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Applications of the Digital Twin in Industrial Manufacturing

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Summary

1. The Digital Twin Concept

1.1. Historical background

The concept of Digital Twin (DT) is not new: the premises for its evolution date back to the space race more than 50 years ago. NASA's need to ensure the safe return of the spacecraft to Earth under critical conditions prompted engineers to develop simulators processed with real-time data from the physical spacecraft in space, analyzing possible scenarios and calculating the optimal decision to instruct crew members to maneuver the spacecraft. That application demonstrated the potential of virtual simulation in linking physical and virtual spaces. A virtual simulation model reflects the constraints of physical assets without errors and direct training on physical assets to extract appropriate solutions through virtual simulation.

1.2. Concept definition and evolution

In 2002 M. Grieves defined DT for the first time in his course "Product Life Cycle Management: Virtual representation of what has been produced."

Subsequently a milestone for the definition of Digital Twins was set by NASA itself in collaboration with the United States Air Force in the field of aerospace equipment maintenance: "A Digital Twin is a multi-physics, multiscale, probabilistic integrated simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin."

In the following decade, the concept of DT began to grow exponentially in popularity. The most relevant additions to the definition are as follows can be seen in Table1.1.

Table 1.1 Digital twin definition evolution

Author	Definition
Chen 2017 [12]	"A digital twin is a computerized model of a physical device or system that represents all functional features and links with the working elements."
Liu et al. 2018 [39]	"The digital twin is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information and can forecast the future of the corresponding physical counterpart."
ZHENG et al. 2018 [78]	"A Digital Twin is a set of virtual information that fully describes a potential or actual physical production from the micro atomic level to the macro geometrical level."
VRABIČ et al. 2018 [65]	"A digital twin is a digital representation of a physical item or assembly using integrated simulations and service data. The digital representation holds information from multiple sources across the product life cycle. This information is continuously updated and is visualized in a variety of ways to predict current and future conditions, in both design and operational environments, to enhance decision making."

Although the concept of DT has evolved over the years and achieved a high degree of complexity and completeness, some aspects still make it difficult to distinguish it from other technological solutions: in general, in many applications it is not easy to distinguish DT from general computational methods, simulations and similar concepts such as digital model, digital shadow and digital twin.

As can be seen in Figure 1.1. The discriminant with respect to the technological solutions mentioned above is the flow of data: a digital model is described as a digital version of a pre-existing or designed physical object; to properly define a digital model, there must not be an automatic exchange of data between the physical model and the digital model. The digital shadow, on the other hand, is a digital representation of an object that has a unidirectional flow between the physical object and the digital object. A change in the state of the physical object leads to a change in the digital object, not vice versa. In the digital twin if data flows between an existing physical object and a digital object, and is fully integrated in both directions, this constitutes the "Digital Twin" reference. A change made to the physical object automatically leads to a change in the digital object and vice versa.

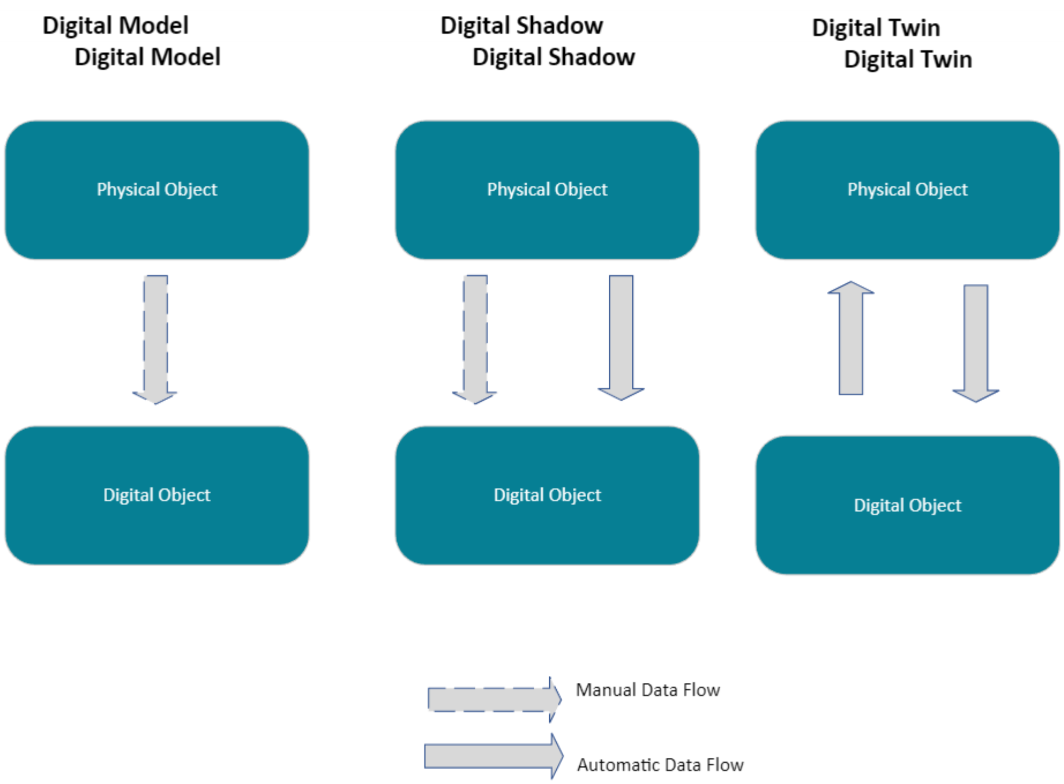

Figure 1.2. Differences among Digital Model, Digital Shadow, and Digital Twin.

1.3. Digital Twin basic structure

Originally proposed as a three-dimensional model by Grieves, the five-dimensional extension model proposed by Tao et al. (2018) [62] laid the foundation most of the frameworks proposed in the subsequent literature. The dimensions (three initial and two extended) are:

1. Physical;

2. Virtual;

3. Service;

4. Data;

5. Connections.

It is important to note that the DT is not just a virtual representation of an object, but can encapsulate an entire process, i.e., a complete diagnostic procedure, with the necessary equipment.

data acquisition, flow and management, connections, and algorithms. The correlation between these layers is illustrated in Figure 1.2.

DT data can be in a multitude of forms, such as physical sensor signals, virtual signals, manuals, tables, databases. Localization can occur simultaneously in the system itself, in adjacent (auxiliary) systems that may or may not be part of the DT itself (even if their data are), and in the cloud. In addition, this data may be raw (e.g., voltage, current, flow, counts, size) or processed (e.g., health indices, state values, grouped or labeled). Therefore, proper management is of critical importance.

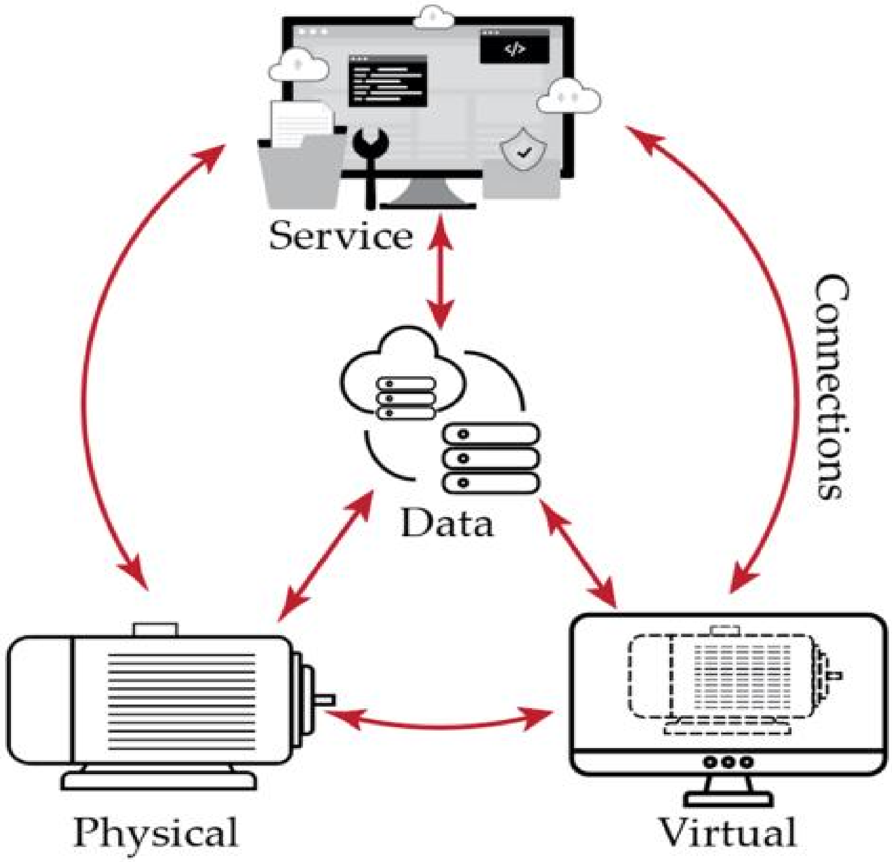

Figure 1.2. DT layers correlation.

1.4. Manufacturing application

Manufacturers are always seeking ways to track and monitor products to save time and money, a core factor and motivation for any manufacturer. That is why Digital Twins seem to have the most significant impact in this context. Connectivity is one of the main drivers for the manufacturing sector to use Digital Twins.

The Digital Twin can provide real-time machine performance status and feedback from the production line. This enables the manufacturer to predict problems in advance. The use of the Digital Twin increases connectivity and feedback between devices, in turn improving reliability and performance. Artificial intelligence algorithms coupled with the Digital Twins have the potential for greater accuracy as the machine can hold large amounts of data, which is needed for performance analysis and forecasting.

The Digital Twin is creating an environment for testing products and a system that operates on real-time data, which in a production environment has the potential to be an extremely valuable asset.

This review explored the services that can be grouped into these categories:

1) Real-time monitoring of the performance and health status of the physical asset;
2) Energy efficiency analysis;
3) Detection and diagnosis of product failures;
4) Predictive maintenance: optimized maintenance strategy obtained by analyzing historical and real-time data of system status by using simulation models and optimization algorithms;
5) Performance prediction: historical and real-time data are used to perform a reliable prediction of future production system state through simulation;
6) Human Operator Analysis, used to obtain the operations done from the users and/or giving them user guidance to visualize the system updates with a user-friendly HMI (Human-Machine Interface);
7) Scheduling optimization in the production planning process;
8) Plant layout optimization in a reconfigurable manufacturing system;
9) Exchange data between other systems such as interaction between Digital Twin and other ERP systems;
10) Controlling, automated feedback from the digital twin to the physical system.

2. Literature survey and data collection

This review aims to investigate the practical implementations of DTs in manufacturing systems in industrial or laboratory environments by understanding the main application purpose of the created DTs, what services are offered among those described in Chapter 1, and how the architecture for data acquisition and simulation (including dataset acquisition and protocol, model, and software used) was constructed.

The literature search was conducted using the Scopus database: search strings were limited to article titles, abstracts, and keywords.

As can be seen from Fig. 2.1a. the concept of DT increased in popularity especially in 2018, so the scope of research was narrowed by limiting the time frame between 2018 and 2023.

A large percentage of the research results came from the United States, Germany and China (Fig 2.1.b., Fig 2.1.c), which are leading the race toward Industry 4.0. A small number of researchers and research organizations contributed nearly 40 percent of the total number of articles on this topic.

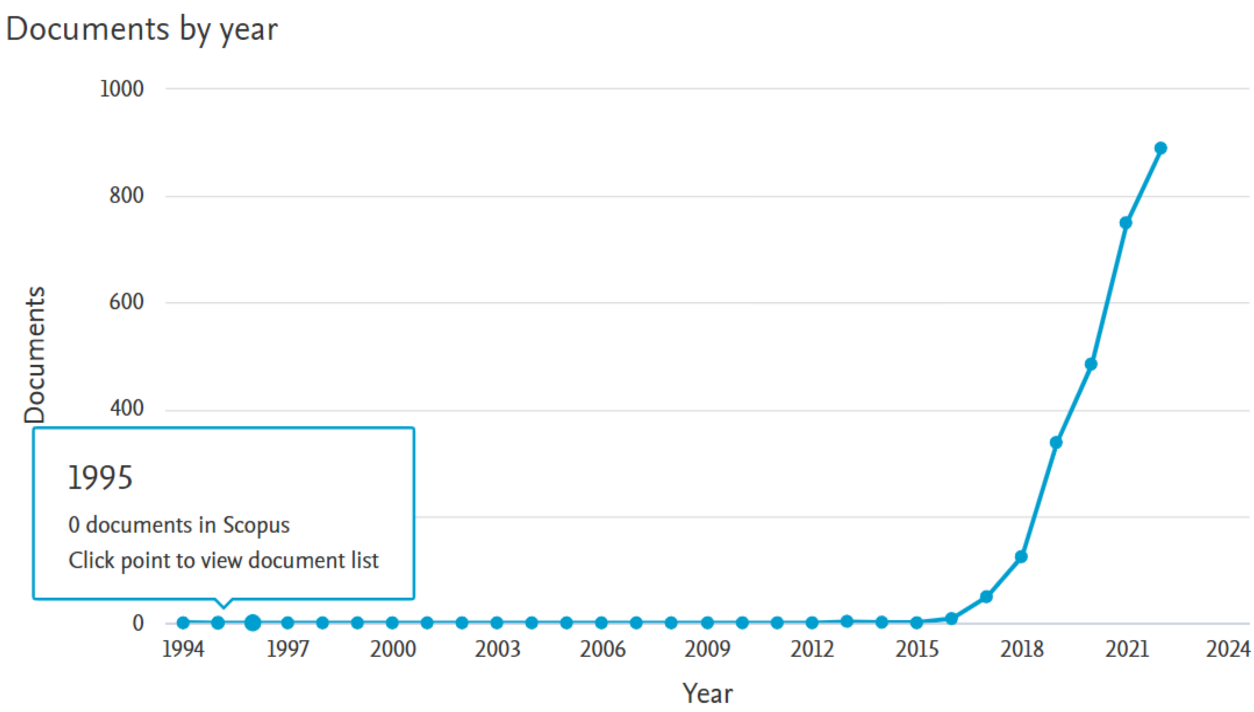

Figure 2.1a. Statistics from Scopus database (TITLE-ABS-KEY ("digital twin" or ("virtual twin") and ("manufacturing" or ("production system"). Documents by year.

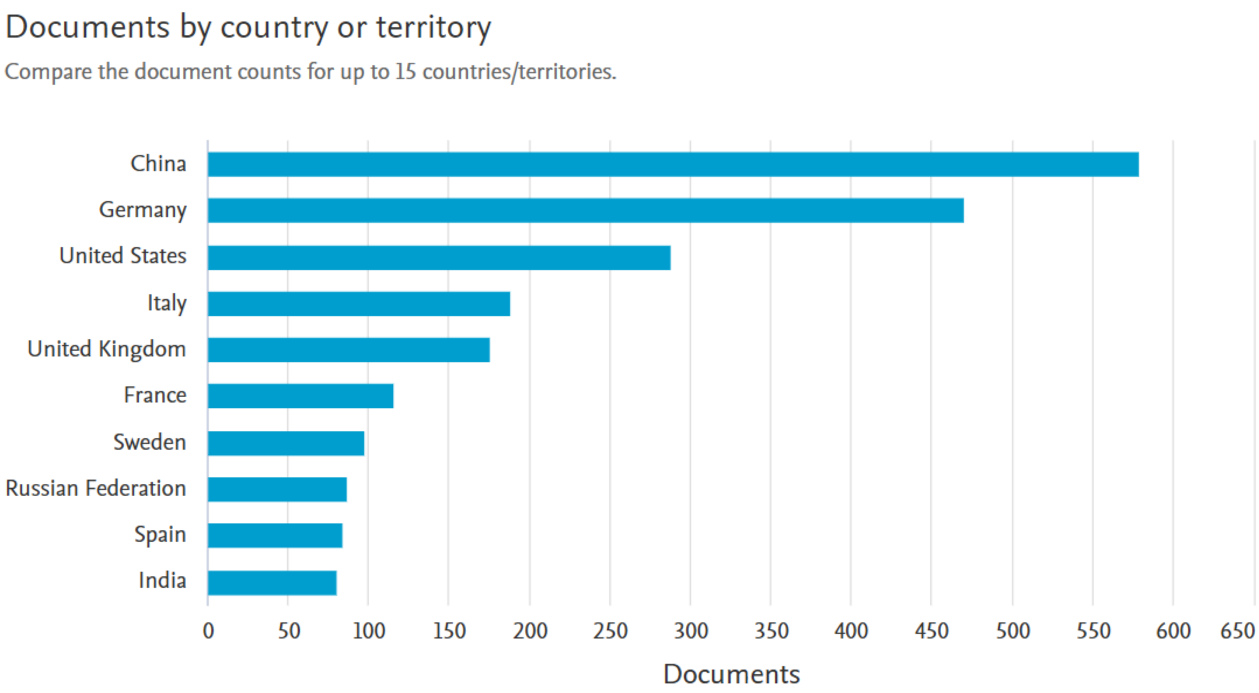

Figure 2.1b. Documents by country or territory.

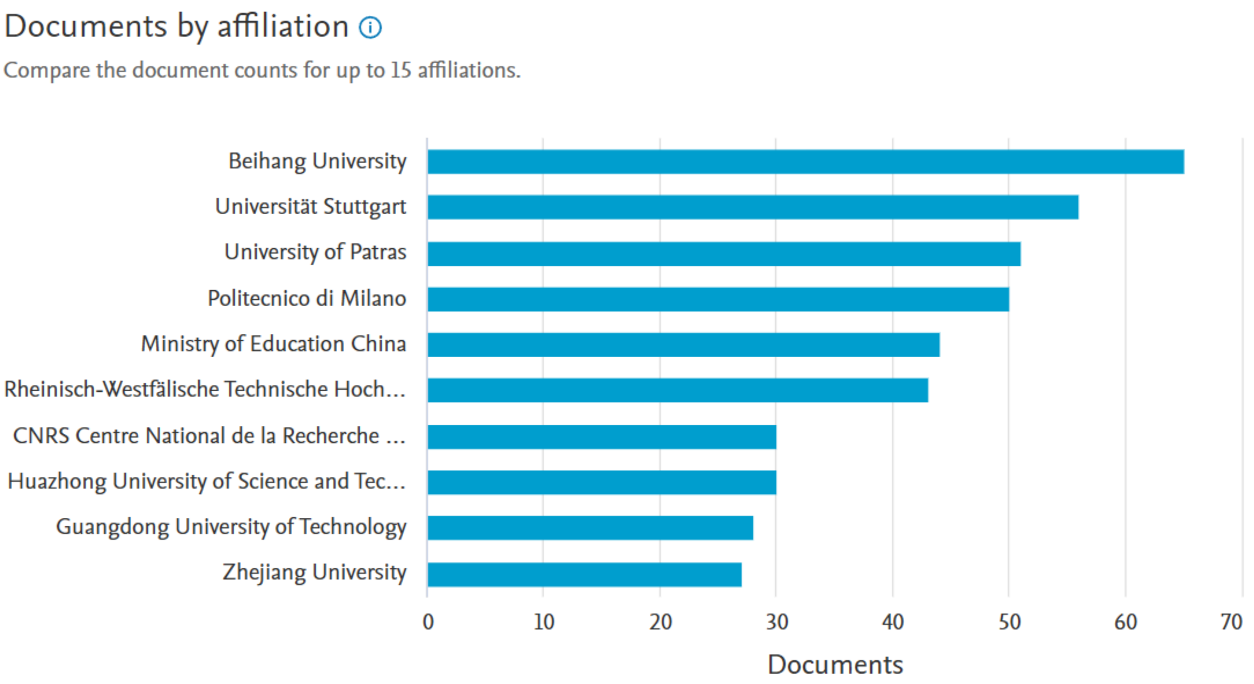

Figure 2.1c. Documents by affiliation.

Table 2.1. and Fig 2.2. illustrate the procedure for selecting articles in this review and the number of articles identified accordingly are as follows. A total of 2698 papers were identified after searching Scopus using the search strings presented in Table 3 for paper selection.

Next, 2638 papers were identified by limiting the search period to "January 2018 to January 2023." This was further narrowed down to 1215 after limiting the document type to "Article" and "Review" 940 after limiting the subject area to "Engineering," and 804 after limiting the language to "English", 740 after limiting publication stage "Final" and finally 418 by setting "All Open Access".

Subsequently, a screening procedure, was performed to determine the relevance of the article by reading the abstract, methodology and conclusion through which 68 articles were identified.

The criteria for papers exclusion from the screening procedure are as follows:

1. Articles presented only content related to the concept of DT with no real application cases;
2. Some of the articles did not explain the development of the DT and the architecture to support it;
3. Articles didn't present a complete compliance to the DT definition given in Chapter 1;
4. Display of methods to improve DT itself rather than apply DT;
5. Articles were not downloadable.

A specific search was carried out for the welding application of DT through which 4 articles were identified, in this case the same selection and screening criteria of the first search were used but with the search string: ("digital twin" or “virtual twin”) and (“welding” or “welder”) and (“manufacturing” or “production system”).

As a result, 72 final articles were included for further analysis, all reporting DT applications in industrial or laboratory manufacturing environments.

The following Table 2.2. reports all the articles clustered by their application target. Articles that were covered by more than one application target were assigned to multiple clusters as can be seen in the Venn Diagram (Fig2.3) while articles with very specific applications for which no common features could be identified were assigned in the cluster named “Others”. The classification and analysis of each cluster will be explained in depth in the next chapter.

Table 2.1. Selection criteria

Searching Index	Specific content
Database	Scopus
Article types	Scientific article and Review
Search string	(“digital twin” OR” “virtual twin”) AND (“manufacturing” or “production system”)
Search period	2018-2023
Subject area	Engineering
Language	English
Open access	All open access
Pubblication stage	Final

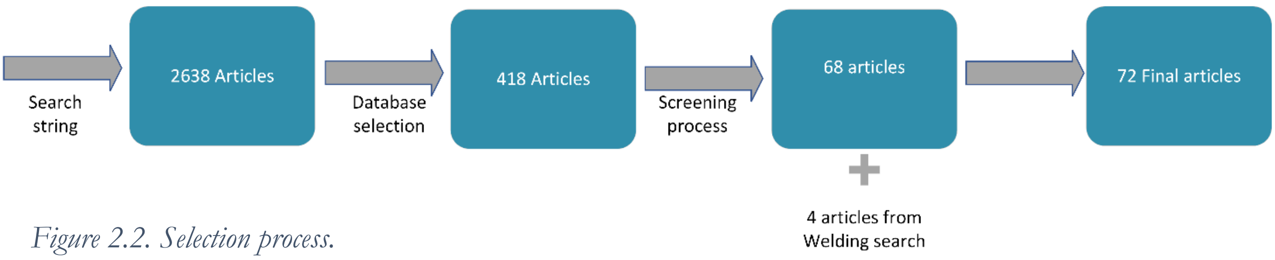

Figure 2.2. Selection process.

Table 2.2. Articles clusterized by application target.

Application	Author-Year-Reference	Descritpion
Production line	Ashtari Talkhestani (2019) [6]	An architecture for a Digital Twin and its required components is proposed, with which use cases such as plug and produce, self-x and predictive maintenance are enabled.
	Liu et al. (2019) [38]	A novel process evaluation method based on digital twin technology. It shows how to evaluate the process plan with the dynamic change of the machining condition and uncertain available manufacturing resources.
	Xu et al. (2019) [70]	A two-phase digital-twin-assisted fault diagnosis method using deep transfer learning (DFDD), which realizes fault diagnosis both in the development and maintenance phases is presented.
	Bambura et al. (2020) [7]	Feasibility demonstration of the DT implementation under real conditions of a production plant that is specializing in manufacturing of the aluminum components for the automotive industry.
	Barni et al. (2020) [9]	Demonstration of how performance losses induced by highly variable cycle times can be recovered using a digital twin.
	Negri et al. (2020) [48]	The paper proposes a way to integrate a Digital Shadow simulation model with the Manufacturing Execution System (MES) in this way creating a DT. The MES integrated DT is used for decision making thanks to the presence of an intelligence layer that hosts the rules and the knowledge to choose among alternatives.

	Perez et al. (2020) [52]	Presentation of a novel methodology for process automation design, enhanced implementation, and real-time monitoring in operation based on creating a digital twin of the manufacturing process.
	Abonyi & Ruppert (2020) [1]	Demonstration of digital twin capability to predict production status and provide information for monitoring of production performance thanks to the real time position data acceleration data and adaptive simulation models.
	Zhao et al. (2020) [77]	Modeling method of Digital Twin process model for manufacturing process. Acquisition method of real-time data and the management method of simulation data are discussed.
	Barbieri et al. (2021) [8]	Define the necessary steps for the development of DTs and for their integration into manufacturing systems through a DT architecture. A methodology based on virtual commissioning is proposed.
	Bavelos et al. (2021) [10]	Presentation of a smart execution control framework for enabling the autonomous operation of flexible mobile robot workers. A DT is deployed.
	Jiang et al. (2021) [27]	Modeling methods for rapidly creating a virtual model and the connection implementation mechanism between a physical world production system at a workshop level and its mirrored virtual model.
	Kousi et al. (2021) [29]	Digital twin-based approach for designing and redesigning flexible assembly systems.

	Leng et al. (2021) [32]	Presentation of a digital twins-based remote semi-physical commissioning (DT-RSPC) approach for open architecture flow-type smart manufacturing systems. A digital twin system is developed to enable the remote semi-physical commissioning.
	Martinez at al. (2021) [42]	Complete DT structure covering all automation pyramid stages using Artificial Intelligence (AI) to model each stage of the Automation Pyramid.
	Resman et al. (2021) [55]	A five-step approach to planning data-driven digital twins of manufacturing systems and their processes
	Villalonga et al. (2021) [64]	A decision-making framework for dynamic scheduling of cyber-physical production systems based on digital twins.
	Ward et al. (2021) [68]	DT applied for real-time vision-based multiple objects tracking of a production process.
	Wu et al. (2021) [69]	Innovative application framework of a digital twin-driven ship intelligent manufacturing system and analysis of operation mechanism.
	Ademujimi e Prabhu (2022) [2]	Approach for engineering digital twins (DTs) that are used to train Bayesian Networks (BNs) for fault diagnostics at equipment and factory levels.
	Arnarson et al. (2022) [5]	Highly flexible reconfigurable manufacturing system (RMS) enabled by digital twin and wireless power transfer solution.
	Cheng et al. (2022) [13]	Digital-Twins-Driven Semi-Physical Simulation for Testing and Evaluation of Industrial Software in a Smart Manufacturing System.

	Ding et al. (2022) [13]	Dynamic scheduling optimization of production based on Digital Twin.
	Eyring et al. (2022) [17]	Analysis of a closed-loop digital twin using discrete event simulation (DES) to evaluate identification and reaction to trends in production.
	Kombaya Touckia et al. (2022) [28]	DT application for reconfigurable manufacturing systems (RMS).
	Ma et al. (2022) [40]	Digital Twin and big data technologies application in a sustainable smart manufacturing strategy based on information management systems for energy-intensive industries from the product lifecycle perspective.
	Magalhaes et al. (2022) [41]	DT application in a flexible manufacturing system (FMS).
	Matsunaga et al. (2022) [45]	How real-time monitoring and simulation of industrial energy consumption can optimize processes and reduce energy waste, potential saving opportunities in manufacturing energy consumption and costs.
	Mendi (2022) [46]	Simulation, process, and validation of each phase of product life cycle to discover the potential problems before the production of real components. The use of digital twin technology in the commercial production phase of the automotive production line is introduced.
	Onaji et al. (2022)[49]	DT framework and its application in Fest Cyber Physical smart factory, pharmaceutical continuous crystallization system and virtual X-ray of electric motors.

	Qamsane et al. (2022) [53]	Evaluation of a DT Framework solution for performance monitoring in process manufacturing systems that aims to avoid unplanned downtime, a prevalent challenge that pressures profitability in manufacturing.
	Miriam Ugarte Querejeta et al. (2022) [63]	Implementation of a digital twin solution for design prototyping and commissioning practices in a Cyber Physical System (CPS).
	Yang et al. (2022) [71]	DT application in a flexible and reconfigurable manufacturing system context. The paper Discussion of the architectural design and implementation of the application, an information model, and an assessment model that enable quantitatively assessment on reconfigurations of manufacturing systems from various aspects.
	Zhang et al. (2022) [75]	Dynamic performance analysis and vulnerability Evaluation for a smartphone Digital Twin workshop under temporal and spatial disruptions.
	Zhang et al. (2022) [76]	A model framework of intelligent workshop manufacturing system based on a digital twin is proposed, driving the deep information integration among the physical entity, data collection, and information decision-making.
	Kumbhar et al. (2023) [30]	A digital twin framework is developed to detect, diagnose, and improve bottleneck resources using utilization-based bottleneck analysis, process mining, and diagnostic analytics.
CNC Machine	Bambura et al. (2020) [7]	Feasibility demonstration of the DT implementation under real conditions of a

		production plant that is specializing in manufacturing of the aluminum components for the automotive industry.
	Jiang et al. (2021) [27]	Modeling methods for rapidly creating a virtual model and the connection implementation mechanism between a physical world production system at a workshop level and its mirrored virtual model.
	Ward et al. (2021) [67]	DT applied for real-time vision-based multiple objects tracking of a production process.
	Wu et al. (2021) [69]	Innovative application framework of a digital twin-driven ship intelligent manufacturing system and analysis of operation mechanism.
	Arnarson et al. (2022) [5]	Highly flexible reconfigurable manufacturing system (RMS) enabled by digital twin and wireless power transfer solution.
	Choi et al. (2022) [14]	Digital twin architecture and system based on an interoperable data model. How to build a digital twin for the integrated control monitoring using edge devices, data analytics, and realistic 3D visualization.
	Ding et al. (2022) [16]	Dynamic scheduling optimization of production based on Digital Twin.
	Guo et al. 2022 [23]	DT applied to a machine tool for speed and accuracy simulation and monitoring.
	Hu (2022) [26]	Digital Twin-driven reconfigurable fixturing optimization for trimming operation of aircraft skins.

	Kombaya Touckia et al. (2022) [28]	DT application for reconfigurable manufacturing systems (RMS).
	Magalhaes et al. (2022) [41]	DT application in a flexible manufacturing system (FMS).
	Mendi (2022) [46]	Simulation, process, and validation of each phase of product life cycle to discover the potential problems before the production of real components. The use of digital twin technology in the commercial production phase of the automotive production line is introduced.
	Zhang et al. (2022) [74]	DT application for dynamic scheduling and adaptive control in a manufacturing cell.
Human-Robot Collaboration	Bilberg e Malik (2019) [11]	Discussion of an object-oriented event-driven simulation as a digital twin of a flexible assembly cell coordinated with a robot to perform assembly tasks alongside human.
	Havard et al. (2019) [25]	DT architecture for design, simulation and optimizaion cyber-physical production system and interaction with it remotely or in a collaborative way using virtual reality.
	Kuts et al. (2019) [31]	Digital twin based synchronized control and simulation of an industrial robotic cell using virtual reality.
	Liu et al. (2019) [37]	A novel process evaluation method based on digital twin technology. It shows how to evaluate the process plan with the dynamic change of the machining condition and uncertain available manufacturing resources.
	Oyekan et al. (2019) [50]	This paper presents the use of a Virtual Reality digital twin of a physical layout as a mechanism

		to understand human reactions to both predictable and unpredictable robot motions.
	Perez et al. (2020) [52]	Presentation of a novel methodology for process automation design, enhanced implementation, and real-time monitoring in operation based on creating a digital twin of the manufacturing process.
	Bavelos et al. (2021) [10]	Presentation of a smart execution control framework for enabling the autonomous operation of flexible mobile robot workers. A DT is deployed.
	Kousi et al. (2021) [29]	Digital twin-based approach for designing and redesigning flexible assembly systems.
	Martinez et al. (2021) [43]	A Digital Twin Demonstrator to enable flexible manufacturing with robotics.
	Diachenko et al. (2022) [15]	Industrial collaborative robot digital twin integration and control using robot operating system.
	Gallala et al. (2022) [19]	DT approach for human–robot interactions (HRIs) in hybrid teams using Industry 4.0 enabling technologies, such as mixed reality, the Internet of Things, collaborative robots, and artificial intelligence.
	Mourtzis et al. (2022) [47]	Robotic Arm Manipulation Based on Mixed Reality in a collaborative manufacturing cell.
Transportation system	Abonyi & Ruppert (2020) [1]	Demonstration of digital twin capability to predict production status and provide information for monitoring of production performance thanks to the real time position

		data acceleration data and adaptive simulation models.
	Bavelos et al. (2021) [10]	Presentation of a smart execution control framework for enabling the autonomous operation of flexible mobile robot workers. A DT is deployed.
	Glatt et al. (2021) [21]	Modeling and implementation of a digital twin of material flows based on physics simulation.
	Kousi et al. (2021) [29]	Digital twin-based approach for designing and redesigning flexible assembly systems.
	Martinez-Gutierrez et al. (2021) [44]	DT design concept based on external service for the transportation of the Automatic Guided Vehicles (AGVs) which are being recently introduced for the Material Requirement Planning satisfaction in a collaborative industrial plant.
	Ward et al. (2021) [68]	DT applied for real-time vision-based multiple objects tracking of a production process.
	Roque Rolo et al. (2021) [57]	Application of a simulation-based Digital Twin for predicting distributed manufacturing control system performance.
	Cheng et al. (2022) [13]	Digital Twins-driven semi-physical simulation for testing and evaluation of Industrial Software in a Smart Manufacturing System.
	Han et al. (2022) [24]	Digital Twin-Based automated guided vehicle scheduling: a solution for its charging problems.
	Onaji et al. (2022) [49]	DT framework and its application in Festo Cyber Physical smart factory, pharmaceutical

		continuous crystallization system and virtual X-ray of electric motors.
	Yang et al. (2022) [71]	DT application in a flexible and reconfigurable manufacturing system context. The paper Discussion of the architectural design and implementation of the application, an information model, and an assessment model that enable quantitatively assessment on reconfigurations of manufacturing systems from various aspects.
	Zhang et al. (2022) [75]	Dynamic performance analysis and vulnerability Evaluation for a smartphone Digital Twin workshop under temporal and spatial disruptions.
Welding Process	Aivaliotis et al. (2019)[4]	Methodology to calculate the Remaining Useful Life (RUL) of machinery equipment by utilizing physics-based simulation models and Digital Twin concept, in order to enable predictive maintenance for manufacturing resources using Prognostics and health management (PHM) techniques.
	Tabar et al. (2019) [61]	A method for identification and sequence optimization of geometry spot welds in a digital twin context.
	Li et al. (2020) [34]	Quality prediction and control of assembly and welding process for ship group product based on Digital Twin.
	Roy et al. (2020) [58]	DT model developed for an advanced manufacturing process named friction stir welding.

	Wang et al. (2020) [66]	Deep learning-empowered digital twin for visualized weld joint growth monitoring and penetration control.
	Aivaliotis et al .(2021) [5]	The Digital Twin is employed to monitor the health status of the robot and ensure the convergence of the simulated to the actual robot behavior: The output of the simulation is used to estimate the future behavior of the robot and make predictions for the quality of the products to be produced, as well as to estimate the robot's Remaining Useful Life.
	Li et al. (2022) [33]	A detection and configuration method for welding completeness in the automotive body-in-white panel based on digital twin.
Additive Manufacturing	Yavari et al. (2021) [72]	Detecting flaws in laser powder bed fusion using a DT solution.
	Yi et al. (2021) [73]	Process monitoring of economic and environmental performance of a material extrusion printer using an augmented reality-based digital twin.
	Liu et al. (2022) [36]	This paper proposes a novel Digital Twin-enabled collaborative data management framework for metal additive manufacturing systems, where a Cloud DT communicates with distributed Edge DTs in different product lifecycle stages.
	Pantelidakis et al. (2022) [51]	Implementation of digital twin ecosystem that can be used for testing, process monitoring, and remote management of an additive

		manufacturing–fused deposition modeling machine in a simulated virtual environment.
	Reisch et al. (2022) [54]	DT implementation for process monitoring in Wire arc additive manufacturing.
Others	Greco et al. (2020) [54]	Ergonomics monitoring during manufacturing production.
	Liang et al. (2021) [35]	Displacement field perception method for component Digital Twin in aircraft assembly.
	Rodriguez-Guerra et al. (2021) [56]	DT application on fault-tolerant control systems to overcome faults without human interaction.
	Sun et al. (2022) [60]	A performance prediction method for a high-precision servo valve supported by Digital Twin.
	Stan et al. (2022) [59]	Development of a Digital Twin for a robotic deburring work cell allowing monitoring and controlling.
	Farhadi et al. (2022) [18]	Digital Twin framework for an industrial robot drilling process.

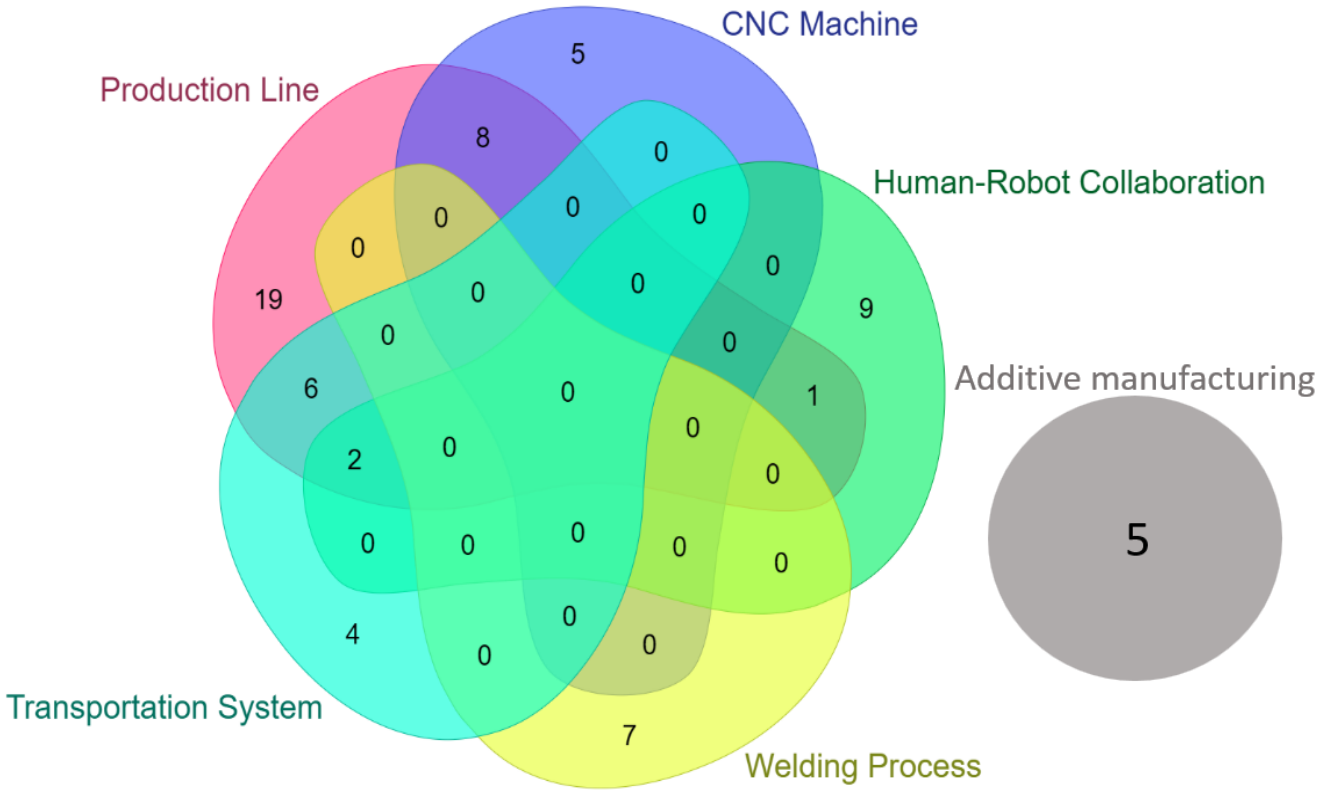

Fig 2.3. Venn Diagram of clusters intersections.

3. Cluster Analysis

Services offered by the DT and the technologies implemented were analyzed, with a focus on data acquisition and transmission and simulation features of the physical production assets.

The analysis was carried out for each cluster except Welding Process and Additive Manufacturing, this is due to too small number of articles per cluster and the difficulty of getting a general overview in DT implementation. In any case, the classification of implemented technologies for these clusters can be seen in the Appendix.

Regarding data acquisition and transmission, when mentioned, the following aspects were analyzed:

- **Sensors and Hardware** for data collection from the shopfloor;
- **Communication Protocol and architecture network**. They represent a critical factor in the creation of the DT. State synchronization between a Digital Twin and its counterpart in physical space is based on two-way communication of real-time data. In this regard, industrial communication protocols are always used to facilitate information exchange between physical devices, processing streams of data or communication with middleware platforms such as the Manufacturing Execution System (MES) and Enterprise Resource Planning (ERP);
- **Process Data Streams Software**: Digital twin applications, such as real-time monitoring, forecasting and control, impose a strict latency requirement for data processing due to continuous real-time analysis and queries. To this end, middleware platforms that enable continuous connectivity were analyzed;
- **Data Storage** options: the amount of data involved makes data storage and management a crucial aspect of the DT application, for this purpose the different data storage options used were analyzed.

As for the simulation features used in the twinning process, it was investigated:

- **Modeling Software**;
- **Model Type**, e.g. 3D, DES (Discrete Event Simulation), FEM (Finite Element Method) etc.

3.1. Production Line cluster

The information about technologies implemented in detail can be found in the Table 3.1.

Table 3.1. Data Acquisition and Transmission-Simulation Features of Production Line Cluster

	Data Acquisition and Transmission				Simulation features	
Reference	**Sensors and Hardware**	**Process Data Streams Software**	**Data storage**	**Communication Protocol**	**Model Type**	**Software Model Name**
Kumbhar et al.(2023)[30]		SCADA system			DES	FACTS Analyzer 2.0
Ma et al.(2022)[40]	RFID tags	MapReduce, Storm Stream	XML, B2MML	Not Specified		
Eyring et al.(2022)[17]	(PLC)	PTC Inc., kepware, ThingWorx	PostgreSQL	EtherNet/IP	3D DES	FlexSim
Ding et al.(2022)[16]	RFID tags	ReCap Autodesk(3D scanning software), Inventor Autodesk.	Redis, MySQL, Influx Data	Not specified	3D	Unreal Engine
Magalhaes et al.(2022)[41]	(PLC) RFID tags	HMI		TCP	3D	V88-113D CIMSoft Amatrol
Matsunaga et al. (2022) [45]	Fluke 434 energy anlyzer, CCK7200 Power multimeter, Beckhoff CLP	Energy Platform			2D 3D DES	Tecnomatix Plant Simulation
Zhang et al.(2022)[75]	PLC				3D 2D DES	Tecnomatix Plant Simulation
Mendi (2022) [46]	E52-Temperature, Telaire Dust density, technometer frequency	Apache Kafka, Apache Flink		MQTT	3D	Unity
Arnarson et al.(2022)[5]	Microcontrollers, Raspberry pi, wifi wireless comunication			OPC UA	3D Kinematic	Visual Components
Kombaya Touckia et al.(2022)[28]			MySql, MongoDb		DES Combinatorial Sequential	Simulink MATLAB (SimEvents and Stateflow)
Cheng et al.(2022)[13]	PLC, RFID tags	SCADA system		OPC UA	3D	
M.Ugarte Querejeta et al.(2022)[63]	TwinCAT controllers			OPC, REST API	3D	Visual Components, Virtual twinCAT controllers
Ademujimi e Prabhu (2022)[2]	Proximity, temperature, and vibration sensors			TCP	3D DES	Simio DES , RobotStudio
Yang et al. (2022) [71]			XLM	TCP/IP	2D 3D DES	Tecnomatix Plant Simulation
Zhang et al.(2022) [76]	RFID tags, PRID camera			OPC/UA	Mathematical	MATLAB
Qamsane et al.(2022)[53]	PID controller				3D DES	Simulink and Simscape(MATLAB)
Leng et al (2021) [49]	RFID tags			OPC UA	2D, 3D, CAD DES	Siemens NX, Tecnomatix Plant Simulator
Ward et al. (2021) [68]	RFID, cameras D435 Intel RealSense, FESTO PLC's	CoDesys (controlling function)		OPC UA, Profinet	2D 3D CAD DES	Tecnomatix Plantsim(DES model)
Leng et al (2021) [32]		SCADA system	XML, MySQL	OPC/Modbus	3D	jMonkeyEngine
Martinez et al.(2021)[42]	Cameras	SCADA system, TIA portal, OPC Scout, Process Simulate	SQL	OPC	Mathematical	LabVIEW
Barbieri et al.(2021)[8]	Raspberry Pi, light barrier sensors			OPC	3D DES	Simulink (MATLAB), Experior, CoDesys
Kousi et al.(2021) [29]			JSON, URDF	ROS	3D DES	Gazebo, WITNESS(DES MODEL)
Resman et al.(2021)[55]	RFID tags, inductive sensors, machine vision system, Rasp berry pie	SCADA system	SQLite	OPC	3D DES	Tecnomatix Plant Simulation
Wu et al. (2021) [69]	RFID		MongoDB, MySQL, JSON	OPC UA	3D	Unity3D, PhysX, 3dsMAX
Bavelos et al. (2021)	Basler camera, RealSense camera, ROBOTCEPTION-160 camera, SICK laser scanner, AprilTAG marker		URDF	ROS	3D	Gazebo
Villalonga et al. (2021) [64]	Siemens PLC, RFID tags, accelerometer		MongoDB	OPC UA	Mathematical	
Jiang et al. (2021) [27]	RFID tags	Apache Kafka	Redis	OPC UA	CAD DES model	
Barni et al. (2020)					3D	DDDSimulator
Ruppert e Abonyi(2020)[1]		ProM			3D DES	Tecnomatix Plant Simulation, AutoCAD
Bambura et al.(2020)[7]	PLC		MySQL	TCP/IP	2D 3D DES	Tecnomatix Plant Simulation
Negri et al. (2020) [48]	RFID tags		XML	OPC UA, TCP/IP		Functions)
Perez et al. (2020) [52]	PLC, FARO Focus 3D scanner				3D	Unity3D
Zhao et al.(2020)[77]	RFID tags and bar codes, laser rangefinder, infrared rangefinder				3D DES	Tecnomatix Plant Simulation
Ashtari Talkhestani(2019)[6]			XML	OPC UA, EtherCAT, CAN-Bus, Profibus	3D	Siemens NX, Open Modelica, Simulink (MATLAB)
Xu et al.(2019)[70]	Process Visibility System (Envision)				2D 3D DES	Process Designer & Process Simulate
Liu et al.(2019)[38]	RFID tags		XML	OPC		

3.1.1 Services

In Table 3.1.1. can be seen all the articles of this cluster are classified by the services mentioned in the Chapter1.

The monitoring service was provided by the totality of the articles analyzed, so it was decided to mention "Monitoring (generic)" only for those that did not mention other specific services in addition to it.

Table 3.1.1. Provided services by DT in the Production Line cluster.

Article	Service
Mendi (2022)[46], Ward et al.(2021)[68], Magalhaes et al.(2022)[41]	Monitoring (generic)
Ma et al.(2022)[40], Eyring et al.(2022)[17], Arnarson et al.(2022)[5], Cheng et al.(2022)[13], Yang et al.(2022)[71], Onaji et al.(2022)[49], Wu et al.(2021)[69], Villalonga et al.(2021)[64], Kumbhar et al.(2023)[30], Kombaya Touckia et al.(2022)[28]	Performance Prediction
Villalonga et al.(2021)[64], Ding et al.(2022)[16], Barni et al.(2020)[9], Negri et al.(2020)[48], Zhao et al.(2020)[77], Liu et al.(2019)[38], Bavelos et al.(2021)[10], Kumbhar et al.(2023)[30], Ruppert e Abonyi(2020)[1]	Scheduling Optimization
Ma et al.(2022)[40], Matsunaga et al.(2022)[45]	Energy Efficiency
Kousi et al.(2021)[29], Zhang et al.(2022)[75], Qamsane et al.(2022)[53], Wu et al.(2021)[69], Bambura et al.(2020)[7], Xu et al.(2019)[70], Ademujimi e Prabhu (2022)[2], Kumbhar et al.(2023)[30]	Anomaly Detection
Arnarson et al.(2022)[5], Kombaya Touckia et al.(2022) [28], Onaji et al.(2022) [49], Wu et.al[69], Bavelos et al.(2021)[10], Zhang et al.(2022)[76]	Plant layout Optimization
Barni et al.(2020)[9], Qamsane et al.(2022)[53]	Predictive maintenance
Arnarson et al.(2022)[5], Negri et al.(2020)[48], Leng et al.(2021)[32], Martinez et al.(2021)[42], Kousi et al.(2021)[29], Bavelos et al.(2021)[10], Leng et al (2021) [32]	Controlling
Cheng et al. (2022)[13], Yang et al.(2022)[71], Negri et al. (2020)[48], Martinez et al.(2021)[42], Resman et al.(2021)[55], Jiang et al.(2021)[27], Ashtari Talkhestani (2019)[6]	Exchange data between systems.

Pantelidakis et al.(2022)[51], Kousi et al.(2021) [29], Bavelos et al.(2021)[10], Perez et al.(2020)[52]	Human Operator Analysis

As can be seen from the Table 3.1.1.and more easily from the Figure 3.1.1., the most common service is Performance Prediction: data from the shop floor are analyzed and with specific algorithms and simulations it is possible to predict the performance of the process in the future or to find alternative solutions that optimize the given process. This is the case with services such as Plant Layout Optimization, Scheduling Optimization and Predictive maintenance. However, as can be seen from the Table 3.1.1., not all DT implementations that include these services also include Controlling. In fact, this is the case where the DT implementation is incomplete: although the proposed framework also includes automatic back action from the DT to the physical "twin", the case study or workshop doesn't focus on that.

When Controlling service is provided, DT not only mimics the behavior of the actual physical asset, but also enables autonomous, real-time two-way communication between the physical and digital parts, thus turning two-way communication into action, triggering certain actions on the MES(Negri et al. (2020) [48]) (Martinez at al. (2021) [42]). This capability results in the ability not only to monitor the physical asset in real time, but also to react to events on the shop floor that might affect the supervised production environment.

More specifically, in the articles of Production Line cluster, Controlling service applies to: commissioning (Leng et al (2021) [32]), FMS (Flexible Manufacturing System) and RMS (Reconfigurable Manufacturing System) in which depending on the data collected from the shopfloor the layout automatically self-adapt (Arnarson et al.(2022)[5])(Kousi et al.(2021)[29]) or in which mobile robots and AGV adapt to shopfloor condition and move across the plant depending on the automatic scheduling optimization (Bavelos et al. (2021)[10]).

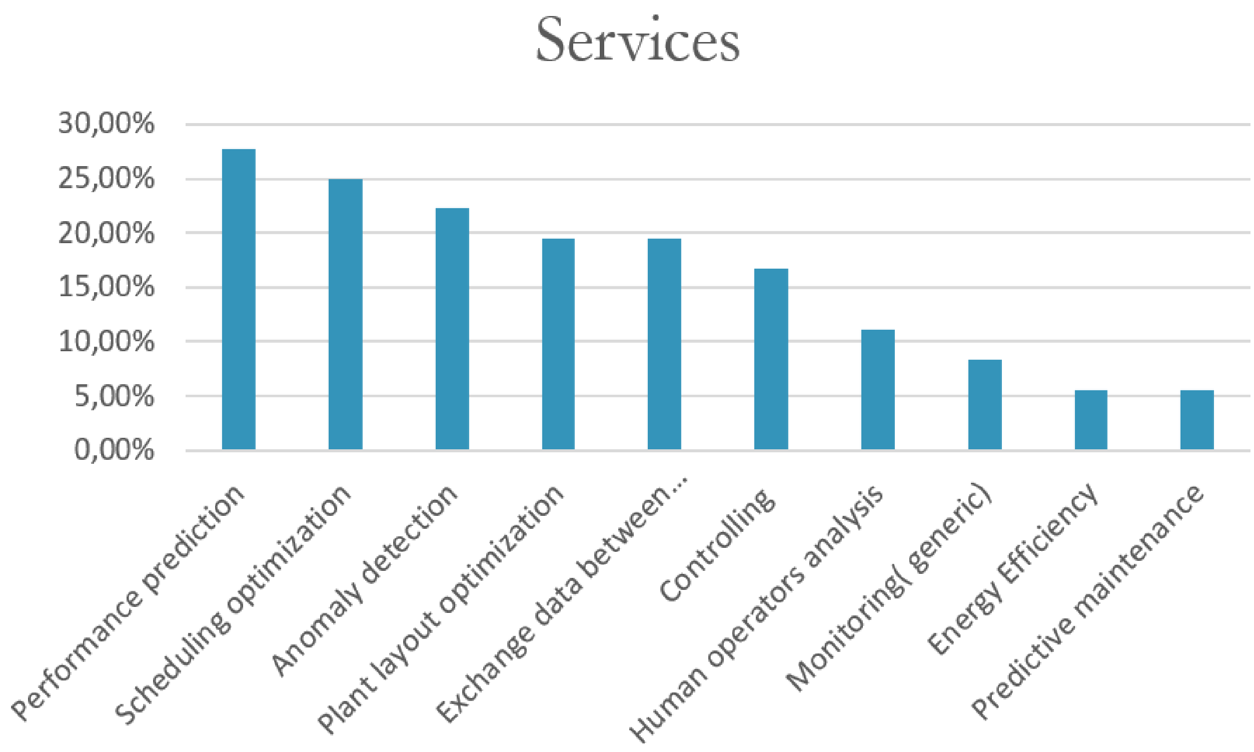

Figure 3.1.1. Frequency of provided services in the Production Line cluster.

3.1.2 Communication Protocol and Architecture Network

As can be seen from the Figure 3.1., a good portion of the articles analyzed do not mention the communication protocols used, among those where it is present the most used are:

- OPC UA (Open Platform Communications Unified Architecture): standard that facilitate the exchange of data between programmable logic controllers (PLCs), human-machine interfaces (HMIs), servers, clients, and other machines for the purpose of interconnectivity and information circulation. (Arnarson et al.(2022)[5]) (Cheng et al. (2022)[13]) (Zhang et al.(2022)[76]) (Onaji et al.(2022)[49]) (Ward et al.(2021)[68]) (Leng et al (2021)[32]), Wu et al. (2021) [69] (Villalonga et al.(2021)[64])(Jiang et al.(2021)[27]) (Negri et al. (2020)[48]) (Ashtari Talkhestani (2019)[6]);
- OPC: predecessor of OPC UA, OPC is a series of standards and specifications for industrial telecommunication (M. Ugarte Querejeta et al.(2022)[63]) (Martinez at al.(2021)[42]) (Barbieri et al.(2021)[8]) (Resman et al.(2021)[55]) (Liu et al.(2019)[38]);

- TCP/IP: communication protocol suite to interconnect network devices (Yang et al.(2022)[71]) (Bambura et al(2020)[7]) (Negri et al.(2020)[48]);
- TCP: main protocol for enabling two hosts to exchange data (Ademujimi e Prabhu (2022)[2]) (Magalhaes et al.(2022)[41]).

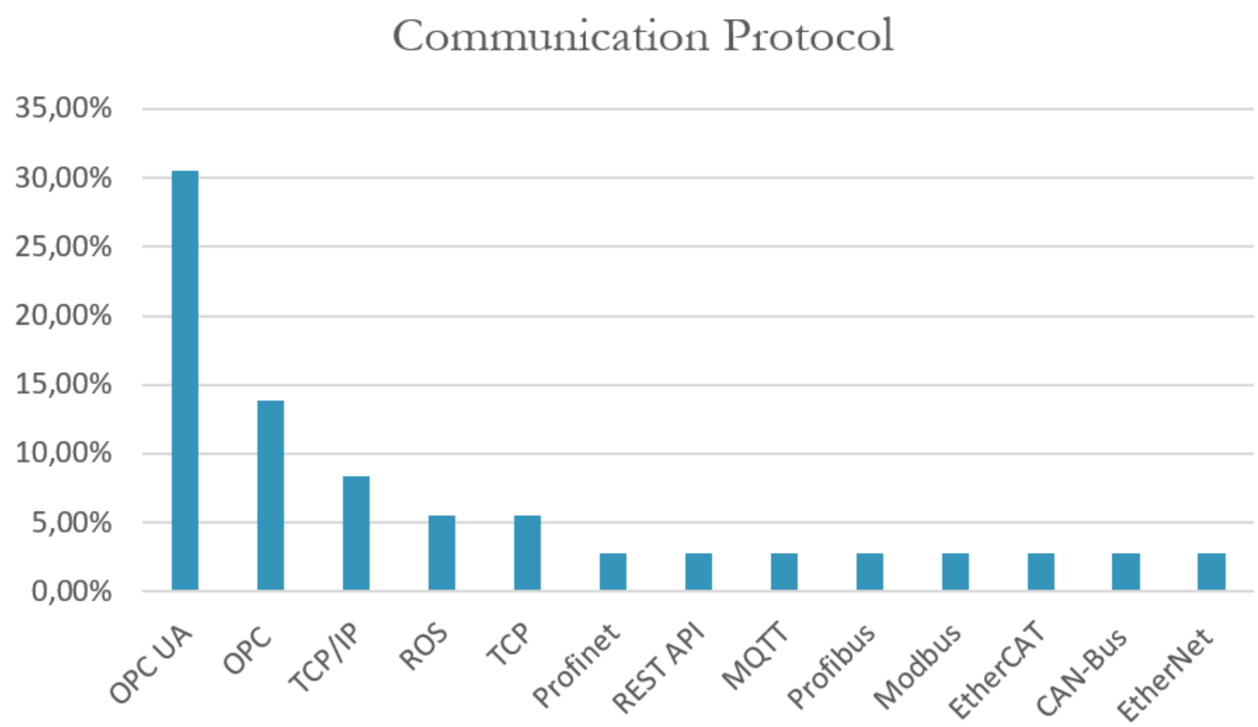

Figure 3.1.2. Frequency of Communication Protocol in the Production Line cluster.

Regarding processing streams of data collected, although few articles mention it, the following can be cited: Storm Stream e MapReduce (Ma et al.(2022)[40]) distributed computing frameworks for cleansing real-time and non-real-time data, respectively, Apache Kafka (Mendi (2022)[46]) (Jiang et al.(2021)[27]) an open-source event-streaming platform, Apache Flink (Mendi (2022) [46]) a framework used for stateful computations on unbounded and bounded data streams e (ProM Ruppert e Abonyi (2020)[1]) a framework for process mining technique.

With respect to data storage, the dataset is often described by specifying the database: these are classified as relational databases and non-relational databases. Usually, relational databases are used for applications that involve the management of complex database transactions and heavy data analysis, because of referential integrity. Non-relational databases are geared towards managing large sets of varied and frequently updated data, often in distributed systems. They avoid the rigid schemas associated with relational databases.

In the article analyzed common non-relational database are (Redis Ding et al. (2022) [16] (Jiang et al. (2021)[27]) (MongoDB Choi et al.(2022)[14]) (Kombaya Touckia et al(2022)[28]) (Wu et.al [69]Villalonga et al.(2021)[64]) Influx data Ding et al. (2022) [16] and as relational database MYSQL(Ding et al. (2022)[16]) (Kombaya Touckia et al.(2022)[28]) (Leng et al (2021)[32] (Wu et.al [69])(Bambura et al(2020)[7]), SQLite (Resman et al.(2021)[55]), PostgreSQL (Eyring et al.(2022)[17]).

Several articles do not mention the database but the data format, among them XML e JSON are the most common.

Concerning Sensors and Hardware for data collection, as can be seen in Table 3.0, it varies greatly depending on the application, however, is common data collection by PLC (Programmable Logic Controller) controllers, often in conjunction with SCADA (Supervisory Control and Data Acquisition) and by RFID tags.

3.1.3. Simulation features

The Figure 3.1.3. above indicates that the most widely used software for modeling are:

- Tecnomatix Plant Simulation (Matsunaga et al.(2022)[45]) (Zhang et al.(2022)[75]) (Yang et al.(2022)[71]) (Onaji et al.(2022)[49]) (Resman et al.(2021)[55]) (Ward et al.(2021)[68])(Ruppert e Abonyi (2020)[1]) (Bambura et al(2020)[7])(Zhao et al.(2020)[77]).
- Matlab Simulink (Kombaya Touckia et al.(2022) [28])(Zhang et al.(2022)[76])(Qamsane et al.(2022)[53])
(Barbieri et al. (2021)[8])(Negri et al.(2020)[48])(Ashtari Talkhestani(2019)[6]).

Both models allow di modelling, simulating, process and system optimization application.

Most articles model the physical system in 2D or 3D, however in several articles they do not use any model, but extract information from the system experimentally, analyzing the acquired data (Villalonga et al. (2021)[64]) (Martinez at al.(2021)[42])(Zhang et al.(2022)[76].

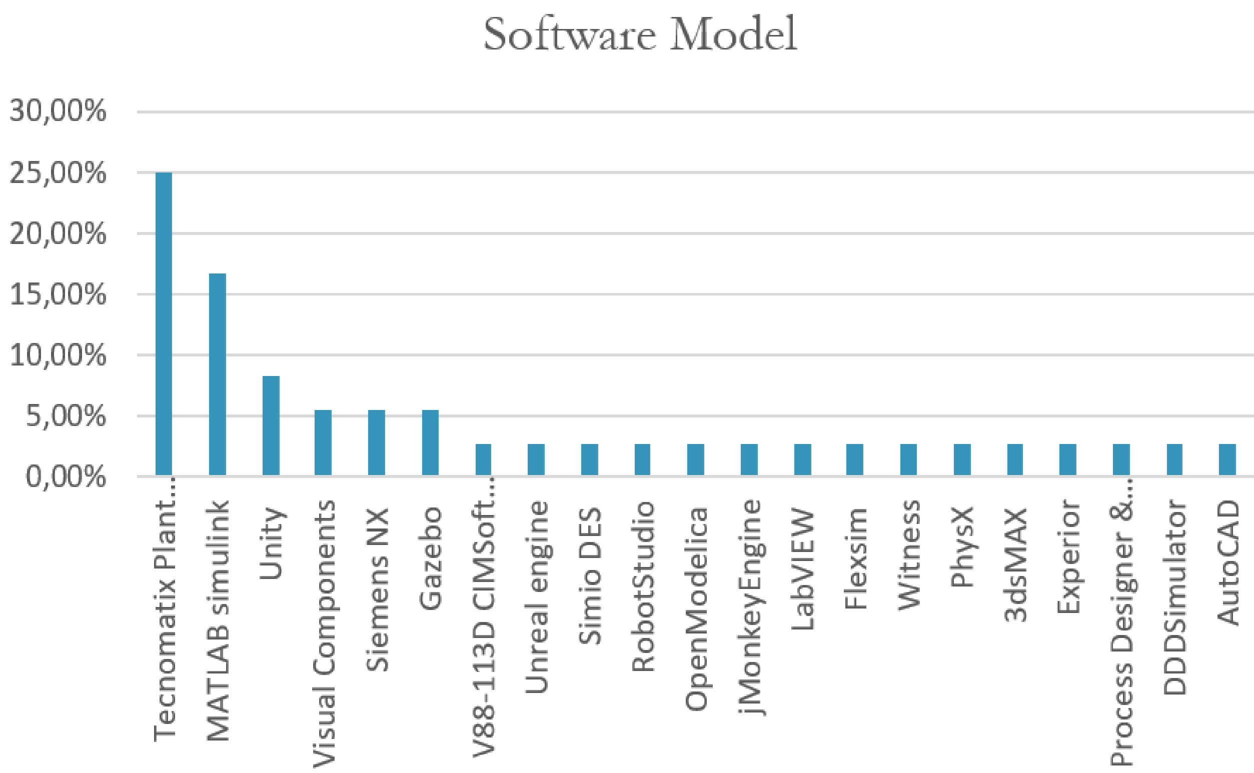

Figure 3.1.3. Frequency of Software Model in the Production Line cluster.

3.2. CNC Machine Cluster

All the information about technologies implemented in DT application can be found in the Table 3.2.

3.2.1. Services

In the following table 3.2.1. the articles of the cluster are classified by the services mentioned in Chapter 1.

Table 3.2.1. Provided services by DT in the CNC Machine cluster.

Article	**Function**
Mendi (2022)[46], Magalhaes et al.(2022)[41]	Monitoring (generic)
Arnarson et al.(2022)[5], Kombaya Touckia et al.(2022)[28], Hu (2022)[26], Guo et al. 2022[23], Ward et al. (2021)[67], Wu et al.(2021)[69]	Performance prediction

Ding et al.(2022)[16], Zhang et al. (2022)[74]	Scheduling optimization
	Energy efficiency
Zhang et al. (2022)[74], Wu et al.(2021)[69], Bambura et al.(2020)[7]	Anomaly Detection
Arnarson et al.(2022)[5], Kombaya Touckia et al.(2022)[28], Wu et al.(2021)[69]	Plant Layout Optimization
	Predictive Maintenance
Arnarson et al.(2022)[5] ,Zhang et al. (2022)[74], Hu (2022) [26], Ward et al. (2021)[67]	Controlling
Jiang et al.(2021)[27]	Exchange Data Between Systems.
	Human Operator Analysis

As can be seen in the Figure 3.2.1., much like the Production Line cluster (with whom the cluster shares 8 articles) the most common service is Performance Prediction, very often also complemented by other services such as Anomaly Detection in the manufacturing process (Wu et al.(2021) [69]) and Layout Optimization (Arnarson et al.(2022)[5])(Kombaya Touckia et al.(2022)[28])(Wu et al.(2021)[69]).

The second most common service is Controlling: (Hu (2022)[26]) in which a trimming operation by a five-axis high-speed milling machine is displayed and, after monitoring and performance prediction, the optimized solution is applied; (Ward R. et al.[67]) 5-axis high performance machining center for a finishing operation, while in (Zhang et al. (2022)[74])controlling solution is implemented on a CNC lathe and milling operations for scheduling purpose.

Table 3.1. Data Acquisition and Transmission-Simulation Features of CNC Machine cluster.

	Data Acquisition and Transmission				**Data Acquisition and Transmission**	
Reference	**Sensors and hardware**	**Process Data**	**Data storage**	**Communication Protocol**	**Model Type**	**Software Model name**
Ding et al.(2022)[16]	RFID tags		Redis, MySQL,	Not specified	3D	Unreal Engine, ReCap Autodesk(3D
Magalhaes et al.(2022)[41]	(PLC) RFID tags			TCP	3D	V88-113D CIMSoft Amatrol
Mendi (2022)[46]	E52-Temperature, Telaire Dust density, Technometer Frequency	Apache Kafka, Apache Flink		MQTT	3D	Unity
Choi et al.(2022)[14]			XML	REST API	3D	
Arnarson et al. (2022) [5]	Microcontrollers, Raspberry pi, wifi wireless			OPC UA	3D kinematic	Visual Components
Kombaya Touckia et al.(2022)[28]			MySql, MongoDb	Not specified	DES, Combinatorial and Sequential	Simulink MATLAB (SimEvents and Stateflow)
Hu (2022)[26]				OPC	3D FEM	Catia Dessault Systeme
Zhang et al.(2022)[74]	RFID			OPC UA	Mathematical (Real-time systems modeled as networks of timed automata), 3D	UPPAAL
Guo et al.2022[23]	PLC		MySql	OPC	3D	Soldid Works, Unity 3D, Polygon Cruncher
Ward et al.[67]	NI USB 6343, Siemens ADAS , Kistler 9255c			Profibus		Matlab
Wu et al.(2021)[69]	RFID		MongoDB, MySql, JSON	OPCUA	3D	Unity3D, PhysX, 3dsMAX
Jiang et al.(2021)[27]	RFID tags	Apache Kafka	Redis	OPC UA	CAD DES model	
Bambura et al.(2020)[7]	PLC		MySQL	TCP/IP	2D, 3D, DES	Tecnomatix Plant Simulation

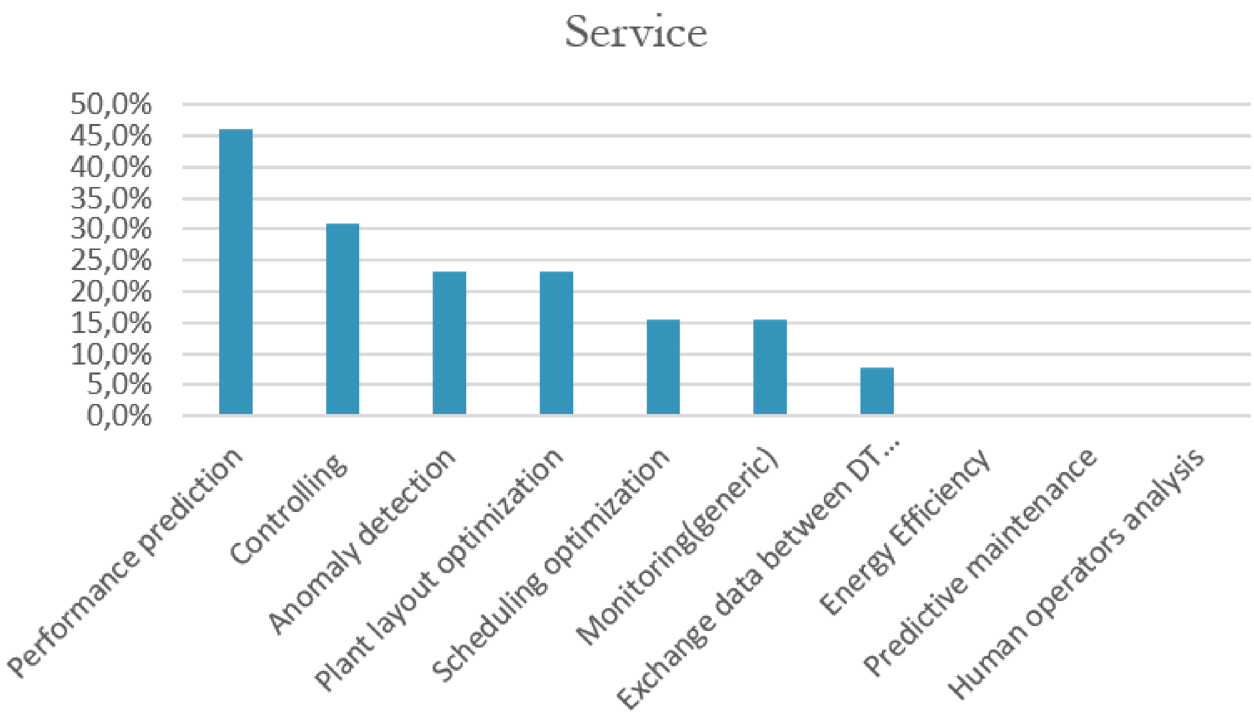

Figure 2.2.1. Frequency of services in CNC Machine cluster.

3.2.2 Communication Protocol and Architecture Network

The Figure 3.2.2. shows the most used communication protocols:

- OPC UA (Aivaliotis et al .(2021)[5])(Wu et al. (2021)[69])(Jiang et al. (2021)[27])(Zhang et al.(2022) [74]) and OPC (Guo et al.2022[23])(Hu (2022)[26]).

Among communication protocols there are also:

- REST API (Choi et al. (2022)[14]) a software architectural style for creating web services;
- Profibus, developed to support the machine-to-machine communications and the remote terminal control of programmable logic controllers, for process and peripheral control/automation.

For what concerns the process of data streams Apache Kafka (Mendi (2022)[46]) (Jiang et al.(2021)[27]) and Apache Flink (Mendi (2022)[46]) are mentioned.

With respect of Data Storage options MySQL is the most common database (Kombaya Touckia et al.(2022)[28], Bambura et al.(2020)[7], Wu et al.(2021)[69], Guo et al.2022[23], Ding et al.(2022)[16]). For the rest of the articles, the details can be found in Table 3.2. "Sensors and Hardware" column where are also present the sensors used in data collection: again, PLC controllers and RFID tags stand out.

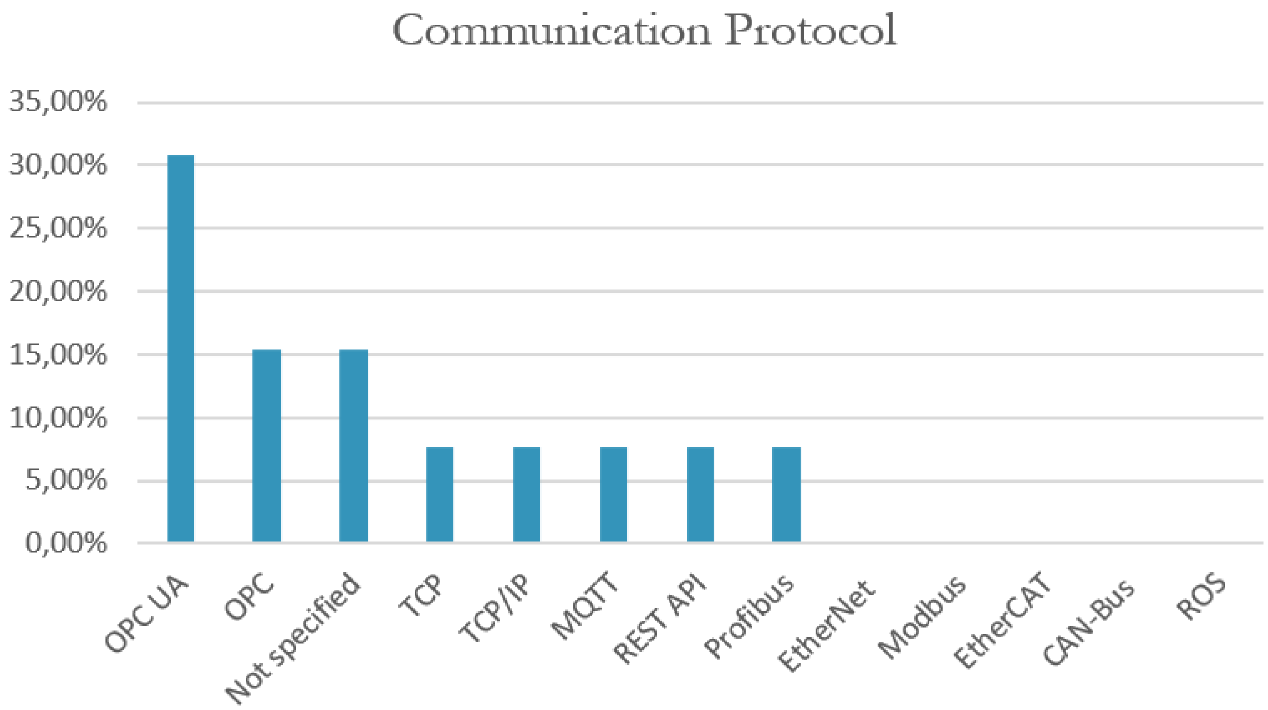

Figure 3.2.2. Frequency of Communication Protocol in CNC Machine cluster.

3.2.3. Simulation Features

Regarding simulation features, as can be seen in the Figure 3.2.3. below and with more details in the "Software Mode Name" column of Table 3.2., the most used is:

- Unity Software (Mendi (2022)[46], Guo et al. 2022[23], Wu et al.(2021)[69])

For the other articles there is great homogeneity. Same situation for what concerns the model ("Model Type" column of Table 3.2.): besides DES model, FEM (Hu (2022)[26]), Kinematic (Arnarson et al.(2022)[5]), Combinatorial and Sequential (Kombaya Touckia et al.(2022)[28]) can be found.

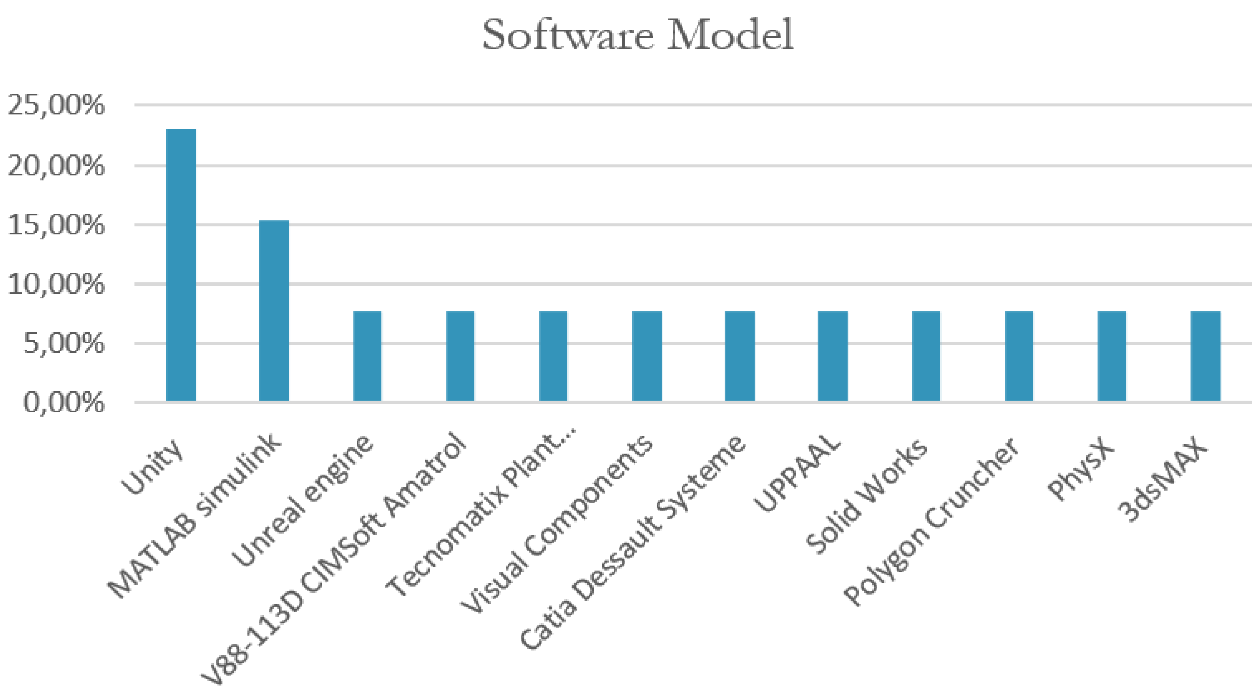

Figure 3.2.3. Frequency of Software Model in CNC Machine cluster.

3.3. Human-Robot Collaboration

All the information about technologies implemented in DT application can be found in the Table 3.3.

3.3.1. Services

In Table 3.3.1. articles in the Human-Robot collaboration cluster were classified according to the services in Chapter 1.

Table 3.3.1. Provided services by DT in the Human-Robot Collaboration cluster.

Article	Function
	Monitoring (generic)
Gallala et al. (2022)[19], Mourtzis et al(2022)[47], Martinez et al.(2021)[43], Bilberg e Malik(2019)[11], Havard et al(2019)[25],	Performance prediction

Oyekan et al.(2019)[50], Kousi et al.(2021)[29], Bavelos et al.(2021)[10]	
Bavelos et al.(2021)[10], Martinez et al.(2021)[43], Kousi et al.(2021)[29]	Scheduling optimization
	Energy efficiency
Kousi et al.(2021)[29]	Anomaly detection
Bavelos et al.(2021)[10], Martinez et al.(2021)[43], Kousi et al.(2021)[29]	Plant layout Optimization
	Predictive maintenance
Gallala et al. (2022)[19], Diachenko et al.(2022)[15], Kousi et al.(2021)[29], Bavelos et al.(2021)[10]	Controlling
Diachenko et al.(2022)[15], Mourtzis et al(2022)[47], Liu et al.(2019)[37], Havard et al.(2019)[25], Kuts et al (2019) [31], Martinez et al.(2021)[43]	Exchange data between systems.
Bilberg e Malik (2019) [11], Havard et al (2019) [25], Kuts et al (2019) [31], Liu et al. (2019) [37], Oyekan et al. (2019) [50], Perez et al. (2020) [52], Bavelos et al. (2021) [10], Kousi et al. (2021) [29], Martinez et al. (2021) [43], Gallala et al. (2022) [19], Mourtzis et al (2022) [47]	Human operator analysis

As can be seen in the Figure 3.3.1. the service Human Operator Analysis is present in all the cluster's articles. In second place, as in the clusters analyzed before, the most common service is Performance Prediction, often associated with other services as Scheduling Optimization and Plant Layout Optimization (Martinez et al.(2021)[43]) (Bavelos et al.(2021)[10]), (Kousi et al.(2021)[29]).

The Controlling service is applied to: (Diachenko et al.(2022)[15]) Omron TM5-900 robot remotely controlled by humans through controllers, (Gallala et al. (2022) [19]) human-robot (KUKA IIWA) interaction remotely using KUKA's Sunrise Workbench controller and VR tools such a MS HoloLens, (Kousi et al.(2021)[29]) collaborative assembly line where robot movements are automatic thanks to performance prediction of human operator, (Bavelos et al.(2021)[10])]) mobile UR10 robotic arm navigation on the shopfloor environment.

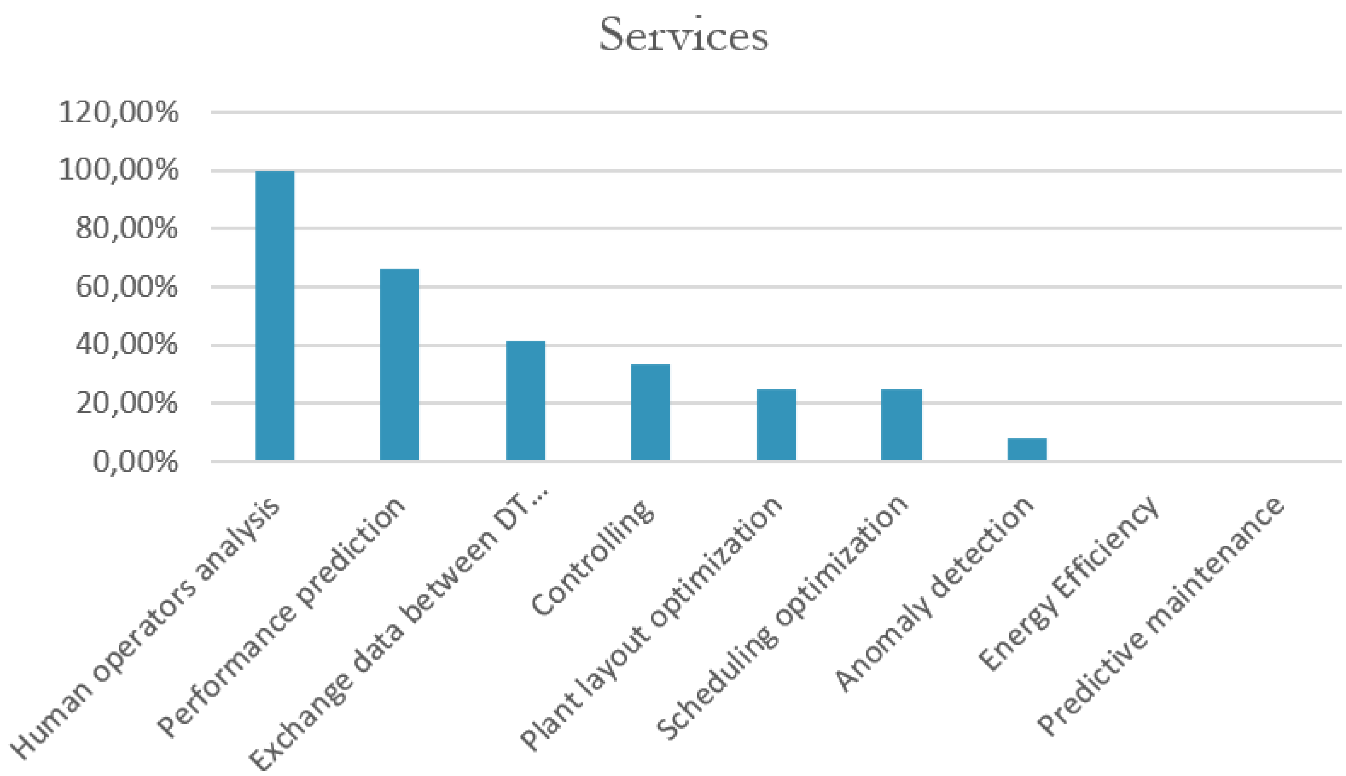

Figure 3.3.1. Frequency of provided services in the Human-Robot collaboration cluster

Table 3.3. Data Acquisition and Transmission-Simulation Features of Human-Robot Collaboration cluster

Reference	Sensors and hardware	Software	Data format	Protocol	Model	Software
Gallala et al.(2022)[19]	Torque sensors, camera, depth sensor		XML, URDF		3D	Unity, Hololens MS
Mourtzis et al(2022)[47]		Mixed reality toolkit, HMI	XML, URDF	TCP/IP, VUFORIA API (RESTFUL API), ROS	3D	Unity 3D, MS HoloLens
Diachenko et al.(2022)[15]			URDF	MQTT, ROS	3D	Unity3D
Kousi et al.(2021)[29]			JSON, URDF	ROS	3D DES	Gazebo, WITNESS(DES MODEL)
Martinez et al.(2021)[43]	Cameras, controllers			TCP/IP	3D	URSim, Experior
Bavelos et al.(2021)[10],	Basler camera, RealSense camera, ROBOTCEPTION-160 camera, SICK laser scanner, AprilTAG marker		URDF	ROS	3D	Gazebo
Perez et al.(2020)[52]	PLC, FARO Focus 3D scanner				3D	Unity3D
Liu et al. (2019) [37]	RFID tags, Dynamometer(Kistler type 9273), Piezoelectric Accelerometer(PCB model 352C65). Data acquisition cardNI PXI-1031	LabVIEW	XML	OPC UA, TCP, MTConnect	3D	Ms Hololens
Oyekan et al.(2019)[50]	Kinect				3D	Unity3D
Havard et al(2019)[25]	Perception Neuron Pro suite (VR)		JSON, XML		3D CAD CAM	Unity 3D, Catia, Modelica (Dessault systems), VR
Kuts et al.(2019)[31]		VirtualReality Toolkit		ROS	3D	Unity 3D, 3DS Max and Maya (Autodesk)
Bilberg e Malik(2019)[11]	3D camera, Kinect sensor				3D	Tecnomatix Process Simuate

3.3.2. Communication Protocol and Architecture Network

As can be seen from graph Figure 3.3.2., the most used communication protocols are:

- ROS (Robot Operating System) (Gallala et al.(2022)[19]) (Mourtzis et al(2022)[47]) (Kousi et al.(2021)[29]) (Bavelos et al.(2021)[10]) (Kuts et al (2019)[31]). ROS is a software architecture which provides the drivers that handle the data of the sensors used and feed it to a digital world model, it acts as a middleware for the translation of the 3D motions into commands for the actual robot, it provides advanced capabilities regarding the calculation of the robotic arm kinematics and reverse kinematics.
- TCP/IP.

Regarding Data Format, as can be seen in the Data Acquisition and Transmission section of Table 3.3., the most widely used are URDF (Unified Robot Description Format) (Gallala et al.(2022)[19]) (Mourtzis et al(2022)[47]) (Kousi et al.(2021)[29]) (Bavelos et al.(2021)[10]) (Diachenko et al.(2022)[15]) used to store robot physical properties and, as in the other clusters, XML, JSON.

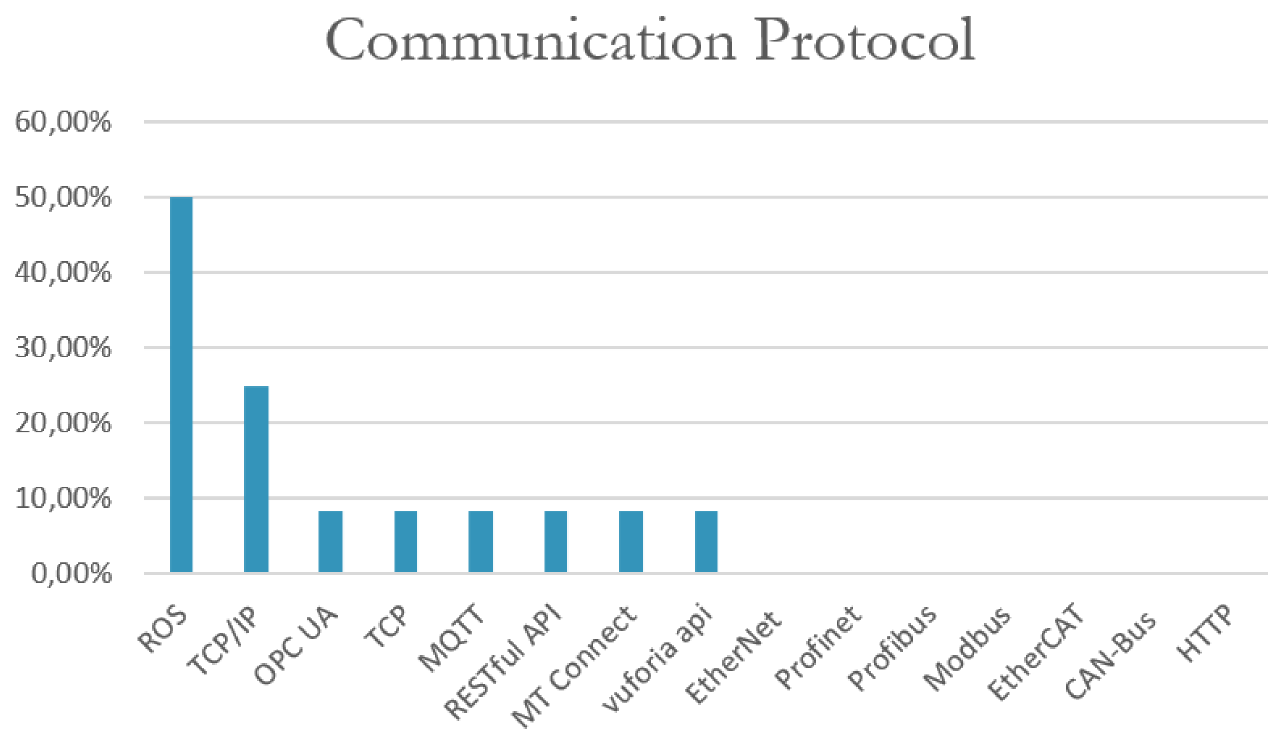

Figure 3.3.2. Frequency of Communication Protocol in the Human-Robot collaboration cluster.

3.3.3. Simulation feature

Regarding the software model used in the realization of the DT:

- Unity stands out, mainly due to the wide range of VR and MR (Mixed Reality) functionalities (Mourtzis et al (2022) [47]) (Gallala et al. (2022) [19]) (Martinez-Gutierrez et al. (2021)[44]) (Bavelos et al. (2021)[10]) (Kuts et al (2019) [31]). Infact the use of Unity is often accompained by the use of VR or MR softwre such as MS HoloLens (Gallala et al. (2022) [19]) (Mourtzis et al (2022) [47]).

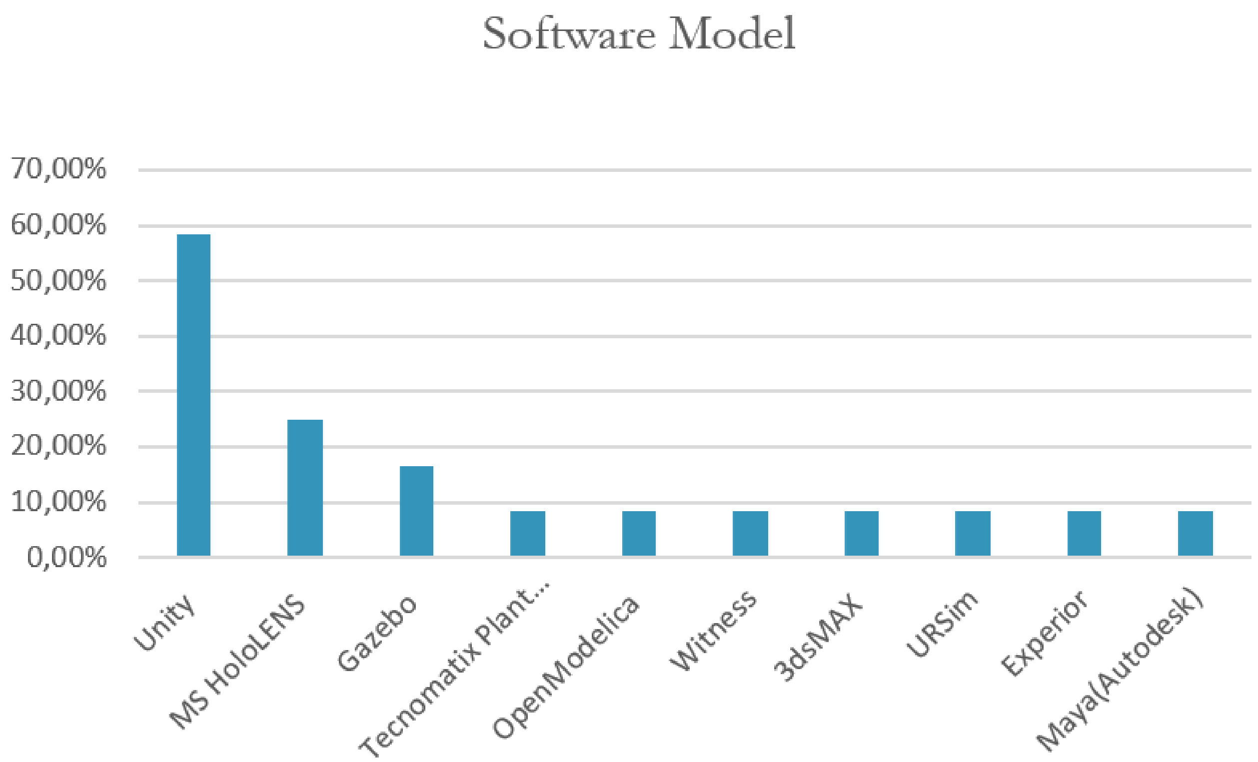

Figure 3.3.3. Frequency of Software Model in the Human-Robot Collaboration cluster

3.4. Transportation System

All the information about technologies implemented in DT application can be found in the Table 3.4.

3.4.1 Services

In Table 3.4.1 below the cluster's articles are classified according to the services explained in Chapter 1.

Unity stands out, mainly due to the wide range of VR and MR (Mixed Reality) functionalities (Mourtzis et al (2022) [47]) (Gallala et al. (2022) [19]) (Martinez-Gutierrez et al. (2021)[44]) (Bavelos et al. (2021)[10]) (Kuts et al (2019) [31]). Infact the use of Unity is often accompained by the use of VR or MR softwre such as MS HoloLens (Gallala et al. (2022) [19]) (Mourtzis et al (2022) [47]).

Controlling service is provide: (Bavelos et al.(2021)[10]) AGV transportation in a human-robot collaborative environment, (Roque Rolo et al. (2021)[57]), distribution control system through MAS (multi agent system) based on conveyors, (Mourtzis et al (2022) [47]AGV transportation controlled by Arduino Nano and Arduino Mega 2560 micro crontrollers , (Leng et al.(2021)[32]) to optimize travel time optimization of autonomous robot carriers (Robotino) in a production line.

Table 3.4.1. Provided Services by DT in Transportation System cluster

Article	Function
Ward et al.(2021)[68]	Monitoring (generic)
Martinez-Gutierrez et al.(2021)[44], Roque Rolo et al.(2021)[57], Mourtzis et al(2022)[47], Cheng et al.(2022)[13], Yang et al.(2022)[71], Leng et al.(2021)[32], Bavelos et al.(2021)[10], Zhang et al.(2022)[76].	Performance prediction
Roque Rolo et al.(2021)[57], Bavelos et al.(2021)[10], Zhang et al.(2022)[76], Han et al.(2022)[24]]	Scheduling optimization
Han et al.(2022)[24]	Energy efficiency
	Anomaly detection
Roque Rolo et al.(2021)[57], Bavelos et al.(2021)[10], Zhang et al.(2022)[76], Leng et al.(2021)[32], Kousi et al.(2021)[32]	Plant layout Optimization
	Predictive maintenance
Martinez-Gutierrez et al.(2021)[44], Roque Rolo et al. (2021)[57], Bavelos et al.(2021)[10], Kousi et al.(2021)[29], Mourtzis et al(2022)[47], Leng et al.(2021)[32]	Controlling
Cheng et al.(2022)[13], Ma et al.(2022)[40]	Exchange data between systems.
Ruppert e Abonyi(2020)[1], Bavelos et al.(2021)[10], Kousi et al.(2021)[29]	Human operator analysis

Table 3.4. Data Acquisition and Transmission-Simulation Features of Transportation System cluster

	Data Acquisition and transmission				Simulation Feature	
Reference	**Sensors and hardware**	**Software**	**Data format**	**Protocol**	**Model**	**Software**
Cheng et al.(2022)[13]	PLC, RFID tags	SCADA system		OPC UA	3D	Not specified
Han et al.(2022)[24]				Modbus TCP	3D	FlexSim
Yang et al.(2022)[71			XLM	TCP/IP	2D 3D DES	Tecnomatix Plant Simulation
Zhang et al.(2022)[76]	RFID, PRID camera			OPC/UA	Mathematical	MATLAB
Leng et al (2021) [32]	RFID			OPC UA	2D, 3D, CAD DES	Siemens NX, Tecnomatix Plant Simulation
Ward et al.(2021)[68]	RFID, cameras D435 Intel RealSense, FESTO PLC's	CoDesys (controlling		OPC UA, Profinet	2D, 3D, CAD, DES	Tecnomatix Plant Simulation
Kousi et al.(2021)[29]			JSON, URDF	ROS	3D DES	Gazebo, WITNESS(DES MODEL)
Martinez-Gutierrez et al. (2021) [44]	LIDAR, RFID		JSON, XML	MQTT	3D	Gazebo
Roque Rolo et al. (2021) [57]			JSON	API	3D 2D	AnyLogic
Bavelos et al.(2021)[10]	Basler camera, RealSense camera, ROBOTCEPTION-160 camera, SICK laser scanner, AprilTAG marker		URDF	ROS	3D	Gazebo
Mourtzis et al (2022) [47]	Arduino nano, arduino mega 2560			OPC UA	3D	pyBullet
Ruppert e Abonyi (2020) [1]		ProM		Not specified	3D DES	Tecnomatix Plant Simulation, AutoCAD

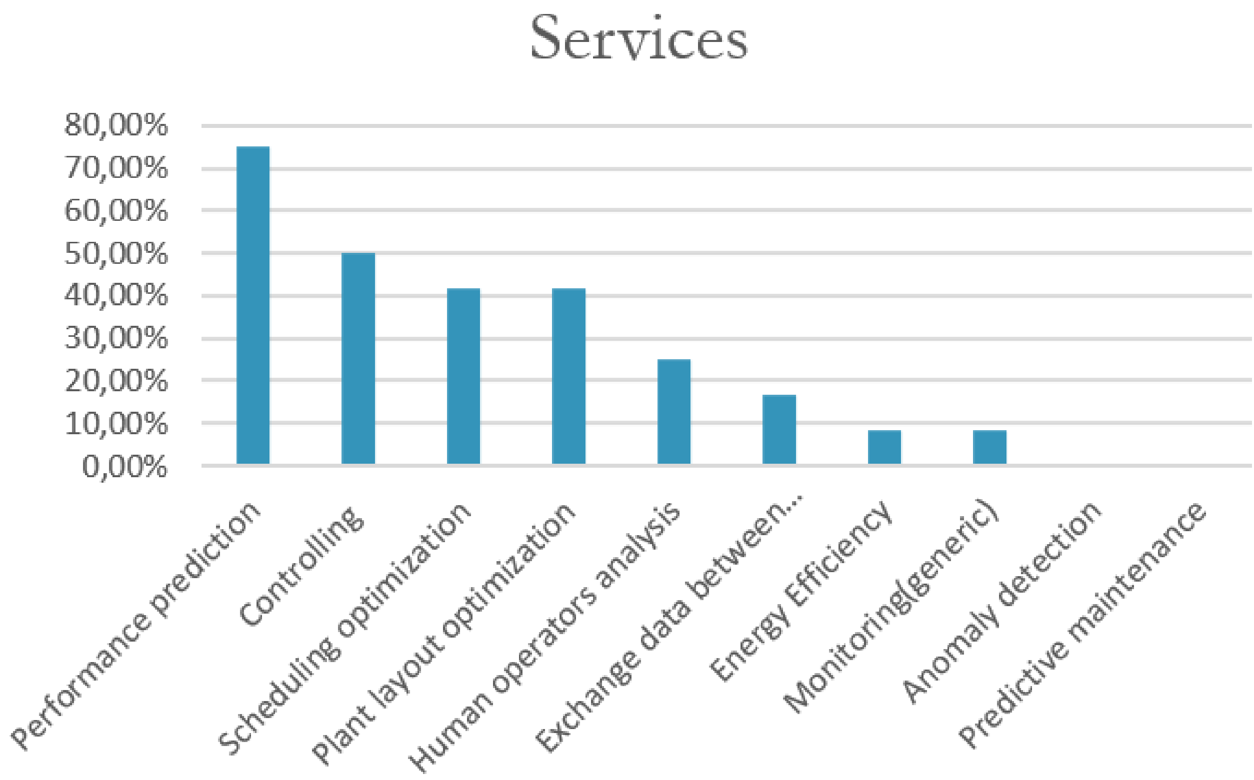

Figure 3.4.1 Frequency of services provided in the Transportation System cluster

3.4.2 Communication Protocol and Architecture Network

From the Figure 3.4.2. below communication the protocols found are:

- OPC UA protocol. It is still the most widely used.

Beside OPC UA, among communication protocols can be found:

- TPC;
- MQTT;
- Profinet (Process Field Network) protocol (Ward et al.(2021)[68]) it is an industry technical standard for data communication over Industrial Ethernet, designed for collecting data from, and controlling equipment in industrial systems;
- Modbus protocol (Han et al.(2022)[24]), developed to support the machine to machine communications and the remote terminal control of programmable logic controllers, for process and peripheral control/automation, in this case implemented with TCP in order to facilitate inter-communication at a higher level such MES and ERP systems.

- control of programmable logic controllers, for process and peripheral control/automation, in this case implemented with TCP in order to facilitate inter-communication at a higher level such MES and ERP systems.

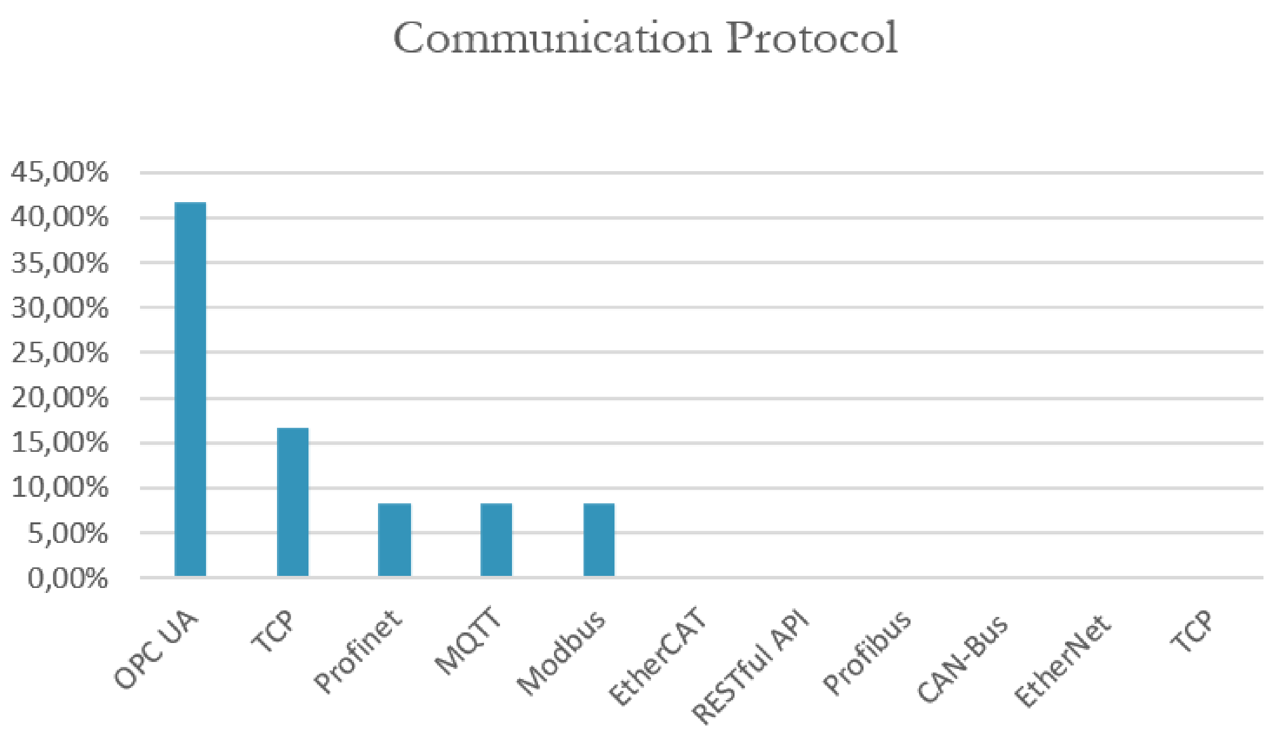

Figure 3.4.2. Frequency of Communication Protocol in the Transportation System

In general, as we can see in Table 3.4. there is little information regarding the software used to process the data streams, while in terms of data format we find the formats common to the other clusters such as URDF (Bavelos et al.(2021)[10]) (Kousi et al.(2021)[29]), XML (Yang et al.(2022)[71]) (Martinez-Gutierrez et al.(2021)[44]) and JSON (Kousi et al.(2021)[29])(Martinez-Gutierrez et al. (2021)[44])(Roque Rolo et al.(2021)[57]).

Regarding the hardware used for data collection from the shopfloor, in addition to the common PLCs e RFID tags, are very frequent cameras for motion caption of robot and environment (Zhang et al.(2022)[76]) (Ma et al.(2022)[40]) (Bavelos et al.(2021)[10]), LIDAR (Light Detection and Ranging*)* and other laser scanners (Bavelos et al.(2021)[10])(Martinez-Gutierrez et al.(2021)[44]) mostly used for the navigation of autonomous vehicles. In the article (Rodriguez-Guerra et al.(2021)[56]) data are collected from Arduino micro controllers.

3.4.3 Simulation features

As can be seen from the Figure 3.4.3 below, the most used software is:

- Tecnomatix and the transport system was mostly modeled with a DES model.

Among the other software can be found:

- WITNESS software (Kousi et al.(2021)[29]), used to model material flows in the assembly line;
- AnyLogic (Roque Rolo et al.(2021)[57])an agent-based simulation for the modeling of transportation system;
- pyBullet (Mourtzis et al(2022)[47]) to model mechanical interaction between rigid bodies, used to model AGV and possible disturbances to its movement

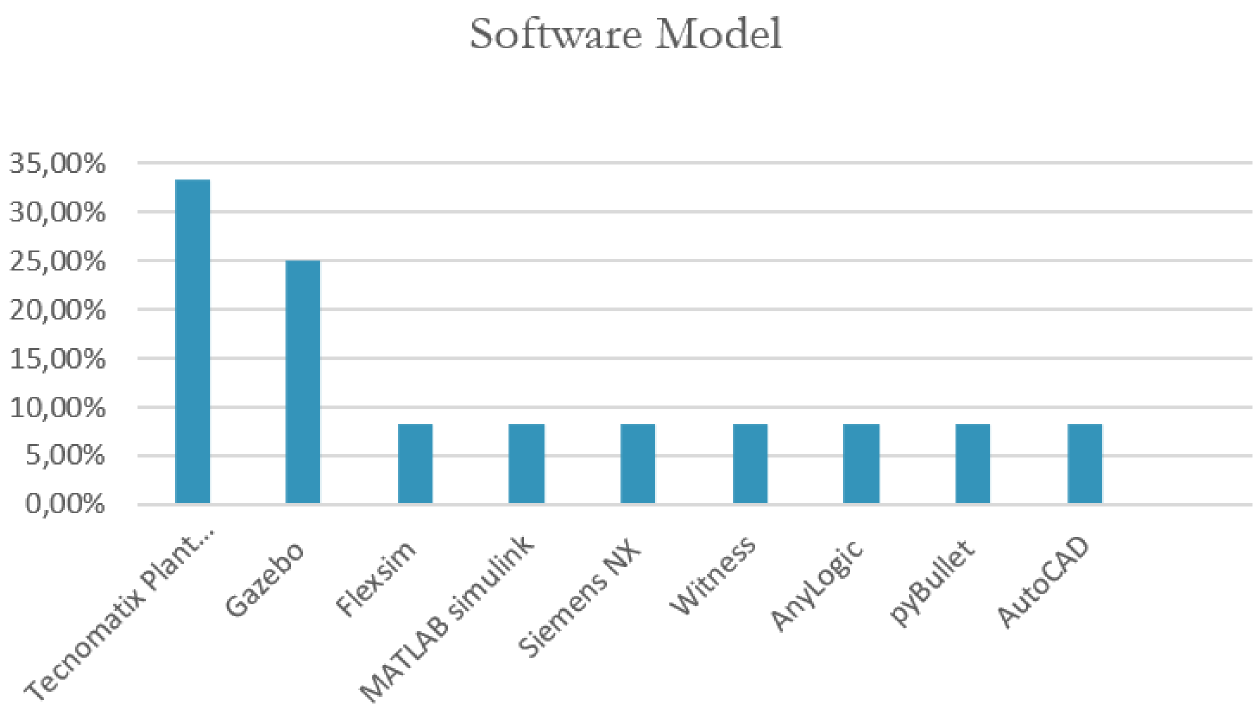

Figure 3.4.3. Frequency of Software Model in the Transportation System cluster.

Chapter 4. Overall findings and trends

In summary, it seems that the application of DT requires almost the same structure regardless of the service offered and the physical asset twinned.

The schema identified is showed in Fig. 4. The System is represented with the layers mentioned in Chapter 1, the construction of the Digital Shadow starts from the data acquisition in a virtual environment, that can be done with different protocols. Successively, the acquired data are analyzed and processed with the use of digital models that open the way to representing the real system in the chosen virtual environment with a (simulation) software. These first steps are needed to give the final shape to the Digital Shadow. When the Digital Shadow is bidirectionally connected to the main controller of the real system, the overall system becomes a proper DT.

Below (Figure 4.0), a framework representing the trends observed in the review is proposed with the main technologies that can meet the DT implementation requirements for each application target considered.

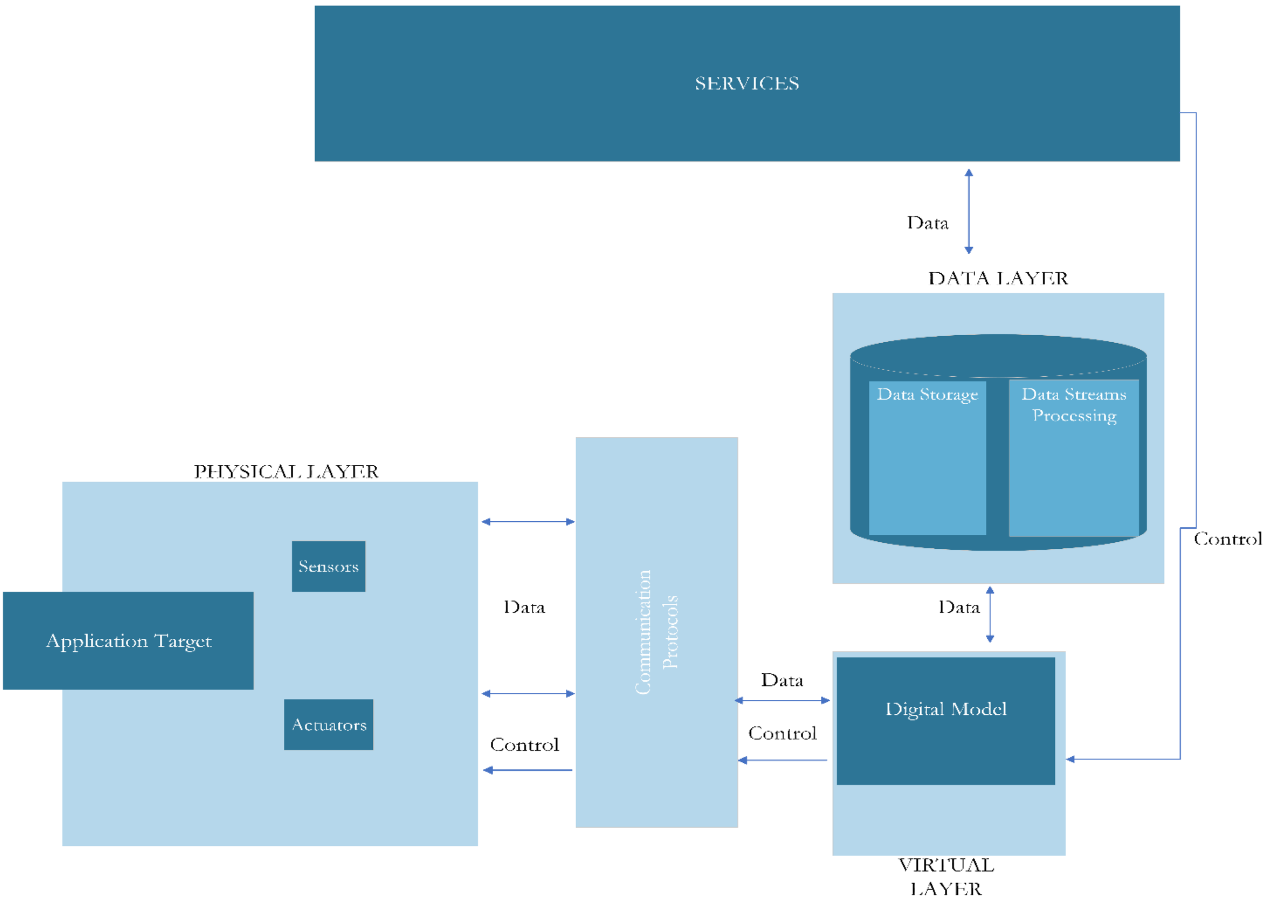

Figure 4. General DT application framework.

As for data collection from sensors, especially PLC and RFID tags, and communication between the different layers of the DT, the OPC UA and TCP/IP protocols are proposed for the Production Line cluster (Figure 4.1.), CNC Machine (Figure 4.2.), Transportation System (Figure 4.3.) and Human-Robot Collaboration. These types of data exchange standard are a safe, reliable, manufacturer independent, and platform-independent industrial communication. They enable secure data exchange between hardware platforms from different vendors and across operating systems.

To meet the very strict requirements for data analysis Apache Kafka, used by many companies for high-throughput data pipelines, flow analytics, and data analysis and Apache Flink, used for stateful computations on unbounded and bounded data streams, are proposed. In these frameworks, signals from the DT platform were stored on Apache Kafka and then forwarded to Apache Flink for analysis. MySQL and SQLite, both relational databases, are proposed for the data storage.

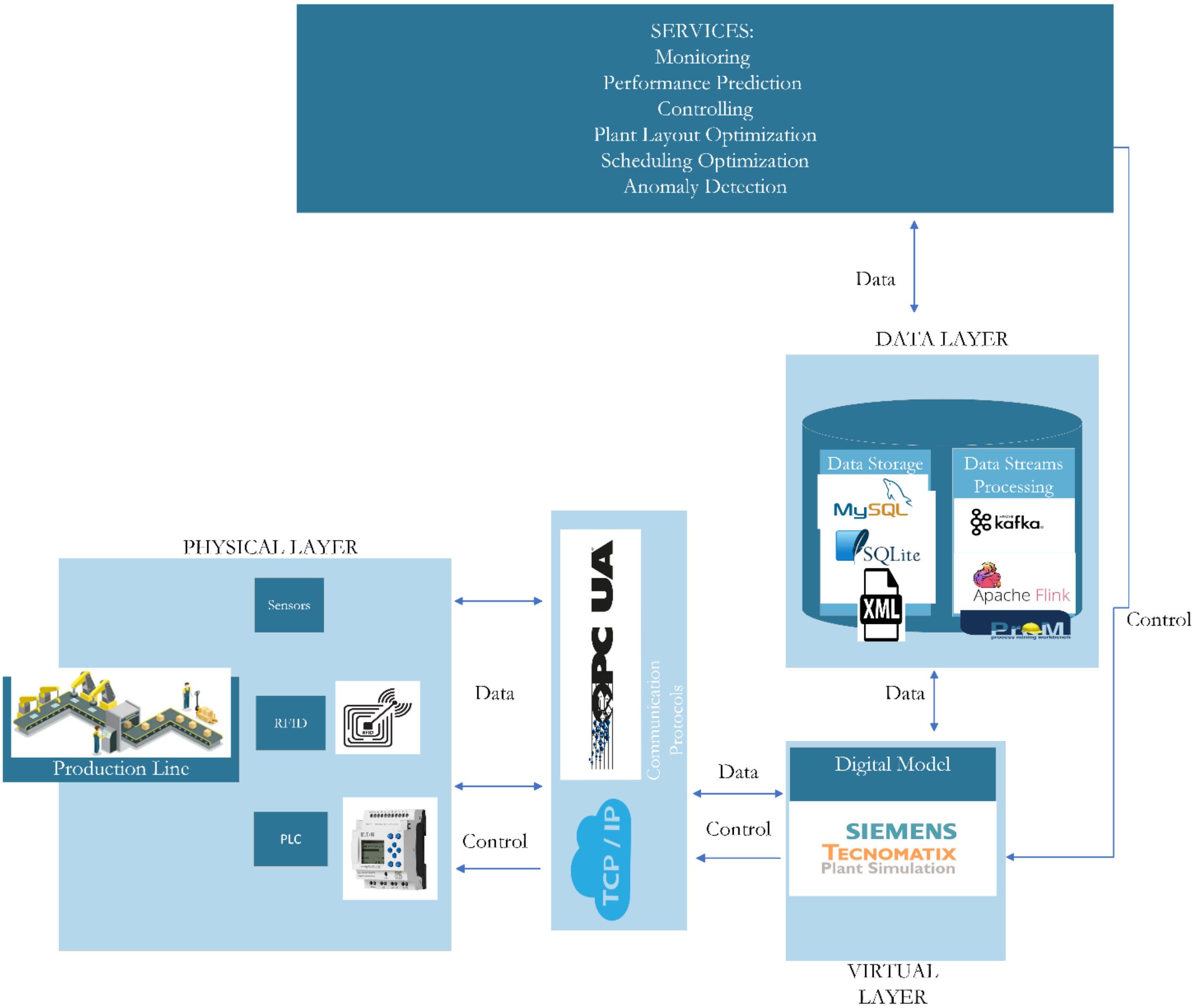

Figure 4.1. DT Production Line application framework.

For Production Line and Transportation System the simulation model Siemens' Tecnomatix Plant Simulation (a platform for agent-based/ discrete event simulations (DES)) is the main trend, it can be used for real-time supervision, control, and visualization of the virtual twin. Tecnomatix uses an object-oriented modeling method. Modeling of production systems is realized by implementation of virtual objects which represent individual production equipment. Machines, workers, transport, and logistic systems such as conveyors, trucks, loaders, warehouse, buffers and other storage objects occurring in manufacturing companies. It can be used for analytics to achieve logistic process improvement, material flow optimization and efficient resource usage. For the Transportation System, Gazebo Software is often present in the implementations: it is particularly suitable for representing human operators and mobile workstations in a human-robot collaboration environment. The only differentiator between the application of DT to the CNC Machine and to the Production line is the modeling software, on the CNC Machine the trends are Unity 3D and Matlab Simulink, used for visualization of the physical asset in the virtual environment.

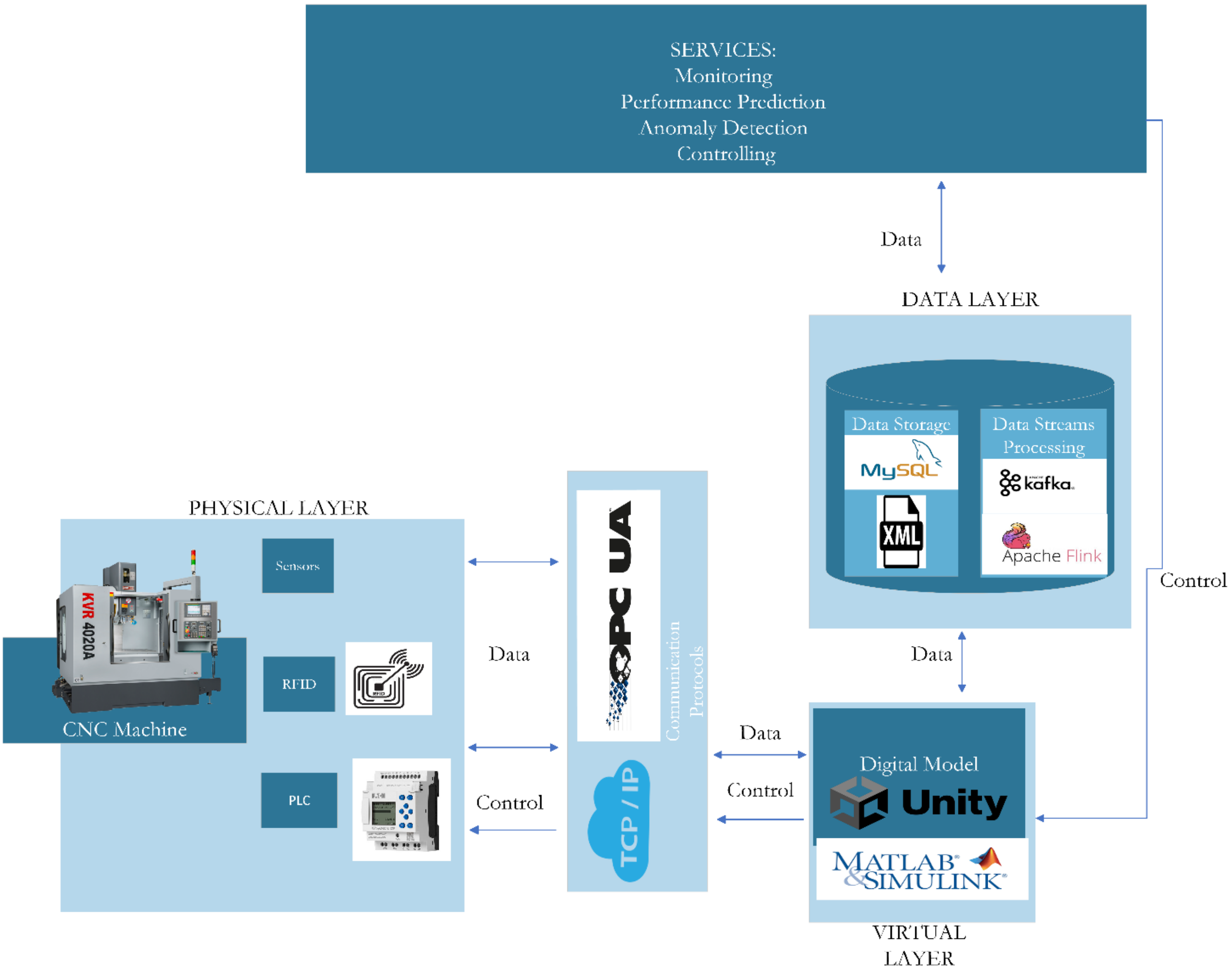

Figure 4.4. DT CNC Machine application framework.

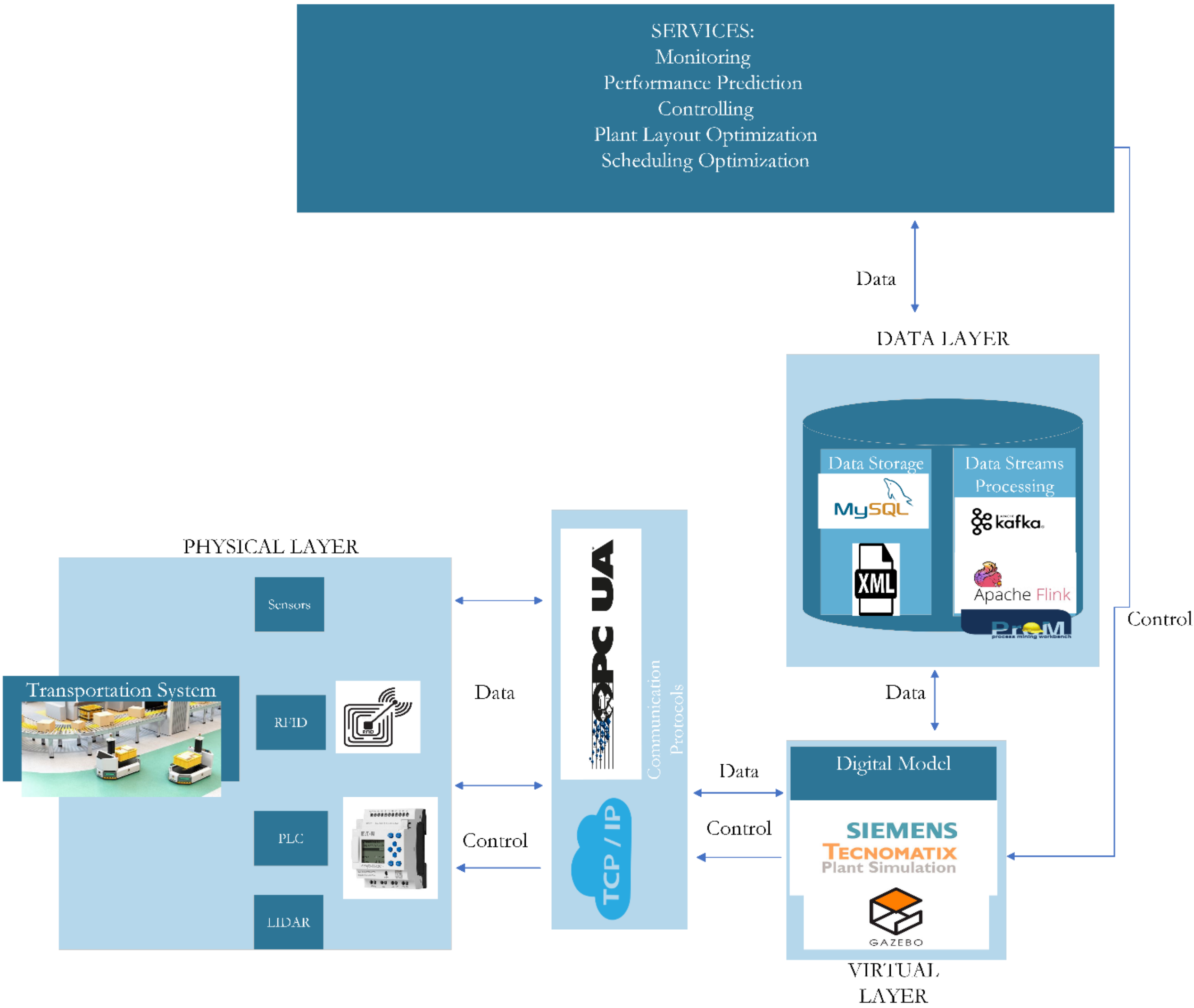

Figure 4.4. DT Transportation System application framework.

Remarkably different, however, is the framework for implementation in a human-robot collaboration context (Figure 4.4.). ROS (Robot Operating System), a reliable standard for industrial robot integration, has been proposed for data collection, especially with cameras and RFID tags, communication, modeling and control of robots. ROS compatibility software is provided by many manufacturers and enables the implementation of modular control units by unifying development practices with the same libraries and methods.

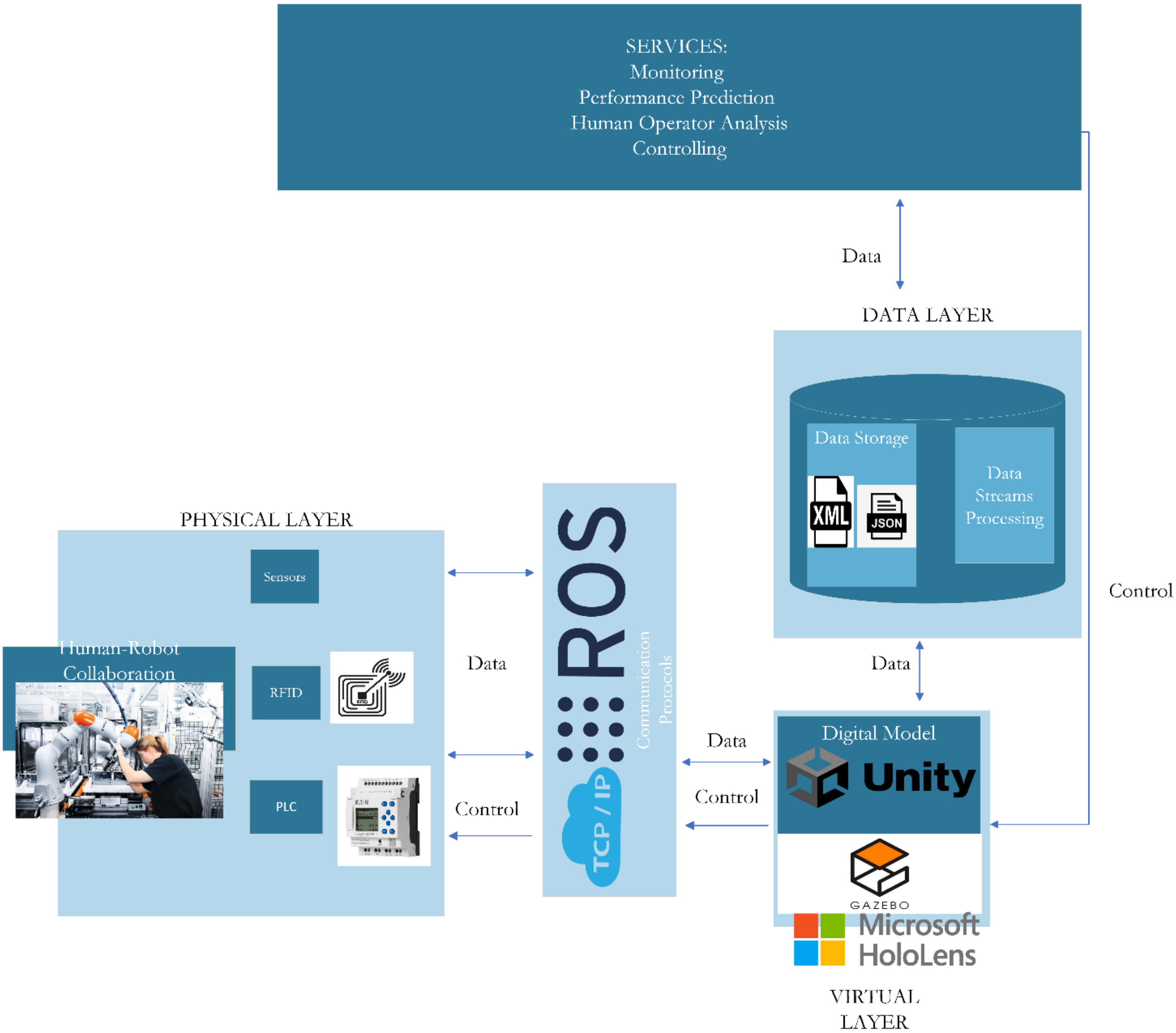

Figure 4.3. DT Human-Robot collaboration application framework.

In terms of the virtual layer visualization model, the most widely used software are Unity and Gazebo, both integrated with ROS, which provide a simple but powerful development environment with a modular approach to programming and also offer integration with all commercially available VR systems, such as MS HoloLens, ideal for human-robot collaboration, in particular robot training for human motion recognition and human training for virtual commissioning or to learn specific task in the industrial environment.

Summary

This thesis brings a contribution to the research on this topic, by exploring the DT application methodologies and related services in the manufacturing environment, enabling DT technology classification by application target, and finally trying to find a framework for DT implementation following the trends in the industry.

This analysis identified some misalignments between the implementation of DT and its description in the literature. First, many studies claim to implement DT without doing so completely. An example is often the lack of technical requirements such as bidirectionality of data between the virtual model and the physical model and thus the lack of fundamental services such as controlling. Also, in terms of the technologies used, many studies omit software and data management methodology, which are fundamental pillars for DT implementation. Moreover, in many cases, DT implementation is only partially illustrated and in the early stages, making it clear that DT research is still in an embryonic stage. The latter aspect can also be observed in many cases of articles in which, even for the same purposes, there is a wide variety of solutions adopted, without a clear trend being identifiable.

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Appendix

Table 5. Data Acquisition and Transmission-Simulation Features of Additive Manufacturing cluster.

	Data acquisition and Transmission				Simulation feature	
Reference	Sensors and hardware	Software	Data form	Protocol	Model	Software
Yi et al.(2021)[73]	Raoberry Pi 3, Thermocouple sensors, IR distance sensors	Octoprint		REST API	3D	Unity
Reisch et al. (2022) [54]	Welding camera, voltage sensor, temperature				3D CAD	Siemens NX1926
Liu et al. (2022) [36]	BSE detector, MeltPoos system, EOSTATE ExposureOT, PLC		XML	EthernetIP, Profinet, TCP, HTTP, REST API (restful api)	3D	MANUELA(pilot line) project
Yavari et al. (2021) [72]	Photodetectors, X-ray tomography					Netfabb
Pantelidakis et al. (2022) [51]	ZMPT101B, ACS12		ProBas	API	3D CAD	Unity, Siemens NX

Table 6. Data Acquisition and Transmission-Simulation Features of Welding Process.

	Data acquisition and Transmission				Simulation feature	
Reference	**Sensors and hardware**	**Software**	**Data format**	**Protocol**	**Model**	**Software**
Li et al. (2022)[33]	Vision and proximity sensors		JSON	MQTT	3D	Open Modelica
Li et al.(2020)[34]	Qr codes, circular codes	Vuforia, HoloLens2		HTTP	3D	Unity3D, HoloLens2
Wang et al.(2020)[66]	Hall sensor, optical code sensor, acceleration sensor, RFID tags, bar codes		XML	OPC UA	3D	
Tabar et al.(2019)[61]	Arc sensors, industrial camera (Point Grey FL3FW03S1C)			IPC	3D	Unity
Roy et al.(2020)[58]					3D, FEM	RD&T
Aivaliotis et al.(2021)[5]				TCP/IP	Data acqui	Labview
Aivaliotis et al.(2019)[4]					3D	Matlab, Open modelica

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