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Digital twinning for smart restoration of classic cars

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Abstract

Classic cars hold substantial value in the automotive industry, and the restoration process plays a pivotal role in increasing their worth. Ensuring the certification of these restoration processes is vital, as is keeping owners well-informed about the ongoing procedures taking place in their appreciated vehicles. By monitoring and controlling these restoration activities, the management of classic car workshops can effectively optimize their operations, empower owners with pertinent information, and preserve the authentic nature of these vintage automobiles.

This study aims to develop a digital twin system for a classic car bodywork restoration shop workshop. The latter integrates multiple sensor technologies, including location tracking, humidity and temperature sensing, accelerometer monitoring, and smart plugs, to facilitate the identification of ongoing activities of classic car bodywork restoration process instances. By leveraging these sensors, the digital twin system may simulate and control workshop operations more effectively.

We perform a systematic rapid review of related work and, based on state-of-the-art practices, we identify existing architectures and software applications used for creating digital twin systems. Then, we propose the architecture for our digital twin system, detailing its functionalities. We aim at contributing to advancing digital twin technology in classic car bodywork restoration, enhancing its authenticity, and fostering improved management practices, and overall experience for classic car owners.

Keywords: digital twin; classic cars; bodywork restoration; digital transformation; industry 4.0; IoT

1. Introduction

Classic cars hold immense historical and cultural significance and are regarded as works of art by collectors and enthusiasts. Consequently, the classic car market experiences high demand, rendering these vehicles highly valuable. Restoring classic cars is essential to preserving their authenticity and ensuring continued value.

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The Charter of Turin [1], established by the Fédération Internationale des Véhicules Anciens (FIVA)[1], sets forth the principles and guidelines for the preservation, use, and promotion of historic vehicles worldwide. It outlines FIVA's commitment to safeguarding the cultural heritage represented by historic vehicles and emphasizes the importance of maintaining their originality, historical accuracy, and technical authenticity by avoiding inappropriate modifications, destruction, and misuse.

Classic car bodywork restoration processes are typically intricate, time-consuming, and involve multiple stakeholders, making it challenging for workshop floors to effectively manage, control, and monitor them. We expect the benefits of the Industry 4.0 revolution [2] to come to the rescue, creating more efficient, flexible, and intelligent restoration shops.

The work described in this paper originates from a collaboration between the Automated Software Engineering (ASE) group of NOVA-LINCS, ISTAR's Software Systems Engineering group, and Raimundo Branco. The latter is a classic car bodywork restoration shop that aims at benefiting from the fourth industrial revolution described before. Additionally, ACP, the largest automobile association in Portugal, and BASF, a German multinational company specializing in chemical production, including Glasurit's product line used for painting classic cars, are participating in this collaborative effort.

This project builds upon previous works [3, 4, 5] within the digital transformation of a classic car bodywork restoration shop and aims to contribute by creating a digital twin (DT) for this specific domain. The latter will facilitate optimization, decision-making, simulation, testing, monitoring, and control, improving efficiency, reducing costs, and enhancing quality within the workshop environment.

The successful implementation of a DT requires accurate and real-time synchronization between the physical object and its virtual representation, elastic storage to hold the ever-increasing data on the captured events, and intelligent reasoning capabilities to analyze that data retrospectively, on the fly, and prospectively.

Section 1 presents the context and description and challenges of this work. The DT concept is explained in section 2.1, as well, important features. Several key enabling technologies, briefly introduced in section 2.2, facilitate the effective implementation of a DT. To elicit the state of the art, we conducted a rapid systematic review of methodologies, architectures, and technologies employed in DTs within real-case scenarios similar to our context, which is reported in section 3. This review allowed us to identify the existence of several tools that have been used to create and run DTs, which were further detailed in 3.2. Then, in section 4, we present the architecture of the DT solution that will enable, among others, space organization and layout optimization, and outline future work. Lastly, on 5, we draw some conclusions and outline future work.

2. Background

2.1. Digital twin

A DT is a virtual representation of a real (physical) object. This concept is often confused with the idea of *digital model* and *digital shadow*. These three concepts differ in how physical objects interact with virtual ones. In a *digital model*, the data flow is manual, changes in the physical object are manually made to the virtual object, and vice-versa. In a *digital shadow* the data flow is automated between physical object and virtual object, but manually vice-versa. Lastly, in a DT there exists an automatic bi-directional data flow between the two kinds of objects [6].

A more detailed definition of a DT is a *"virtual construct that represents a physical counterpart, integrates several data inputs with the aim of data handling and processing, and provides a bi-directional data linkage between the virtual world and the physical one"* [7]. This data is usually collected through sensors and synchronization is an important aspect. According to the literature [8], a DT should allow:

- **Data visualization** - visualizing virtual models in 2D or 3D, as plots of different data in the DT through the sensors.

[1] FIVA is an international federation dedicated to the preservation, protection, and promotion of historic vehicles, including cars, motorcycles, and other modes of transportation.

- **Modelling and Calibration** - creating models, i.e. representations with behavior as faithful as possible to the physical counterpart, and calibrating them, i.e. fitting model parameters.
- **State estimation** - estimating the current system state, which changes through time.
- **Monitoring and controlling** - monitoring and controlling the physical object or processes through the DT. This is the type of features found in cyber-physical systems (CPS).
- **What-if simulation** - experimenting and testing with different conditions and scenarios (i.e. assessing the consequences of doing something) based on the data captured from the physical system.
- **Predictive maintenance** - predicting when maintenance may be required in the physical object, therefore avoiding potential failures.
- **Self-adaption** - self-reconfiguration and optimization, usually using ML-based algorithms.

Combining these features is expected to bring improved performance, cost savings, and increased sustainability, safety, collaboration, and quality control to a physical system, such as a shop floor or a factory.

2.2. Key enabling technologies

We will now briefly review why several key enabling technologies, such as IoT, cloud computing, and machine learning, are required for the effective implementation of a DT.

2.2.1. Internet of Things (IoT)

IoT was defined as *"the network of things, with device identification, embedded intelligence, and sensing and acting capabilities, connecting people and things over the Internet"* [9]. IoT is therefore about multiple interconnected devices collecting information from physical objects, exchanging information about them, and controlling them.

IoT is a crucial technology to a DT because it establishes the connection with physical objects, allowing data collection in real-time, monitoring and controlling devices and processes. Therefore, IoT is an enabler of many of the DT features identified in section 2.1.

2.2.2. Machine learning

Machine learning (ML) is also an important aspect of improving efficiency and enabling some features of a DT. ML algorithms allow advanced analysis and interpretation and prediction capabilities upon the data coming from IoT.

ML algorithms may be used in the context of a DT for anomaly detection (i.e. finding deviations from expected behavior), predictive analytics (i.e. making predictions about future behavior), optimization and control (i.e. finding the best settings or control parameters to achieve desired outcomes), data imputation and reconstruction (when data is missing or incomplete), and what-if analysis through simulation (to analyze the impact of different scenarios and provide insights into the behavior of the system under various conditions) [10].

2.2.3. Cloud computing

Cloud computing is the delivery of computing resources, including servers, data storage, database, processing power, networking, and software, over the internet.

Cloud computing plays a crucial role in the implementation and utilization of DTs namely to grant scalability and resource management [11]. Since DTs usually require optimal performance to allow real-time response, cloud platforms can offer a scalable infrastructure to handle varying processing workloads efficiently. DTs often generate large amounts of data, calling for efficient data ingestion, organization, and retrieval, to ensure that historical and real-time data is readily available for modeling and analysis. Cloud computing platforms offer those capabilities. The same can be said for facilitating collaboration among stakeholders involved in the DT ecosystem while enabling seamless data sharing and integration between different systems. Cloud computing also provides powerful computational resources and pre-built tools for the ML features described in section 2.2.2.

3. State of the art

3.1. Rapid Review

We performed a *Rapid Review* (RR), a lightweight systematic literature review (SLR) technique widespread in Software Engineering [12]. The latter delivers the results in a shorter time review, with simple processes, compared to a full SLR [13], while maintaining the rigor and quality of the search for scientific evidence.

This RR was leveraged by the use of *Parsifal*, an online tool designed to support researchers to perform SLRs within the context of Software Engineering. *Parsifal* documents the whole review process. During the planning phase, records the objectives, *PICOC*[2], research questions, search string, keywords, and synonyms, selecting the sources, the inclusion and exclusion criteria. It also provides mechanisms to build a quality assessment checklist and data extraction form. During the conducting phase, allows to import *BibTeX* files and select the studies, find duplicates among all the different sources, execute the quality assessment, and extract data from the papers.

This RR undertook three stages:

- *Planning the research* - here we defined the research questions, search string, sources, and selection criteria;
- *Conducting the research* - in this stage, we evaluated the quality of the selected papers;
- *Discussion and analysis of the results* - here we analyzed the information collected in the selected articles.

3.1.1. Planning the research

Research Questions

The PICOC framework was used to clarify the RR scope, as seen in table 1, before the formulation of the research questions and definition of the search string.

Table 1: Rapid Review scope

PICOC	
Population	Scientific papers
Intervention	Digital Twins in the context of Digital Transformation
Comparison	Digital Twins vs other systems
Outcomes	A systematic study of methodologies, practices, techniques, and tools that characterize the current state of the art in the identified context
Context	Industry 4.0 in the automotive industry

The research questions to which we wanted to get an answer are the following:

- How are DT integrated into the automotive industry?
- What architectures have been used for setting up DT?
- What technologies have been used for building DT?

Search String

The following search string was derived from the research questions:

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"digital twin" AND "industry 4.0" AND "cyber-physical system"
AND ("automotive industry" OR "smart factory" OR "car industry"
OR "shop floor" OR "smart manufacturing")
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[2] Population, Intervention, Comparison, Outcome, and Context, a framework to describe the research scope

This search string allows finding papers where the main focus are DTs. The substring on Industry 4.0 systems is due because the DT concept being highly related to such systems. Another substring is on CPS, a key component for a DT, as mentioned in section 2.1.

As explained in section 1, the case study of this project is a classic car bodywork restoration shop, so it is important that the papers are in the context of the automotive and car industry. However, since there are very few papers with that context, we generalized it by adding the substrings: *smart factory*, *shop floor*, and *smart manufacturing*.

The search engine used was Scopus by applying the search string only in the title, abstract, and keywords[3] and it returned 108 results. All articles found were in English and the publication year was not before 2015, evidencing this is a relatively new research area.

3.1.2. Conducting the research

Study Selection

After getting the potential articles, we read the abstract of all of them to determine the relevant ones (true positives) by applying a set of inclusion and exclusion criteria. This step was leveraged by the use of Elicit, a LLM-based[4] AI tool that summarizes paper takeaways (i.e. extracts key information from them), to help with brainstorming, summarization, and text classification. In this step, 30 articles were selected, i.e. 78 were considered false positives.

Quality Assessment

In this phase, the accepted articles were read entirely to make a quality assessment. Each quality question was answered in the following ranking scale: *Strongly agree*, *Agree*, *Neither agree or disagree*, *Disagree* or *Strongly disagree*, what allowed to rank the previously selected papers. In the next section, we will discuss the results presented in the 8 best-ranked papers.

3.1.3. Discussion and analysis of the results

In [14], the case study is the Volkswagen AutoEuropa, in Palmela, Portugal, and the main goal was to produce a big data platform for data analytics, visualization, and control of a logistics-based DT. The designed architecture for this case has 3 entities, the physical factory, the big data infrastructure, and the DT. The physical factory sends data to the other entities.

The big data infrastructure has five layers: data collection and ingestion layer, data storage layer, data processing layer, data analytics layer, and data visualization layer. Lastly, this entity has a bidirectional communication with the DT tool chosen, the Visual Components simulation environment. For the validation of this work, the DT simulation quality was tested and compared with the logistics processes in real life. The second validation was a *"What-if scenario"* to solve an optimization problem. Both these tests required a comparison with KPI[5].

A DT and manufacturing simulation platform is proposed in [15] with the main purpose of monitoring and simulation. The architecture is composed of a *CPS Bus* that transmits data, a *Physical Shop Floor* (i.e., the machines), a *Shop-floor Service System* that controls and monitors the shop floor, and the *DT* using Unreal, a game engine. A five-dimensional (Geometry, Physics, Capabilities, Behaviour, and Rules) architecture underlies the DT. For validation, a simulation of two configurations of the production line is performed, and their efficiency is compared.

A framework of DT-CPPS[6] composed of two parts, physical and cyber shop floor, is proposed in [16]. The physical shop floor is where the sensors and the network connectivity are required to collect the data. The cyber shop floor is the DT of the physical shop floor, as tools it is recommended to use Plant Simulation by Siemens Digital Industries Software or Demo 3D. It presents the operating flow of this DT with the information interaction between the two parts. The data processing of the DT-CPPS encompasses two phases (local and global data processing). Finally, the predictive machine sequencing model is shown, with the purpose to find the best machine sequence for a certain process flow learned from historical data, and responsive production scheduling strategies, through the real-time data

[3] using the TITLE-ABS-KEY option in Scopus
[4] large language model
[5] Key Performance Indicators
[6] CPPS = Cyber-Physical Production System

it is possible to create a production plan Gantt Chart and then a scheduling strategy is made. This architecture is applied on a shop floor with several machines and industrial robots.

A DT based on both product and process twins, based in a six-layer framework is proposed in [17]:

- *Integrated physical assets* - All the entities like sensors and RFID that collects data;
- *Integrated faithful product/process virtual models* - A virtual model needs to be faithful to its physical object, the more similar, the more accurate and precise the DT becomes;
- *Intelligent layer* - This layer has AI and ML algorithms to make decisions in the DT;
- *Data layer* - In this layer all the data generated from the physical assets are stored and processed;
- *Enterprise layer* - This is responsible for services, business models, decision-making, event, and rule handling.

This framework was studied at the Festo cyber-physical smart factory. The Siemens NX tool created the 3D CAD model of the factory and the DT tool was the *Plant simulation*.

A DT-CPPS framework is presented in [18] to overcome the performance and efficiency hurdle of personalized production. The system has five services: production planning, automated execution, real-time monitoring, abnormal situation detection, and dynamic response services. The DT-CPPS is a four-layer architecture comprising: device, network, service, and application. The service layer contains a product, process, plan, plant, and resource (P4R) information database. There are five applications in the DT-CPPS: the DT, context-aware, advanced planning, advanced scheduling, and device control. The case study of this work was a micro smart factory. The DMWorks simulation engine by *eZRobotics*, a factory simulation solution that covers a wide range of robotics applications, was used. The authors claim that this solution has fast execution and quick responses compared to normal production.

A DT based on configuration, motion, control, and optimization (CMCO) is proposed in [19] for flow-type smart manufacturing systems, as follows:

- *Configuration design* - refers to physical static design;
- *Motion planning* - refers to motion path of actuator;
- *Control development* - refers to CPS;
- *Optimization* - refers to manufacturing execution engine;

Two key technologies are presented for enabling the CMCO model: the generalized encapsulation of quad-play and the DT. This architecture is tested in a hollow glass processing enterprise in China as the case study. The prototype was developed based on Unity 3D, a simulation engine. All the four modules were implemented in the engine. Finally, the DT was tested with a study of the utilization rate of the tempering furnaces showing that the factory can save costs by managing the furnaces better. The final test was an optimization problem of the number of trays compared to two other algorithms, showing the DT faster and better results.

The paper [20] presents a four-component DT architecture for production management and control. The layers are: physical assembly shop floor, assembly shop floor DT, assembly shop-floor big data storage and management platform, and DT and big data-driven assembly shop-floor service/application platform. The case study of this paper was a satellite assembly shop floor. Four key technologies were used:

- Real-time acquisition, organization, and management of the data - through the construction of an IoT network on the shop floor.
- Construction of the DT - it was built following three levels, element, construction of 3D geometric models of the machines in the shop floor. Behavior, connections between elements, tools recommended are FlexSim, *Unity3D*, and 3DVIA Composer. The rule consists of making sure the operations of the DT match the physical shop floor mechanism.
- DT and big data-driven prediction.
- DT-based production management and control service.

A DT-based CPS applied in an automotive body production line in the Republic of Korea was proposed in [21]. The purpose of this work is to have a system capable of predicting the operation and production in the case study, considering abnormal situations, and consequently, increasing system efficiency.

This DT-based CPS is the connection between a DT and a web-based integrated platform. This framework has five components, the physical world, a legacy system, a web-based integrated manufacturing platform, a P4R information model, and the DT application. The data comes from the physical world through sensors and it is transmitted to the web-based platform, where it is transformed in the form of P4R information, and then transmitted to the DT. Lastly, the new data and predictions made in the DT come back to the web-based platform. This framework consists of a three-layered architecture, communication, information, and application layer. *Plant Simulation* was used as the simulation engine for the DT. For the validation of the DT-based CPS, an experiment was carried out to calculate the prediction accuracy ratio between the predicted production volume (calculated by the DT) and actual production volume (produced on the production line). All the different processes on the production line had over 95% average prediction accuracy ratio.

3.2. Available DT Tools

In section 3.1.3 several software platforms were mentioned that allowed to creation of different DTs. Those platforms may have different contexts of application, specific functionalities, and scripting languages, may have different popularity in the community, may or may not have integrated APIs, have documentation or not, and have either open access or require a commercial license, as represented in Table 2.

Table 2: Digital Twin Tools/Platforms Comparison

Digital Twin Tools	Main context	Functionalities	Scripting language	Popularity[7]	API	Open Access	Docum.
Visual Components	Manufacturing	3D Layout Configuration Statistical Analysis Process modeling Basic Virtual Commissioning Robot Programming and Control	Visual Components Script (VSC), based on .NET Framework and C#	1	Yes	No	Yes
Plant Simulation	Industrial engineering, manufacturing and logistics	3D simulation environment, Object-oriented Modeling Dynamic Simulation Statistical Analysis Optimization and What-If Analysis Material Flow Analysis Resource Management	SimTalk	1	Yes	No	Yes
Demo 3D	Manufacturing	3D Visualization Simulation Control System analysis and optimization	JScript and C#	1	Yes	No	Yes
Unreal Engine	Architectures, real state and build environment	Realistic 3D Visualization Blueprint Visual Scripting Physics Simulation Data Integration and Visualization Multi Platform Deployment Level of Detail (LOD) Optimization	C++ and Blueprint	3	Yes	Yes	Yes
DMWorks	Manufacturing	3D Visualization Simulation Manufacturing Process Validation Robot Offline Programming Robot and Workcell Calibration		1	No	No	No
Unity 3D	Smart cities, facilities and products	3D visualization Physics Simulation Data Integration and Visualization Multi Platform Deployment Scripting and Programming Level of Detail (LoD) Optimization	C#	2	Yes	Yes	Yes
FlexSim	Manufacturing, Material handling, Healthcare, Warehousing and Supply chain	3D visualization Data integration Process modeling What-if simulation	FlexScript, based on C++	1	Yes, C++	No	Yes
3DVIA Composer	3D Design	3D visualization Simulation	3DVIA Composer Scripting Language (3DSL)	1	Yes, C#	No	No

Only two tools are open-source, *Unity 3D* and *Unreal Engine*, so they were the best candidates. Both have robust physics engines that can handle simulations and interactions within the DT, and both offer APIs and tools for integration. The main reasons why we chose *Unity 3D* were:

- *Unreal Engine* has a steeper learning curve than *Unity 3D*, due to its advanced features and customization options for cutting-edge graphics capabilities and visual effects required in gaming, but not in a DT;

[7] Scale: 1 - Little, 2 - Average, 3 - Great

- *Unity 3D* has broader platform compatibility, including support for desktop, web, mobile, and VR/AR devices. *Unreal Engine* primarily focuses on desktop and high-end platforms, although it does support other platforms to some extent;
- *Unity 3D* has a larger and more established user community than *Unreal Engine*, which means there are extensive resources, tutorials, and reusable assets available.

3.3. Previous works

The research described herein is part of a larger project that started two years ago. Several subsystems of this project, corresponding to the non-colored components in Figure 1, were already developed, tested, and are in operation in situ, having been found helpful for the involved stakeholders: shop managers, classic car owners, and certification companies.

The *IoT Subsystem* uses several types of IoT sensors (e.g. BLE - Bluetooth Low-Energy, and smart plugs with Wi-Fi for metering power consumption), and edge computers (Raspberry Pis). The latter, herein called "sensor boxes", include humidity, temperature, and vibrations sensors, and are attached to classic cars with magnets. The *Cloud Service Provider* runs in a cloud-based virtual machine managed by OpenStack. This subsystem digests IoT sensors' data and processes it (e.g. fingerprinting algorithms for identifying car positions and identifying the tools being used). A *Web Application* monitors sensor boxes' operation (e.g. charge level, and malfunction detection) [4].

The *Charter of Turin Monitor* is a process-aware subsystem fueled by a BPMN workflow engine. Is in charge of process monitoring and uses a process-aware graphical user interface (GUI) with a BPMN model matching FIVA's Charter of Turin practices [1]. This process-aware GUI allows associating media evidence to each activity of the restoration process for each classic car. A multimedia report (text, images, and videos) is generated at the end of each restoration process. Lastly, the *Cameras Hub* component allows classic car owners to remotely control cameras mounted on a showroom, and record pieces of evidence themselves at specific moments of the restoration process [5].

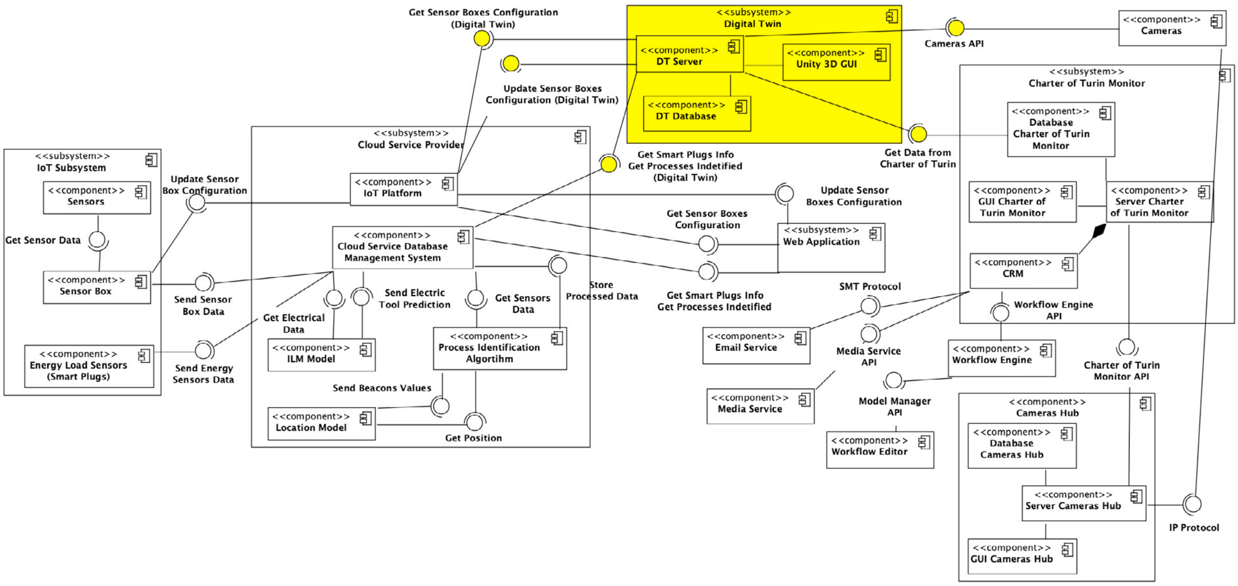

Fig. 1: Component Diagram of the proposed system architecture

4. Conceptualisation

As introduced before, the purpose of this work is to create a DT of a classic car workshop, for monitoring, controlling, data visualization, and simulations purposes. It should have a 3D virtual representation of the plant shop floor and use the data provided by the *Cloud Service Provider* to allow visualizing what is happening in real-time, like where and what activity is being performed in a certain car in the shop floor. We plan that the DT will have the following data sources:

- **Real-time data from sensors** - Data collected from the physical workshop through the sensor boxes, smart plugs, and process identification in real-time. So it is possible to monitor and control in real-time, what is happening in the workshop;
- **Historical data from sensors** - Data saved in the database of past events used for simulation of semi-realistic scenarios;
- **Static data** - Data created by the user in the DT, so it can create several scenarios and what-if simulations;

As mentioned in section 2.1, our DT will allow data visualization, modeling and calibration, monitoring and controlling, what-if simulation, and self-adaption. Its integration with the remaining subsystems described in section 3.3 is depicted in the overall system architecture represented in Figure 1. The *Digital Twin* subsystem, represented in yellow, will have the represented provided and required interfaces. Two are connections with the *IoT Platform* consisting of sensor configuration information, so it is possible to collect data from the sensors and update them. One other connection is from the *Cloud Service Database Management System*, to get data from the smart plugs and the processes identification. Finally, there will be a connection to the database of the *Charter of Turin Monitor*, to get information about the processes occurring in the classic cars associated with media evidence, and another to the PTZ cameras used by the *Cameras Hub*.

5. Conclusion

The ongoing work described in this paper is an extension of previous work on the digital transformation of a classic car bodywork restoration workshop. In concrete, we are developing a digital twin with features aiming for data visualization, modeling and calibration, monitoring and controlling, what-if simulation, and self-adaption. By performing a systematic rapid review we confirmed this is a not yet covered niche by digital twins. We also concluded that, for this context, Unity 3D is the most suitable platform to support the visualization aspects to allow functionalities such as real-time synchronization with the physical workshop, space organization, and layout optimization. We also proposed how the digital twin will fit into the overall software architecture.

One of the most interesting challenges for future research work is devising traceability links between visual process awareness (the one provided by the digital twin) and model-based process awareness (the one provided by the *Charter of Turin Monitor* subsystem).

Besides the current remotely controlled PTZ (Pan-Tilt-Zoom) cameras, the *Cameras Hub* component will also have a remotely controlled *rotisserie*, a rotating cradle holding the car's body securely, to allow the classic car owner to rotate it 360 degrees horizontally, being able to observe it from different angles. It is still an open issue how this hub can be used in conjunction with the digital twin.

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