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# Middle of Life Digital Twin: Implementation at a Learning Factory

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**Abstract.** In recent years, several IT systems have been applied to collect different types of data concerning the full product lifecycle. As a result of Industry 4.0 developments, the amount of product information collected over the entire lifecycle has been growing. Information and communication technology is employed to digitally mirror the lifecycle of a corresponding physical product in Digital Twin applications. These applications are middleware architectures that apply physical world information to support real-time decisions. Therefore, a Digital Twin may be used to enhance simulation, to improve traceability, and to expand the value-added services offering along the lifecycle. However, studies on Digital Twin applications are mainly focused on the beginning of life (BOL) or manufacturing optimization. In this paper, Product Lifecycle Management (PLM) theory and Internet of Things (IoT) solutions and technologies are applied to build a Digital Twin able to collect and cast middle of life (MOL) information to the other lifecycle phases. Based on the scenario implementation in a Learning Factory, the objective is to discuss the information flow that is required for a Digital Twin to be considered for closing the information gap between the product in the use phase and other lifecycle phases. The results show how a middle of life Digital Twin can impact processes and information flow. Future research work should integrate the information of multiple IT systems from the entire product lifecycle in a comprehensive Digital Twin.

**Keywords:** Digital Twin; Learning Factory; Product Lifecycle Management.

## 1 Introduction

The convergence between physical and virtual spaces has gained wide attention in the digitalization era [1]. To deal with this convergence, the Digital Twin (DT) creates a tunnel between the physical parts and its bytes representation [2]. Therefore, a DT consists of three main components: the physical entities in the physical world, the virtual models in the virtual world, and the connected data that tie the two worlds [1].

Digital Twin application contributes to information transparency and to create a real-time production control [3]. Considering the complexity of data integration, a thoroughly DT implementation is still complicated, and most studies demonstrate partial process views [3]. Several IT systems have been applied to collect different types

of data concerning the full product lifecycle [4]. Examples are related to the integration between PLM (Product Lifecycle Management) and ERP (Enterprise Resource Planning) systems [5]. Indeed, PLM is defined as a systematic concept for the integrated management of all product and process-related information through the entire lifecycle, from the initial idea to end-of-life [6]. However, how to acquire and integrate real-world data in a functional DT is still an open question in the literature.

Digital Twins are used as a tool to shorten time to market and to create further benefits along the entire lifecycle. It is used not only for representation purposes but also for predicting product behavior [7]. Besides, Digital Twin's ability to link enormous amounts of data to simulation makes it possible to perform real-time optimization of products and production processes [8].

Current studies on DT applications are mainly focused on the beginning of life (BOL) or manufacturing optimization. In this paper, Product Lifecycle Management theory and Internet of Things (IoT) solutions and technologies are applied to build a Digital Twin capable of transmitting middle of life (MOL) information back to the beginning of the lifecycle. The purpose of this approach is to propose a flexible data decision interface that closes the PLM information loop.

The paper is structured into five sections. After the introduction of the research topic in Section 1, Section 2 provides the research approach developed in the paper. In Section 3, the requirements brought by literature to the Digital Twin concept are presented. Section 4 presents the scenario implementation. Finally, the conclusion and an outlook on further research needs are discussed in Section 5.

## **2 Methodology**

This research started by conducting a literature review [9] on IoT, DT, and PLM (presented in section 3). Based on the gaps from the literature, a middle of life DT model has been implemented in a Learning Factory at the University of São Paulo in Brazil.

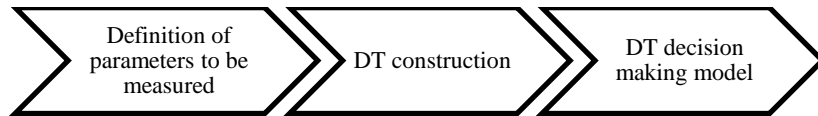
A Learning Factory may be defined as a close to real production environment used to perform research, technology tests, teaching, and professional education. Learning Factories usually consider a real physical product to perform its activities and test scenarios. The selected Learning Factory is based on the assembly of a customizable skateboard in the context of Industry 4.0. This Learning Factory features a real IT systems environment, including a PLM, an ERP, and a MES (Manufacturing Execution System) software. Each of these systems is installed in a virtual server at the university cloud services. The existing IT environment provides the ground for analyzing the digital thread related to the Digital Twin. Figure 1 shows a partial view of the Learning Factory assembly line.



**Fig. 1.** Learning Factory at the University of São Paulo

This paper focuses on a Digital Twin for the MOL, capable of transmitting middle of life information back to the beginning of the lifecycle. In this paper, the MOL is considered the product usage phase by the client. Data collected during the usage phase can be considered as an input for product development and also for providing value-added services, such as predictive maintenance.

The research methodology involved three main steps for the DT model deployment: the definition of MOL parameters to be measured based on IoT data collection technologies, the DT construction, and the DT application to decision making (Fig. 2).



**Fig. 2.** Research steps

A practical implementation scenario has been constructed presenting a MOL Digital Twin of a connected skateboard (product produced at the Learning Factory). The following requirements and constraints were considered for the DT in this scenario:

- Allow data to be transfer through the internet;
- Measure different parameters of the skateboard;
- Provide alternative information aggregation for different stages of the lifecycle.

The proposed MOL Digital Twin should also be designed to support future integration with PLM, ERP, and MES data in a comprehensive product data aggregation tool.

### **3 Literature Review**

This section presents a discussion on Internet of Things (3.1) and Digital Twin (3.2).

#### **3.1 Internet of Things**

Internet of Things can be defined as a mechanism of interaction between physical objects and virtual data environments [10]. It is considered one of the major communication advances in recent years, which offers the basis for the development of independent applications [11]. With IoT technology, a product can be equipped with a uniquely identifiable code that can then be monitored and tracked by using sensors and wireless networks [12].

The implementation of intelligent factories is possible considering the evolution of manufacturing and information technologies, being able to receive different information from multiple sources, and produce items that are more complex in a reduced time and different locations. This change in production technologies requires a new representation of product models and manufacturing processes. This representation would be reached by a Digital Twin.

#### **3.2 Digital Twin and PLM**

Digital Twin is a multi-physical, multi-scale, and probabilistic simulation model of a complex product. It uses updated sensors and physical models to mirror physical life in the digital world and vice versa [13, 14].

The Digital Twin is essential to provide the subsystems all required information [15, 16]. It should be able to import background data, component information, and configuration information from the physical component [17–19]. The Digital Twin is used to string different existing IT systems, i.e., Product Lifecycle Management, Manufacturing Execution Systems, among others. It is initiated based on digital knowledge from the product design phase. The physical and environmental knowledge of the product is also embedded in the product 3D model, which forms the initiation of the Digital Twin [20]. The virtual reality-based 3D digital model can meet the intelligent and personalized needs, which is the future of the digital factory [21].

The role of the PLM system is collecting and managing data of product definitions, processes, resources, and decisions across the whole product lifecycle supporting changes and enabling traceability of these changes through a product model [22].

The product model that supports the data interfacing (and then systems interoperability) should describe, with the same semantic, various data. In a low trust level, the product model is used to manage the product information separately in different databases [23]. Therefore, managing the interaction between the physical and digital world starts from the product model. The DT must manage the interaction of the product model and the physical world, and its requirements must reflect that. The question is on how to integrate different types of data to close the PLM loop and connect different stages of the product lifecycle.

## 4 Results and Applications

This section presents the main research results considering the definition of parameters to be measured (Section 4.1), the DT implementation (Section 4.2), and the use of the DT as data input for different stages of the PLM (section 4.3).

### 4.1 Definitions of Parameters to be Measured

In order to monitor the skateboard use during the middle of life, it was necessary to define the parameters to be measured and to specify how to measure these parameters – transforming a regular skateboard on a connected skateboard.

Considering the skateboard, critical parameters to be measured in the product usage lifecycle phase include the instant speed, the travel distance, and the vibration and position of the board. To measure the speed and the travel distance, the proposal considered counting the number of wheel turns. The equation I is applied to calculate the speed, and equation II is used to calculate the travel distance.

$$Speed = 3600 \frac{2\pi r * n_{turns}}{\Delta T} \quad (I)$$

$$Travel = travel + 2\pi r * n_{turns} \quad (II)$$

The number of turns in the wheel can be counted by two alternative solutions: the hall effect sensor and the encoder speed. Table 1 presents the strengths and weaknesses of each approach.

**Table 1.** Strengths and weakness of alternatives for counting wheel turns

	Strengths	Weakness
<b>Hall effect</b>	<ul style="list-style-type: none"> <li>• Easy to implement</li> <li>• Do not interfere in the skate design</li> </ul>	<ul style="list-style-type: none"> <li>• Electromagnetic interference</li> <li>• Need to use a magnetic</li> </ul>
<b>Encoder speed</b>	<ul style="list-style-type: none"> <li>• High precision measure</li> </ul>	<ul style="list-style-type: none"> <li>• Measure impacted by vibration environments</li> <li>• Need to change skateboard design</li> </ul>

By analyzing Table 1, the best option to capture the number of turns and, therefore, the speed and travel distance, was the hall effect sensor.

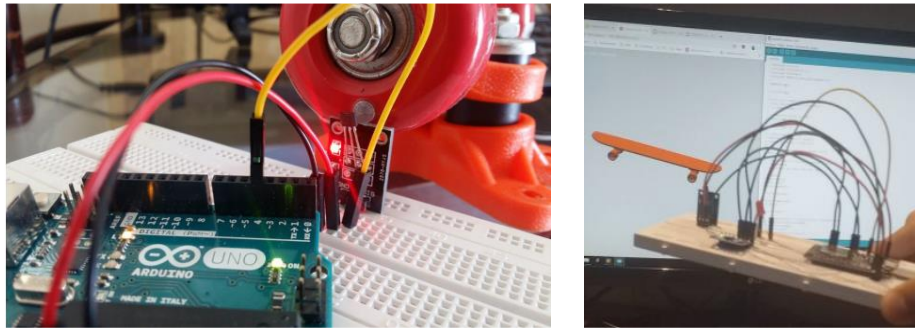
Two possible alternatives were considered to measure the position/vibration of the board and develop a real-time 3D model to mirror the skate movements: an accelerometer and gyroscope, and the use of the user smartphone sensors to collect the data. Table 2 represents the strengths and weaknesses of each approach.

**Table 2.** Strengths and weakness of alternatives for position/vibration measurement

	Strengths	Weakness
<b>Accelerometer and gyroscope</b>	<ul style="list-style-type: none"> <li>Precise monitoring</li> <li>Integration with microcontroller</li> </ul>	<ul style="list-style-type: none"> <li>Small impact resistance</li> </ul>
<b>Smartphone integration</b>	<ul style="list-style-type: none"> <li>Do not require additional implementation</li> </ul>	<ul style="list-style-type: none"> <li>Low precision</li> </ul>

By analyzing Table 2, the best option to capture the position/vibration was the accelerometer and gyroscope.

Figure 3 shows the initial implementation and tests. The hall effect sensor counts the number of times that the magnetic passes on the sensor, counting the number of times that the wheel turns (Fig. 3 left side). The accelerometer and gyroscope capture the board position (Fig. 3 right side).



**Fig. 3.** Hall effect sensor (left side) and accelerometer implementation (right side)

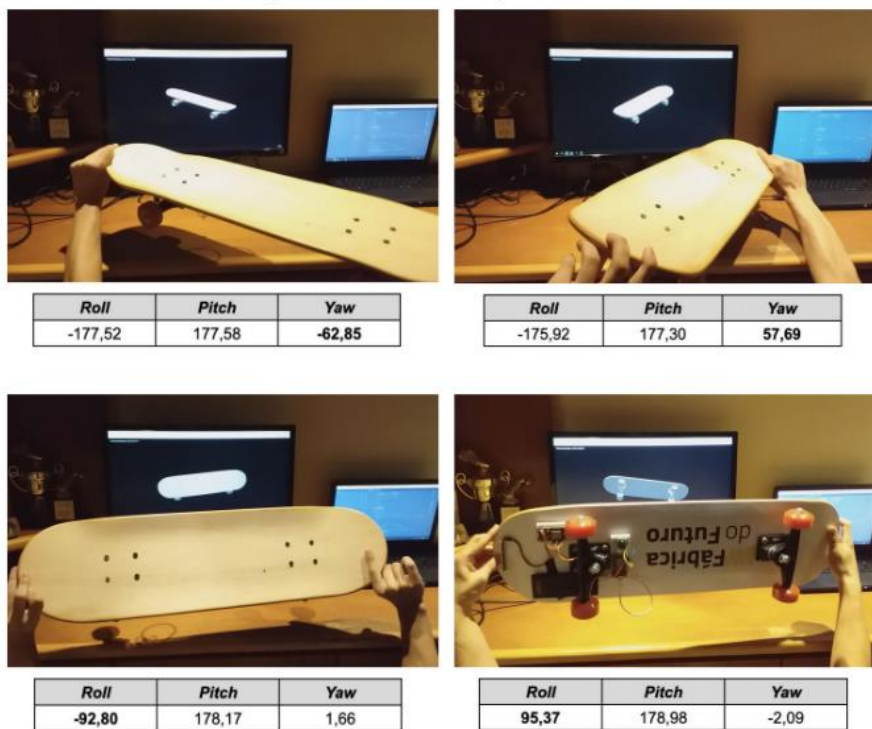
#### 4.2 Digital Twin Implementation

After the sensors' definition, an integrated circuit was developed and installed in the skateboard (Fig. 4), and a digital model was developed to show the movements of the skateboard in real-time. Figure 5 shows the impact of skate movement on the digital model.





**Fig. 4.** Implementation of sensing technology



**Fig. 5.** Digital model

The implementation was then deployed using C in Arduino ESP8266 and HTML, CSS and Java Script connecting the database and creating a user interface at localhost to perform initial testing. Figure 6 shows a part of Arduino coding (left side) and a part

of front-end development (right side). The complete code is available at [github.com/duraoluiz](https://github.com/duraoluiz).

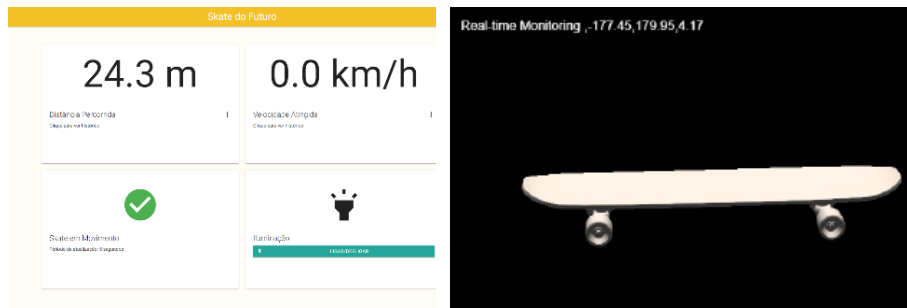
```

1 #include <ESP8266WiFi.h>
2 #include <ESP8266WiFiAP.h>
3 #include <ESP8266WiFiGeneric.h>
4 #include <ESP8266WiFiMulti.h>
5 #include <ESP8266WiFiScan.h>
6 #include <ESP8266WiFiSTA.h>
7 #include <ESP8266WiFiType.h>
8 #include <WiFiClientSecure.h>
9 #include <WiFiServer.h>
10 #include <WiFiUdp.h>
11 #include <Base64.h>
12 #include <ESP8266HTTPClient.h>
13 #include <I2Cdev.h>
14 #include <MPU6050_6Axis_MotionApps20.h>
15 #if I2CDEV_IMPLEMENTATION == I2CDEV_ARDUINO_WIRE
16 #include <Wire.h>
17 #include <FirebaseArduino.h>
18 #endif
19
20 #include <WiFiUdp.h>
21
22 MPU6050 mpu;
23 WiFiUDP Udp;

```

**Fig. 6.** Arduino ESP8266 implementation (left side) and front-end coding sampling (right side)

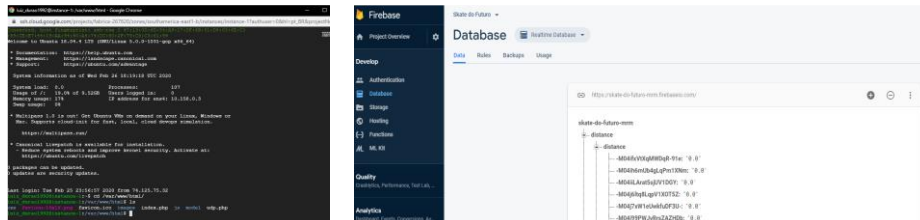
Figure 7 presents the final user interface of the speed and distance monitoring as well as the 3D Digital Twin.



**Fig. 7.** Digital Twin front-end

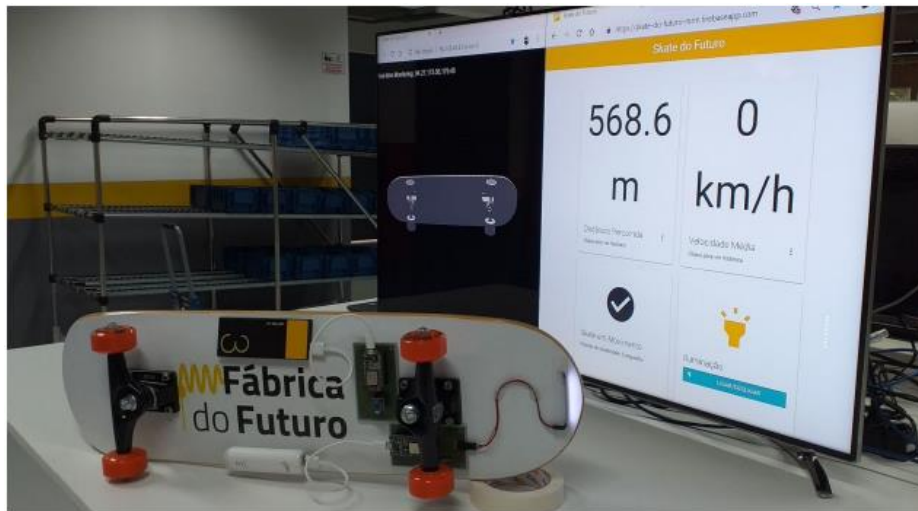
With the front-end developed and a back-end running at localhost, it was required to establish a virtual machine to run the Digital Twin and to structure the data. The selected platform to receive the DT was a gcloud Ubuntu 18, and for the back-end, a

Firestore was used. Figure 8 shows the Ubuntu server (left side) and the Firebase implementation (right side).



**Fig. 8.** Server implementation (left side) and Firebase data implementation (right side)

The implementation was then finished as a basic Digital Twin. It can capture real-world information about the product use phase and display this information in real-time in the virtual world. Besides, one can change digital data and impact the real world by turning the skate lights on. Figure 9 presents the physical product and the Digital Twin implementation.



**Fig. 9.** Digital Twin

### 4.3 DT Application

Digital Twin implementation enabled analysis of the most important ways to take advantage of the information captured on the product usage phase into the early stages of the product lifecycle. There are different ways to do that, such as anticipating wheels demand for manufacturing, changing the product design considering the most common maneuvers, and the balance of weight, among others. However, for this project, the information that is reused is the speed and average speed by the users. With that

information, the manufacturer can suggest the most appropriate wheel diameter for a specific user.

A python script was developed to capture the information from the online database of the user, processing the information, and analyzing the most common acceleration and speed as an input for the manufacturing of new wheels more suitable for the type of use. This information flow closes the information loop from the usage phase to services, using real-time information to improve product use.

Additional value-added services can be derived from the MOL Digital Twin data analysis, such as maintenance and training.

The product usage profile gathered in the Digital Twin database can also serve as a relevant field input to support new product development and product improvement. Therefore, design engineers can analyze detailed user patterns.

## **5 Conclusions and Future Work**

This paper set out to answer if it is feasible to apply Digital Twin concept to connect different stages of the product lifecycle and allow real-time and personalized decision making. In this sense, the role of lifecycle management is collecting and managing data of product definitions, across the whole product lifecycle.

A Digital Twin was developed in a Learning Factory in Brazil. This Learning Factory has as its base product a skateboard. Therefore, all the monitoring and information are related to a skateboard as a scenario reference description for other industries.

The first step was to define the parameters to be measured (speed, distance, and vibration/position) and to define the sensors to be used. The physical product was connected to the internet, providing a real-time digital mirror of the physical world.

Having real-time data is not the final stage of a Digital Twin implementation. The information should be connected to different lifecycle processes and IT systems to follow-up product information. In this paper, an example has been implemented in order to consider real-time data from the usage phase to support decision making on wheels diameter for specific customers based on usage data. The example shows how a middle of life DT can support connecting different stages of the product lifecycle and promote real-time decision making to enhance services.

Current studies in this area usually focus on early product lifecycle phases and on Digital Twin implementation to support simulation. However, the discussion of a multi-phase Digital Twin and the implementation of a Digital Twin on the product use phase is still open in the literature. In this study, we focus on the use phase as a starting point for the Digital Twin deployment.

This research has limitations regarding the use of opensource platforms and a Learning Factory scenario. Future research work should integrate the information of multiple IT systems from the entire product lifecycle in a comprehensive Digital Twin. In this sense, establishing a detailed digital thread to support Digital Twin may be a promising research avenue.

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