Exploring the Digital Twin implementation for sustainable production

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Abstract: The Digital Twin (DT) is the representation and real-time integration of physical systems in a digital model using several technologies. The DT development can be an effective solution for improving sustainability indicators of production activities. Despite the growing interest in this research area, there are still many problems with enabling an efficient application of DT to improve the sustainable performance of production activities. To contribute to the construction of knowledge in this domain, this paper aims to investigate, by a literature review, how the DT is currently applied to support sustainable production and what are the main components characterizing the existing DT frameworks or architectures. Production activities and objectives, the main layers and enabling technologies considered by literature frameworks, and some examples of sustainability goals and indicators considered by the DT literature for sustainable production were identified. Based on the review results, the main elements that characterize architectures or frameworks based on DT for the sustainability of production activities were established.

Keywords: Digital twin, sustainability, production performance, sustainable manufacturing, literature review.

I. Introduction and background

The digital transformation of industrial systems supports data-driven decision-making and offers many opportunities to achieve sustainability in business practices [1,2]. The last and ongoing advances in computer science, information, and communication technologies, such as the Internet of Things (IoT), cloud computing, big data analytics, and Artificial Intelligence (AI), enable the progressive convergence of the physical and virtual worlds toward the digitalization [3]. An important technology that is driving this transformation is the Digital Twin (DT) [4].

There are several definitions of DT in the literature for the industry context. As a common understanding, the DT is a digital counterpart of a physical product, asset, process, or system based on simulation models [5-7]. Krtizinger et al. [6] identify that the DT literature considers different levels of connection between the physical and digital counterparts. Thus, the authors propose a classification of DTs into three subcategories according to their level of data integration: Digital Model (DM), Digital Shadow (DS), and DT. DM is characterized by manual data flow between the physical and digital elements; DS has an automated data flow from the physical to the digital part and manual in the opposite direction; DT has an automatic exchange of data between physical and digital objects [6]. Thus, digital models have the lowest level of integration while digital twins have the highest. Even so, in the literature on DT these 3 terms are often used synonymously [6].

The DT application is associated with other technologies, known as DT enabling technologies, which are well investigated in the literature, such as by Qi et al. [3], who summarize the most used DT technologies and tools.

Field data allows the analysis, monitoring, simulation, and prediction of the behavior of a system in the digital model, which is often connected to an intelligence layer that contains a series of functionalities, such as optimization algorithms, to improve decision-making [4,8]. Then, the virtual counterpart can send feedback to the physical system to modify the behavior of the real entity or component [4]. This makes it possible, for example, to save resources, avoid waste, optimize efforts, and therefore, DT has considerable potential to support sustainable operations [9].

A recent definition of sustainable manufacturing is "the creation of manufactured products through economically-sound processes that minimize negative environmental impacts while conserving energy and natural resources. Sustainable manufacturing also enhances employee, community, and product safety" [10]. This definition implies that the journey toward sustainable manufacturing deals with sustainability goals and initiatives from which the environment, the business stakeholders, and the customers can benefit. Evaluating this transition and assessing the sustainability of organizations requires the proper definition of sustainable indicators [11]. Akbar and Irohara [12] identify a list of commonly used indicators in the manufacturing sector and group them into the three sustainability dimensions: environmental, economic, and social.

This study deals with the use of DT to improve the sustainability of production activities in industrial operations. In the scientific literature, there is a growing interest in this field of research. Some reviews conducted in this domain are reported in the following: He and Bai [5] analyze some issues related to sustainable smart manufacturing systems based on digital twins; Warke et al. [13] investigate the literature on the DT frameworks in the domain of smart manufacturing; the study conducted by Pater and Stadnicka [9] aims to show how sustainable development and DT are discussed in the literature and which are the most argued topics; Melesse et al. [7] identify the state-of-the-art of DT models in industrial operations, especially in production, predictive maintenance, and after-sales services; and the research conducted by Corallo et al. [8] focuses on investigating the characteristics of the DT for shop floor purposes.

Although existing literature reviews contribute to the advancement of the research in this field, there are still many gaps in enabling an effective application of DT to improve sustainability in productive activities. Moreover, except for Parte and Stadnicki [9], the existing studies do not focus on the three dimensions of sustainability.

The potential of using DT for sustainable production is high: several production activities can benefit from DT application, and many sustainability-related gains can be achieved. Accordingly, this research aims to investigate the potential of the DT for sustainable production and the main components of existing DT architectures through the development of a scientific literature review.

The Research Questions (*RQs*) addressed in this study are the following:

> *RQ1*: What is the current state-of-the-art on DT applications in production activities for supporting industrial sustainability?
>
> *RQ2*: What are the main characteristics of DT-based architectures and frameworks for sustainable production?

To answer the above *RQs*, a Systemic Literature Review (SLR) was performed, identifying and analyzing the relevant documents to the field using a structured research method. Considering the lack of shared understanding of the DT concept, the documents assumed to deal with DT, regardless of the level of integration considered, are in the interests of this research.

II. RESEARCH METHOD

To evaluate the state-of-the-art on sustainable production based on DT, an SLR approach has been used. This method efficiently identifies, assesses, and interprets existing works relevant to a particular research question or topic of interest [14].

The methodology utilized is described by Franciosi et al. [11], which is composed of 3 main steps: (A) Definition of research databases and keywords; (B) Literature search and paper selection; (C) Analysis and information extraction process. The application of the three steps in our study is listed in the following.

A. Definition of research databases and keywords

The SCOPUS and Web of Science databases were used in the SLR, which are two of the most reliable and popular multidisciplinary scientific databases, including peer-reviewed literature. The set of keywords was defined for designing the string to adopt in the selected databases, according to the review’s objective and its RQs. The following string was then used: (“*digital twin*” OR “*digital shadow*” OR “*digital model*”) AND *production* AND (*sustainability* OR *sustainable*).

B. Literature search and paper selection;

Articles that included the chosen keywords in their title, abstract, or keywords were searched in the defined databases. The literature search was implemented in February 2022. Only papers in English and published in peer-reviewed journals, conference proceedings, or books were selected. Excel software was used for document management and analysis.

A screening phase was carried out to choose records consistent with the purposes of the study. The documents were classified as included or excluded based on two Exclusion Criteria (EC): 1st EC: Entire conference proceedings; 2nd EC: out of topic, i.e., documents that do not consider the use of DT for sustainable production are excluded. Thus, manuscripts that regard, for example, the use of digital twin to support production activities but without considering aspects of sustainability (covering at least 2 of the 3 sustainability dimensions) were not included.

Regarding the DT integration level, all documents that used a DM, DS, or DT, defined as DT, were included. Papers that used the terms DM or DS but considered a bidirectional and automatic data exchange between physical and virtual counterparties were also included. Documents that dealt with a DM or DS without referring to the DT are instead not part of the scope of this study. The articles for which the full text was not found were also excluded and sub-classified as “not available”.

The paper selection phase was conducted in two steps. In the first step, the paper was analyzed based on its title, abstract, and keywords, and in the second step, the entire text of the previously selected works was taken into account.

C. Analysis and information extraction process.

At this stage, the documents included were analyzed to identify the state-of-the-art in the research field of interest and related papers about DT-based frameworks and architectures for sustainable production. The documents were classified according to different criteria, allowing a descriptive and content analysis that answers the research questions. As a result of this phase, a DT-based framework for sustainable production was also defined.

III. RESULTS DISCUSSIONS

The review process and its associated results are provided in Fig. 1. The initial search yielded 182 articles, 120 from the SCOPUS database and 62 from the Web of Science database. After removing the duplicates and non-English papers, 139 articles were identified to be analyzed. After the first screening, 75 documents were selected, and after the second, 32 papers were identified as relevant to this research.

The papers included were analyzed according to the *RQs* provided in section 1. The first sub-section (A) below refers to the *RQ1* and aims to identify the state-of-the-art of DT for sustainable production, considering the 32 selected documents. The second sub-section (B) refers to the *RQ2*, and the analysis focused on the 16 papers that provided an architecture or framework for the DT, highlighting the DT's main characteristics.

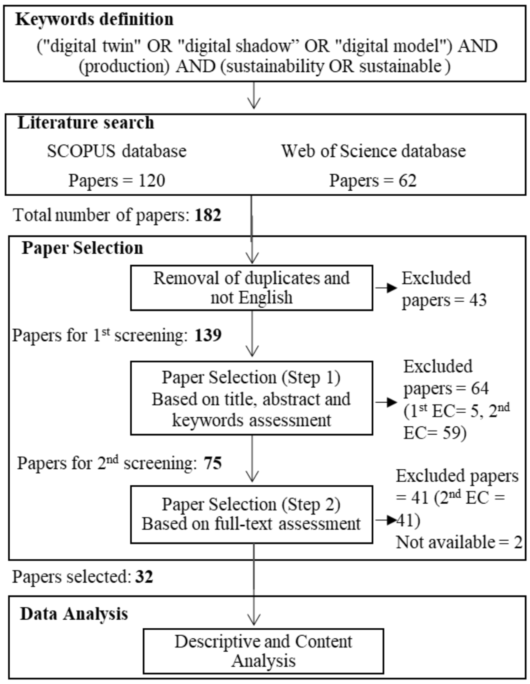

Fig. 1. Review Results

A. State-of-the-art: DT for sustainable production

A descriptive analysis was initially carried out to identify the state-of-the-art of DT to support the sustainability of production activities, followed by a content analysis, which will be presented below. Finally, the last subsection (C) shows the main elements that must be considered and defined when developing frameworks for sustainable production based on DT.

The 32 selected papers were classified according to the publication year, industrial sector, document type, research method, and contribution. Fig. 2 displays the distribution of these publications over the years, from 2018 to 2022: it is possible to identify an upward trend in the number of scientific publications on the use of digital twins in sustainable production; in particular, from 2020 onwards, research has suddenly increased. The year 2022 has fewer articles than the previous year, as the analysis was carried out in February 2022. This indicates that this area of research is new and is attracting increasing interest.

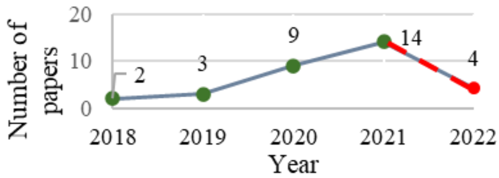

Fig. 2. Number of publications per year

As expected, since this research deals with production activities, most of the documents analyzed (93.8%) refer to the manufacturing sector [15-43], for which DT is considered a technology with great potential for improving its sustainability. Only 2 articles consider another application context, i.e., Fathy et al. [44], who address the use of DT to support sustainable energy production, and Beloglazov et al. [45], who exemplify the use of DT for remote training and control of the process of the mining industry.

Most of the studies included in the final selection were articles (59.4%), followed by conference papers (25.0%), reviews (12.5%), and book chapters (3.1%). The documents were also classified according to research method (Table I) and type of contribution (Table II). Regarding the method used to carry out the research, 40.6% used a case study, 37.5% used theoretical research or literature review, 9.4 % used experimental research or simulation, 6.3% used a combination of two research methods (e.g. theoretical research and case study), and 6.3% used another type of research method (e.g., action research).

TABLE I
PAPER CLASSIFICATION BASED ON RESEARCH METHOD

Research Method	Number of papers	(%)
Case study	13	40.6 %
Theoretical research / Literature review	12	37.5 %
Experimental research / Simulation	3	9.4 %
Combination of research methods	2	6.3%
Another type of research method	2	6.3%

Concerning the kind of contribution, 34.4 % proposed a theoretical framework or architecture, 18.8 % developed methods, methodology, or models, 15.6 % were state-of-the-art, 9.4% developed a combination of contributions, and 21.9 % presented another type of contribution.

TABLE II
PAPER CLASSIFICATION BASED ON CONTRIBUTION

Contribution	Number of papers	(%)
Proposition of theoretical framework / architecture	11	34.4 %
Another type of contributions	7	21.9 %
Development of method/ methodology/ model	6	18.8 %
State-of-the-art	5	15.6 %
Combination of contributions	3	9.4%

Content Analysis

In this part of the analysis, the following aspects were identified: DT application level, DT production activities and services, and examples and considerations of how sustainability aspects (e.g., goals for sustainable production or performance indicators) are addressed.

The DT technology has been applied at different levels in sustainable production, i.e., machine, system, company, network, and product levels. Most studies consider more than one level, which is often hierarchically related, for example, assuming a DT at the machine or device level and a DT at the production system level. Table III presents some examples from the literature for each of the mentioned levels of DT application, considered separately or in combination with another level.

TABLE III
DT APPLICATION LEVEL: EXAMPLES FROM THE LITERATURE

Levels	Example	Description
Machine and System	Borangiu et al. [21]	The paper defines the DT Architecture for the Supervised Control of the Radiopharmaceutical Production System, considering the virtual twins of the three main subprocesses, and their machines, in the production plant.
Company and Network	Glatt et al. [23]	The paper develops a concept for a Digital Twin framework for sustainability assessment in production networks that encompasses the network level of several companies and the company level.
Product	Riedelsheimer et al. [35]	The paper presents a methodology to develop DTs of physical IoT-based products for optimizing sustainability along the product life cycle.

The DT can support the sustainability of production activities for different purposes. Some considered examples are: Real-time process control, including parameters monitoring [27], optimization of material usage [39], management of energy and resource flow [29]; optimization of production scheduling [40], and master production schedule for the Supply Chain [37]; product quality control, e.g., detecting contour deviations of workpieces by permanently monitoring the machine tool process in real-time [27]; remote operator training in the production process [45] and online control of predictive maintenance [30].

These activities are related to goals for sustainable production and can contribute to improving economic, environmental, and social indicators. Often the same activity can impact more than one SD simultaneously. For example, Leiden et al. [29] emphasize the need to consider key performance indicators (KPIs) to support decision-making based on DT and use the DT to improve energy and resource efficiency, which positively impacts the environmental and economic dimensions. The authors consider the Global Warming Potential (GWP) as an environmental indicator and the Energy Cost as an economic indicator in their application example.

Instead, the social dimension of sustainability is addressed, for example, by Beloglazov et al. [45]. They use DT, which allows full simulation of the real activity of process flow operators, to train operators to deal with mining and processing emergencies. As a result, operator safety can increase, and accidents decrease.

The sustainability goals to be considered depends on the specific characteristics of the application context. For example, the use of DT to support energy efficiency improvement may be relevant for the milling process due to its high energy requirement [26]. Still, it may not be significant for production processes that deal with low energy consumption.

B. *Digital Twin-based frameworks and architectures for sustainable operations*

Of the 32 documents selected in the review, 16 (50,0 %) provide Digital Twin-based frameworks or DT architectures [16-18, 21, 23, 24, 26, 29, 31, 36, 37, 40-44]. These documents were analyzed to identify the level of integration between the physical and virtual counterparts of the DT, the sustainability issues, the main layers, and some examples of enabling technologies considered by the current literature frameworks and architectures, which will be presented below.

Level of integration and sustainability issues considered by literature frameworks

To identify the level of integration between the physical and virtual world of the DT, it was analyzed whether they presented bi-directional and real-time data exchange between them. Of the 16 architectures available in the literature, 10 (62.5%) offer these two characteristics. In contrast, the other 7 (37.5 %) do not, of which 3 [21, 23, 26] consider the exchange of data in real-time but unidirectional (physical part to virtual part). For 3 of them [16, 24, 44], this classification is not applicable since the proposed frameworks do not present the physical counterpart of the DT. This reaffirms the use of the terms DM, DS, and DT as synonyms in the literature on DT, as identified by Krtizinger et al. [6].

Regarding sustainability issues, of the 16 documents that provide an architecture or a framework for DT, only 3 (18,8%) explicitly present some sustainability aspects [24, 40, 43]. Table IV shows how sustainability is considered by these documents.

TABLE IV
CONSIDERED SUSTAINABILITY ISSUES

Reference	Economic	Environmental	Social
[24]	Raw material optimization; Energy reduction, Production increase; Smelt pot life enhancement	Raw material optimization, Energy reduction	-
[40]	Energy efficiency process optimization and job scheduling	Energy efficiency process optimization and job scheduling	-
[43]	Energy-efficient operation optimization	Energy efficiency	-

As shown in Table II, a DT architecture or framework for sustainable production that considers the social dimension of sustainability or the three dimensions simultaneously was not found. The 3 identified works consider economic and environmental aspects simultaneously and, specifically, all take the energy issue into account, while only Gupta and Basu [24] address other aspects of sustainable production. This shows that the integration of sustainability aspects into DT-based frameworks for sustainable production is still little explored, and considering the potential of DT for improving the sustainability of industrial operations, this could be an opportunity for future research.

Main layers and enabling technologies considered by literature frameworks

This section introduces the main layers and enabling technologies considered by literature frameworks. The most frequent framework layers that were identified are the *virtual layer*, *physical layer*, *data layer*, and *service layer.* Fig. 3 shows how many documents (and the percentage) consider each of these layers.

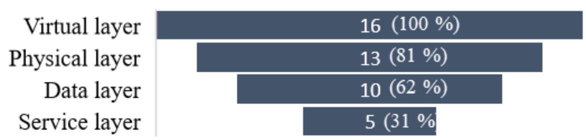

Fig. 3. Number and percentage of documents per framework layer.

Considering the definition of a DT, in all the analyzed architectures/frameworks, a layer related to the virtual model is present. In particular, two documents more precisely define its components: Wang et al. [40] consider that the model view is composed of Knowledge-based models, Mathematical models, and Discrete event simulation models related to the device and process level; Ayerbe et al. [17] define the model layer as the combination of a geometric model, position model, and status model, which include several models, such as simulation, mechanism, classification, prediction, evaluation, optimization, and control. In addition to the virtual layer, most of the architectures (81,3%) report the physical layer.

10 articles include the data layer: various data types, such as product, energy flow, or planning data are considered [23, 29, 31]. These data can be obtained from different sources, for instance, sensors, manual input, or retrieved from other systems, such as the Manufacturing Execution System (MES) and the Enterprise Resource Planning (ERP) [29]. Data may or may not be in real-time [40,41]. Borangiu et al. [21] determine that this layer is responsible for data acquisition and transmission, while Wang et al. [40] consider cleaning, processing, and storage operations. Wang et al. [41] present this layer in more detail, with data processing and storage as its main function; they consider the following modules: big data pre-processing (data reduction, cleaning, transformation, and integration of data), big data distributed computation and processing (Storm, Hadoop, and TensorFlow) and bid data storage (structured, semi-structured, and unstructured).

The service layer is very well defined by Wang et al. [40]. The authors, who propose a framework for DT-based energy-efficient operation of manufacturing systems, have established two types of services: online and offline. The first group considers, for example, Event-driven energy-saving decisions and data-driven system performance forecasts, while the second group energy-efficient process optimization and energy-efficient job scheduling. The DT model for the nonferrous metal industry proposed by Liu et al. [31] presents the services layer; however, the established services types are not defined or exemplified in the proposed framework. Although Barata et al. [18], and Gupta and Basu [24] do not call a service layer in their architecture/framework proposed, they define a layer with a similar function. Barata et al. [18] consider the Smart Industry Management Control layer, which includes the Manufacturing Status Data, and Gupta and Basu [24] established Raw Material Optimization in the Business Value layer.

Concerning the DT enabling technologies, 9 (56.3%) of the frameworks based on DT establish the presence of at least one technology. Table V shows which technologies were identified as main (technology column) and which documents consider in the proposed framework (reference column).

The combination of sensor technologies connected to physical assets and IoT can be applied to real-time data acquisition and transmission [42]. Big data techniques can be used for pre-processing (data reduction, cleaning, transformation, and integration) and store these data (through Structured, Semi-structured, and Unstructured databases), for example, on cloud platforms [41]. The framework proposed by Wang et al. [40] uses discrete event simulation models for system evaluation and optimization, and the one defined by Gupta and Basu [24] uses artificial intelligence, specifically machine learning, for predictive analysis and optimization of process parameters, to improve process efficiency, productivity, and reliability.

TABLE V
DT ENABLING TECHNOLOGIES THAT HAVE BEEN CONSIDERED

Technology	Reference	N
Modeling and simulation	[17, 24, 37, 40- 42]	6
Sensing	[21, 24, 40- 42]	5
Artificial Intelligence	[24, 37, 41, 42]	4
Big Data	[40-42]	3
Cloud	[26, 31, 41]	3
Internet of Things (IoT)	[41, 42]	2

C. *Architectures and frameworks for sustainable production: Main elements*

Based on the results of the literature analysis on DT for sustainable production, it was possible to identify the main elements that must be taken into account and defined during the construction of a framework for sustainable production based on DT. Fig. 4 shows the 6 aspects that were identified: (1) Application-level, (2) production activities and services, (3) goals for sustainable production, (4) sustainability indicators, (5) layers and their functions, and (6) key technologies. It can be used as a starting point for future studies and the implementation of DT-based architectures to improve the sustainability of production activities.

According to the literature review, DT can represent different levels of a real system, including a single component or even an entire production system, so it is crucial to define the representation level of a given architecture. The production activities that will be considered and the service purpose must also be specified. It is essential to know the objectives for sustainable production, which are evaluated through sustainability indicators (economic, environmental and social). Thus, it is possible to define the architecture layers, the function of each one of them, and the key technologies that will be implemented to enable each layer to fulfill its role. More details about each of these elements and some examples can be found in subsections III-A and III-B of this paper.

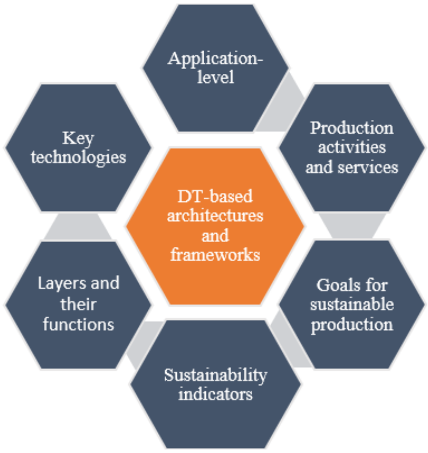

Fig. 4: Main elements to be considered for the definition of a DT-based architecture or framework for sustainable production

IV. CONCLUSIONS

This document reports the results of a Systematic Literature Review, which aimed to identify the state-of-the-art of DT to support the sustainability of production activities and to highlight the main characteristics of DT-based architectures or frameworks for sustainable production. The review shows a growing interest in this research field, which focuses on the manufacturing sector. DT can support improvements in sustainability indicators (economic, environmental and social) of different productive activities.

Concerning DT-based architectures for sustainable production, 4 main layers were identified: virtual layer, physical layer, data layer, and service layer, which were associated with the following technologies: Modelling and simulation, Sensing, Artificial Intelligence, Big Data, Cloud, and Internet of things (IoT). Based on these findings, the main elements to be considered for the definition of DT-based architectures and frameworks for sustainable production were identified. The results of this study contribute to the research and the effective application of DT to improve sustainability in productive activities.

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