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REVIEW

Decision support in productive processes through DES and ABS in the Digital Twin era: a systematic literature review

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ABSTRACT

The use of simulation to support decision-making in productive processes (goods and services) is already an established research field. However, with the availability of solutions and technologies, simulation is no longer a tool with limited scope and analysis. In this case, the integration of simulation with physical systems is considered to allow virtual models to be sensitive to physical changes and aligned with the current state of processes, forming the so-called Digital Twin. Therefore, the main purpose of this article is to present a systematic literature review of the use of simulation as Digital Twin to support decision-making. We considered studies published in scientific journals and conference proceedings that include the use of Discrete Event Simulation (DES) and/or Agent-Based Simulation (ABS). Although the Digital Twin concept has appeared in recent years, we noted that its principle has been used for decades when it comes to decision-making through simulation. Moreover, there are still many discussions and uncertainties regarding the simulation model in this research field, such as the degree of autonomy, synchronisation, and connection. These and other key issues are discussed and some research opportunities are highlighted, such as the need for constant model validation and integration between various models.

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KEYWORDS
Digital Twin; discrete event simulation; agent-based simulation; decision-making; systematic literature review

1. Introduction

Computer simulation has been consolidated in recent decades as a valuable decision support technique in productive processes (Rodič 2017; Mourtzis 2020; Scheidegger et al. 2018). We considered as a productive process all activity capable of generating goods and services. In this case, applications in several sectors stand out, including manufacturing, hospitals, logistics, military, among others (Negahban and Smith 2014). Moreover, among the different types of simulation, the main ones in this context are the Discrete Event Simulation (DES), Agent-Based Simulation (ABS), and System Dynamics (SD) (Scheidegger et al. 2018). Despite its applicability, the use of simulation has changed over the years, ceasing to be a 'stand-alone' tool, with limited scope and analysis, to become integrated to physical environment and of constant use (Beregi, Szaller, and Kádár 2018; Goodall, Sharpe, and West 2019). In this way, Tiacci (2020) and Zhuang, Liu, and Xiong (2018) highlight that the simulation lives the era of the so-called Digital Twin (DT). The DT refers to virtual copies capable of connecting to physical systems, mirroring their behaviour, and guiding decision making (Wright and Davidson 2020). Tao and Zhang (2017) reveal that the adoption of DT by decision-makers is an inevitable trend, while Santos et al. (2020) highlight that the use of simulation as DT is aligned with the fourth industrial revolution.

By integrating the simulation model with physical systems through sensors, smart devices, databases, and management systems, we obtained a highly synchronised virtual copy that is sensitive to physical changes (Beregi, Szaller, and Kádár 2018). Several studies that address simulation as DT of processes have been highlighted in the literature in recent years (Grube, Malik, and Bilberg 2019; Steringer et al. 2019; Terkaj et al. 2019; Beregi, Szaller, and Kádár 2018). Terkaj et al. (2019) report that simulation as DT is an alternative to DT commercial solutions, which tend to be more expensive and limited. Lu et al. (2019) highlight that the simulation as DT is an excellent alternative given the dynamic characteristics of the production systems. However, although DT is a relatively recent concept, connecting simulation models to physical systems and updating them according to real behaviour is a practice that has been adopted for decades. In this context, several nomenclatures have been

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used over the years to refer to this approach, such as 'Cyber-physical System', 'Symbiotic Simulation', 'Online Simulation', 'Data-driven Simulation', 'Real-time Simulation', 'Near real-time simulation', and 'Semi-physical simulation' (Choi and Kang 2018; Onggo et al. 2018; Saez et al. 2018; Scholl et al. 2012; Sormaz and Malik 2018; Vahdatikhaki and Hammad 2014; Leng et al. 2020).

Moreover, several literature reviews address the use of simulation in decision support in productive processes. Mourtzis (2020) presents an analysis of the state of the art and future trends in simulation in manufacturing systems, while Salleh et al. (2017) focus on papers that use simulation in healthcare, and Oliveira, Lima, and Montevechi (2016) address the use of simulation in logistics processes. Regarding the simulation techniques, Scheidegger et al. (2018) present a review addressing the main approaches used for problems related to industrial engineering and productive processes. However, Harper and Mustafee (2019b) emphasise that simulation as DT is mainly focused on making short-term decisions, a fact that implies several unique characteristics of this use, which were not addressed in the mentioned works. In this case, we did not find any literature reviews focused on this approach. Characteristics such as autonomy, connection, and synchronisation of the virtual model may vary according to the DT objectives (Wright and Davidson 2020) and such considerations are also valid for DT through simulation. Therefore, it is evident the lack of a solid theoretical basis on this topic, capable of guiding researchers and professionals in the development of solutions for decision making.

Therefore, the main objective of this article is to develop a Systematic Literature Review (SLR) addressing the state of the art of using simulation as DT to support decisions in productive processes. We considered the different nomenclatures used to refer to the use of simulation as DT and the main types of simulation used in this context (DES and ABS). The SD was not considered, since it has a high level of abstraction (Scheidegger et al. 2018) a feature that goes against the characteristics of the simulation as DT (Rodič 2017). Furthermore, we do not intend to address all the characteristics and functions of a process DT, which would involve other analyses and discussions, extrapolating the simulation field. We focus on addressing the use of simulation as DT and all the implications of this approach.

Therefore, we intend to answer the following research questions: (i) What are the application areas and the decision objectives associated with the use of simulation as DT? (ii) What platforms are used to build DT simulation models and how are they connected to physical systems? (iii) What is the time horizon considered for updating the DT simulation model in the face of physical changes? (iv) What is the degree of autonomy of the DT simulation models? (v) Are there methods for the development and periodic validation of models of this nature? (vi) What are the main advantages, challenges, and opportunities linked to this approach? In an attempt to answer these questions, this article contributes to the theoretical development related to the use of simulation as DT and fills a gap in the literature on the subject. The rest of this paper is organised as follows: Section 2 provides a literature review to clarify the main concepts and themes covered in this paper. The research method is described in Section 3. Section 4 is dedicated to presenting findings and discussions, as well as answering the research questions. Finally, Section 5 concerns the conclusions and future directions.

2. From traditional simulation approaches to Digital Twin Era

The simulation is one of the most widely used techniques in Operational Research area, standing out for its numerous applications in the planning and analysis of production systems (Law 2014; Taylor 2019). Among its advantages, Fishman (2001) reports that the simulation is capable of providing answers for decision making at a relatively low cost, while Banks et al. (2010) and Greasley and Owen (2018) highlight that the simulation allows investigating complex systems, conducting 'what if' experiments without interfering with them. Rodič (2017) adds that the simulation has been consolidated in the last decades in the most diverse sectors, contributing to the development and improvement of products, processes, and services. Finally, Jahangirian et al. (2010) report that simulation can meet different layers of decision in business systems.

What differentiates each type of simulation are the methods and characteristics of modeling and, according to Law (2014), the choice of the best type of simulation depends on the nature and objectives of the modeled system. DES is based on a modeling of systems (processes, services, and products, for example) that change their states based on the occurrence of events, which occur at discrete time intervals (Nance and Sargent 2002; Law 2014). On the other hand, ABS is based on modeling the behaviour of so-called agents, that can represent people and groups of processes or machines for example, and who interact with each other and with the environment in which they operate (Siebers et al. 2010; Abar et al. 2017). Among both, DES is currently the most used, considering applications in productive processes (Uriarte, Ng, and Moris 2018), however, Siebers et al. (2010) report that ABS has stood out in recent years due to the growing number of problems that cannot be modeled through DES.

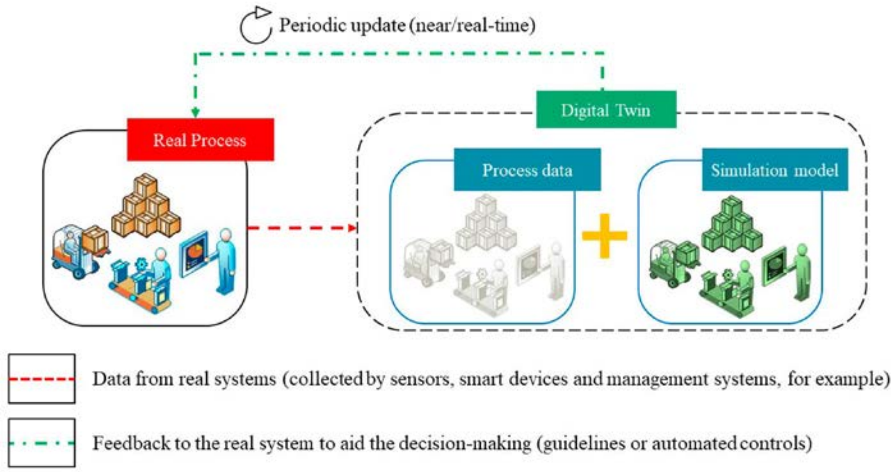

Figure 1. DT structure through simulation.

Despite being widely used in recent decades, simulation, considering its main types, has been changing over the years to adapt to the new requirements and characteristics of decision making (Rodič 2017). Skoogh, Perera, and Johansson (2012) highlight that many companies have failed to take advantage of the benefits brought by simulation, when considering the traditional approach. In this case, Lu et al. (2019) report that the cost of the simulation may be higher than its potential benefits since traditional projects generally involve a limited scope, the need for trained professionals, and long project times. Such characteristics tend to be incompatible with the dynamic character of the productive processes, as mentioned by Vijayakumar et al. (2019). The authors point out that there is a need for constant adaptation and updating of the simulation models to keep them valid for decision-making. Bergmann, Stelzer, and Straßburger (2011) report the need to connect and integrate the simulation model with physical systems to mirror them and support operational decisions. Other features demanded for simulation models in recent years include intelligent models, user-friendly interfaces, advanced graphics, a low degree of abstraction, hybrid simulation (using more than one type of simulation), among others (Mourtzis 2020; Rodič 2017; Sormaz and Malik 2018).

Considering the mentioned characteristics, simulation has been experiencing a new era in recent years (Mourtzis 2020). According to Mourtzis (2020), Tiacci (2020), and Zhuang, Liu, and Xiong (2018), given the rapid technological development, simulation has the role of the so-called Digital Twin (DT). The term DT was coined by Shafto et al. (2010) to reference virtual copies of physical systems belonging to the American aerospace agency, NASA. Since it was created, the DT concept has been refined from applications in the most diverse areas, such as manufacturing, healthcare and services, being valid for both processes and products (Wright and Davidson 2020). The DT of processes was approached by Tao and Zhang (2017) as being an important milestone for the production systems, bringing better decisions through the monitoring and control of the physical systems. Virtual models that represent DT can be connected with real processes via sensors, smart devices, databases, and process management systems, for example (Alam and Saddik 2017; Tao and Zhang 2017). Finally, according to Alam and Saddik (2017), DT can be used to support decisions in three approaches: (1) diagnosis, aiming to evaluate past analysis decisions; (2) monitoring, to monitor and control the processes; and (3) prognosis, aiming to anticipate and predict behaviours.

Using simulation models as DT represents an alternative to commercial DT solutions, which usually involve high investments and limited scope (Terkaj et al. 2019). According to Wright and Davidson (2020), what differentiates a traditional simulation model from a DT approach is the ability to extend its use over time scales where the physical system will constantly change. Therefore, a simulation model capable of connecting to physical systems and adapting constantly according to their current states can be classified as a DT (Ashrafian et al. 2019; Santos et al. 2020). Such models can be called 'DT simulation models' and Figure 1 illustrates its general structure. According to Tao and Zhang (2017), planning a process DT requires four components: (i) Physical System (PS), (ii) Virtual System (VS), Service System (SS), and DT Data (DTD). The PS consists of humans, machines and materials, while the VS consists of virtual models that describe the physical behaviour and which can be represented by the simulation model (Santos et al. 2020). The SS and DTD include the structure capable of allowing communication between the physical and virtual environments and the set of data and information that is transmitted between both, respectively. When referring to SS and DTD, it is important to highlight the key technologies and solutions such as the well-known Information Technology (IT), Internet of Things (also called IoT and which allows connection between processes, equipment, and systems), Big Data (data processing with large volume and variety), and Cloud Technology (data and information flow without physical resources). All of them were fundamental for the dissemination of DTs (Lu et al. 2019; Tao and Zhang 2017).

We can also understand the decision characteristics through DT according to the phase of the processes in which it is used (before and during their operation). On the one hand, the use of DT to guide decisions before processes operation is linked to design and configuration stage, where we can test scenarios and check the effect of decisions before implementing them, validating the physical system (Liu et al. 2020; Liu et al. 2019). On the other hand, when considering the use of DT during the processes operation, we intend to carry out a parallel control and evaluation in a timely manner (Leng et al. 2019; Alam and Saddik 2017). Another important characteristic regarding the use of DT concerns the capacity for coevolution existing between the physical and virtual environments (Tao et al. 2019). In this case, DT offers guidance for more efficient decision-making and, consequently, it is expected that DT will also adjust to the physical part with each improvement step, providing a mutual evolution between both physical and virtual environments (Tao and Zhang 2017). When considering the use of simulation as DT, this coevolution process is directly linked to the key characteristics of the simulation model, such as its update intervals, its autonomy, and its validity in the face of physical changes.

Despite the benefits of using DT to guide decisions, there are still constraints regarding its adoption. Tao and Zhang (2017) report that the biggest challenge is to guarantee the integration, communication, and synchronism between the physical and virtual environments, a fact that often requires a technological structure composed of sensors, intelligent systems, databases, processing capacity, among others. In this case, the authors report the need to evaluate the benefits of implementing DT given the necessary investments. According to Santos et al. (2020), although such technological structure is not so evident in traditional simulation approaches, we must consider such premises from its use as DT. Finally, Zhuang, Liu, and Xiong (2018) highlight that the difficulties in implementing DTs increase proportionally to their level of intelligence.

Furthermore, Wright and Davidson (2020) emphasise the importance of DT reliability, since its use may be associated with decisions of great impact. In other words, it is necessary to evaluate the DT performance. During its building phase, Zhuang, Liu, and Xiong (2018) suggest the evaluation under three main metrics: (i) Element, (ii) Behaviour and (iii) Rule, which are related to graphic representation, the ability to mirror physical behaviours, and the synchronism with physical environments, respectively. Moreover, after DT building, Tao and Zhang (2017) reveal that verification, validation, and accreditation routines must be carried out to ensure its correct functioning and performance, while Wright and Davidson (2020) state that statistical procedures are great alternatives for this purpose. In this sense, Meng et al. (2013) report that, compared to traditional approaches, evaluating the performance of simulation models as DT is generally a more complex and critical task.

The literature presents several applications involving the use of simulation as DT of productive processes, with emphasis on publications in recent years (Karakra et al. 2018; Murphy et al. 2020; Prajapat et al. 2019; Beregi, Szaller, and Kádár 2018; Grube, Malik, and Bilberg 2019; Steringer et al. 2019; Terkaj et al. 2019; Vijayakumar et al. 2019). However, although DT is a highly promising solution, it is not yet a fully explored area (Mourtzis 2020). There are still several questions about the characteristics and functions necessary for a DT and, when considering DT simulation models, such issues must also be addressed (Santos et al. 2020). Among the main issues in this case, we highlight the virtual models building steps, the time interval between model updates, the level of detail and integration of the model with physical systems, the need for periodic validations, the security related to autonomous models, among others (Santos et al. 2020; Tao and Zhang 2017; Wright and Davidson 2020).

Although the use of simulation as a DT is relatively recent, other similar approaches indicate that this concept has been explored for decades. In 1993, a study published by Katz and Manivannan (1993) proposed to connect the simulation model to the manufacturing equipment to monitor them, calling the approach 'Online Simulation'. We noted that the objectives are similar to those adopted in DT approaches and, like this case, several other nomenclatures were used to refer to this approach over the years. Another important point to be addressed concerns the evolution of the use of simulation as DT. It is expected that some difficulties reported in the past have already been overcome due to technological advances and, on the other hand, there will be new challenges and opportunities to be explored in future works. Given these considerations, we noted that this research field still lacks exploratory works, in line with Mourtzis (2020), who points out that the evolution of simulation tools and technologies remains a fertile field for research and applications. Finally, since there is no theoretical research that explores the use of simulation as DT, this paper is justified and will serve as a basis for future developments by researchers and professionals.

3. Research method: a systematic literature review

While a literature review (LR) allows the development of exploratory research without necessarily following rigorous methodological standards, the SLR approaches the literature in a structured manner, based on well-defined steps to answer certain scientific questions (Trigueiro et al. 2019; Oliveira, Lima, and Montevechi 2016). Tranfield, Denyer, and Smart (2003) point out that SLR is a fundamental scientific activity based on two fronts: (i) scientific examination of the main works in a given area and (ii) statistical procedures aimed at synthesising the findings and giving credibility to the results. Booth, Sutton, and Papaioannou (2012) complement that a systematic study must consider the following premises: be explicit, transparent, methodological, objective, standardised, structured, and reproducible. Therefore, this article presents an SLR addressing the use of simulation as a DT of productive processes, which was structured according to the steps suggested by Oliveira, Lima, and Montevechi (2016):

(i) Planning: the key research objectives and questions are defined;
(ii) Searching/Screening: the literature is explored according to the defined criteria;
(iii) Analysis/Synthesis: findings analysis and statistical procedures are performed;
(iv) Presentation: the results and main conclusions are described.

3.1. Planning

To define the objectives and the Research Questions (RQ), the first step was to conduct an exploratory search on the topic addressed in this paper. The Scopus® database was used, which, according to Scheidegger et al. (2018), is one of the largest and main multidisciplinary databases available. This first search for articles included the keyword 'Simulation' with the Boolean logic 'AND' and the term 'Digital Twin'. At the first moment, the type of simulation was not specified and we focused on work aimed at making decisions on productive processes, published in scientific journals and conference proceedings, and peer-reviewed. In addition to the articles found in this first stage, other works referenced by them were read in due time. This stage consisted of several meetings to discuss and investigate aspects related to the use of simulation as DT from the read papers. Professors and a doctoral student from four academic institutions participated in this stage, who have extensive experience in the field of simulation and Digital Twins. The researchers identified the main nomenclatures used to refer to the use of simulation as DT, in addition to certain issues not yet defined concerning this approach, which served as the basis for the formulation of the RQs.

Considering different nomenclatures and approaches, several variants of the simulation have been identified as DT over the years. According to Choi and Kang (2018), the so-called 'Cyber-physical Systems' are based on virtual copies synchronised with the physical systems and that integrate simulation with other systems and tools to support the decision. On the other hand, Gupta and Sivakumar (2005) and Scholl et al. (2010) reveal that the 'Online Simulation' is based on the connection of the simulation model with real systems to assist in decision making, taking into account the dynamic behaviour of operations. Another approach that has stood out in recent years is the 'Symbiotic Simulation'. Bergmann, Stelzer, and Straßburger (2011) and Onggo et al. (2018) report that this approach uses real data collected in real or near real-time to update the model and allow decision making through automated suggestions or commands. There is also the so-called 'Data-driven simulation' which, according to Meng et al. (2013) and Sormaz and Malik (2018), is based on updating and adapting the simulation model from data coming from real systems. The approaches 'Near Real-time Simulation' and 'Real-time Simulation', according to Saez et al. (2018) and Vahdatikhaki and Hammad (2015), allow the simulation models to be updated according to the state of the real processes and, in this case, what differs both approaches is the time interval between each model update. Finally, Leng et al. (2020) associate the term 'Semi-physical Simulation' with the DT features, creating a model synchronised to physical changes.

Regarding the application field, most of the analysed works are focused on the production of goods (Lu et al. 2019; Terkaj et al. 2019; Steringer et al. 2019). However, there are also publications related to services, as proposed by Lopes et al. (2019) and Vijayakumar et al. (2019). Regarding the methods for DT development through simulation, only the presence of specific frameworks was observed, as presented by Lu et al. (2019) and Vijayakumar et al. (2019), without the existence of more general methods. Both commercial simulation software (Grube, Malik, and Bilberg 2019; Terkaj et al. 2019), and programming languages (Lu et al. 2019) were considered. As for the validation of the simulation model, only the traditional validation methods were observed, which are carried out during the model building. Regarding the connection of the model with the real systems, there were connections directly with equipment (Mieth, Meyer, and Henke 2019; Beregi, Szaller, and Kádár 2018), and other connections through intermediate systems (Karakra et al. 2018; Steringer et al. 2019). In this sense, there are cases where DTs are autonomous and perform actions without human intervention (Donhauser et al. 2018; Beregi, Szaller, and Kádár 2018), and others in which there is only a decision suggestion (Eyre, Scott, and Freeman 2018; Mieth, Meyer, and Henke 2019). Finally, there are approaches where DT is continuously updated (Real-time) (Bottani, Murino, and Vespoli 2017), and others where the update is performed periodically (Near Real-time) (Zörrer et al. 2019).

Based on the mentioned considerations, we noted that there is still a gap in theoretical studies that address the use of simulation as DT and the works that involve this approach should be analysed, compared, and classified to provide a solid theoretical basis on the subject to researchers and professionals. Figure 2 illustrates the main gaps found in this first exploratory stage of the SLR.

Given the above considerations, the objectives of this research are:

(a) Develop an extensive literature scan on the use of simulation as DT;
(b) Analyse each work from the aforementioned gaps;
(c) Create a solid theoretical basis on this research field;
(d) Identify future perspectives.

Once the objectives were defined, the RQs were formulated:

RQ1: What are the application areas and the decision objectives associated with the use of simulation as DT?

RQ2: What platforms are used to build the DT simulation model and how is it connected to physical systems?

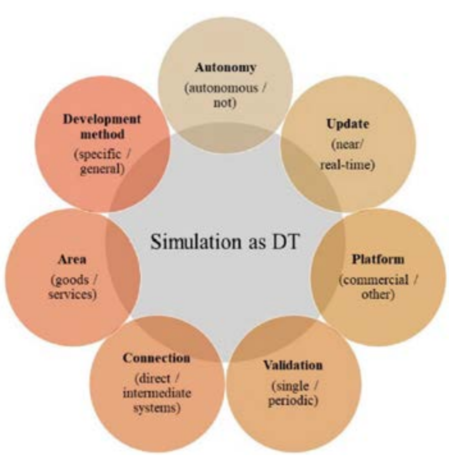

Figure 2. Gaps related to the use of simulation as DT.

RQ3: What is the time horizon considered for updating the DT simulation model in the face of physical changes?

RQ4: What is the degree of autonomy of the DT simulation models?

RQ5: Are there methods for developing and periodically validating models of this nature?

RQ6: What are the main advantages, challenges, and opportunities linked to this approach?

3.2. Searching/screening

The first step is the selection of the databases to be used in the literature scan. Five (5) databases were considered: Scopus®, Web of Science®, Scielo®, IEEE Xplore®, and Science Direct®. Then, the search keywords were defined and, to obtain more precision in the search results, the simulation was stratified into its main types, as already mentioned: 'Discrete Event Simulation' and 'Agent-based Simulation'. From now on, for the sake of simplicity, DES and ABS will be designated simply as 'simulation'. Furthermore, the terms referring to the use of simulation as DT have been included, which are: 'Digital Twin', 'Cyber-physical System', 'Real-time Simulation', 'Near Real-time Simulation', 'Symbiotic Simulation', 'Online Simulation', 'Data-driven Simulation', and 'Semi-physical Simulation'. Boolean logics (AND / OR) were used to obtain all possible combinations between the terms. About 80 searches were carried out, considering the chosen databases. Moreover, in each search the following criteria were included to consider the article in the SLR: (i) the terms searched must be present in the title, abstract, or keywords of the article; (ii) articles published in the last thirty years, considering the end date as March/2020; (iii) complete articles published in scientific journals or conference proceedings and peer-reviewed; (iv) only papers written in the English language; (v) articles of practical content and focused on making decisions about productive operations.

In a first moment, 169 articles were found that fit the search criteria, already discounting redundancies. Then a screening stage was carried out with the selected papers, where the abstracts were read to identify those that are aligned with the objectives of the SLR. In this step, articles that did not fit the previously defined research criteria were excluded. After screening, 75 articles were considered for full-text reading. Figure 3 shows the distribution of these articles in the chosen databases and Figure 4 summarises the procedures performed in the Planning and Searching/Screening phases. It is important to highlight that the focus of this SLR is restricted to the search for scientific articles in the main research bases,

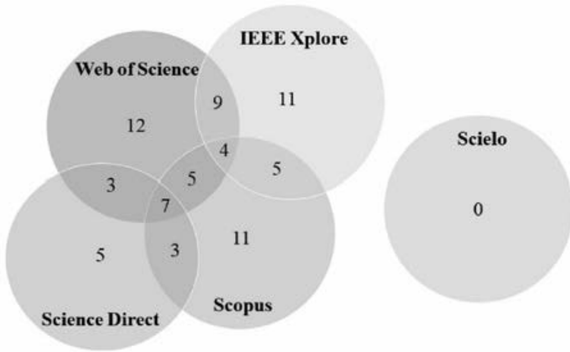

Figure 3. Articles per database (after screening).

not addressing patents or any other form of product registration.

3.3. Analysis/synthesis

The analysis and synthesis of the results were performed using an MS Excel® spreadsheet. In this way, it was possible to compile information from all 75 articles read. Each article was recorded in the spreadsheet according to guidelines related to the RQs and the extracted results were analysed using descriptive statistics. The analyses were based on each of the RQs and demonstrate the best practices and main perspectives related to the use of simulation as DT.

3.4. Presentation (reporting)

The presentation of the findings will be discussed in section 4, where the subsections will correspond to each RQ. Tables and graphs were used to summarise the results and assist in their interpretation. Therefore, the discussions presented will be extremely important to understand the evolution of the simulation as DT over the years, as well as the future perspectives of this approach. In addition to the current state of the art on this topic, discussions are presented about the advantages, limitations, and research opportunities regarding the use of simulation as DT.

4. Findings and discussion

We observed that there is a balance between the number of publications in scientific journals and conference proceedings and just over half (about 50.7%) of the publications are from conference proceedings, as shown in Figure 5. The first article on the topic was published in 1993, but it was only from the 2000s that publications on this topic became frequent. Moreover, we noted that there is a trend of growth in publications over the period analysed. In this case, the highlight is for the last five years, a period in which around 58.7% of the total published works were concentrated. The sharp growth of publications recently might be associated with the fertile field of research related to the implementation of DTs, driven

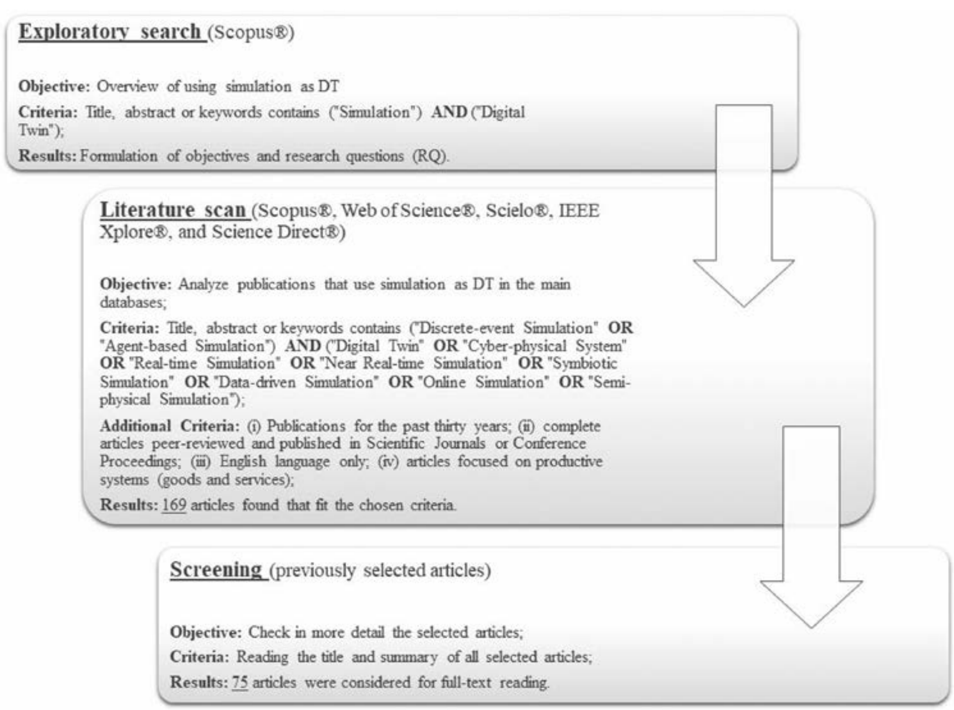

Figure 4. Procedures performed in the Planning and Searching/Screening stages.

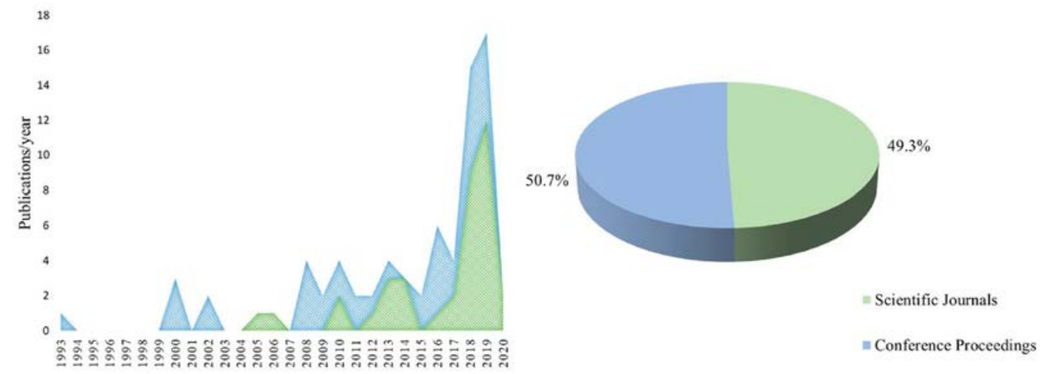

Figure 5. Papers that use simulation as DT (stratified by type of publication).

by the great technological development experienced in recent years, as highlighted by Tao and Zhang (2017).

The 75 articles analysed were published in 25 scientific journals and 24 conference proceedings. Table 1 presents the top 10 publication journals and proceedings. The first five journals presented correspond to about 43.2% of the published articles. Moreover, among the proceedings, the Winter Simulation Conference stands out, corresponding to 34.2% of all published works and being a reference in this research field.

We also analysed the works regarding the main researchers, as well as their affiliations and nationalities, and Table 2 presents the main findings. We found about 221 authors among the analysed articles and, based on the top 10 researchers, we observed that the difference in publications between them does not exceed 2 articles, which demonstrates that there is no a continuous production of articles in this area by the researchers. Furthermore, we can reach the same conclusion about the main affiliations and it is not possible to affirm that there is a cluster or a research center that is a reference in this field. Finally, when analyzing the countries with the most prominence among the analysed works, we noticed that the United States, United Kingdom and Germany stand out among the 25 nationalities that have publications in this area.

The articles were also stratified according to the nomenclature used to refer to the use of simulation as DT. Figure 6 shows that the term ‘Digital Twin’ appears in 29.3% of publications, being present from 2016. Since the term ‘Digital Twin’ was proposed in 2010, six years passed before the simulation could be seen as an alternative to the DTs development. The first work that refers to the idea of using simulation as DT was published in 1993 and adopted the nomenclature ‘Online Simulation’, as previously mentioned. This work, published in the Winter Simulation Conference, represented the beginning of an era marked by the connection of simulation models with real systems and processes to support operational decisions. The terms ‘Near Real-time’ and ‘Real-time’ correspond to most publications (34.7%) while the term ‘Cyber-physical System’ also represents a significant portion of the articles (16%). We noted that the term ‘Semi-physical Simulation’ did not appear in any selected article. Finally, the terms ‘Symbiotic’ and ‘Online Simulation’

Table 1. Top 10 publications locations.

Rank	Journal	No.	%	CUM (%)
1	Procedia CIRP	5	13.5%	13.5%
2	IFAC PapersOnline	4	10.8%	24.3%
3	Procedia Manufacturing	3	8.1%	32.4%
4	Automation in Construction	2	5.4%	37.8%
5	Simulation Modelling Practice and Theory	2	5.4%	43.2%
6	IEEE Transactions on Smart Grid	2	5.4%	48.6%
7	Applied Energy	1	2.7%	51.4%
8	Computers and Industrial Engineering	1	2.7%	54.1%
9	Computers in Industry	1	2.7%	56.8%
10	International Journal of Production Research	1	2.7%	59.5%
	Others	15	40.5%	100.0%
Rank	**Proceedings**	**No.**	**%**	**CUM (%)**
1	Winter Simulation Conference	13	34.2%	34.2%
2	Annual Simulation Symposium	2	5.3%	39.5%
3	International Mechanical Engineering Congress and Exposition	2	5.3%	44.7%
4	Spring Simulation Conference	1	2.6%	47.4%
5	International Conference on Computer Systems and Applications	1	2.6%	50.0%
6	Annual Computer Software and Applications Conference	1	2.6%	52.6%
7	World Automation Congress (WAC)	1	2.6%	55.3%
8	International Conference on Intelligent Manufacturing and Internet of Things	1	2.6%	57.9%
9	International Conference on System Simulation and Scientific Computing	1	2.6%	60.5%
10	International Conference on Industrial Informatics	1	2.6%	63.2%
	Others	14	36.8%	100.0%

Table 2. Top 10 researcher, affiliations, and nationalities.

Rank	Researcher	No.
1	Appa Iyer Sivakumar	4
2	Amir H. Behzadan	3
3	Cathal Heavey	3
4	Navonil Mustafee	3
5	Reza Akhavian	3
6	Young-Jun Son	3
7	Zhenrui Wang	2
8	C. Taylor	2
9	Mingyang Li	2
10	Wolfgang Scholl	2
	Another 211 researchers	
Rank	**Affiliation**	**No.**
1	University of Arizona	3
2	University of Exeter	3
3	Nanyang Technological University	3
4	RWTH Aachen University	2
5	Carleton University	2
6	Virginia Tech	2
7	University of Sheffield	2
8	Tsinghua University	2
9	University of Limerick	2
10	California State University	2
	Another 83 affiliations	
Rank	**Nationality**	**No.**
1	United States	17
2	United Kingdom	9
3	Germany	9
4	Canada	6
5	Singapore	6
6	Italy	5
7	China	5
8	France	3
9	Ireland	3
10	Austria	2
	Another 15 countries	

have ceased to be used in recent years, while the other still appear in the main recent publications.

Finally, we can evaluate the publications according to the type of simulation used. Figure 7 shows that DES is present in 92% of publications, followed by 5.3% of works that use ABS and, finally, 2.7% that consider both. In the latter case, there is what we know as 'hybrid simulation', where more than one type of simulation is used in an integrated manner, as proposed by Braglia et al. (2019). For Mourtzis (2020), the hybrid approach is one of the main trends when considering the evolution of the simulation.

Finally, to answer the proposed RQs, the following sections will present the findings and discussions according to each question, in the same sequence.

4.1. Operation area and decision-making objectives using the simulation as DT

Regarding the application areas and the objectives of decision making through simulation as DT, we noted that there is great diversity among the articles. Based on the selected articles, we divided the application areas into six main ones (i) Manufacturing (corresponds to activities related to the production of goods); (ii) Service (activities related to general services, such as laboratories, energy supply, IT, etc.); (iii) Logistics (related to logistics activities, such as routing, material handling, etc.); (iv) Healthcare (related to health operations such as hospitals, clinics, etc.); (v) Construction (activities related to civil construction); and Others (which do not fit into any

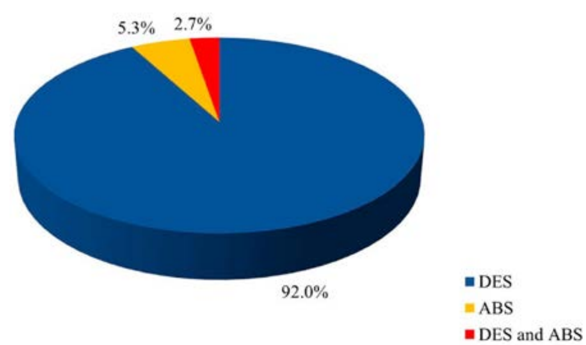

Figure 7. Papers that use simulation as DT (stratified by simulation type).

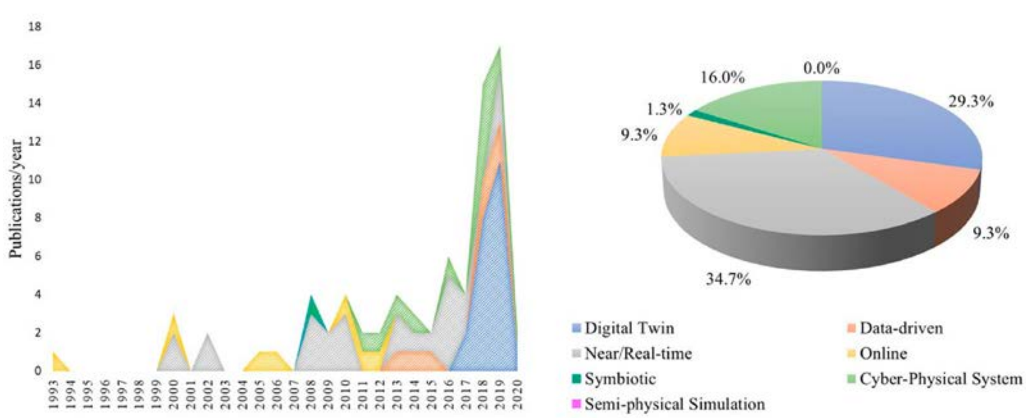

Figure 6. Papers that use simulation as DT (stratified by approach name).

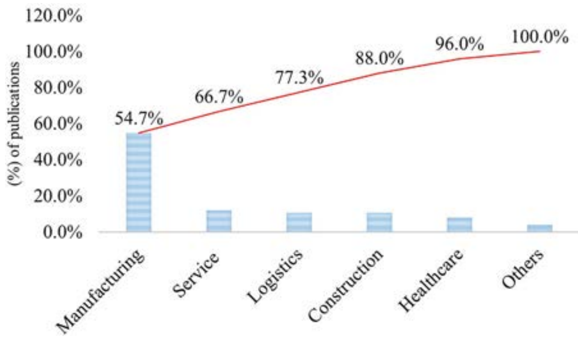

Figure 8. Pareto chart of the main operation areas.

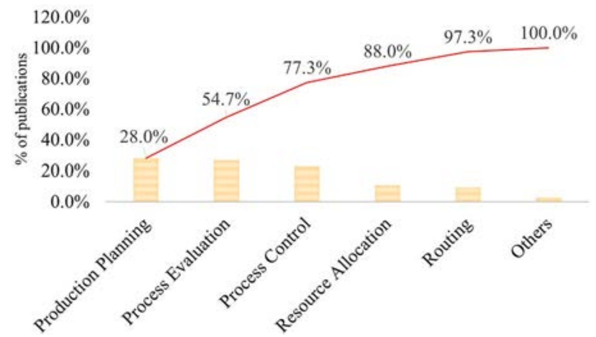

Figure 9. Pareto chart of the main decision-making objectives.

of the other areas). Thus, Figure 8 shows the percentage of articles related to these areas of activity.

We observed that the Manufacturing area is responsible for about 54.7% of the evaluated papers. In this case, among the main segments belonging to the manufacturing area, we highlight the aeronautical (Steringer et al. 2019), automotive (Lu et al. 2019), and metal-mechanic (Terkaj et al. 2019). It is important to mention that manufacturing operations have been going through a transition period over the years, with the increasing trend of digitising its processes seeking better decision making. This scenario is illustrated by the so-called 'Smart Manufacturing' or 'Digital Manufacturing' and inserted in the Industry 4.0 context, reference to what would be the fourth industrial revolution (Tao and Zhang 2017; Mourtzis 2020; Alam and Saddik 2017). The Service area represents about 12% of the articles and covers several sectors, such as laboratory activities (Lopes et al. 2019), energy sector (Thanos et al. 2017; Wan et al. 2014; Lin et al. 2012; Lin et al. 2011), and Information Technology (IT) (Bradford, Simmonds, and Unger 2000; Simmonds, Bradford, and Unger 2014; Xiaobo et al. 2009).

The third most representative area is the Logistics (about 10.7% of the articles), covering works focused on logistics operations (Ashrafian et al. 2019; Reniers and van de Mortel-Fronczak 2018) and also others that address integrated logistics to other processes (Vijayakumar et al. 2019). With the same percentage of articles, the Construction area presents DT proposals for different decision characteristics, covering activities directly linked to construction (Akhavian and Behzadan 2014), support activities (Elnimr, Fagiar, and Mohamed 2016), and smart buildings examples (Wang, Qianchuan, and Yin 2013b; Lilis, Van Cutsem, and Kayal 2019). In Healthcare (8% of the articles), the simulation was used as DT in several hospital areas, such as the Emergency Room (ER) (Harper and Mustafee 2019a) and the Intensive Care Unit (ICU) (Sormaz and Malik 2018). Finally, the Others area (4% of the articles) is marked by several applications, such as drone activities (Khaleghi et al. 2013) and military operations (Zhou, Huang, and Hu 2008).

Regarding the decision-making objectives, there are also six main ones, according to the evaluated articles: (i) Production Planning (DT provides guidelines related to processes planning, scheduling, downtime and maintenance planning, etc.); (ii) Process Evaluation (the DT allows the monitoring of physical processes through performance indicators); (iii) Process Control (the DT allows controlling the physical systems) (iv) Resource allocation (the DT provides guidelines related to the allocation of resources); Routing (DT provides route analysis and optimisation); and Others (which do not fit into any of the other objectives). Figure 9 shows the percentage of articles linked to each of these objectives.

We noted that decisions related to Production Planning and Process Evaluation are responsible for more than half of the publications (about 54.7%). Considering Production Planning, there are decisions both in specific processes, with limited scope (Shirazi, Mahdavi, and Solimanpur 2010; Zupan, Janez, and Herakovič 2018; Chinnathai et al. 2018), and general approaches, covering different processes and activities (Prajapat et al. 2019; Steringer et al. 2019). Regarding the Process Evaluation, the main focuses are related to the performance evaluation (Eyre, Scott, and Freeman 2018; Lu et al. 2019; Vijayakumar et al. 2019; Choi and Kang 2018; Salama and Eltawil 2018), but there are even approaches linked to commercial objectives (Terkaj et al. 2019). When referring to Process Control, most of the works refers to automated systems, as proposed by Shang and Wainer (2008) and Sickel and Lee (2009). However, there are also indirect controls, where there are no automated systems, as approached by Wang et al. (2013a). In the case of Resource Allocation, the articles mainly deal with human resources allocation (Augusto, Murgier, and Viallon 2018; Lopes et al. 2019), but there are other cases, such as the allocation of computational resources (Thanos et al. 2017). Finally, regarding Routing, there are cases of route optimisation for automated vehicles, such as the Automated Guided Vehicles (AGV) and transporters (Ashrafian et al. 2019; Bottani, Murino, and Vespoli 2017), and others for non-automated vehicles, such as trucks (Elnimr, Fagiar, and Mohamed 2016) and vehicles in general (Barcik, Möller, and Vakilzadian 2016). The Others category is represented by specific objectives, such as decisions related to military processes (Zhou, Huang, and Hu 2008).

4.2. Platforms and connections adopted in DT simulation models

When considering the platforms used to build DT simulation models, several practices were observed. About 54.7% of the evaluated works used 16 different software and commercial packages. In this case, the top 10 software used corresponds to 85.4% of publications and includes: Tecnomatix® (24.4%), Arena® (14.6%), AnyLogic® (9.8%), FlexSim® (7.3%), Quest® (4.9%), Simio® (4.9%), Simul8® (4.9%), Repast® (4.9%), Symphony® (4.9%), and Network Simulator® (4.9%). In this case, the preference for commercial packages is mainly due to the features available, such as graphical interface, easy model building, and customised reports (Lu et al. 2019). On the other hand, approximately 32% of the papers reported the use of programming languages to develop the simulation algorithms, without considering commercial solutions. Among the languages used, we highlight the Pyton® (Olaitana et al. 2014; Lilis, Van Cutsem, and Kayal 2019), Java® (Tiacci 2020), CD ++ ® (Moallemi and Wainer 2010), and Stroboscope® (Akhavian and Behzadan 2018). The use of programming languages can solve some difficulties found in commercial solutions (Olaitana et al. 2014), such as the lack of resources for certain application areas (Elnimr, Fagiar, and Mohamed 2016) and considerable investments (Chong and Sivakumar 2002). Finally, in about 13.3% of the papers, we could not identify the platform used to build the DT simulation models.

Regarding the connection between the simulation model and the physical systems, we observed different practices. The connection between the model and the physical systems is a prerequisite for implementing a DT through simulation, and the level of integration between the virtual and physical environments depends on the characteristics of each application. Ashrafian et al. (2019) report that the operations data are the basis for the design of the DT through simulation and, in this case, the main data sources are process management systems, databases, sensors, and intelligent devices, also called IoT devices (Alam and Saddik 2017). Figure 10 shows the proportion of works that adopt each type of connection.

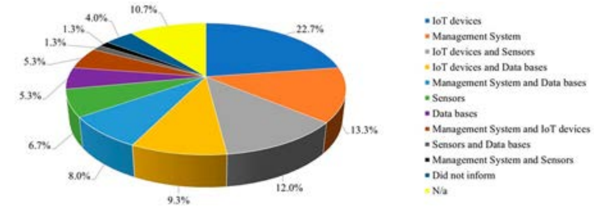

Figure 10. Papers that use simulation as DT (stratified by connection type).

The connections with IoT devices correspond to 22.7% of publications, while 13.3% of the works adopt only the connection with management systems, and 6.7% connect with sensors. Finally, about 5.3% adopt only the connection with databases. Moreover, about 37.3% of the papers adopted more than one connection source to obtain data from real systems. Among the connections with IoT devices, there are models capable of connecting with Programmable logic controllers (PLCs) (Sivakumar and Gupta 2006; Gupta and Sivakumar 2005; Saez et al. 2018), mobile communication devices via Bluetooth and GPS (Song, Ramos, and Arnold 2008; Kitazawa et al. 2016a), AGV-type transport vehicles (Bottani, Murino, and Vespoli 2017; Katz and Manivannan 1993), entities with radio frequency communication (RFID) (Altaf et al. 2015; Goodall, Sharpe, and West 2019), among others. Furthermore, when it comes to management systems, there is an emphasis on Enterprise Resource Planning (ERP) (Meng et al. 2013; Steringer et al. 2019; Bergmann, Stelzer, and Straßburger 2011). The possibility of connections with databases and management systems is extremely important for the dissemination of DTs, since it is not always possible to implement smart devices and sensors (Vijayakumar et al. 2019). This statement is especially valid for manual processes, as highlighted by (Alam and Saddik 2017). Three studies (4%) did not detail the types of connection adopted (D'Angelo and Chong 2018; Olaitana et al. 2014; Tiacci 2020). Finally, eight studies (10.7%) did not present any form of connection with the physical systems, resembling traditional approaches of simulation (Ashrafian et al. 2019; Elnimr, Fagiar, and Mohamed 2016; Lopes et al. 2019; Chinnathai et al. 2018; Reniers and van de Mortel-Fronczak 2018; Antons and Arlinghaus 2020; Wang, Qianchuan, and Yin 2013b; Barcik, Möller, and Vakilzadian 2016).

Furthermore, to allow the connection between simulation models and physical systems, Tao and Zhang (2017) report that there must be one or more integrating systems capable of allowing the data flow between the physical and virtual world, as well as formatting and preparing the data to ensure the correct functioning of the DT. In this case, we observed that some works mention intermediate interfaces used to allow the connection between the physical systems and the simulation model (Grube, Malik, and Bilberg 2019; Steringer et al. 2019; Murphy et al. 2020). However, most articles only mention the connection, without detailing the intermediate systems used. When considering the functioning of DTs, the intermediate systems and interfaces are also related to process security. Wright and Davidson (2020) report that the most likely applications of DTs are of high value or critical to organisations' security and it is important to ensure the reliability of the virtual model. In this case, Barlas and Heavey (2016) complement that intermediate interfaces and integrating systems are essential to ensure the safe functioning of the simulation model in the face of physical changes.

4.3. Updating and timing of DT simulation models

When it comes to updating and synchronising the simulation models in the face of physical changes, there are two possible approaches: Real-time updating (RT) and Near Real-time updating (NRT). In RT, the simulation model is synchronised with real systems and there is an almost instantaneous update of the model in face of real changes (Saez et al. 2018). On the other hand, NRT is more flexible and allows the model to be updated in longer time intervals, depending on the characteristics of the decision-making (Vahdatikhaki and Hammad 2014). In the case of the DT simulation models, Kunath and Winkler (2018) and Tao et al. (2018) report that the data collection from physical systems should be performed in real-time to allow updating the model when necessary, however, Santos et al. (2020) emphasise that the DT simulation model updating does not necessarily have to occur in real-time, but when the decision-making is necessary. Among the studies analysed, the vast majority (about 72%) adopt the NRT and an important factor is regarding the interval between updates. There are approaches where the time interval between updates is fixed (Cassettari et al. 2017; Khaleghi et al. 2013; Steringer et al. 2019; Braglia et al. 2019), and also approaches where the model update occurs at different time intervals, varying according to the need to make decisions (Sivakumar and Chong 2000; Harper and Mustafee 2019b; Lilis, Van Cutsem, and Kayal 2016).

Among the works that adopt the RT approach (about 28%), we noted that the objectives are almost always related to the process evaluation and/or process control (Rossmann, Schluse, and Waspe 2008; Wan et al. 2014; Kitazawa et al. 2016b; Beregi, Szaller, and Kádár 2018). This fact is in line with Saez et al. (2018), which associate RT with monitoring and evaluation activities. In addition, the RT is also associated with the characteristics of physical systems, such as the degree of automation and system robustness (Mieth, Meyer, and Henke 2019). Therefore, based on the results obtained through the analysed studies, we concluded that there are still a few processes that adopt the RT approach. Saez et al. (2018) reveal that the complexity of the physical systems, the stochastic nature of the data, and the automation required are factors that hinder the adoption of RT. Moreover, Song and Eldin (2012) emphasise that the adoption of real-time tools can be both a practical and financial challenge considering the structure needed to continuously perform data collection and model updating. Alam and Saddik (2017) complement that the NRT approach is especially valid in processes that do not have a sufficient structure for RT, without compromising the level of importance of the DT in decision support.

4.4. Degree of autonomy of DT simulation models

The degree of autonomy of DT simulation models is another important issue and can lead to some confusion regarding whether or not to classify a model as DT. The autonomy of a DT is directly related to its responses, which can exercise direct command in the physical system (autonomous) or only suggest actions (Santos et al. 2020). In the case of autonomous DTs, decision making occurs without human intervention and is associated with automatic systems (Beregi, Szaller, and Kádár 2018; Donhauser et al. 2018). Although the adoption of automated systems has been a growing trend in recent years, there is still some limitation in the adoption of autonomous DTs. Among the studies analysed, only 18.7% demonstrated autonomous approaches. Some of them deal with experimental scopes or with reduced scale, not including the performance in complex and industrial-scale processes (Lee, Ramakrishnan, and Wysk 2002; Moallemi and Wainer 2010; Beregi, Szaller, and Kádár 2018). On the other hand, there are also papers that present approaches on an industrial scale, such as the works proposed by Sickel and Lee (2009) and Thanos et al. (2017). We noted that the percentage of papers with autonomous systems does not match the percentage of DTs focused on process control (22.7%), as shown in section 4.1. This is because there are works in which the processes control still needs human intervention to be carried out, so they were not considered as autonomous approaches.

It is important to highlight that autonomous DT simulation models are related to the 'Smart Factory' concept and, according to Lee, Bagheri, and Kao (2015), the self-adjustment capacity is the highest level of a smart process. Lass and Gronau (2020) complement that there is an increasing tendency to opt for decentralised control systems with a certain degree of autonomy, such as DTs.

Another important point regarding the autonomy of the DT simulation models is concerning operations security. Tao and Zhang (2017) reveal that security related to the functioning of DT is an extremely important factor and that must be considered. Therefore, automating decision-making without human interference is still a challenge. This fact can help to explain the great adherence by non-autonomous systems (about 70.7% of the papers). In this case, the responses of the DT simulation models are guidelines and directives, and it is up to the decision-maker to comply with them or not. Considering non-autonomous approaches, the applications are mostly related to the objectives of Process Planning, Process Evaluation, Resource allocation, and Routing. Furthermore, DT simulation model responses can be formatted by intermediate systems, such as dashboards, spreadsheets, etc., providing decision-makers with more precise guidelines (Terkaj et al. 2019; Cassettari et al. 2017; Murphy et al. 2020). However, there are cases where the decision-maker must interpret the answers directly from the simulation model (Lopes, Almeida, and Almada-Lobo 2018). Finally, about 10.7% of the papers did not report the degree of autonomy of the DTs.

4.5. Development and periodic validation methods for DT simulation models

Methods for developing simulation models are extremely important and present steps that guide their development (Law 2009). In the case of traditional simulation models, Montevechi et al. (2015) evaluated the most used methods in simulation projects, comparing them in terms of their main steps and activities, as well as their robustness. In this context, the methods proposed by Balci (2012), Law (2009), Montevechi et al. (2010), and Sargent (2013) stand out. However, despite the existence of methods already consolidated in the literature, when considering simulation as DT, certain aspects must be taken into account during the development of the model. Therefore, new steps and considerations must be included to adapt the model to the scope and objective of DT, such as the integration of the model with the physical systems and its periodic updating. The works considered in this SLR were analysed according to the method used for planning and implementing the simulation models and about 90.7% of them do not mention the method adopted. This percentage includes works that only suggest general frameworks on the connection of the model with the physical systems, without addressing the steps followed during the simulation model building (Eyre, Scott, and Freeman 2018; Mahdavi, Shirazi, and Solimanpur 2010; Thanos et al. 2017). The remaining works (9.3%) present specific methods for the study approached, without representing generic steps for building models of this nature (Vijayakumar et al. 2019; Moallemi and Wainer 2010; Chong and Sivakumar 2002; Goodall, Sharpe, and West 2019; Lu et al. 2019; Meng et al. 2013). Finally, two works, proposed by Onggo et al. (2018) and Taylor et al. (2018) mention precisely the need to establish methods to support the development of DT simulation models.

Regarding the periodic validation of DTs, Zhuang, Liu, and Xiong (2018) report that this is one of the areas to be explored in the literature. Such consideration also applies to the case of DT simulation models, and there is a need to establish methods that aim to guarantee the validity of these models in the face of physical changes. For Meng et al. (2013), the simulation models' validation is more critical when considering models that adapt according to the real system, since there is the possibility that certain errors will accumulate during the model updates. Unlike the validation of traditional simulation models, which occur in the model building phase (Sargent 2013), we must compare the physical and model results frequently to guarantee valid and accurate systems (Tao and Zhang 2017). Moreover, when considering periodic validation, important issues such as the speed and frequency of validation procedures must be taken into account (Anagnostopoulos and Nikolaidou 2003). Therefore, the selected articles were analysed from the validation techniques adopted. In this case, only one study adopted the use of periodic validation procedures (Cho et al. 2019). The authors propose the execution of hypothesis tests every time the model is updated to compare its results with the real system. The other studies (about 98.7%) do not address the periodic validation of the models. Finally, despite not adopting periodic validation routines, Onggo et al. (2018) cite the need for such a practice.

4.6. Advantages, issues, and opportunities regarding the use of simulation as DT

Although the use of simulation as DT has been explored for years, there are still countless opportunities to be explored in both practical and theoretical terms, given the difficulties and challenges still associated with this approach. Therefore, the papers considered in this SLR were analysed from the advantages associated with the use of simulation as DT, the issues of this practice, as well as the opportunities highlighted by the authors. Table 3 summarises the main findings related to this analysis.

5. Conclusion and future directions

The Digital Twin (DT) has been a revolutionary concept concerning decision-making in productive processes. In this case, virtual copies connected to the processes can

Table 3. Summary of the main findings related to the use of simulation as DT.

Features	Findings
Advantages	✓ Enables analysis at various stages of the process's life cycle (Steringer et al. 2019); ✓ Allows integration with other analysis tools, such as optimisation, forecasting, and BI solutions (Donhauser et al. 2018; Onggo et al. 2018; Steringer et al. 2019); ✓ It is a simpler, cheaper, and more flexible alternative compared to DT commercial solutions (Lu et al. 2019; Terkaj et al. 2019; Donhauser et al. 2018; Goodall, Sharpe, and West 2019); ✓ Allows easy modeling of physical systems to create a similar and synchronised virtual environment (Braglia et al. 2019); ✓ Enables easy integration of the simulation model with physical systems (Vijayakumar et al. 2019); ✓ Allows easy use of the model by the decision-maker, without the need for specialists (Grube, Malik, and Bilberg 2019; Sormaz and Malik 2018); ✓ Provides a revolution in the use of simulation to support decision-making, with increasingly accurate models (Mieth, Meyer, and Henke 2019; Beregi, Szaller, and Kádár 2018; Akhavian and Behzadan 2018); ✓ Enables decisions at operational and strategic levels (Salama and Eltawil 2018).
Issues	✓ Despite the evolution of simulation software, auxiliary systems are often still needed to compose the decision-making (Steringer et al. 2019); ✓ Applications are still frequently associated with large companies, mainly due to the structure required for their implementation (Lu et al. 2019; Olaitana et al. 2014; Terkaj et al. 2019); ✓ Ensuring the quality of process data is still a challenge, a fact that directly impacts the efficiency of decision making (Mieth, Meyer, and Henke 2019; Murphy et al. 2020); ✓ The speed and processing time of DT models can be critical factors in some processes (Beregi, Szaller, and Kádár 2018; Meng et al. 2013; Thanos et al. 2017; Saez et al. 2018); ✓ The communication between physical and virtual components still needs to be improved (Murphy et al. 2020; Onggo et al. 2018); ✓ There are still limitations regarding the use of simulation as DT in certain application areas (Elnimr, Fagiar, and Mohamed 2016); ✓ Security related to DT simulation models is still a critical factor, which limits its autonomy and wide use (Karakra et al. 2018); ✓ Ensuring the validity of the DT simulation model is a challenge given the dynamic nature of physical systems (Harper and Mustafee 2019b); ✓ The need for high computational power can also be a critical factor in certain applications (Steringer et al. 2019; Scholl et al. 2010; Salama and Eltawil 2018).
Opportunities	✓ Broaden the scope of the simulation as DT, focusing on management-level decision making (Zörrer et al. 2019); ✓ Adopt virtual reality and augmented reality features integrated to DT simulation models for better decision-maker experiences (Steringer et al. 2019); ✓ Simplify, systematise and improve the model's connection with physical systems (Braglia et al. 2019; Donhauser et al. 2018; Murphy et al. 2020); ✓ Develop modeling tools and softwares with a generic approach, capable of supporting libraries related to unconventional scopes (Tiacci 2020); ✓ Use Artificial Intelligence techniques to ensure the correct functioning and improvement of DT models (Eyre, Scott, and Freeman 2018; Goodall, Sharpe, and West 2019); ✓ Develop procedures and methods for periodic validation of DT simulation models (Scholl et al. 2012; Onggo et al. 2018; Harper and Mustafee 2019b); ✓ Creation of models capable of self-correction in the face of possible problems (Scholl et al. 2012); ✓ Develop methods that allow the creation and replication of DT models in a more efficient and automated way (Eyre, Scott, and Freeman 2018).

mirror the physical systems and guide decisions in a more efficient and optimised way. Moreover, the simulation stands out as an alternative in the design of DTs. Therefore, this paper addressed the use of simulation as a DT of productive processes through an SLR, aiming to explore the literature about the main characteristics associated with publications in the area. We analysed 75 articles published in scientific journals and conference proceedings, available in the main literature databases, considering the main types of simulation, DES and ABS. Research questions (RQs) were structured and answered in the analysis sections. We observed that DES is present in the vast majority of publications, followed by ABS and, finally, hybrid approaches. Moreover, although the term Digital Twin is relatively recent, the use of simulation as DT has been explored for decades. This is due to the different nomenclatures used to refer to the practice of connecting simulation models to real processes and systems to mirror them and optimise decision making. The first paper that explores this approach was published in 1993 and since then, several works have been published, exploring the most diverse application areas. Moreover, there is a growing trend in research in the area, especially in the last five years.

With regard to the areas associated with the use of simulation as DT, works focused on manufacturing operations are still the majority, but there is a significant percentage of approaches focused on services, logistics, construction, and healthcare. In this case, the main objectives associated with this use include production planning, process evaluation, process control, and resource allocation. Regarding the platforms used to build DT simulation models, most articles described the use of commercial software, a fact that can be explained due to the available features, such as graphical interface and easy handling. On the other hand, there is also a significant percentage of works that opted for the use of programming languages âĄčâĄčin order to overcome some limitations of commercial packages, such as necessary investment and limited customisation.

When referring to the connection between DT simulation models and physical systems, most articles present connections through IoT devices and management systems. There is also the use of sensors, databases, and approaches that explore the use of more than one type of connection. Regarding the model updating, most studies still have a near real-time approach. This result may be related both to the characteristics of the processes, where there may be some difficulty in collecting data in real time, as well as to the DT objectives, in which the real-time approach is not necessary or mandatory. However, there are cases where the real-time updating has been successful, mainly associated with automated processes. Likewise, in relation to the degree of autonomy, the vast majority of DT simulation models presented are non-autonomous, which still depend on human interference for decision-making. This result is in line with the difficulties reported by several authors regarding autonomous models, such as security and complexity. However, some studies describe successful cases of autonomous models. Finally, concerning methods of development and periodic validation of DT simulation models, the analysed works approached both superficially. No work has presented a method for DT models building and only one article mentions the model periodic validation, without detailing the procedure.

Among the main advantages associated with the use of simulation as DT is the fact that it is a simpler, cheaper, and more flexible alternative, when compared to the commercial solutions available. Moreover, some issues are still highlighted concerning the use of simulation as DT, such as the adoption of this approach by small and medium organisations and the security related to the operation of the DTs models, especially the autonomous ones. Finally, we highlight several opportunities in this research field, such as the need for techniques to simplify and improve the integration of DT models with physical systems, development of periodic validation techniques for DT models, development of methods focused on the DT models building, and approaches that explore the use of several DT models in an integrated manner. It should be noted that this paper did not intend to analyse all types of simulation as DT, but rather the main types used in decision making in the productive processes. Therefore, research involving other types of simulation and areas of expertise may to be developed to complement the theoretical basis proposed here. We also suggest analyzing other research sources that include patents and registered products. Finally, this article proposed an analysis at a network-level approach and we suggest to replicate these analyses at the node level, focusing on each component that compose the DT architecture through simulation.

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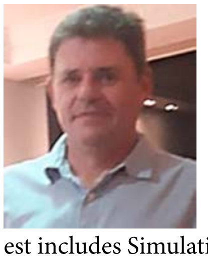

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