Digital Twin of Polymer Processing Pilot Line

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Abstract

In the context of Industry 4.0 and digital factory, digital twin technology is emerging as a key enabling technology to simulate, optimize, maintain, and predict processes and production systems. Digital Twin (DT) refers to the virtual copy or model of any physical entity (physical twin), both interconnected via real-time data exchange. Conceptually, a DT mimics the state of its physical twin in real-time and vice versa. In AIT (Athlone Institute of Technology, Ireland), we are developing a DT of the polymer processing pilot line consisting of: an injection moulding machine; robotic arms; conveyor belts; and inspection cameras. This paper presents the DT system for smart polymer processing at AIT, including the components of the system and the tools used to build the system. The project focuses on developing unit-level DTs of individual components of the pilot line and subsequently integrate these DTs to build the DT of the entire system. The project is in its initial stages, with the current focus on the development DT of the ABB IRB 1200 robotic arm (6DoF) in addition to the 3D scanner. This paper is a concept paper introducing the framework for developing the required DT.

In the pilot line, when a part from the injection moulding machine is loaded onto the conveyor belt, it can take any orientation and can fall anywhere on the belt. The 3D scanner camera detects the orientation and coordinates of the part and passes the information to the robotic arm. With this information, the robotic arm knows how and where to pick the part from the conveyor belt. For simulating the robot in the virtual world, Visual Components will be used, and Robot Operating System (ROS) will be used as the primary framework for bi-directional communication. HALCON is used to extract data from the camera. In AIT, the tools we are using are state-of-the-art industrial solutions that can be employed by industry without many modifications. The developed DT will be used for real-time monitoring, optimization of the robotic arm and conveyor belt movement, and predictive maintenance.

Key Words: Digital Twin; Industry 4.0; System Optimization; Predictive Maintenance

1. INTRODUCTION

The whole concept of the fourth industrial revolution or Industry 4.0 revolves around the digitalization of and intelligence within the manufacturing process (Vaidya, Ambad, & Bhosle, 2018). One of the key enabling technologies for the Industry 4.0 digital solutions is Digital Twin (DT) (Durão, Haag, Anderl, Schützer, & Zancul, 2018; Pires, Cachada, Barbosa, Moreira, & Leitão, 2019). Although NASA was the first to introduce the concept of DT, in the context of the Industry 4.0 paradigm, Michael Grieves pioneered the initial efforts (Singh et al., 2021). DT consists of three components (Figure 1): physical twin in physical space, digital twin in virtual space, and bi-directional data connection between two spaces (Grieves, 2014). The latter enables the DT to mimic the changes in the physical world. This then allows the user to plan the next steps virtually and execute them by sending command via DT. With a DT, the current as well as the future states of its physical twin can be displayed, which can be used for various purposes such as real-time monitoring, predictive maintenance, process evaluation and optimization, designing, asset management etc. (Liu, Fang, Dong, & Xu, 2021).

DT is also one of the driving forces in Smart Manufacturing (Lu et al., 2020). In manufacturing, all products go through four main phases throughout their life cycle: design, manufacture, operation, and disposal (or reuse). Smart manufacturers can leverage DT throughout the entire product/system lifecycle by ensuring data continuity which not only improves the quality and service of one generation of the product but also of the next generations (Liu et al., 2021; Shao et al., 2019). Benefits of using DT technology in smart manufacturing include: reduced time to market; increased user engagement; increased visibility; ensured optimal operations; reduced

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maintenance cost; and reduced energy consumption etc. (Aheleroff et al., 2020; Tao, Zhang, & Nee, 2019). However, to avail these benefits DT needs to have the following characteristics (Lee, Azamfar, Singh, & Siahpour, 2020):

(i) Ubiquitous connectivity.
(ii) Advanced analytics.
(iii) Cooperative decision making.
(iv) Autonomous and rapid model building and updates.
(v) Autonomous disturbance handling and resilience control.

With the advent of technologies such as industrial internet of things, artificial intelligence, deep and transfer learning, Immersive eXtended Reality, 5G, big data, blockchain etc. realization of DT in manufacturing systems could significantly improve (Fuller, Fan, Day, & Barlow, 2020; Lee et al., 2020; Perkis et al., 2020). According to Zhou et al., the next stage of smart manufacturing is going to be intelligent manufacturing which will be attained by knowledge-driven DT manufacturing cell that can perceive, simulate, understand, predict, optimize, and control strategy intelligently in order to make manufacturing more autonomous (Zhou, Zhang, Li, Ding, & Wang, 2020).

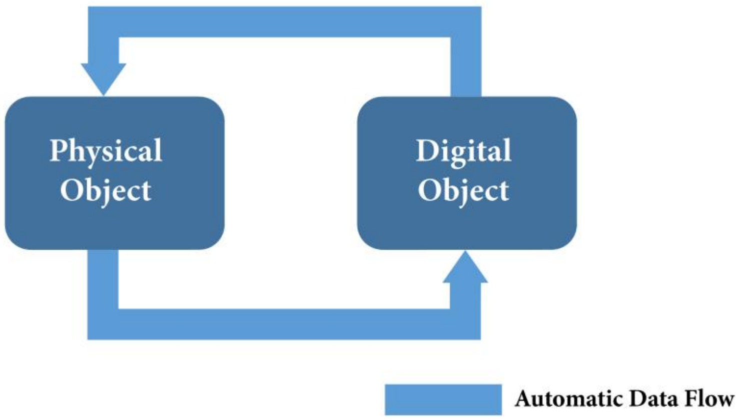

Figure 1 Block diagram of DT

It will be impossible to transfer to the next manufacturing paradigm without industrial robotics (Ermolov, 2020). One of the major components which is transforming industry 4.0 and smart manufacturing into fully integrated, automated, and optimized production flow is autonomous robotic systems (Rüßmann et al., 2015; Vaidya et al., 2018). Growing interest for developing DT for the robotic arm is evident from the increasing number of publications (limited to the English language) found on Google Scholar, ScienceDirect, and Scopus containing the term 'Digital Twin' along with 'Robotic arm' or 'Robot arm' in the article title, abstract, or as keywords from 2016 to 2020 (Figure 2). For 2021, the number of publications has already reached 240 in Google scholar as compared to the 282 for 2020 for the entire year (last checked 17 July 2021).

Though there are a plethora of frameworks/architectures for the implementation of DT in the manufacturing industry, the real-life implementation is still lacking. Bambura et al. (Bambura, Šolc, Dado, & Kotek, 2020) demonstrated the feasibility of DT implementation in the real condition of a production plant that manufactures aluminium components for the automotive industry. They used the Technomatix Plant Simulation software to create the virtual model, PLC sensors for data acquisition, and an optimization tool to realise the complete DT. Barenji et al. (Vatankhah Barenji, Liu, Guo, & Li, 2020) developed DT driven framework for robotic arm based on the parameters of the existing physical twin for the optimization of motion planning for reducing energy consumption. DT of grinding process using 6DoF (Degree of Freedom) industrial robot was developed by Oyekan et al. (Oyekan, Farnsworth, Hutabarat, Miller, & Tiwari, 2020) for effectively removing the surface material from the fan-blade of an aircraft engine by exploring the required grinding force parameters needed using DT. More recently, Matulis-Harvey (Matulis & Harvey, 2021) utilised reinforcement learning for the realisation of a robot arm digital twin. They created a virtual space using Unity3D, link it with the 3D printed replica of its real-world robot arm and space twin, and through Tensorflow and hyperparameter tuning provide the required foundation or the DT architecture. Liang et al. (Liang, McGee, Menassa, & Kamat, 2020) developed a DT system for human-robot collaboration in the construction and digital fabrication by leveraging ROS, Gazebo, and Rviz to develop the digital robot module and MQTT Bridge as the communication module to connect it to the physical robot. Finally, V. Havard et al. (Havard, Jeanne, Lacomblez, & Baudry, 2019) have suggested similar industrial workstation DTs and extend their work on human-robot interaction and collaboration.

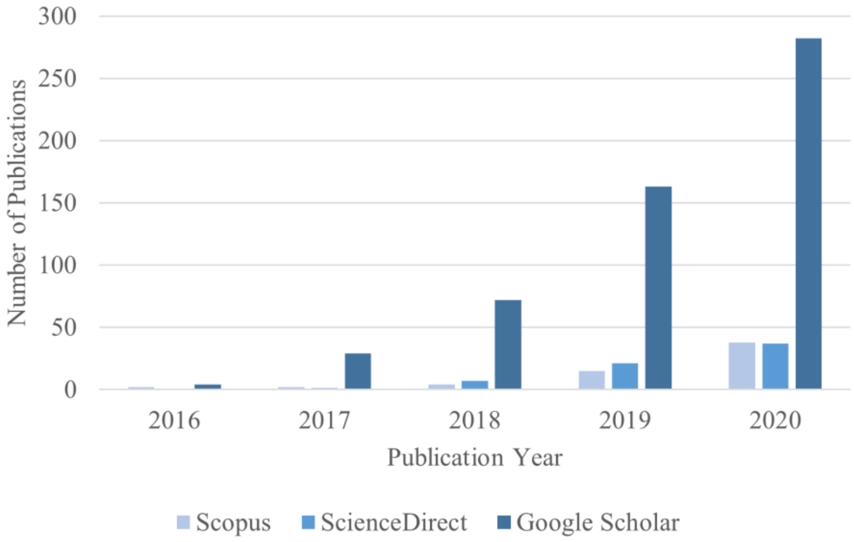

Figure 2 Number of DT and robotic arm related publications on Google Scholar, ScienceDirect, and Scopus by year

There is a gap in the literature with respect to the DT setup of a manufacturing line where a multi-process system including the manufacturing and transferring, as well as the real-time image processing for product detection and robotic gripper actuation for the gripping mechanism are needed. Most of the work in the literature in this domain is limited to either only robotic arm DT or the manufacturing line DT. Vision systems/cameras in the manufacturing line have been implemented for burr or defect detection (Schmidt, Grandi, Peruzzini, Raffaeli, & Pellicciari, 2020), observations of the environment state (Matulis & Harvey, 2021) or tracking and guidance of material removal (Oyekan et al., 2020). An inter-linked process that is closer to a real-world situation such as detecting part within conveyor belt has not been explored yet. The aim of the project is to achieve synchronization between the states of a small manufacturing cell comprising of the robotic arm, conveyor belts and inspection camera and its DT with high accuracy to capture the pilot line from the injection moulding machine to the picking and transferring of the fabricated products from and to the conveyor belts. This architecture is envisaged to lay a foundation for future automation industry by determining the requirement of the environment and the machines required to complete the process effectively. The virtual space and the hardware setup are designed such that the communication and control are two-way, and the robot actuation mechanism is also controlled through the same.

The paper has been divided into 3 sections. Section 1 introduced the role of DT in Industry 4.0 and smart manufacturing. It described few examples from the literature where DT has been implemented and identified the gap in the research. Section 2 gives the information regarding the setup of the pilot line at AIT which includes the physical components of the line (hardware), software being used, and the manufacturing process in brief and Section 3 details different layers of the DT and the framework for developing the DT for the project by showing the flow of data across different components of the pilot line.

2. SET UP

2.1. Hardware

Figure 3 show the manufacturing cell in Athlone Institute of Technology (AIT), Ireland. The main part creating machine of the pilot line is an injection moulding machine, Arburg Allrounder 370 E ("Arburg Allrounder 370 E "), equipped with Kistler ComoNeo system ("ComoNeo - Process Monitoring System,") which records the cavity pressure during the moulding process, allowing it to document, optimise, monitor, and predict outcomes during the injection of the material into the mould cavity. Other components of the line include robotic arm, conveyor belts, and camera.

Figure 3 Manufacturing pilot line in AIT, Ireland

The project focuses on creating DTs of individual components of the pilot line first and then bringing them together to develop the DT of the entire system. Thus, the project aims at three components of the line first which are (Figure 4): robotic arm for picking and placing parts, conveyor belt for transporting the part from one location to another and 3D scanning camera for inspection. The robotic arm in the line is ABB IRB 1200-7/0.7 which is specifically designed for manufacturing lines that use flexible robot-based automation. It is a 6-axis industrial robot with a payload of 7kg and 0.7m reach (ABB, 2019). PhoXi 3D Scanner S from Photoneo is being used for scanning the parts produced by the injection moulding machine. It uses a structured light projection to reconstruct the geometry of the inspected part in 3D space. It is suitable for scanning different materials, from metal to plastics with expectations being liquids and transparent objects etc (Photoneo, 2021b). The specifications of this 3D scanner are in Table 1 (Photoneo, 2021a).

Table 1 Product specifications of inspection camera in the pilot line

Parameter	Value
Resolution	Up to 3.2 million 3D points
Scanning range	384 - 520 mm
Optimal scanning distance (sweet spot)	442 mm
Scanning area (at sweet spot)	360 x 272 mm
Point to point distance	0.174 mm
Calibration accuracy (1 σ)	0.050 mm
Scanning time	250 - 2250 ms

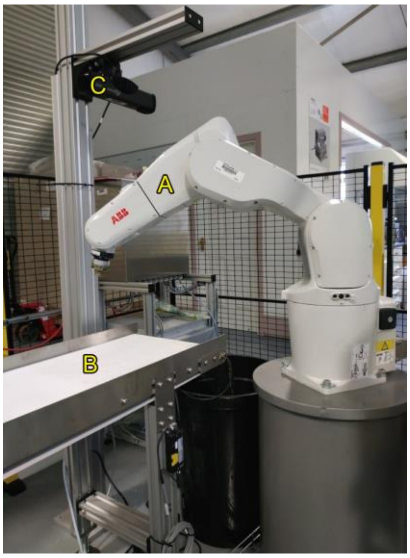

Figure 4 Robotic arm(A), conveyor belt(B), and Photoneo(C) of the pilot line

2.2 Software

One of the most critical aspects of DT is bi-directional data flow for which ROS (Robot Operating System) Kinetic Kame is being used. ROS is a flexible framework for writing software for robots. It aims to simplify the task of creating complex and robust robot behaviour across a wide variety of robotic platforms by providing a collection of tools, libraries, and conventions ("About ROS,"). For generating useful information out of the images captured by the inspection camera a software named HALCON is being used. HALCON is a machine vision software that provides a comprehensive vision library. The library comprises all types of image processing methods, from image acquisition to advanced shape-based matching (MVTec). The manufacturing line is being replicated in the virtual world using Visual Components, a 3D simulation software for manufacturing. Visual Components Premium 4.2.2 version is being used for creating the digital model of the manufacturing cell (Figure 5). Since different software run optimally on different operating systems, a virtual machine is being set up so that Windows and Linux operating systems can work on the same system. Ubuntu 16.04, an open-source operating system on Linux, is best for running ROS programmes (Quigley, Gerkey, & Smart, 2015) and Windows is for HALCON and Visual Components. A more detailed diagram about the component relationship is presented in the next section.

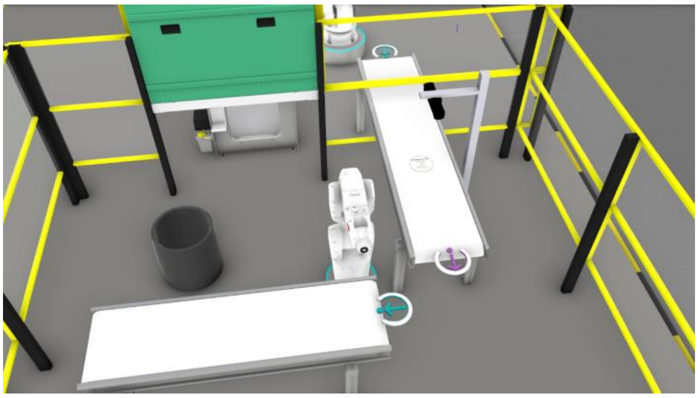

Figure 5 Digital simulation of the manufacturing cell developed in Visual Components

2.3 Manufacturing Process

Figure 6 summarizes the manufacturing process the project focuses on. The process starts with moulded parts made by the injection moulding machine which are transferred to the inspection system via a conveyor belt where it is 3D scanned by Photoneo and data related to the orientation of the part within the conveyor belt is captured. This data is then used to tell the robotic arm the coordinates of the part. Once the command is sent to the robotic arm using ROS, it picks up the part and puts it onto the next conveyor belt for further processing.

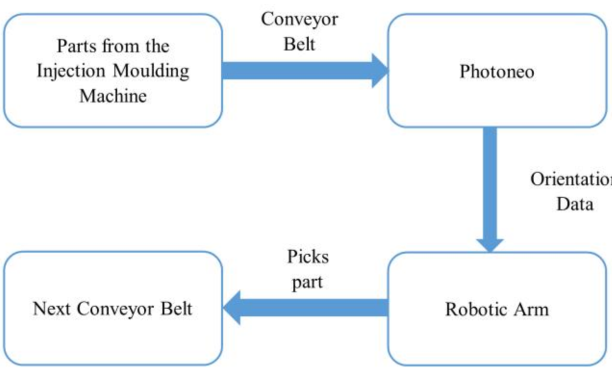

Figure 6 Flow of product through the manufacturing line

3. METHODOLOGY

The DT, as discussed earlier, has three layers: Physical, Digital, and Communication (Figure 7). Our physical layer comprises conveyor belts, robotic arm, and camera; the digital layer has simulation build upon the CAD models of the individual parts; and the communication layer is for receiving and sending the data to both physical and digital layers. The communication layer can be seen as the information processing layer as the bidirectional mapping and interoperation of other two layers, physical and digital, are realized through the data interaction in this layer since it is responsible for storing, processing, and mapping the data (Bambura et al., 2020; Zheng, Yang, & Cheng, 2019). Besides ROS and HALCON, the communication layer has an OPC UA server which is going to serve as a bridge between ROS framework and simulation in Visual Components since there is no framework available in Visual Components to connect it directly to ROS yet.

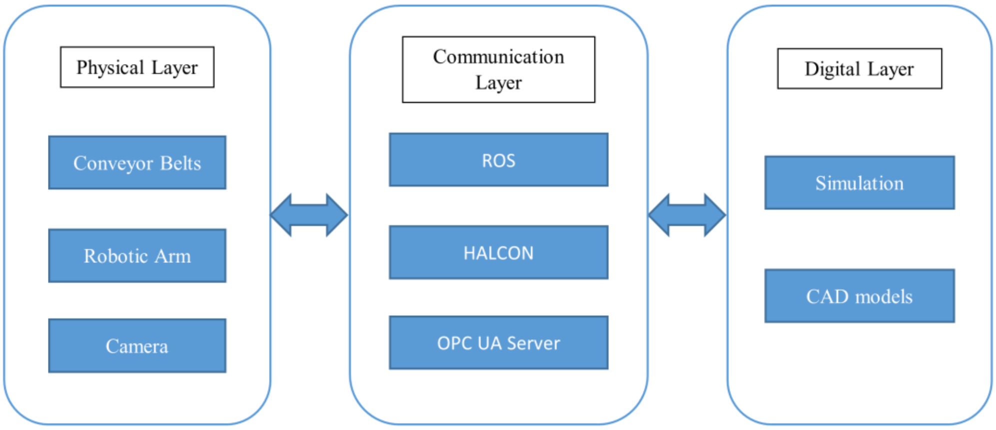

Figure 7 DT mapping between layers [Adapted from (Bambura et al., 2020)]

The proposed framework to develop the DT for the project is shown in Figure 8 which gives the flow of data across different components of the pilot line. After Photoneo captures the image of the part on the conveyor belt, HALCON will convert it into the data points which will be saved as a .dat or .txt file. Since HALCON software is being used on Windows operating system and ROS on Ubuntu, a core functionality of ROS will be set up on Windows which will work as a publisher for sending the data points as well as a subscriber for receiving the inverse kinematics of the robotic arm so that it can be replicated by the virtual one. MoveIt! package of ROS can be used for motion planning and inverse kinematics ("MoveIt," 2021). Inverse Kinematics is used for telemanipulation as it transforms the user input into the corresponding joint values for the robotic arm (Jang et al., 2021; Vatankhah Barenji et al., 2020). On Ubuntu, ROS subscriber will receive the data regarding the part orientation and will control the robotic arm accordingly. OPC UA server and ROS also have bidirectional communication to reflect the status of the physical robotic arm on VC and vice versa. The four main points that will be needed to be taken into consideration while developing the DT are precision and level of details, data acquisition and validation, data model, and synchronization (Kuts, Cherezova, Sarkans, & Otto, 2020).

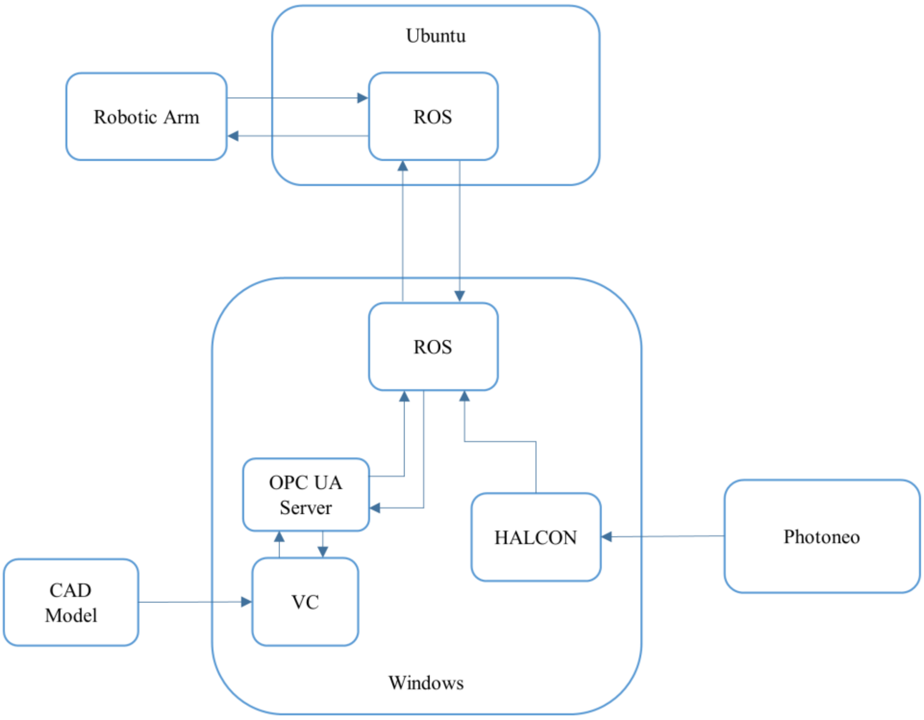

Figure 8 Data flow between different components of the pilot line

4.CONCLUSION

Although DT technology for smart manufacturing is still in early stages and much further work is required (Sawant, Narwane, & Siddavatam, 2020), in this concept paper we have proposed a novel DT framework to simulate the behaviour of the manufacturing cell for robot gripping and transferring processes on the conveyer belt through real-time image processing techniques. The proposed architecture will be implemented on the project. The 3D scanning of the fabricated parts and the two-way communication with the robotic gripper arm will be established through HALCON and ROS platform, for easy and smooth detection of the parts on the conveyer belt. We propose Visual Components to simulate the current state of the manufacturing cell and synchronise them with the entire operation. We strongly believe that once the robotic arm and DT are synced with high accuracy, it will open doors for further research in the area such as DT technology in bringing a significant change in manufacturing operations and systems traditionally work. The automation industry will find ways to further cut down costs, work with high efficiency, and determine the life cycle of the proposed design. Future work will include developing algorithms for system/process optimization and predictive maintenance to further explore the DT and work on its high accuracy and performance in a real-time environment.

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