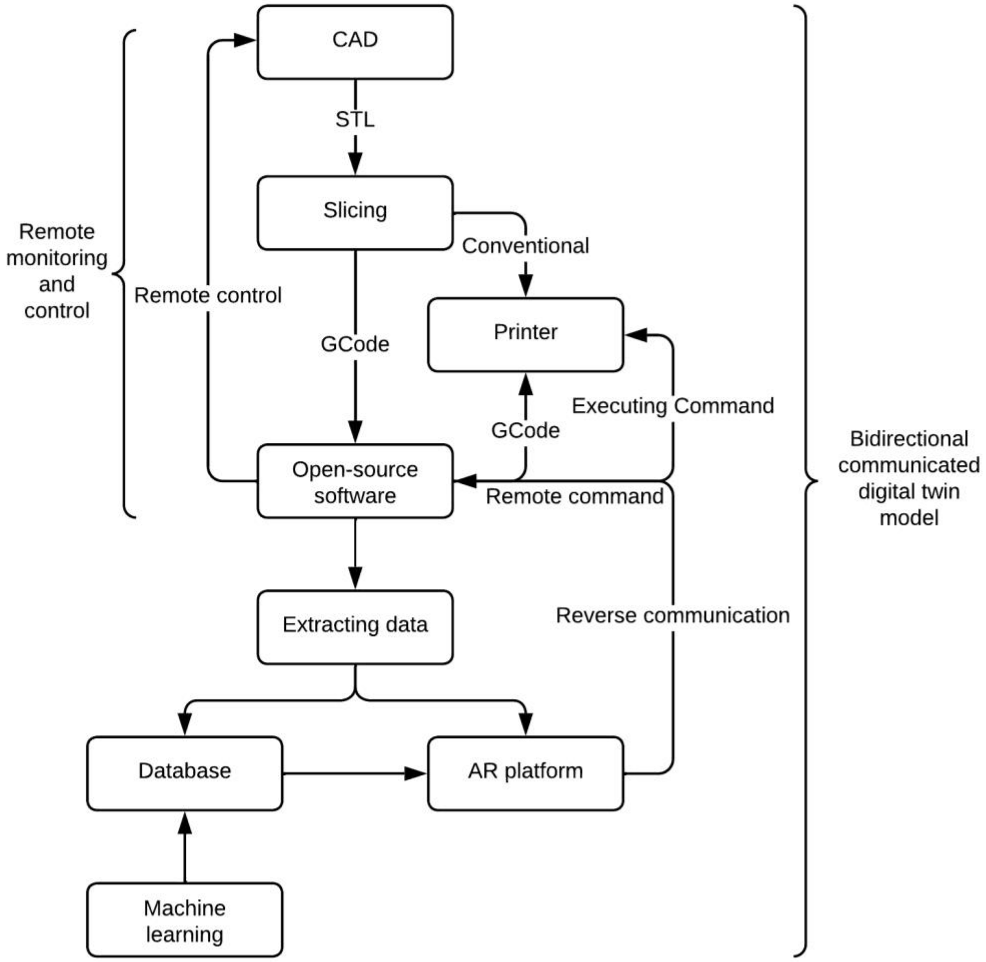


Figure 27. Digital Twin Workflow for FDM printers

First, a CAD file is designed and created for printing. Before printing, the CAD is sliced to generate G-code so that the 3D printer can read it. The printer then receives the G-code and begins printing layers at a time. With the aid of a microcomputer linked to the FDM printer, all data regarding printing may be retrieved from the printer and transferred to open-source software as illustrated in Figure 27. Thanks to open-source software, all manual work may now be done from a distance. In order to deploy a pre-trained machine learning model to real-time quality control and forecast potential printing defects of parts, and to give the augmented reality platform a user-friendly interface, all printing information and parameter data may then be collected from the software and stored in a database. The database sends a signal to the AR platform asking if there is a fault at the same moment. When a flaw is detected, AR alerts the software, which then instructs the printer to pause or cease printing. As can be observed, this methodology and the suggested research meet the key requirements of the digital twin paradigm, including two-way communication between physical and digital machines and intelligence through the use of a machine learning algorithm that foregoes human participation.

4.5 Experimental Setup for Developing of DT for FDM Printer

In this research work, the experimental setup has adopted the developed digital twin implementation architectural design for FDM printers, as shown in Figure 26. Before illustrating a whole structure, it is important to present block by block so it can be convenient to understand and observe. The FDM printer, chair lamp, and camera are illustrated in Figure 28. The chair lamp assists in camera vision by providing extra light, so the machine learning model works well. There is a small printer display that can control the printer through this display. There is an SD card insert slot for sending G-codes to the printer so the printer can recognize what to print and run.

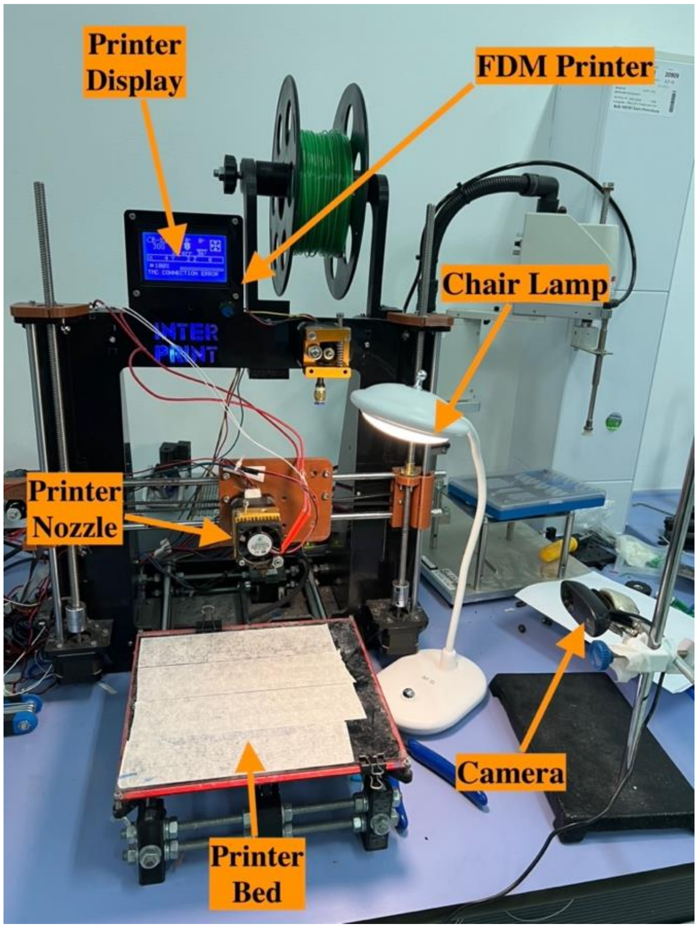


Figure 28. Experimental Setup Printer Site

On the other side, monitor site of the experimental part, plays a significant role in allowing users to monitor and control the FDM printer remotely. The illustration of the experimental setup in monitor site is as shown in Figure 29. There are a monitor, keyboard, mouse, and Raspberry Pi. The Raspberry Pi requires a monitor, keyboard, and mouse to use a microcomputer same as a desktop computer but to control the FDM printer. Raspberry Pi is very susceptible to power supply and cable connections; hence it is an open board. Thus, a 5V standard adapter is used for these Raspberry Pi.

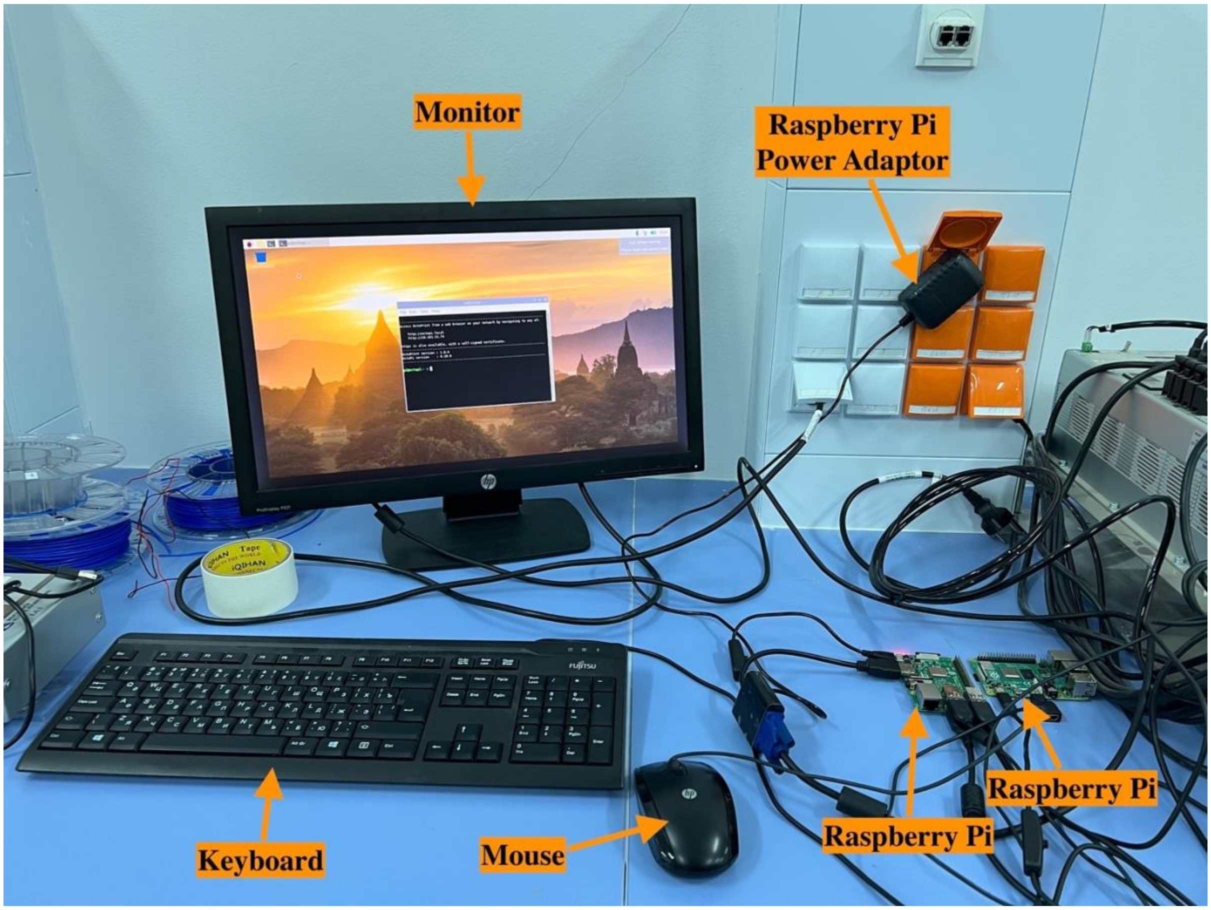


Figure 29. Experimental Setup Monitor Site

The complete experimental setup is illustrated in Figure 30. There is two Raspberry Pi used in this experiment one for remotely monitor and controlling the FDM printer and one for running video and image processing for the machine learning algorithm. Two Raspberry Pi requires an additional monitor, keyboard, and mouse. However, these extra components can be neglected by using one, disconnecting from one Raspberry Pi, and connecting a second Raspberry Pi once the remote connection is established. Additionally, a notebook or smartphone is required for remote monitoring and control through an open-source web-based platform.

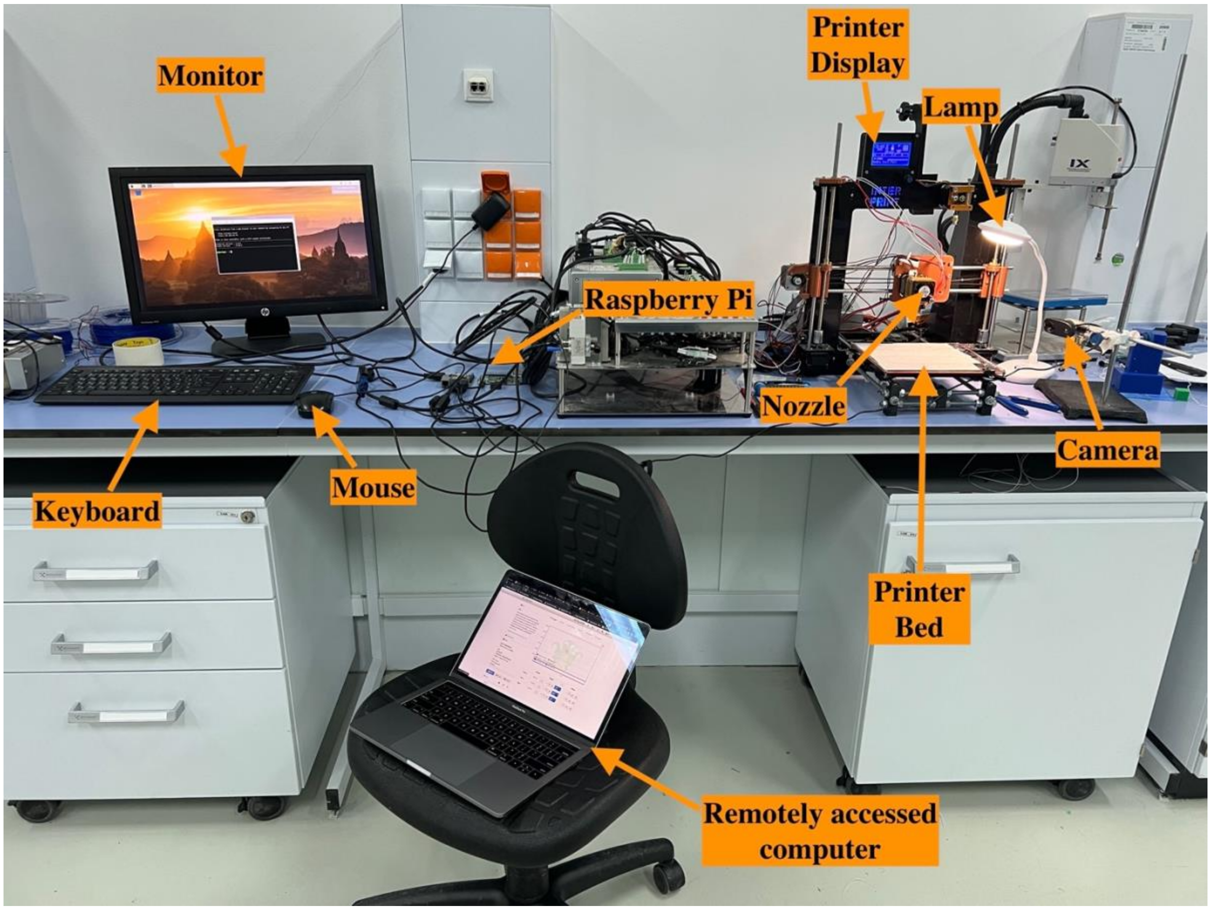


Figure 30. Complete Experimental Setup

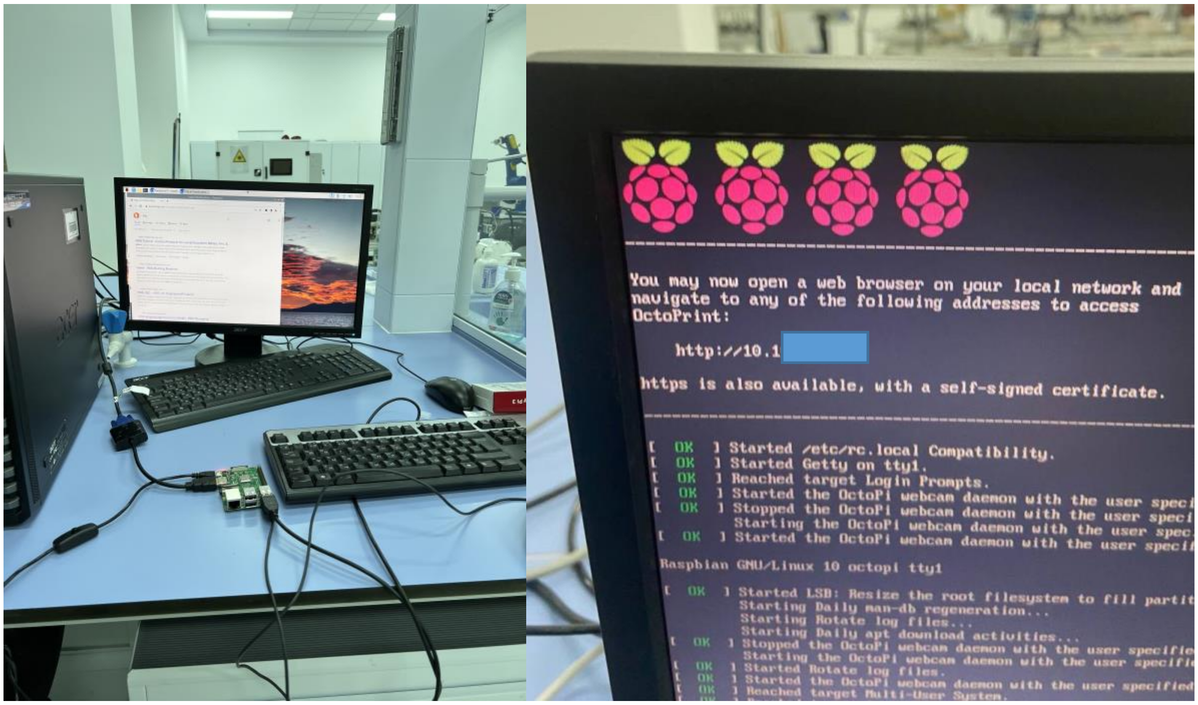
4.6 Design Layout of the Digital Twin of an FDM Printer

In traditional FDM printers, sliced files are uploaded to the SD card, and it is inserted into the printer so the printer can execute the G-codes. In this research work, we neglect this extra work; instead, we upload G-code files directly without any physical SD card. First of all, the Octopi image was downloaded and installed on a 32GB SD card. There are two ways to do it.

1. Downloading Raspberry Pi Imager from Pi foundation, then installing the Octopi using Raspberry Pi Imager software. It is essential to format the SD card before installing Octopi software.

2. Download Octopi software from its official website and install it into an SD card using flashing software. It is highly recommended to format the SD card before installing OctoPi software into the SD card.

When installing Octopi into an SD card, it is important to configure network information such as name and passport. Because Octopi provides remote access to the FDM 3D printer through a Wi-fi network locally, it means within the same wi-fi network. If network configuration hasn't been done during installation, it can also be done after installation by accessing the octopi-network txt file. After installing Octopi, it is time to boot the system. In order to boot the system, the Raspberry Pi microcomputer is needed. The challenge faced in this stage is non-connection between Raspberry Pi and the computer due to the constant changes in the IP address of the Raspberry Pi device. In order to tackle this issue, it is important to connect the monitor to the Raspberry Pi device so the IP address can be visible to the user, as shown in Figure 31, because a user can only access via IP address to the Octoprint on the computer.

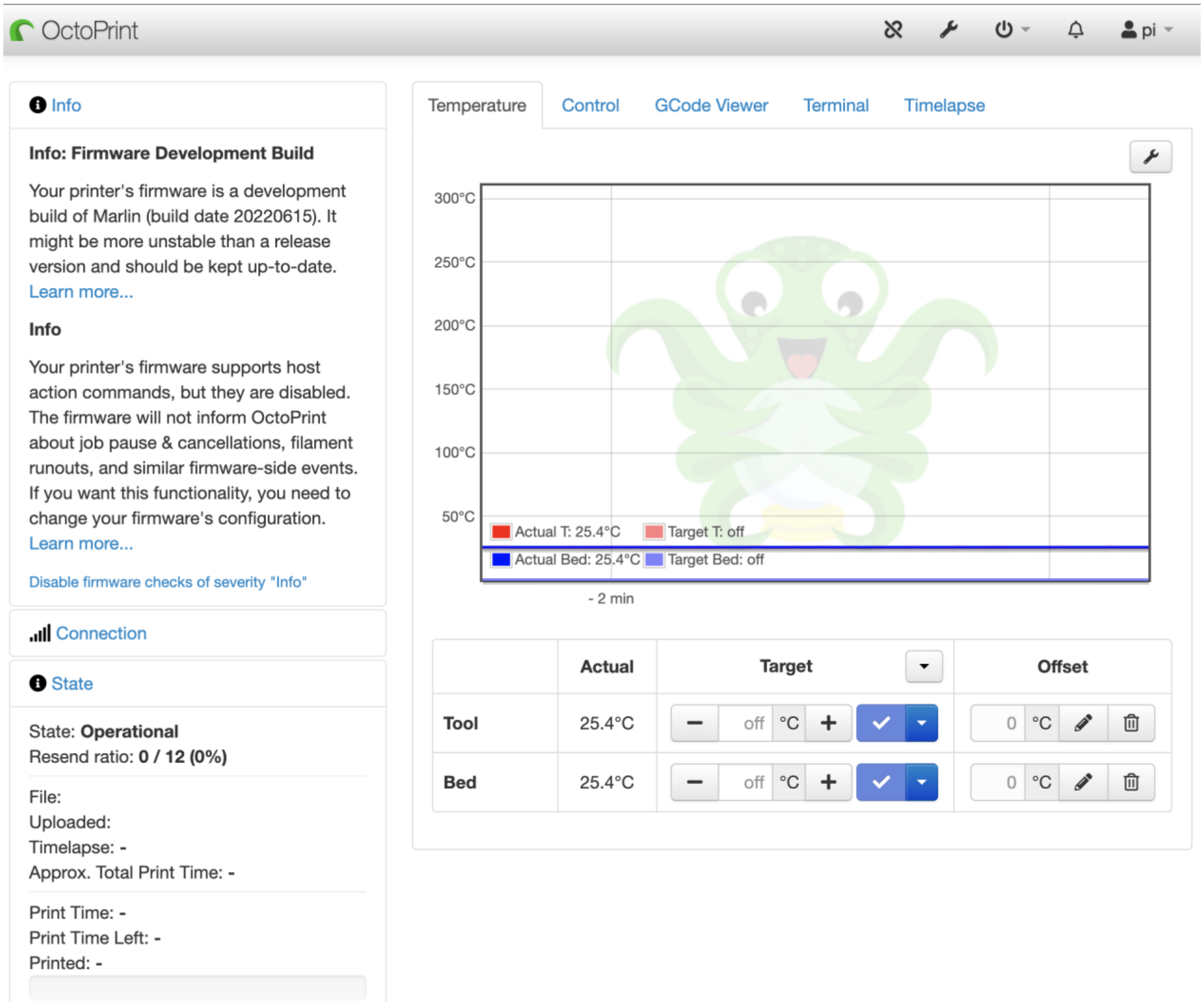


```
You may now open a web browser on your local network and
navigate to any of the following addresses to access
OctoPrint:

    http://10.1[redacted]

https is also available, with a self-signed certificate.

[  OK  ] Started /etc/rc.local Compatibility.
[  OK  ] Started Getty on tty1.
[  OK  ] Reached target Login Prompts.
[  OK  ] Started the OctoPi webcam daemon with the user spec
[  OK  ] Stopped the OctoPi webcam daemon with the user speci
         Starting the OctoPi webcam daemon with the user spec.
[  OK  ] Started the OctoPi webcam daemon with the user specif

Raspbian GNU/Linux 10 octopi tty1

[  OK  ] Started LSB: Resize the root filesystem to fill partit
         Starting Daily man-db regeneration...
         Starting Rotate log files...
         Starting Daily apt download activities...
[  OK  ] Stopped the OctoPi webcam daemon with the user specifie
         Starting the OctoPi webcam daemon with the user specifie
[  OK  ] Started Rotate log files.
[  OK  ] Started the OctoPi webcam daemon with the user specified
[  OK  ] Reached target Multi-User System.
```

Figure 31. OctoPi Installation to Raspberry Pi (Left) & IP address of Pi device (Right)

After successfully installing and accessing Octopi, the 3D printer is connected to the Pi device, and configurations should be done on Octoprint so the user can obtain remote access to the FDM printer through Raspberry Pi. One of the main issues is the constant change of IP addresses, oftentimes after starting Raspberry Pi. The Octoprint web page interface is shown in Figure 32.

There are important process parameters that can be seen on this page, such as nozzle and bed temperatures, printing time and remaining time also visible during the printing process, temperature, and printer control buttons available. The software's smoothness was tested with several prints; as a result, it was smooth and responsive. Figure 33, shows the temperature change intervals from starting to finishing or canceling point for the printer bed and nozzle.



Info: Firmware Development Build

Your printer's firmware is a development build of Marlin (build date 20220615). It might be more unstable than a release version and should be kept up-to-date. Learn more...

Info

Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "Info"

State: **Operational**
Resend ratio: **0 / 12 (0%)**

File:
Uploaded:
Timelapse: -
Approx. Total Print Time: -

Print Time: -
Print Time Left: -
Printed: -

	Actual	Target	Offset
Tool	25.4°C	off °C	0 °C
Bed	25.4°C	off °C	0 °C

Figure 32. OctoPrint Interface

Info: Firmware Development Build

Your printer's firmware is a development build of Marlin (build date 20220615). It might be more unstable than a release version and should be kept up-to-date. Learn more...

Info

Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "Info"

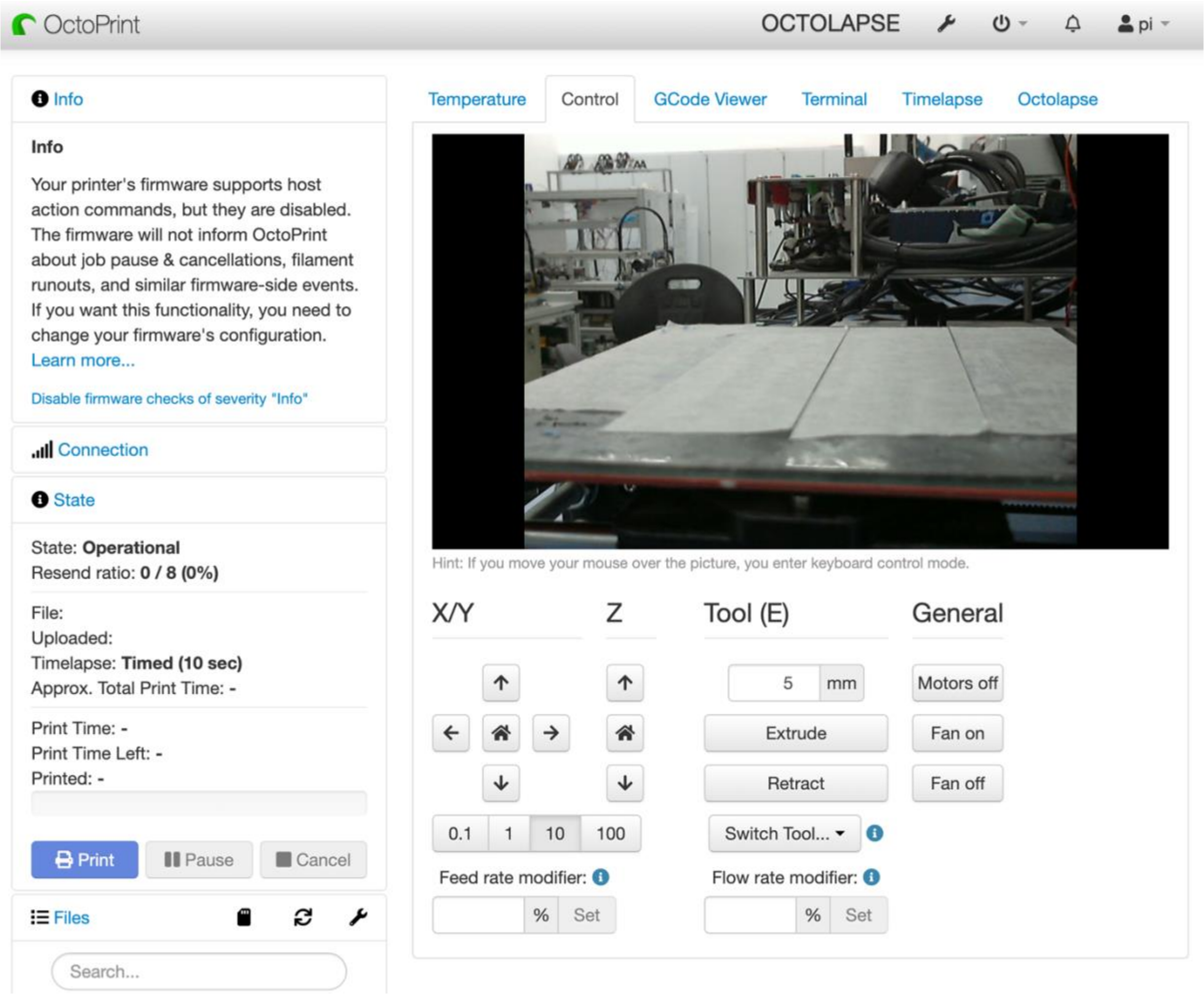
State: **Operational**
Resend ratio: **0 / 5.6K (0%)**

File: **filamentchangetest-part-1_02mm_pla_mk3s_5m.gcode**
Uploaded: **2022-10-03 20:19:13**
User: **pi**
Timelapse: **-**

	Actual	Target	Offset
Tool	190.0°C	off °C	0 °C
Bed	56.9°C	off °C	0 °C

Figure 33. Graph after several prints

In the control tab, as shown in Figure 34, the user can easily and remotely control the printer nozzle using this software. However, there is 1-2s latency between the physical FDM printer and the web-based command. In our study, the important thing is pausing, and stopping the physical 3D printer operations remotely. Also, the webcam camera can be connected to the Raspberry Pi, so real-time operations can be seen from the control tab display, as shown in Figure 34.



Info

Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "Info"

State: **Operational**
Resend ratio: **0 / 8 (0%)**

File:
Uploaded:
Timelapse: **Timed (10 sec)**
Approx. Total Print Time: -

Print Time: -
Print Time Left: -
Printed: -

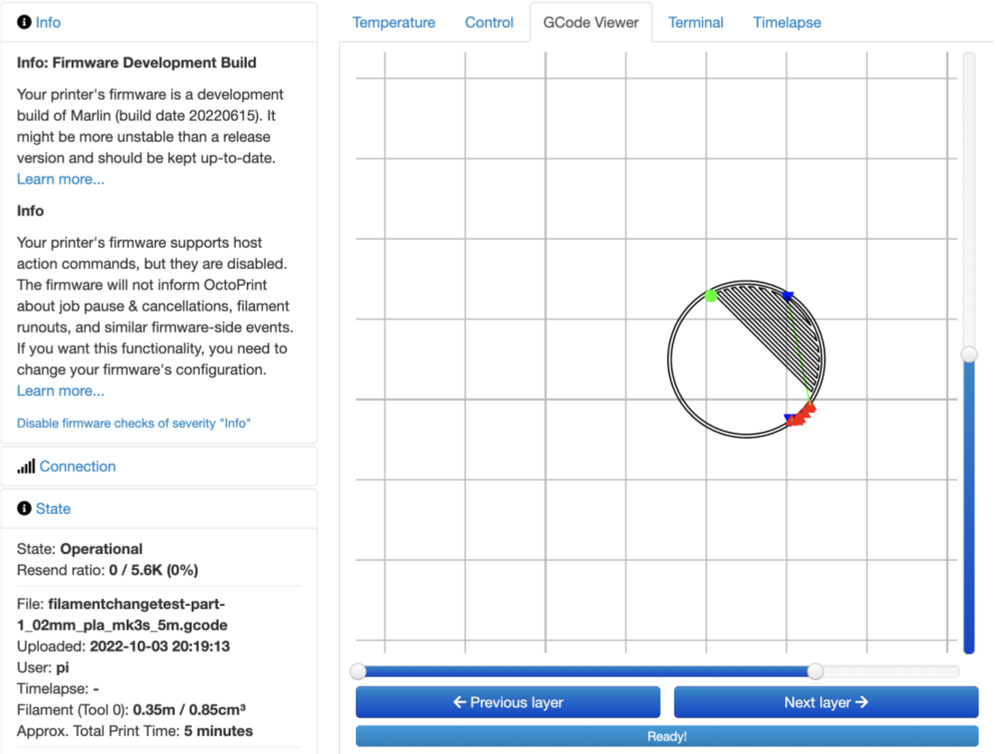
Hint: If you move your mouse over the picture, you enter keyboard control mode.

Feed rate modifier:

Flow rate modifier:

Figure 34. Control tab

In addition, the nozzle's printing footprint can be real-timely seen in the G-Code viewer tab, as shown in Figure 35 layer by layer. At the same time, the coordinates of the nozzle are also seen in real-time in aa terminal tab of the Octoprint. In the terminal tab, the data received from in-built sensors in FDM printers can be seen as shown in Figure 36. All these data are extractable so they can be used in Unity client to feed the digital twin of FDM printers.



Info: Firmware Development Build

Your printer's firmware is a development build of Marlin (build date 20220615). It might be more unstable than a release version and should be kept up-to-date. Learn more...

Info

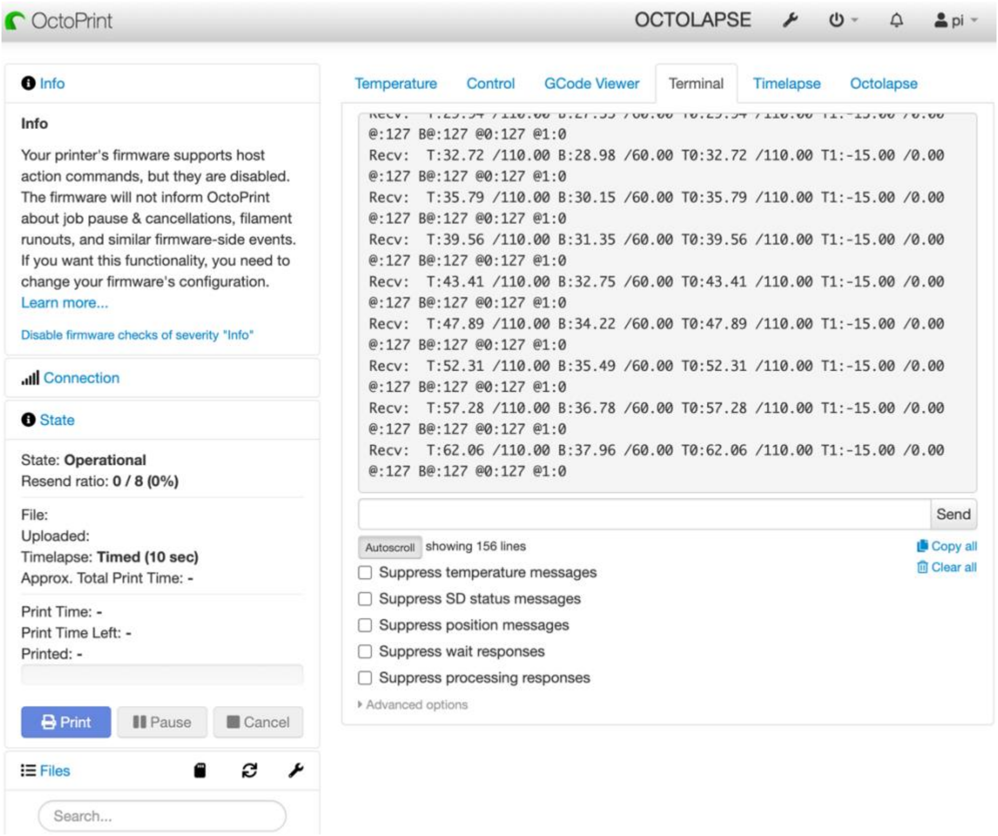
Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "Info"

State: **Operational**
Resend ratio: **0 / 5.6K (0%)**

File: **filamentchangetest-part-1_02mm_pla_mk3s_5m.gcode**
Uploaded: **2022-10-03 20:19:13**
User: **pi**
Timelapse: **-**
Filament (Tool 0): **0.35m / 0.85cm³**
Approx. Total Print Time: **5 minutes**

Figure 35. G-Code viewer tab



Info

Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "Info"

State: **Operational**
Resend ratio: **0 / 8 (0%)**

File:
Uploaded:
Timelapse: **Timed (10 sec)**
Approx. Total Print Time: -

Print Time: -
Print Time Left: -
Printed: -

```
@:127 B@:127 @0:127 @1:0
Recv:  T:32.72 /110.00 B:28.98 /60.00 T0:32.72 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:35.79 /110.00 B:30.15 /60.00 T0:35.79 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:39.56 /110.00 B:31.35 /60.00 T0:39.56 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:43.41 /110.00 B:32.75 /60.00 T0:43.41 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:47.89 /110.00 B:34.22 /60.00 T0:47.89 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:52.31 /110.00 B:35.49 /60.00 T0:52.31 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:57.28 /110.00 B:36.78 /60.00 T0:57.28 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
Recv:  T:62.06 /110.00 B:37.96 /60.00 T0:62.06 /110.00 T1:-15.00 /0.00
@:127 B@:127 @0:127 @1:0
```

showing 156 lines

☐ Suppress temperature messages
☐ Suppress SD status messages
☐ Suppress position messages
☐ Suppress wait responses
☐ Suppress processing responses

Figure 36. Terminal tab

At this stage, G-Code files can be uploaded to the Octoprint remotely so it can send codes to FDM printers to be executed. In addition, it is possible to monitor the printing processes and monitor visually through a camera. At the same time, the FDM printer can be controlled remotely by commands such as cancel, pause, stop, and start. This stage is a very important part of the whole system. Because this research work proposes to retrieve all printing data, such as temperature, time, and nozzle coordination, from one platform, Octoprint. Unity client, as an end or digital model part of this research work, plays an important role in integrating the machine learning model, model visualization, and gathering all control and data in one platform.

Representational state transfer application programming interface (REST API) is a set of rules that provide how communication and connection are defined with each other. It offers greater flexibility to system developers. In this research work, the data retrieval from the FDM printer is through REST API protocol which is clearly explained in “REST API, Octoprint documentation.” The simplified design layout of all these connections from physical to digital is depicted in Figure 37 and from digital to physical in Figure 38.

Figure 37. Design Layout of physical to digital

Firstly, Octopi installed pi is connected to the FDM printer. Then, through Octoprint, it can be remotely accessible to the physical printer and can all data retrieval from the physical printer to the Unity client through REST API directly from Octoprint. At the same time, the machine-learning model runs on Raspberry Pi. If it detects unusuality, then it can be seen from the monitor that defect is detected. All the final data and messages are in the Unity client interface in the form of 3D visualization.

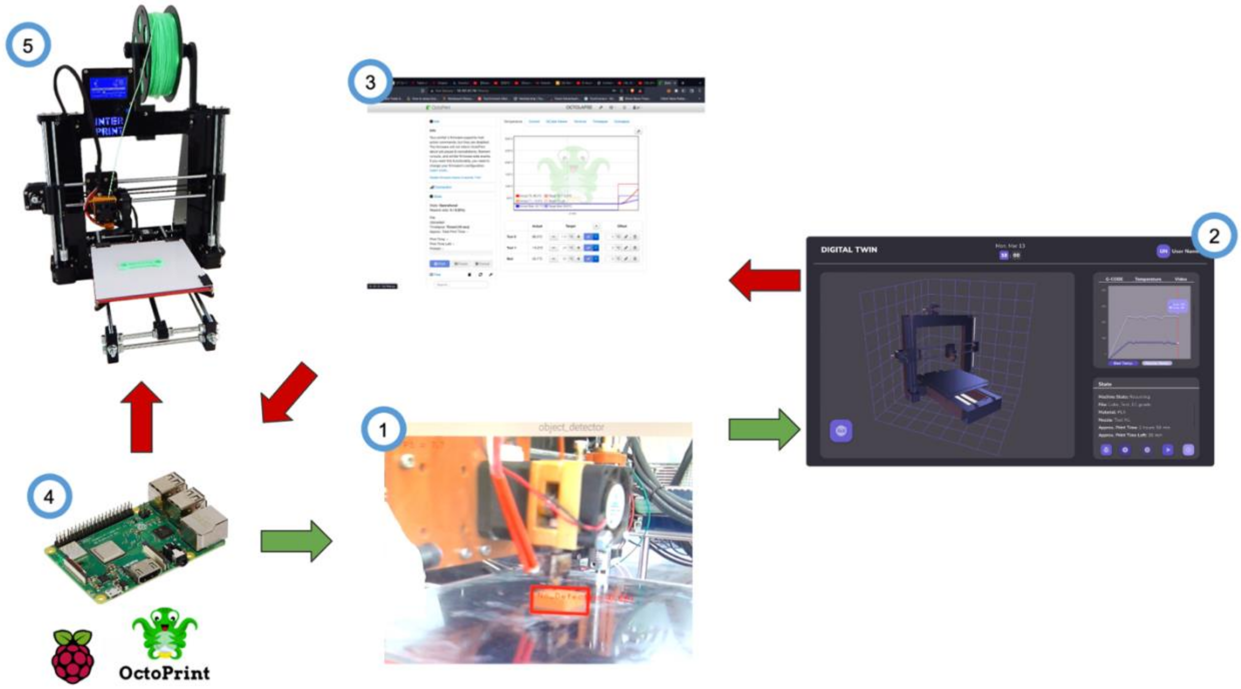
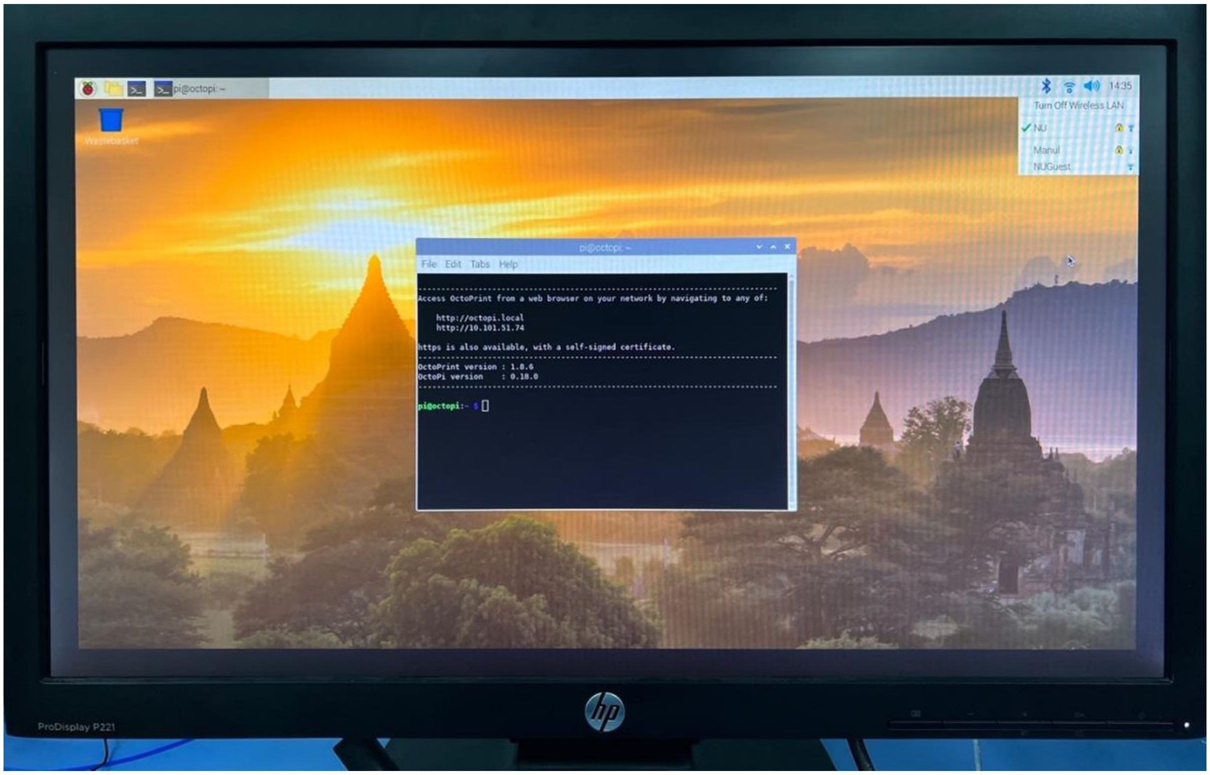


Figure 38. Design Layout of digital to physical

The reverse communication starts with the Unity client. There are virtual buttons such as cancel, pause, continue, and start. If one of the buttons is pressed, the command goes to Octoprint so that the Octoprint initiates the command to the physical printer through the Raspberry Pi microcomputer. The graphical user interface is installed on the Raspberry Pi so that Pi can be useful for complex purposes and functions. The GUI is illustrated in Figure 39. Thus, every time the connection requires IP addresses that changes constantly can be accessible in the terminal of the Raspbian OS as shown in Figure 39; in this case, it was http://10.101.51.74. For installation of the GUI to Raspberry Pi, there are several useful commands such as “sudo raspi-config” for configuration, “sudo/home/pi/scripts/install-desktop” for installing the graphic user interface, “sudo apt update” for update to the latest version, and “sudo reboot” for restart the Raspberry pi. It is important to note that, during this process, it requires an internet connection.



```
------------------------------------------------------------------------------
Access OctoPrint from a web browser on your network by navigating to any of:

    http://octopi.local
    http://10.101.51.74

https is also available, with a self-signed certificate.
------------------------------------------------------------------------------
OctoPrint version : 1.8.6
OctoPi version    : 0.18.0
------------------------------------------------------------------------------

pi@octopi:~ $ 
```

Figure 39. The Graphical User Interface for Raspberry Pi

The printing sample part for this research work is used a cube regardless of its dimension but is limited to the operating platform of the FDM printer with an infill density of 10%, as shown in Figure 40.

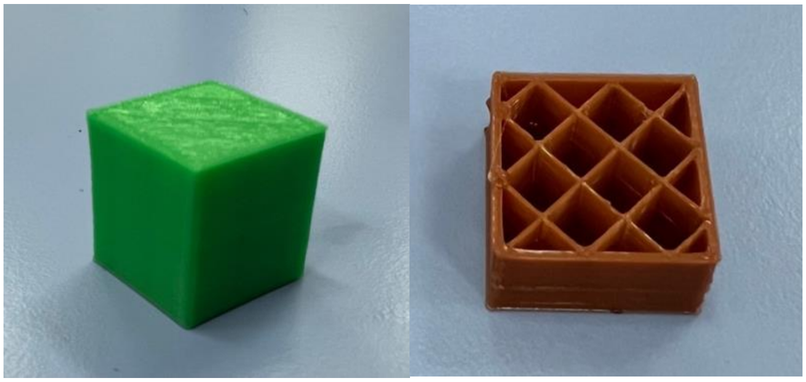
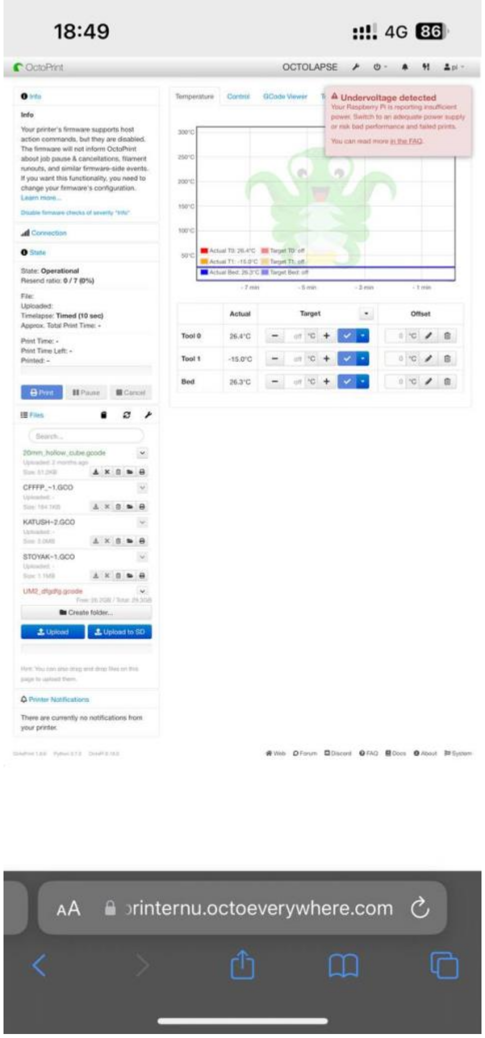


Figure 40. Printing sample cube (infill density is 10%)

The access to proposed and developed digital twin system for FDM printers can be accessed remotely, only within the same wi-fi network via notebook, computer, tablet, and smartphone. In this research study case, anywhere on the campus. The connection through a smartphone outside the laboratory is illustrated in Figure 41.



Info

Your printer's firmware supports host action commands, but they are disabled. The firmware will not inform OctoPrint about job pause & cancellations, filament runouts, and similar firmware-side events. If you want this functionality, you need to change your firmware's configuration. Learn more...

Disable firmware checks of severity "info".

State: **Operational**
Resend ratio: **0 / 7 (0%)**

File:
Uploaded:
Timelapse: **Timed (10 sec)**
Approx. Total Print Time: -

Print Time: -
Print Time Left: -
Printed: -

20mm_hollow_cube.gcode
CFFFP_~1.GCO
KATUSH~2.GCO
STOYAK~1.GCO
UM2_dfgdfg.gcode

There are currently no notifications from your printer.

Undervoltage detected
Your Raspberry Pi is reporting insufficient power. Switch to an adequate power supply or risk bad performance and failed prints.

You can read more in the FAQ.

Actual T0: 26.4°C
Target T0: off
Actual T1: -15.0°C
Target T1: off
Actual Bed: 26.3°C
Target Bed: off

	Actual	Target	Offset
Tool 0	26.4°C	off °C	0 °C
Tool 1	-15.0°C	off °C	0 °C
Bed	26.3°C	off °C	0 °C

Figure 41. Remote access via phone

The primary benefit of using the Octoprint is the ease of necessary data retrieval to feed the Unity client so the digital twin can be fed by real-time data. However, the amount of data is a very big. For example, the 130 seconds of printing data is around 1500 lines or 44 pages in a word file. The example of codes (temperature and nozzle coordinate) is in Apendix A. The real-time temperature data for 130seconds including bed and nozzle heating time is shown Figure 42 and Figure 43 respectively. From these graphs, it can be seen that robust temperature rise when target temperature is set for printer bed and nozzle. After achieving the target temperature both printer bed and nozzle real-time temperature data hugging or hovering around temperature data to maintain target temperature as seen in Figure 42 and Figure 43. The temperature data retrieved from the Octoprint is in Appendix B.

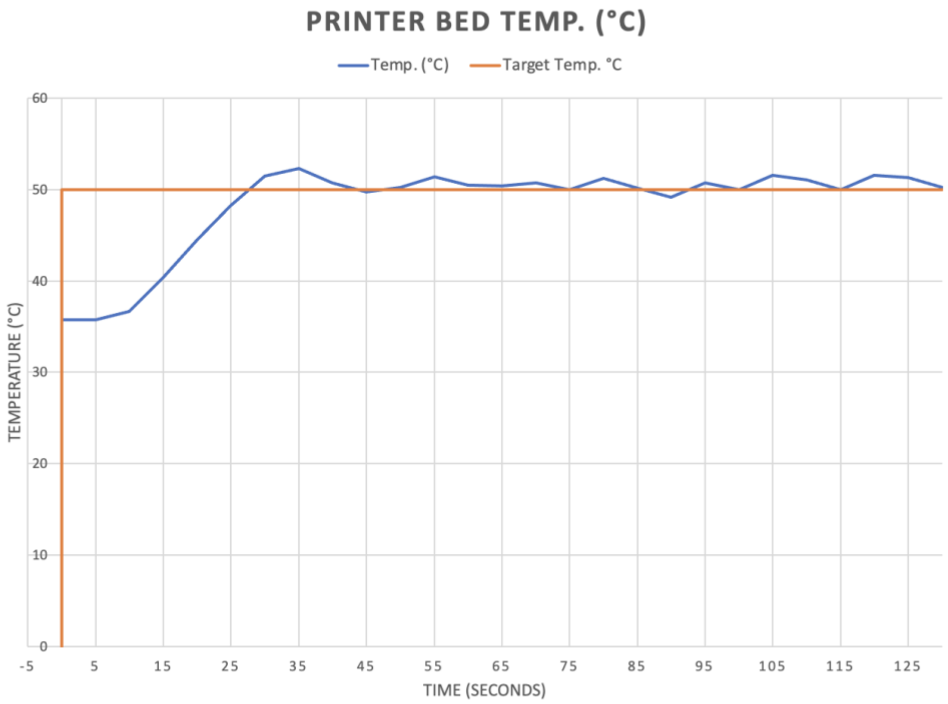


Figure 42.Real-time Printer Bed Temperature

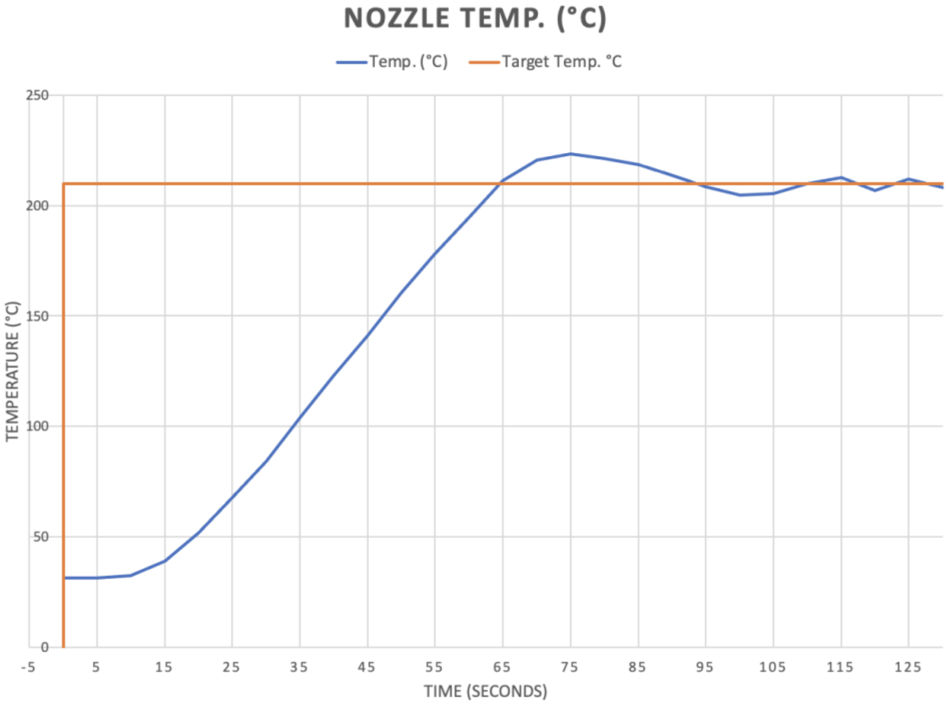


Figure 43. Real-time Nozzle Temperature

4.7 Verification & Validation

Digital twin itself is considered a key for product or process verification and validation in the industries. However, verification and validation (V&V) of a digital twin is the one of many challenges in the area of digital twin implementations. There are numerous different studies and suggestions made for V&V. Considering all the inputs from the literature review, this research work is verified and validated through three different approaches as shown in Figure 44.

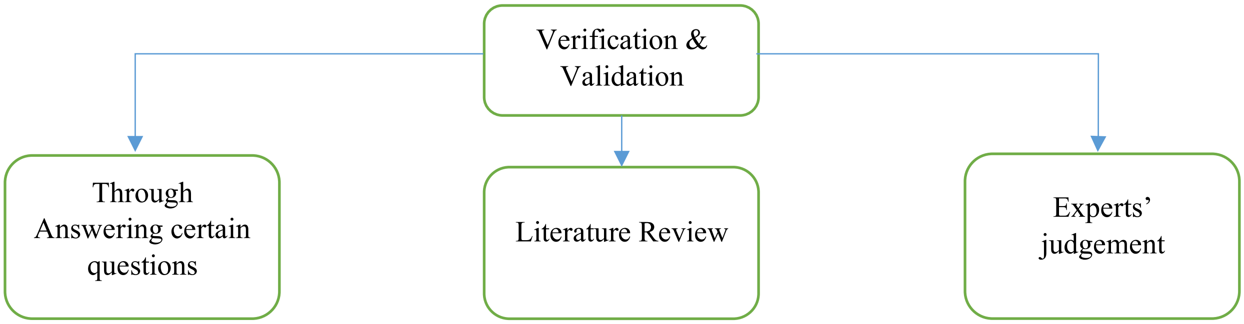


Figure 44. Verification & Validation

First, verifying and validating the developed system through asking certain questions. The question for verification is "Does this developed digital twin system work properly?" In this research case, yes. The data flow from physical model to digital and from digital to physical is achieved. The system works perfectly fine and still working. The question for validation of the developed system is "Does this developed digital twin system meet its requirements?" Which were three essential functions of a digital twin such as real-time monitoring and controlling, bidirectional communication, and certain level of intelligence. All three requirements are met. Secondly, the developed framework and architecture are extracted from different literatures and integrated into one to develop a digital twin. Since all the inputs extracted from literature, it is valid through literature review. Finally, judgement of experts on developed digital twin system. The developed digital twin system presented and approved by Professors from Nazarbayev University, and from Cranfield University in England with some further comments for improvement. It is important to note that there are contributions to training of machine learning and unity development part from other researchers.

5. DISCUSSION & CONCLUSIONS

5.1 Introduction

This chapter focuses on discussion of the key research findings and conclusions of this research work. The discussion section consists of three subsections that focused on the research methodology and DT development for FDM printers, current limitations of the developed digital twin for FDM printers, and recommendations. Then, solid contributions of this research studies are addressed in key research contribution to the knowledge section of this chapter. Finally, conclusions section concludes this research work and future research directions are discussed the main directions for research.

5.2 Discussion of the Key Research Findings

The additive manufacturing area is a vast area that consists of a wide variety of 3D printing techniques and the use of a wide range of materials for printing, as mentioned in Chapter 2. Thus, the methodology of developing digital twins for AMs may differ from each other. This research work focused on fused deposition modeling type of AMs, FDM 3D printers. The developed method of creating DT for FDM 3D printers is discussed in detail in this particular study. The ultimate purpose of this research is to develop digital twin implementation for FDM printers with minimum external components such as sensors and other components to reduce the complexity of the whole system in a user-friendly way. Thus, the DT framework and architectural design for implementations are developed for this study in a way that meets its functional requirements according to the inputs from the recent literature review studies and industrial implementation approaches. More importantly, this model meets its DT functions, which are real-time monitoring and controlling, two-way information flow between models, and leveraged with a certain level of intelligence. Indeed, there are strengths and weaknesses of this DT development technique.

5.2.1 Research Methodology & DT Development for FDM Printers

The main five research questions were answered during this research work. First three research questions were answered in chapter 2 of this research study and of objective one. RQ1 is about FDM printing parameters and their effects on final product defects which was addressed as key findings from literature review in subsection 2.2 in chapter 2. At the same time, it was Objective 1 of this research study. RQ2 is about DT implementation benefits and challenges in additive manufacturing which was addressed in subsections 2.4.4 and 2.4.5 in chapter 2. RQ3 is about recent development of this area that was addressed in 2.5 subsection of chapter 2 as key findings. Chapter 3 & 4, and objectives 2, 3, 4 are covered the answer for research question four and five. RQ4 and the objective 2 of this research study were to develop DT framework development and architectural design of DT implementation for FDM printers that were addressed in chapter 4. The developed DT framework and implementation architectural design for FDM printers are developed by the inputs from literature review and industrial applications. RQ5 and the objective 3 is about methods and DT creating steps which were addressed in chapter 4. There are eight main steps are formulated to create a digital twin for FDM printers that discussed in detail in chapter 4. Objective 4 is about verification and validation of the developed system for FDM 3D printers which was addressed in the final section of chapter 4 done by thorough literature and experts' judgement from the universities in England and Kazakhstan.

There are some strengths of this DT creation methodology. The whole system is less complex because there are fewer external components used, and most of the desired data is extracted from one open-source platform, the Octoprint, from inbuilt sensors. Moreover, the information flow is quick, and commands are responsive due to the data travel on fewer platforms, from the printer to the Octoprint and from the Octoprint to the Unity client. The information flow latency, in this case around 1s, entirely depends on the speed of the wireless network. Finally, the availability of upgrades and changes to the system is not very complex. This means once establishing essential connection and development, it is possible to integrate other desired functions into the developed digital twin model. However, one important thing to note is its computational burden while upgrading the digital twin model. During the development of this system, many challenges are encountered, such as system interoperability, the computational burden due to the integration of machine learning models, remote connections, and information communication technology challenges. Due to the interoperability, computational, and ICT challenges mentioned in Chapter 2, two Raspberry Pis are used, one for Octoprint and one for the machine learning model. At the time of testing, the RAM of Raspberry Pi was 1GB, and it is recommended to test it on a more powerful microcomputer.

5.2.2 Limitations and Recommendations for the Developed Digital Twin

There are limitations to this developed digital twin model. The remote connection to the FDM printer is established only in the same WI-FI or local networks. When solving this issue using a ready-made plug-in, octoeverywhere, it causes a blockage to the data flow from Octoprint to the Unity client. Moreover, visual remote monitoring is limited to 20 seconds with the free version and 2 minutes with the premium version every 5 minutes. Thus, this solution was not appropriate for this research study. At the moment, the remote connection works within the local network. In addition, the machine learning model is trained with a limited sample and shape. It recognizes only cubes and defects such as spiral and unusual geometric deviations. The most critical limitation, yet very challenging, of the currently developed digital twin is the lack of function to optimize printing processes. In other words, lack of a closed-loop improvement system due to the complex working principle of 3D printers. Once G-code is uploaded and initiates the printing, it is very challenging to interfere and change parameters in the G-code and send it again. Finally, the developed system lacks proper database which is also addressed by researcher from Cranfield University. He suggests that local database is enough for one FDM printer, if there are more than one then cloud database is preferable. Moreover, distributed architecture for data storage is required due to the challenges regarding data types from various types sensors, thus SQL or noSQL database might be helpful in this case.

The currently developed digital model meets its functional requirements and has limitations in some aspects. Thus, it is recommended to do the following upgrades and addition to the existing model to acquire a more functional digital twin model in the immediate future. The very first improvement can be made by upgrading the local network connection to a wide network connection so users can connect to the physical model through the digital model from anywhere in the world. Another recommendation is to create a database for continuous improvement of the DT model. Without a database, it is just a real-time intelligent machine without any previous records and memory, which is one of the essential functions of a digital twin. Regarding visualization, exact 3D visuality is recommended for an interactive and user-friendly interface. The current machine learning model is very limited in terms of functionality, types of defects, and complex geometries. Thus, a new sophisticated machine learning model should be developed that has the ability to detect most of the defects, processing printing parameters to detect defects and geometrically challenging shapes. The current study uses two Raspberry Pi, one for Octoprint and one for a machine learning model for real-time video processing to detect defects. Thus, integrating these into one reduces the complexity and solves the challenges of interoperability difficulties and proper shared memory for computational burdens. An excellent and easy-to-understand user interface is crucial for both technical and non-technical, so there would be no misunderstanding among different departments of the company or tutors and students. Thus, developing augmented reality (AR) for interactive use is crucial. It opens up possibilities such as teaching at a distance using a virtual printer connected to the real one. Finally, it is recommended to have an all-in-one mobile app so it can be accessible to anyone who wants or develop the models.

5.3 Key Research Contribution to Knowledge

The additive manufacturing field is gaining tremendous interest in both academia and industries. Significantly, FDM 3D printers are widely used type in the world due to their affordability and convenience to use. Thus, it is important to note that more advancement and development in FDM printers lead the more adoption and production. The current important challenges of this technology are real-time monitoring and controlling for long hours of printing and automatic defect detection mechanism to save up money, time, and materials. All those challenges can be addressed and solved by implementing digital twin technology. The developed digital twin model in this study has a number of contributions to the knowledge, such as the benefits of a digital twin in different levels of DT implementations, digital twin challenges in AM industry, a digital twin framework, architectural design for DT implementation for FDM 3D printers, building blocks, acquisition of bidirectional communication mechanism between models, integration of intelligence in FDM printers, and real-time remote monitoring and controlling. To summarize the solid contributions, this novel digital twin model allows monitoring and controlling both in the laboratory and outside the laboratory within the campus range. There are substantial contributions to the digital transformation and creation of intelligent manufacturing systems in industrial enterprises in Kazakhstan and worldwide.

5.4 Conclusions

In the context of Industry 4.0, a digital twin is an emerging and developing technology. The reliable decision-making and control procedures in the field of additive manufacturing are expected to be resolved by digital twin technology. This study focuses on the deployment of digital twins in FDM 3D printers, its most recent advancements, its benefits, its difficulties, and its development process from the digital twin framework to the end product. First, the literature review is conducted to formulate the proposed DT framework and architectural design for the implementation of the FDM 3D printer area. Then, the necessary hardware and software are selected to develop the digital twin for the FDM printer. Finally, the developed model is tested to determine whether it meets its requirements. As a result, it fulfills its functional needs, such as bidirectional communication between models, integration of minimum-level intelligence by using a machine learning model, and remote real-time controlling and monitoring. Even though there is sometimes communication latency due to network connection, the system works properly and fine.

5.5 Future Research Direction

There are lots of improvements and integrations required to acquire a perfectly working and functional digital twin model for FDM printers and each type of AMs. Thus, future studies should research and develop a universally accepted digital twin framework and architecture compatible with all sorts of AMs, including all kinds of manufacturing fields. Also, the system would benefit immensely by incorporating most of the digital twin's components into a single system to reduce cost and complexities, such as machine learning and virtual reality, with simple controls. Extended reality might be made available for the easy use and supervision of non-technical individuals. The creation and application of digital twin technology for the process optimization of FDM printers and building a closed-loop effective digital twin model for continuous improvement is another fascinating study field. Ultimately, with the aid of the feedback loop from the digital twin, product optimization and designs can be modified in design stages of the products. The health monitoring system can also be included in the digital twin creation process to create an entirely automated, finished digital twin.

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