Unveiling the Future of Smart Manufacturing: A Review of Scientific Articles on Digital Twin Shop Floor and Optimization Analyses

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ABSTRACT

Digital Twin Shop Floor (DTS) is a recent tool that has attracted attention from both industries and scholars. It offers possible benefits to the production and logistic systems by building a virtual replica of the shop floor and establishing an interaction between the digital model and its physical counterpart. However, there is a lack of scientific articles in the literature reviewing the application of DTS in industries. In that context, this paper reviews the scientific literature. It analyzes the optimizations proposed to find improvements applicable to an already existing digital twin of a large automotive parts manufacturer in Brazil. The present work also brings an analysis of technologies used in the reviewed papers, as well as modeling and simulation methods. Additionally, each paper is discussed individually, focusing on their achievable contributions to the manufacturer. Finally, future work regarding the optimization of the DTS from the manufacturer is outlined.

RESUMO

Digital Twin Shop Floor (DTS) é uma ferramenta recente que tem chamado a atenção tanto da indústria quanto dos estudiosos, oferecendo possíveis benefícios para os sistemas de produção e logística ao construir uma réplica virtual do chão de fábrica e estabelecer uma interação entre o modelo digital e sua contraparte física. No entanto, há uma falta de artigos científicos na literatura que revisem a aplicação do DTS nas indústrias. Nesse contexto, este artigo revisa a literatura científica e analisa as otimizações propostas para encontrar melhorias aplicáveis a um gêmeo digital já existente de um grande fabricante de autopeças no Brasil. O presente trabalho também traz uma análise das tecnologias utilizadas nos artigos revisados, bem como dos métodos de modelagem e simulação. Além disso, cada artigo é discutido individualmente, focando em suas contribuições alcançáveis para o fabricante. Por fim, são delineados os trabalhos futuros relacionados à otimização do DTS pelo fabricante.

1. INTRODUCTION

Throughout the world, manufacturing companies look for ways to march toward smart manufacturing and Industry 4.0. In this context, the concept of a Digital Twin Shop Floor (DTS) has become the focus of several studies, since it can offer advantages such as production flexibility, cost saving, and process optimization by integrating both virtual and physical worlds. In addition, using the data originating from the shop floor, forecasting, and simulation methods integrated into the DT supports the decision-making process. Given the high complexity originating from internal and external factors regarding the production system, especially when dealing with unpredictable variables, the capacity of the DT to aid the decision-making process or even do it by itself in real time might lead the manufacturers to a new level of efficiency, strengthening the benefits brought by Industry 4.0. However, as the DT represents a recent technology, which still has some limitations and a lack of clarity about the possible benefits, there is some concern among the industries about the feasibility of investing in the development of a Digital Twin.

Among the limitations related to DTs is the difficulty to have real-time synchronization between the virtual replica and its physical counterpart, which interferes negatively with the system. [1] proposes a neural network to cope with this problem, estimating the perception and control delays and using those values to generate the proper control commands. Other authors, like [2], prefer to work with near real-time approaches as a way to avoid problems that can arise from those delays on a real-time approach.

With the scalability promoted by mass production, manufacturers are obliged to deal with challenges stemming from structural complexity, increased dynamics, uncertainties, risks, and multiple feedback cycles, stunting optimal design and control of production logistics systems ([3]). Even projects with a sparse number of processes and machines can suffer from scalability problems. As an example, [2] studied a case with 4 Kanban stations and 24 possible supply routes, but argued that 5 and 6 stations would produce, respectively, 120 and 720 routes, rapidly increasing the complexity of the problems and requiring different approaches. As a way to deal with the huge number of possible options when looking for the optimal solution for process scheduling, [4] used parallel processing, which is a key method to enable the solution of problems when working with a scalable number of scenarios, especially in a real-time approach, as the computing time must be as short as possible.

Regarding promising implementations of DT in industries, [5] explored 14 applications, including product design, virtual prototype, process planning, production scheduling optimization, logistics, and equipment control and assembly. Indeed, the applications in the paperback in 2018 were also found in the articles studied in our paper.

Subsection 1.1 explains important definitions and concepts about what a digital twin is. Further on, Subsection 1.2 shows the study's objective. Section 2 explains the methodology adopted by the authors for the literature review. The remainder of the article is organized as follows: Section 3 explains some important technologies for digital twins, also mentioning papers that make use of them; Section 4 displays some modeling and simulation techniques used to date; Section 5 contains the analysis of the papers chosen for a detailed review; Section 6 brings some considerations about the works previously mentioned, outlining the study and its contribution and the future work.

1.1. DIGITAL TWIN: DEFINITION AND FUNDAMENTAL CONCEPTS

The concept of digital twins in manufacturing was initially proposed in 2003 in a paper by Michael Grieves at the University of Michigan, being firstly a concept for PLM (Product Lifecycle Management). Although it was not exactly a DT, the paper conceived its initial idea and components. The National Aeronautics and Space Administration (NASA) also applied the DT's concept to their flight system and used it to perform diagnostics and prognostics, allowing continuous safe operations through the system's life cycle ([3]). In 2017, [6] established the basis of a Digital Twin Shop-floor (DTS), examining the technology's state-of-the-art and the next steps being taken on the subject. The paper also proposed the basis of a DTS, introducing its conceptual model and its operation mechanism, and also describing the interconnection and interaction between entities on the physical shop floor, the evolution of the virtual models, and the enabling key technologies, among other important points concerning a DTS.

To date, the maturation level of the DTS allows an interaction between the virtual replica and the physical counterpart. On this level, the linkage usually relies on a perception process and a control one, with the physical part sending the data needed and the virtual model taking part in the decision-making processes. [6] outlines the next stage as a further interaction and an eventual convergence of both worlds.

1.2. STUDY AIM

Although the concept of Digital Twin has been used in many applications by companies, [7] highlighted that no paper focused on the review of implementations of DTs in the field of industries prior to their study. So, the present paper aims to analyze papers that deal with Digital Twins Shop Floor, looking for the improvements proposed by each one by reviewing the scientific literature. Besides, the objective is to show manufacturing industries what articles might be useful to build or optimize a DT, as the literature is composed of a heterogeneous mix of different genres, e.g., reviews, frameworks, and case studies. That said, the focus of the present paper mainly consists of reviewing scientific papers and analyzing the optimizations proposed by each one. After this step, each paper was examined and evaluated individually in the search for new ideas to improve the DT of a large factory belonging to Robert Bosch GmbH installed in Brazil in the city of Curitiba. The production unit in question is responsible for producing diesel injection systems sold in the national and international markets and has attracted attention in the field of shop-floor simulation due to the development and implementation of a digital twin. Therefore, with the composition of this paper, the authors expect to acquire more expertise on the theme and eventually apply that knowledge to the digital twin. Finally, Figure 1 shows both the production line and its virtual representation. However, it is noteworthy that the figure represents only a part of an individual production line, as the entire facility of the company has been digitalized, with several more lines.

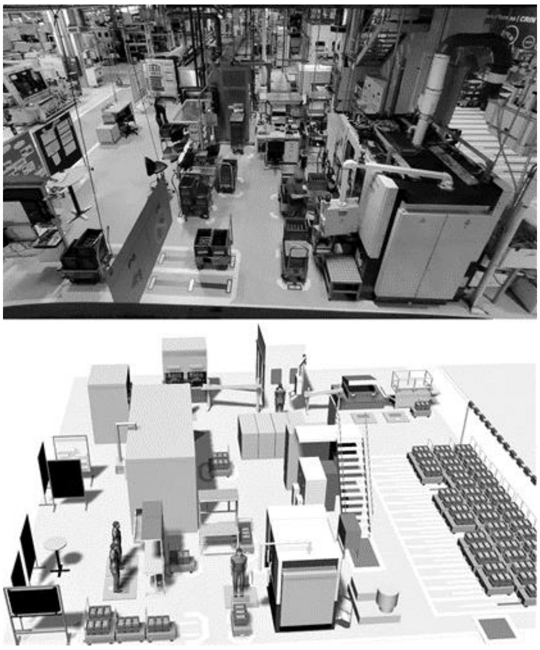

Figure 1. Physical and virtual plats

2. METHODOLOGY

The first step taken at the beginning of the research was defining a search tool to find potential articles that could offer innovative ideas applicable to the company's DTS. For that matter, Scopus was chosen as the main tool, since it has valuable research tools and offers the option to export the articles to a Microsoft Excel file. For the search, we used the keys shown in Figure 2 and exported the 75 documents found in the .xlsx format. At last, five more articles were added after some search on Google Scholar after being judged as relevant to the case, resulting in a total of 80 articles reviewed.

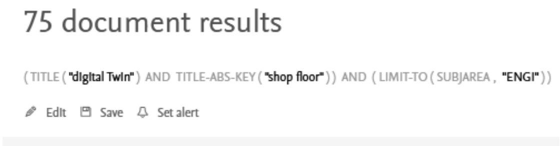

Figure 2. Search Keys

After the process of collecting the articles was complete, the next step was to filter them by relevance to the case. To do so, the abstracts of each paper were read, and each one was accessed and evaluated individually, considering the optimization and new ideas proposed. The final selection is presented in Table 1, where the selected articles represent the most meaningful ones to the case. Considering the first column from Table 1, "No access" represents the articles that could not be accessed by the authors due to the places they were published. Nine more papers were removed due to the language, as all of them were in Chinese instead of English. Also, despite the term "digital twin" being used in many applications and areas, for instance, aerospace and smart cities, our paper focuses only on "Digital Twin Shop Floor". Considering that, 16 more articles were removed, shown on the row "Out of Scope". Finally, from the partial total of 50 works, after the mentioned filters were applied, only 16 were selected for further analysis, once their abstracts and general contents were deemed more relevant for the study. It's noteworthy that some filtered elements were also significant to the case but were removed on account of time and resource factors. At last, despite being removed from a deep and complete analysis, some of them were also used as references to the article. It's worth mentioning that all 16 papers selected were read in full text.

Table 1. Filters applied

Filter	Articles Removed	Partial Total
No access	5	75
Not in English	9	66
Out of scope	16	50
Not selected	34	16
Total selected for further analysis		16

3. ENABLING TECHNOLOGIES AND TOOLS

As commented in 1.1, even though the concept of using digital twins in industry is roughly two decades old, just recently both academia and industry have started dedicating more time and resources to it. One main reason for that is related to the great improvement of technology in recent years, with new tools being developed and becoming mature. Therefore, some previous limitations affecting the development and use of digital twins in industries could be overcome, such as the difficulty to synchronize and process data in real-time. Hence, the following subsections explore some of those tools and their application in DTSs.

3.1. SIMULATION

Simulations are of extreme importance for a wide variety of fields such as science, economics, engineering, and industry due to their ability to predict and analyze outcomes. In the context of industries, the simulations are used, for instance, for prediction, risk reduction, optimization, training, and innovation, allowing analysis and decision-making based on real data. An application of simulation in the DT context is given by [8], who used a what-if simulation model to build a DT aiming at the energy management of AGVs (Autonomous Guided Vehicles) in a battery pack assembly line. Therefore, the simulations are the key to a successful DTS, as all of its outcomes depend on the reliability of the simulations and the accuracy of the models used. Section 4 brings more information about methods and applications concerning the topic.

3.2. IoT

The Internet of Things (IoT) refers to the network of interconnected devices that are embedded with sensors, software, and other technologies to collect, exchange, and analyze data. The technology encompasses a wide range of applications, spanning from household and wearable devices to vehicles, infrastructure, and industrial machinery. In the context of industry, IoT has found numerous applications, with industry 4.0 being a prominent area of focus, since it's powered by the integration of IoT, data analytics and Big Data, Cyber-Physical Systems (CPS), Cloud Computing, Artificial Intelligence etc. These are also key technologies commonly used in digital twins. Some key applications of IoT in DTs include allowing:

• Real-time monitoring and control: enables real-time monitoring and control of the manufacturing process, allowing the synchronization of information sent and received from a database through a middleware;

• Tracking and monitoring assets: enables tracking and monitoring of goods such as tools, equipment, and inventory, allowing better utilization of resources, maintenance planning, reduction of downtime, and an eventual improvement of efficiency;

• Predictive maintenance: the data collected by the IoT sensors about equipment performance and health allow predictive maintenance to be performed based on real-time data. Consequently, unplanned downtime is avoided, also reducing maintenance costs and extending the lifespan of the monitored equipments;

• Energy consumption monitoring: IoT sensors can monitor the energy consumption on the shop floor, which can lead to an eventual optimization of energy use based on monitoring and analyzing the equipment consumption;

• Safety: the IoT sensors can also oversee hazards such as temperature, humidity and toxic gases in the workplace. As soon as the conditions no longer match the established thresholds, alerts to workers and managers can be triggered, improving the safety of workplace environments, and reducing accidents.

In an industrial context, the integration of internet-connected devices and systems within industrial environments originated the IIoT (Industrial Internet of Things), which enables the optimization and automation of industrial processes, permitting the monitoring of the shop floor in real-time. Figure 3 shows some concepts related to the Industrial IoT.

As an example of the use of IoT in a DT, [9] conducted a case study about the synchronization of the virtual model and the physical counterpart of the DT by using an IIoT middleware. However, there are still some issues with the IoT technologies when dealing with many devices and protocols, different technologies, high traffic models and demands, security risks, among other factors, hindering the use of IoT in industries with numerous devices ([10]).

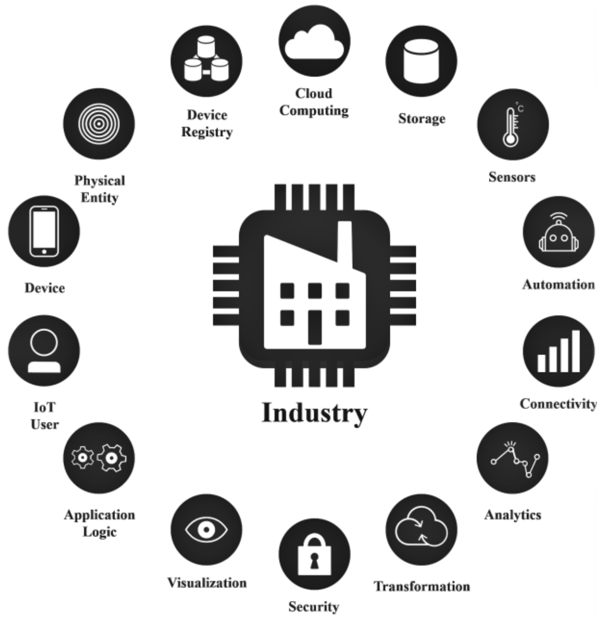

Figure 3. Industrial IoT

3.3. RFID

RFID stands for Radio-Frequency Identification and is a wireless-based technology that uses tags and readers to identify and monitor objects and assets, also representing a key technology when using IoT. The tags attached to objects contain a microchip and an antenna, so the readers can communicate with the tags wirelessly. Through that communication, the tracking system gains visibility, accuracy, and efficiency. Due to the necessity of monitoring the position of the pieces on the production line, [11] used the RFID technology to feed the DT with assets' position. In the case of the diesel injectors' manufacturer of our study, the tags are deposited inside the parts containers and approximated to the sensors by the employees every time a container is placed or removed. Figure 4 shows how the technology is used in the manufacturer studied.

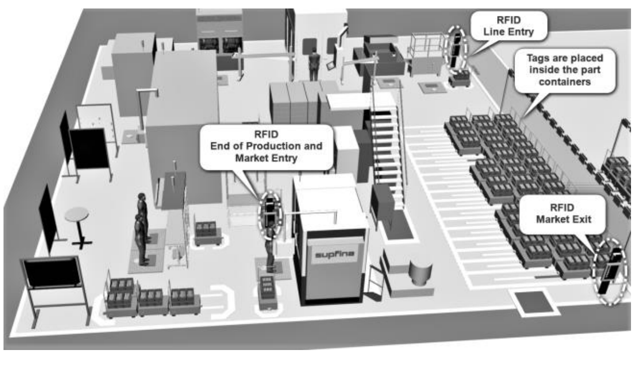

Figure 4. RFID

3.4. ARTIFICIAL INTELLIGENCE

With the exponential advancement of the Artificial Intelligence (AI) in recent years, the technology has attracted the attention of several industries, as it can be designed to have human-like abilities, such as learning and interpreting information. Hence, the prior limitations regarding the programs' restriction of just following instructions and solving only repetitive and fixed tasks were overcome, giving room to new applications which include tasks that previously demanded human intelligence. That said, some implementations allow image recognition, language knowledge, virtual assistants, problems-solving and decision-making. In this scenario, its applicability and potential benefits have been studied and applied in many companies. [1] proposes a framework of an AI-driven DT, supported by three pillars: perception, control and interaction consistency. Besides, the authors also recommend machine learning and neural networks integrated and commanded by the AI to improve the DT, with the former being used in a machine vision approach to monitor the real-time system data and the latter being used to forecast the values of assessment indexes. Some of the subfields of AI are shown in Figure 5.

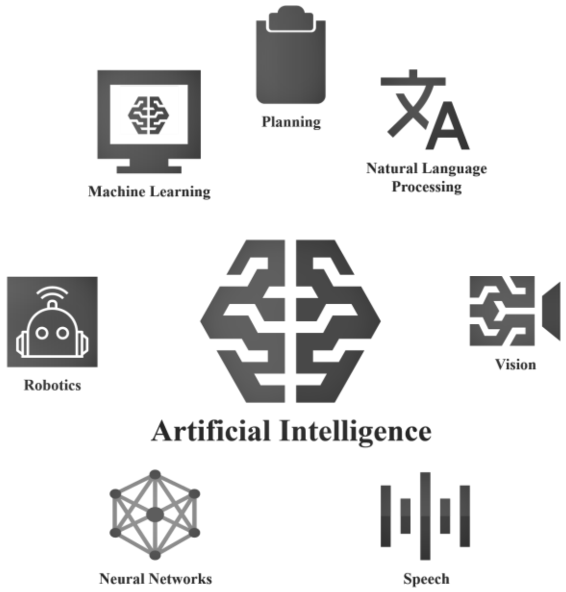

Figure 5. AI subfield

3.5. MACHINE LEARNING

Among the subfields of AI, Machine Learning's objective is to build up algorithms and models based on data, without any explicit programming, learning from the data provided, thus being able to perform activities such as voice and video recognition, status prediction and recommendation systems. Therefore, it is a key technique when dealing with pattern recognition and decision-making based on the data from the shop floor. [1] suggests its use to predict target parameters as equipment lifespan, results from the manufacturing and energetic costs, thus helping with the decision-making process. The paper also suggests merging machine learning and IA to efficiently handle interaction problems between the physical and virtual parts of the DT.

3.6. NEURAL NETWORKS

A neural network is a computer algorithm designed to process information like the human brain. It is made up of interconnected nodes, or neurons, organized in layers. Each neuron receives input data, processes it, and produces an output signal. Neural networks can learn from labeled data during training, where they adjust the weights of connections between neurons to minimize differences between predicted and actual outputs. Neural networks have been successful in a variety of applications, including image and speech recognition, natural language processing, and autonomous vehicles. Additionally, there are mainly two types of data that can be used during the training of the neural network: labeled and unlabeled data. Labeled data refers to the data which have the right output, i.e., the algorithm compares its output and the one used as reference, in a process of supervised training. The other type is when the algorithm is not given the right output when working with unlabeled data, resulting in a process called unsupervised training.

The applications of neural networks in industries are not so recent. [12] created a neural network support tool to predict the maintenance of rotational equipment, estimating the lie percentile and failure times of roller bearings and thus optimizing the costs per unit time. More recently and in a digital twin context, [1] suggested a neural network to generate predictive values that are compared to the real-time data to evaluate the shop floor's situation, defining, and developing the control strategy to be used by an AI-enhanced DT.

3.7. BIG DATA

Since there is a great volume of information being sent, received, and analyzed on the layers of the digital twin, the development of areas such as Big Data were crucial to permit an assessment in real-time, as strategies were developed to deal with the increasing complexity of managing and analyzing large sets of data. That said, data fusion is a tool commonly used in DTs, offering benefits such as the improvement of the data reliability. The technique is mainly based on the use of data from different origins, as sensors, machines etc., to improve their accuracy, for example. The process of data fusion consists of three steps: data preprocessing, data mining and data optimization. Initially, the preprocessing is performed in order to cope with the large amount of data from multiples sources, executing processes of data cleaning, conversion and filtering. Then, the preprocessed data passes through a data mining operation involving methods like fuzzy sets, intelligent algorithms, and others. At last, a data optimization is carried based on theories in the field to try to uncover patterns regarding the data evolution ([7]).

3.8. AUGMENTED REALITY AND VIRTUAL REALITY

When it comes to merging the physical and virtual worlds, Augmented Reality (AR) permits the visualization and interaction of both at the same time, with the digital image overlaying the physical world. So, changes in the real world have the potential to affect the digital part and vice versa, representing a powerful tool used by many industries. Another trending technology in industries is the use of Virtual Reality (VR), which can simulate the production line and show it to the user, allowing interaction, or even monitoring of the production's state in real-time, even when the user is far from the factory. Thus, in the context of digital twins, though not being a key enabling technology, the use of AR and VR can represent tools that bring improvement. [13] used VR as a complement to the DT, permitting the researchers to cooperate and monitor the system in a deeply engaging and interactive manner, despite being in different locations.

3.9. OTHER TECHNOLOGIES

Besides the tools and technologies discussed throughout Section 3, there are also others that are noteworthy, since they are applicable to digital twins as well, but will not be further discussed. They include cloud computing, cybersecurity, edge computing, etc.

4. MODELING AND SIMULATION

In the context of DTs, when it comes to modeling and simulation, there are several tools and concepts described in the literature. In that way, a suitable model should produce reliable simulation outputs that match reality, as control of the physical plant requires both sensors' data and simulation outputs that predict its behavior. Additionally, regarding the level of maturity and integration, the model can be classified into Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT) ([14]), as shown in Figure 6 and discussed in the following subsections. [14] highlights the existence of misconceptions in the literature involving digital models, digital shadows, and digital twins, such as the idea that DTs need to have 3D models or even that the construction of a 3D representation means having a DT.

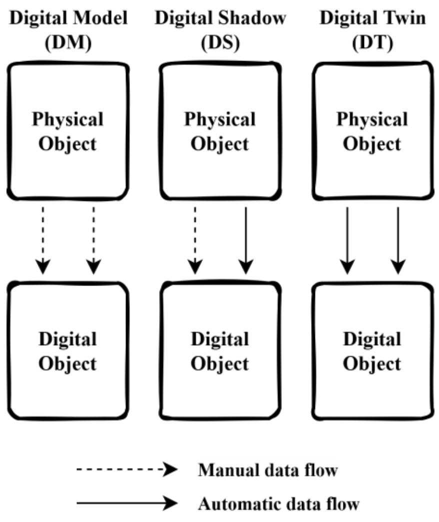

Figure 6. DM, DS, and DT

4.1. DIGITAL MODEL

A Digital Model consists of a digital representation of a physical object and can represent, for instance, mathematical models. The DM is marked by the lack of automatic data exchange between both the model and the physical object, for all the data is manually provided to the DM. Consequently, changes in either virtual or real objects don't interfere with each other. Thus, if the object changes one of its states, that datum must be manually fed to the model.

4.2. DIGITAL SHADOW

Following the concept of DM, a Digital Shadow has a similar concept, but with an automatic one-way flow of data from the physical object to the virtual one. That way, when parameters from the physical object change, the digital one is automatically updated, but the inverse doesn't occur.

4.3. DIGITAL TWIN

The further development of a DS can lead to a DT, where data travels in both directions. This means changes in the physical world affect the digital one and vice versa, conferring the capability to control the real object to the digital part.

4.4. 3D MODELING

Even though the construction of a 3D model isn't mandatory in order to have a system categorized as a Digital Twin, it's still an important tool when it comes to the visualization of the physical plant through a virtual environment. However, some common limitations to the development of 3D models are the time and resources required, involving costs such as qualified employees and licenses of CAD software. Aiming for the reduction of these costs and efforts, [15, 16] suggested an approach that uses fast scans on the shop floor to recognize the objects with point cloud and create an automatic object recognition integrated into the DT. The main advantage of this proposal is, according to the authors, the automatization of steps to produce the CAD model, therefore reducing the effort to achieve a Digital Twin and benefiting especially Small and Medium-sized Enterprises (SMEs). On the other hand, [6] cited SolidWorks, 3D MAX, AutoCAD, and CATIA as usual tools for building 3D models.

4.5. ALGORITHMS USED IN SIMULATIONS

Given the number of possible combinations and scenarios to be analyzed when running simulations, the time, and resources demanded to do so gain relevance, ideally being as minimized as possible. Some examples of algorithms often used are present in scenarios [17], where the authors varied the scenarios' parameters, such as percentage of machine utilization and flexibility, and fed them to the algorithms to be compared. Namely, the algorithms studied were: Reinforcement Learning Enhanced Genetic Algorithm (RLEGA), Genetic Algorithm (GA) and Tabu Search (TS).

4.6. DEFINITIONS OF DIGITAL TWIN

Another important key point is the definition of Digital Twin, with three being the most substantial and used ones, namely: Grieves, Glaessgen and Stargel, and Tao et al. Albeit the existence of various studies published about DTs, still no common definition was established [3]. However, common points between the three cited definitions can be traced. Firstly, Grieves proposed a model focused on a new PLM paradigm and composed of three dimensions, consisting of the data and virtual and physical layers. Then, a more general definition was suggested by Glaessgen and Stargel, focusing on NASA and the vehicles from the U.S. Air Force. Finally, the model defined by Tao et al. is a refinement of the one from Grieves, including two more layers: service system and DT data. So, the Figures 7, 8 and 9 show, respectively, the model from Grieves, its expanded model proposed by Tao et al. and the difference between the 3 definitions mentioned.

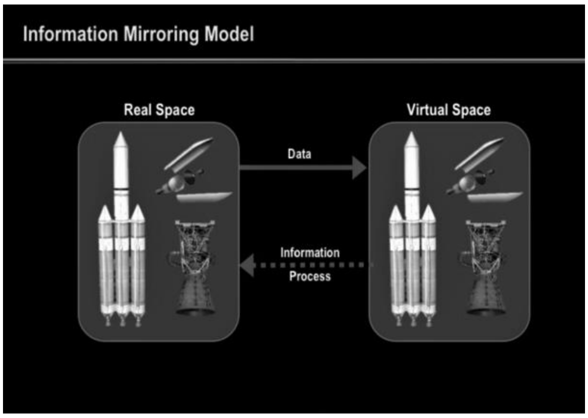

Figure 7. Three-layer model [18]

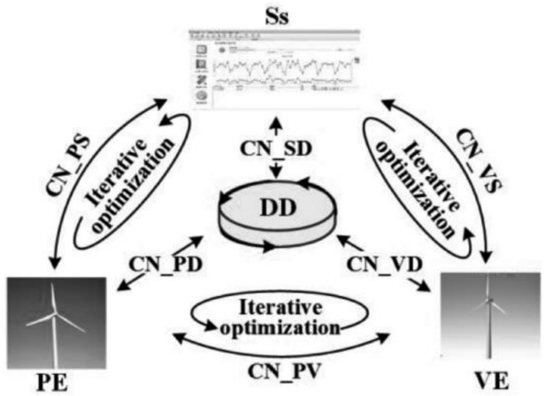

Figure 8. Five-layer model [19]

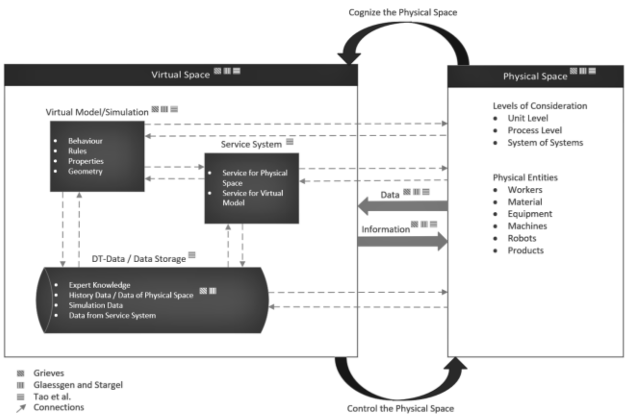

Figure 9. Different definitions of DT [3]

5. CASE STUDIES

After the contextualization of digital twins given in the previous sections, dealing with theoretical concepts and key methods and technologies, this section focuses on the review of the selected articles in a deeper analysis. First, the Table 2 brings an overview and categorization of the paper. Then, the Subsection 5.1 makes a brief statistical analysis of them. In the sequence, in Subsection 5.2, each paper is addressed individually, with some notes about the applicability of the works on the automotive parts' manufacturer, pointing out which ones have the potential to help the improvement of its digital twin.

5.1. STATISTICAL ANALYSIS

Considering Table 2, the graph shown in Figure 10 displays the most outstanding categories of each study reviewed.

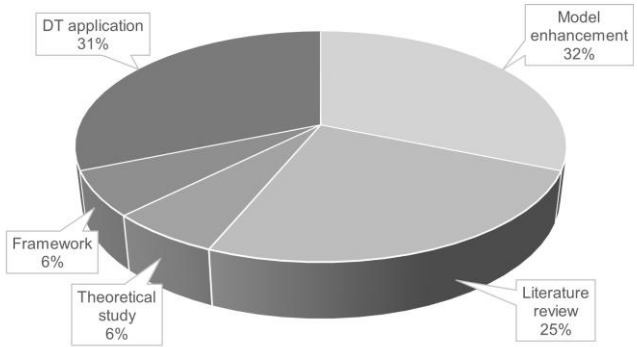

Figure 10. Categories

5.2. INDIVIDUAL ANALYSIS

The following subsubsections contain the articles organized by alphabetic order and their summarizations. Table 2 shows some key information about the article, such as category, optimization proposed, and area of application.

5.2.1. Article: A decision support tool for operational planning: a Digital Twin using simulation and forecasting methods

[2] proposes a continuous decision support system, a DT, integrating discrete event simulation and forecasting methods, applying the developed tool in a real process to validate it. The proposed method can be used both on the shop floor and at management levels.

In the introduction, the authors comment that, although many studies in the literature use integrated simulation and forecasting techniques, there is a certain delay in using them to create a continuous support tool, such as the DT. They also comment that they chose to integrate the DT into the company's ERP and used a Near Real-Time approach, using the model developed in the aerospace industry with the main objective of obtaining metrics to help in decisions regarding staffing levels and supply route planning.

After, an analysis was made of the literature and methods that underpinned the work. Attention is given to the use of Moving Average (MA) and Exponential Smoothing Methods as methods for forecasting values, also showing the equations and differences relating to each one. Although others are mentioned, only the MA, Single Exponential Smoothing, and Double Exponential Smoothing methods were used.

Besides, the chosen approach includes optimizing the material supply process at the Kanban stations of an aerospace industry, based on the information obtained from the ERP to acquire historical material demand data. The proposed approach for creating the DT is shown.

The developed dashboard automatically accesses the ERP and analyzes the data to turn it into information, allowing for the automatic execution of forecasting methods. With this, the dashboard compares the results obtained through forecasting techniques and chooses the result with the smallest error, based on three metrics: Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Deviation (MSD). Therefore, the system automatically opens and runs the simulation model based on the expected demand, which is stratified for each of the Kanban stations. Based on the results shown on the dashboard, the person responsible for decision-making is assisted through the information provided, such as expected demand at the stations, the best route for minimizing distance traveled and delivery time, supply metrics Lead Time, and the optimal number of employees to meet the demands of a workday. Another specification of the dashboard is the possibility of operating it remotely. Finally, its main phases are explained: (1) construction of the simulation model; (2) construction of the prediction model; (3) construction of the integration and decision support interface.

The objectives aimed at for the system are discussed, considering the needs of the person responsible for decision-making and who will be assisted by the DT. Thus, the main objectives were: the construction of a DT, composed of a simulation model and value prediction techniques, capable of connecting the real process and support tools, also proposing a model of constant updating; providing a continuous support tool for supply routes and necessary employee numbers.

With respect to the 3D model, it was developed with the aid of the FlexSim software. To validate the simulation model, a validation parameter was used that consists of dividing the total time per supply round by the amount of material supplied at a time. Thus, it was possible to validate the model by comparing the values of the real parameters with those simulated. The inputs and outputs required by the model were also defined, as well as the selection of data for the prediction tools to select the one that is suitable for the case, validating the prediction model made in Excel by comparing the results obtained with those generated by the statistical software Minitab. Finally, the graphical interface of the dashboard was defined, explaining its operation.

At last, the work reveals the achieved results, showing a real improvement in the reduction of traveled distance as a consequence of optimized routes generated by the DT and, thus, a significant saving of hours per year of approximately 100 hours.

An interesting point in the article is the fact that it shows concrete results, unlike the vast majority of articles on the subject. That is, while other works show only frameworks, simulation-based case studies, this is one of the few ones that show quantitative results, providing significant percentage gains in a real application, culminating in increased efficiency and eventual cost reduction. Another observation is that, while other articles on the subject always seek a real-time application, the present one shows a near real-time approach, making it evident that the method used, despite not being as efficient as the first, was able to generate satisfactory results from a more simplified approach.

Table 2. Articles Reviewed

Reference	Year	Category	Optimization	Area of Application
[2]	2020	Model enhancement	Through optimization via simulation, it was possible to achieve improvements in decision-making time	Aeronautics
[20]	2021	Model enhancement	A time machine is proposed to virtually evaluate different designs based on their performance over time. Then, a design is selected to be implemented in the physical plant. In other words, it optimizes the designs	Framework
[1]	2021	Model enhancement	The use of AI to optimize the DTS / The AI-enhanced DTS provides a method to ensure synchronization between perception state and control execution	Theoretical
[7]	2018	Literature review	Doesn't apply	Theoretical
[21]	2018	Literature review	Doesn't apply	Theoretical
[6]	2017	Theoretical study	Doesn't apply	Theoretical
[22]	2018	Framework	Predictive manufacturing in the satellite assembly stage; There aren't as many optimizations	Framework
[17]	2022	DT application	An effective increase in production efficiency. Authors claim that "RLEGA has higher solution quality and can effectively solve dynamic events in the actual production process," presenting advantages when compared to genetic algorithms, tabu search, and various other scheduling rules	Laboratory
[23]	2022	DT application	The DT allows testing scheduling before implementing it in the real shop floor, adapting production parameters in response to deviations, and rescheduling the shop floor in real-time based on internal and external events	Perfumery
[24]	2019	DT application	Optimization of decision-making in the industrial sector	Simulation
[25]	2018	Model enhancement	Optimization of decision-making in the industrial sector	Laboratory
[11]	2023	DT application	Development and use of algorithms capable of, based on the information received from the factory floor with the help of RFID technology, conducting simulations that assist in production planning	Automotive
[4]	2022	DT application	The results confirmed that the DT system was able to establish a scheduling process that accommodates rapid real-time changes	Laboratory
[26]	2021	Literature review	Doesn't apply	Theoretical
[3]	2022	Literature review	Doesn't apply	Theoretical
[13]	2019	Model enhancement	Optimization of production efficiency	Laboratory

5.2.2. Article: A unified digital twin framework for shop floor design in industry 4.0 manufacturing systems

[20] provides a framework that integrates 4 levels of DTs: (1) unit; (2) system; (3) integrated cyber-physical; and (4) business. A time machine approach is proposed, using historical data in the process of designing and implementing DT, and offering an approach to assess the suitability of different designs for a given set of tasks and applications. The authors claim that, among the references they studied, none presented a systematic framework to integrate all aspects of shop floor design and implementation in integrated cyber-physical network applications and business. They also claim that historical data from operations and interconnections between different aspects of production are often ignored in the design of new configurations and elements on the shop floor, or even in the updating of existing ones. As for the integration between layers (1), (2), (3), and (4), a model is proposed in which designs are initially proposed in layer (1). Then, those selected move forward to the next layer until the last one, i.e., (4). This creates a cycle of continuous implementation and optimization.

Additionally, the time machine approach assists in the DT development process by comparing and optimizing snapshot collections and peer-to-peer processes. The benefits and novelties are listed as follows: (1) data is collected only when a significant change occurs; (2) snapshots of a system are compared with other systems in a peer-to-peer process to find the most similar patterns and use them to model the system's behavior; (3) unlike classical DT development, the time machine approach uses historical information to model system behaviors; (4) in the proposed framework, different time machines from the shop floor, cyber-physical system, and business application integrate an end-to-end solution design and work together to achieve the best results.

At each stage of the time machine, if the generated design meets the requirements, KPIs are normalized and averaged to obtain performance scores. Thus, overall performance is obtained using weights for each score, with each weight defined according to its importance. Therefore, the result can be used to evaluate the best design, ensuring that it meets short- and long-term business requirements and generates expected and predictable results.

One factor that draws attention in the article is the existence of a business-oriented DT level, taking into consideration the possible impacts of the changes on the shop floor on the business and synthesizing the results for better decision-making. Another interesting point is the weighting of the scores according to the importance given to each category. However, the absence of a case study leaves open whether the proposed model is viable and whether it will present good results when implemented by industries.

5.2.3. Article: Artificial intelligence enhanced interaction in digital twin shop-floor

[1] developed an AI-enhanced DTS framework, said that the use of Artificial Intelligence enhances interaction through predictive control. The interaction mechanisms of AI in DT and the technologies that enable interaction in DT are also presented, which are: perception, control, and interaction consistency.

Concerning modeling problems, the authors state that a high-fidelity virtual model must describe both internal mechanisms and relationships between data. Thus, a model fusion considering both items in a hybrid algorithm is an effective method, combining the mechanical and the statistical model. Moreover, over time there are performance changes, and it is the task of the DT to notice the deviation and update the model parameters. Although some researches offer effective approaches to solve the data and model problems, there are still few methods to solve the interactive synchronization problems in DTs. So, the paper proposes an AI-based method to deal with the issue, commenting that the use of AI has been widely used to solve manufacturing problems, including scheduling, assembly, fault diagnosis, and prognosis. Chapter 2 deals with the main problems of real-time interaction between the physical and virtual plant, these being: (1) state assessment; (2) control strategy; (3) interaction consistency. The mentioned points generate, according to the authors, low accuracy and efficiency of the interaction. So, they propose methods to deal with the problems given.

For the first one (state evaluation), the AI-enhanced DT acquires data from sensors such as cameras, RFID, and temperature sensors. Cameras are applied to capture workers' activities to make correct decisions in the manufacturing process, as well as ensure manufacturing safety. Next, the DT classifies the images and, with the use of algorithms, recognizes the activities. It is also proposed to use voice control recognition in the DT, evaluating the impacts of the commands given by the operators. For plants where images or voice cannot be used, the acquisition of relevant data via sensors is suggested. Since the AI-enhanced DT collects data from multiple sources, establishing semantic rules or statistical models to detect and eliminate abnormal data, such as inaccurate, conflicting, or redundant data, is necessary. Based on relevant knowledge and real-time and historical data, DT by AI makes accurate predictions of plant equipment. To build and train the prediction model, DT selects recent historical data as a data sample. DT's evaluation considers production efficiency, production quality, and energy consumption. The neural network calculates predictive values of the evaluation indices, which are used by the AI-enhanced DT to calculate the overall evaluation considering different weights for the three indicators.

As for the second (control strategy), according to the general evaluation of the shop floor, the DT establishes the optimal control strategy to adjust the production process considering the current production state and the desired state, considering the productivity of equipment and workers. Thus, DT calculates the productivity of equipment, workers and collaborative units according to the analysis of the most recent production data. Importantly, according to the proposed model, DT simulates the control strategy first in virtual space, evaluating it before sending it to the physical plant. If the simulation results are not satisfactory, DT generates a new strategy, repeating the cycle until it finds one that is satisfactory. If there is an unexpected event, such as a sudden equipment failure on the plant floor, the DT can realize the abnormal state in time with real-time data, adjusting the control strategy and showing emergencies in the service system. Consequently, workers can find the cause of the abnormality in time.

In the third and last (interaction consistency), DT uses a neural network to solve interaction delay problems, which are separated into perception delay and control delay.

The also explores the use of AI on the factory floor, citing distinct types of algorithms used to create optimal plans and decisions in terms of planning, scheduling, assembly, logistics, and other services. Also commented on is the use of machine learning to predict target parameters such as equipment life, production results, and energy cost, thus aiding in decision-making. The paper also suggests that, by combining machine learning with AI, DT can efficiently deal with interaction problems. Using cameras on the plant floor, the machine vision system monitors the state in real-time. With this, the AI-enhanced DT evaluates the overall state of the physical plant based on the predictive values generated by the neural network, and after the state evaluation, a genetic algorithm is used to develop the control strategy. Furthermore, the neural network can accurately predict future situations based on actual current and historical data, providing an effective method for synchronizing physical responses and command controls.

Furthermore, the authors affirm that interaction in DT ensures data exchange between the physical and virtual plant, containing a bidirectional flow of data, called perception (physical-virtual) and control (virtual-real) processes.

Finally, in the conclusion, it is commented that there are limitations in the proposed framework due to the ambiguity of the internal logical structure of the neural network. Hence, the reliability of the data generated by the neural network still needs further study. Another problem that needs more attention is the robustness of the DT control system.

Regarding the quality of the paper, it is undeniable that the authors have indeed great knowledge in the field, and it is a dense work that can surely help in outlining both the creation and optimization of industries' digital twins. Thus, several interesting ideas are given regarding how to make use of new technologies and apply them to DTs, such as AI, neural networks, and machine learning, among others. However, there are three major problems that arise from the study. The first is that there has been no case study, either by simulation or in a real application. Therefore, it is not possible to know whether, by implementing the framework in a real case, good results will be achieved. The second problem is the impression that the system as a whole works "miraculously" to some extent. That is, many functions and responsibilities are proposed for the AI-enhanced DT, giving various responsibilities and capabilities to the AI. Thus, even if the current technology possibly allows the system to be developed, it will require a lot of time and resources before the framework is fully implemented, making the feasibility of the project a factor to be considered. Furthermore, it would be necessary to develop the areas of machine learning and neural networks in parallel and connect them to the AI that assists the DT. Finally, the last problem stems precisely from the fact that the article brings only a framework, showing the problems and proposing solutions that end up being, to some extent, vague. Thus, it is shown what should be done and how to set up the system as a whole, but not what exactly should be done in the micro, only in the macro. As an example, one can cite the use of neural networks, i.e., the authors explain what they are and at which points they can be applied in the DT, but not which topology to use or any more in-depth points.

5.2.4. Article: Digital Twin in Industry: State-of-the-Art

[7] conducted a study regarding the current stage of development of digital twins applied to industry, involving all kinds, not only digital twins shop floor. The authors affirmed that, back when the paper was written, there were no articles about the review of DTs applied to industries. The methodology used for the study was explained, with the total of 50 papers, 8 patents and 6 best practices of leading companies being thorough reviewed. [7] cite studies defending the use of three- or five-dimensional models on DTs and briefly contextualize the history behind digital twins, showing its relevance and classifying as a promising technology. Concerning the development of DTs in industries, the author divided the topic in five parts: (1) Theoretical Foundations of DTs; (2) DT Modeling and Simulation; (3) Data Fusion; (4) Interaction and Collaboration; (5) Service.

The study also assessed the main application of DTs on industries in three main parts: (1) DTs in Product Lifecycle; (2) DT-Related Patents; (3) DT Applications by Industry Leaders. In (1), the author defended the superiority of DTs over the traditional methods, also showing the areas where the technology was applied in the reviewed papers in the product lifecycle, dividing them into four parts: design, production, PHM (Prognostics and Health Management), and others. In (2), the paper recognized the existence of eight patents related to digital twins from two companies, four from General Electric (GE) and four more belonging to

Siemens. However, only two from GE were presented as applied to wind farms, with the other two remaining without further information. On the other hand, all patents from Siemens were presented, each one related to the same focus on machine-human interface. Finally, in (3), some DT applications in industry leaders were analyzed, such as: Siemens used DTs in the power system and wastewater plant; GE achieved an improvement of 20% in efficiency when compared to traditional methods by applying DTs; British Petroleum used a digital twin to cope with problems concerning monitoring and maintaining oil and gas facilities; Airbus created an assembly line DT and pursues the digitalization of the company's factories; SAP SE proposed the use of DT-driven PHM services to avoid failures of subsea equipment; International Business Machines Corporation used DT in automatic vehicles, possibly leading to a more efficient engine.

Besides, [7] make observations and recommendations regarding PHM, modelling, cyber-physical fusion and others.

Despite being published in 2018, the article still provides a solid background about the use of DTs by the industry, bringing several examples of applications of the technology, also outlining two promising exploration areas in dispatching optimization and operational control.

5.2.5. Article: Digital Twin in manufacturing: A categorical literature review and classification

[21] focused on the categorical review and classification of the literature involving digital twins in the context of manufacturing, using the study as a baseline for future work on the theme. To do so, the authors established and explained the definitions and methodology used. The categorization method uses four different assessing categories: (1) type; (2) level of integration; (3) focused area; (4) technology. Each one is divided into subcategories. In (1), the possible types of the articles were: definition, review, concept, and case study. In (2), the level of integration between physical and digital objects was categorized according to three terms: Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT). Their characteristics and differences are explained in detail. In (3), the areas were: layout planning; product lifecycle; manufacturing in general; PPC; process design; maintenance. Finally, in (4), the technologies were: discrete event simulation; OPC-UA; CPS (CPPS); etc.

In the sequence, a table with 42 articles categorized according to the four mentioned criteria is presented along with a brief statistical analysis, where a focus on PPC (Product Planning and Control) was identified. The paper also detected a misuse of the term "Digital Twin", as, despite its use in most of the papers, only 18 percent of them were in fact about DTs.

Additionally, the authors advocated in favor of DTs in industries and their benefits. At the same time, they found a gap regarding case-studies making use of concepts involving the technology in concrete cases, defending the need of more studies in the field.

Finally, the authors proposed the establishment of a common definition regarding the field of study and argued that the development of digital twins is still immature.

5.2.6. Article: Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing

[6] wrote one of the most influential papers to the current stage of development of the digital twin shop floor, as the article established key points for its evolution. During the introduction, the authors show the current stage of development and the next, where great interaction and convergence between physical and virtual spaces is achieved. So, with the evolution, it's expected that the physical space will be replaced by the virtual one when it comes to evaluation, verification, and optimization. That said, the virtual part's paper also relies on the recording of the data sourced by the shop floor, providing optimization and prediction as well. Hence, the production is led by data from the physical and virtual worlds.

In the sequence, the article shows how the traditional production process in manufacturing usually works and the new information technologies that are used. After, the concepts and operation mechanisms of the DTS are discussed in detail. The implementation of the DTS was divided into four parts, where the relationship between them was proposed and shown in a diagram, namely: (1) physical shop- floor (PS); (2) virtual shop-floor (VS); (3) shop-floor service system (SSS); (4) shop-floor digital twin data (SDTD).

Ahead, several key technologies for implementing a DTS are given, as well as the challenges when constructing a digital twin.

5.2.7. Article: Digital twin-based smart production management and control framework for the complex product assembly shop-floor

[22] proposes a framework centered around four core techniques: (1) real-time acquisition, organization, and management of shop floor data; (2) DT construction; (3) shop floor prediction based on DT and Big Data; (4) DT-based production control and management.

The introduction of the article provides a historical overview of production control and management approaches, while also providing a perspective on the future of the field. The authors note that a product is considered complex when it is complex in terms of consumer demand, product composition, technology, manufacturing process, and management design, such as missiles, satellites, rockets, and airplanes. In the context of the current work, a framework was proposed for a satellite assembly shop floor. Under this premise, the authors discuss and explain four stages of management and control methods: passive (reactive), real-time, predictive, and proactive.

The authors state that various shop floor production processes and activities, such as scheduling, logistics planning, and resource allocation, can be simulated, evaluated, validated, and verified through the virtual space of the DT, making it an effective tool for selecting and conducting a simulation-based production strategy. Additionally, the paper propounds a DT and Big Data-based application/platform service composed of a prediction service platform and a management and control platform. The former incorporates prediction functions for product quality, working hours, production progress, production bottleneck, production disturbance, equipment failure and lifespan, material requirements, etc. The latter includes optimizations for assembly processes, production logistics, manufacturing resources, working hours, production scheduling, equipment maintenance, etc.

The article states that shop floor data can be managed based on the product’s BOM (Bill of Materials) and DTs, listing and detailing three approaches. Furthermore, the DT can be constructed following three levels: element, behavior, and rule. Four key points that needed to be studied to ensure the effectiveness and high fidelity of the DT are also listed. Additionally, the article comments on the inputs and outputs of the prediction process using Big Data and DT.

A case study is conducted based on satellite assembly, delving into the details and showing how the parts work. However, there is no information on whether a real or fictional shop floor was considered.

Finally, the main contributions of the work are: (1) providing a prediction service for satellite manufacturing by integrating DT and Big Data technologies; (2) proposing a framework for the management and control of satellite assembly shop floor production; (3) presenting a case study to illustrate the application of the proposed framework.

It is commented that, due to the complexity of building a digital equivalent of the physical plant, very little progress has been made in the area of DT applications, especially in the manufacturing of complex products. Thus, the relevance of the work developed by the BSS team from the injectors’ manufacturer, points out that the results obtained may help the scientific community in the field.

Given the definition of complex product, there is evidence supporting the idea that the products produced at the manufacturer fit into this category, and therefore, the article may help in optimizing the BSS.

Finally, as it is a framework, it only shows the steps that should be taken to implement production planning and control based on Digital Twin and Big Data, but not how to take them, that is, no method is shown for building the DT or creating the prediction service based on Big Data.

5.2.8 Article: Digital Twin-Driven Adaptive Scheduling for Flexible Job Shops

[17] cope with the optimization of production scheduling to aid in solving the FJSSP (Flexible Job-Shop Scheduling Problem). Additionally, it explains that DT technology can deeply integrate the real world and the virtual world. The virtual part can be improved with data and then send useful information applicable to the real plant. However, the authors affirm that there are few works in the literature that combine DT and production schedules, justifying the study. It proposes a DT based on an adaptive production scheduling method. The FJSSP was modeled, and the results were obtained using RLEGA (Reinforcement Learning Enhanced Genetic Algorithm). It is worth noting that, according to the authors, the use of genetic algorithms is one of the most classic in the job-shop scheduling field. Furthermore, the paper states that sensor networks and MES (Manufacturing Execution System) can be used to obtain dynamic real-time data. As noisy data seriously affects the synchronization of the DT simulation, FCM (Fuzzy c-means Clustering Algorithm) and a method based on Euclidean distance were used for filtering. The case study was conducted in the laboratory, not in the real manufacturing industry, with three algorithms being used in the problem, namely: RLEGA, GA (Genetic Algorithm), and TS (Tabu Search), with the first presenting the best results for dynamic scheduling for flexible shop-floors. For future work, it is mentioned that only RLEGA was used for scheduling, achieving an even faster real-time response time. The mathematical equations and programming behind the results were well explained, presenting convincing results. The future work mentioned at the end of the article appears to be interesting, but has not yet been published to date.

5.2.9. Article: Digital twin-driven dynamic scheduling of a hybrid flow shop

[23] deals with the problem of dynamic scheduling of a real hybrid Flow Shop applied to a perfume manufacturing company, proposing a DT involving optimization and simulation. For optimization, a MILP (Mixed Integer Linear Programming) scheduling model was used, and for simulation, a 3D model of the factory floor was used. With the combination of the two, the DT is able to reschedule production according to internal and external events.

The article is part of a project developed by researchers in partnership with a perfume company that is undergoing changes in its market, requiring high flexibility and adaptability in the production system. The production process is relatively simple and involves a few steps. However, there are some complicating factors, such as the fact that the maceration time is difficult to acquire, depending on the results of chemical tests. The scheduling problem involves 10 requirements. Considering that all products go through three main stages of production (maceration, storage, and packaging), the authors argue that this is a HFFS (Hybrid Flexible Shop), not an FSMP (Flow Shop with Multiple Processors). The proposed DT system works, in summary, as follows: data from the physical plant and the ERP (Enterprise Information System database) feed the DT, which is composed of the shop-floor model block and the production scheduling block. Thus, these two blocks talk to each other, with the scheduling block returning the updated production schedule to the real plant. An HMI was developed for input data capture and visualization. The developed MILP model allows working with both FSMP and HFFS. As a result of the study, the company will be able to switch from a dynamic scheduling tool on demand to an automatic real-time rescheduling tool.

Based on other papers to support the argument, [23] affirm few articles about literature surveys indeed have applicability in the industry, although even more publications have been made in recent years involving real cases applications. The mathematical equations and programming parameters used were well explained, achieving good results in the perfume company. The level of detail in what was done is noteworthy, showing the intricacies of the study and presenting a considerable density. A solid foundation on the subject is necessary to fully understand the article. The material may be of great value for the optimization project of the BSS.

5.2.10. Article: Industrial IoT integrated with simulation – A digital twin approach to support real-time decision making

[24] focus on the development of an integrated simulation system and IoT platform with the ability to collect real-time data and return performance indicators to assist in decision-making, also in real-time. The work includes an MES producing production schedules, an IoT platform, a simulator, and a program serving as a user interface. According to the authors, the main contributions of the article are the data structure for developing simulation models, the integrated IoT platform developed with simulation software, and the applicability of the proposal in a real case. A case study was carried out on an automobile production line.

The proposal for real-time decision-making is relevant since it is a recurring open issue in the literature. Nonetheless, the scenario used in the case study for model validation is extremely simplistic, with very few elements.

5.2.11. Article: Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system

[25] proposes a Digital Twin that acts as a representative of employees, assuming communication and coordination of tasks within the production system, granting the possibility of participating in computational decision-making. The DT uses a database that emulates user behavior. The authors argue that, given the unfeasibility of using sensors to monitor human employees, the properties, and behaviors of the proposed DT should be based on feedback and recorded patterns of users instead of measured data. Thus, an approach is described for developing a DT that takes part in automated and decentralized production control, particularly in resource allocation. Its implementation can provide the possibility for the employee to contribute and manipulate the production system while simultaneously using computational resources for process planning and control automation.

The authors argued that human resource planning is typically based on average values, considering available time and performance. However, since the estimated capabilities are used for production process calculations, such estimations are insufficient for short-term prediction, as they are average values that can fluctuate due to various factors.

Regarding the system-user interaction, it can be summarized as follows: when a machine makes a worker request, the request is sent to the employees, who decide whether to accept the service or not. Thus, using algorithms, profiles that best fit the request, either by skills, time or other factors, are selected. Additionally, a constant improvement of the system is proposed, adapting the DT according to the user. An example is given of frequently accepted or rejected requests by users that can be used for automatic responses, also allowing the users to interact and change the automatic response’s system to match better with their preferences.

An implementation was carried out in a production laboratory, proving the general technical feasibility of the proposal. It is stated that, up to that point, the implementation was limited to the user’s skills, experiences, and preferences. The flexibility of the system explored in the article is evident, as it evaluates each employee individually and helps to decide which service is most suitable for each one. With this, it should be possible, for example, to select which machine employees will be assigned to based on their equipment operation skills, potentially increasing manufacturing efficiency and productivity. Another possible benefit is an increase in the level of worker satisfaction, as they can select services that best fit their preferences.

5.2.12. Article: Modeling production disorder: Procedures for digital twins of flexibility-driven manufacturing systems

The article discusses the potential use of digital twin technology to address challenges related to manufacturing flexibility. The authors argue that while achieving mix flexibility is important for competitive advantage, it can also create disruptions on the shop floor that hinder managers' ability to diagnose problems, predict behavior, and make decisions effectively. They propose that digital twin, with its continuous updating capabilities and management support services, can help restore operational visibility for managers.

[11] acknowledge that while some studies have explored the use of digital twin for specific flexibility-related challenges, there is a lack of a normative and systematic approach to guide its application across a comprehensive range of flexibility scenarios. To bridge this gap, the authors present procedures for designing, implementing, and utilizing the digital twin within organizations facing flexibility-driven disruptions. They demonstrate the application of these procedures through a case study in a large automotive parts manufacturer, showing that the procedures effectively enable the achievement of a flexible production strategy.

The value of this study, according to the authors, lies in two key aspects. First, it systematically investigates how to apply the digital twin architecture to overcome the challenge of manufacturing flexibility. Second, it explores how to operationalize the digital twin concept into explicit organizational procedures, providing guidance for its comprehensive application. The authors claim that this may be the first normative contribution explicitly aimed at addressing mixed flexibility using the digital twin.

Overall, the article highlights the potential of digital twin technology in addressing the challenges posed by manufacturing flexibility and offers a systematic approach to its implementation. The case study presented adds empirical support to the proposed procedures. The paper's organization provides a clear structure for readers to follow the argument and understand the contributions made by the study.

The conclusion of the article highlights the procedures developed to apply the digital twin in supporting operations managers dealing with mix flexibility challenges. The authors propose a digital twin general architecture and provide design, implementation, and usage procedures based on industry observations and expert knowledge. The research process followed a design science research protocol to create a technology-related procedural artifact that combines scientific innovativeness with practical relevance. The conclusion acknowledges limitations, including the need for further testing and a broader view of organizational processes. The authors suggest future research directions to enhance generalizability, explore different production systems, and investigate the broader implications of the digital twin approach on training, management, and decision-making processes.

5.2.13. Article: Real-time resilient scheduling by digital twin technology in a flow-shop manufacturing system

[4] presented a DT architecture for building a decentralized scheduling system that is resilient to disruptions on the factory floor, seeking to adjust and process changes in the environment based on real-time data. The framework has the following contributions to the scientific literature: the fully decentralized scheduling approach of the virtual mirror, the communication protocol to perform communication between twins, DT mechanism for connecting the physical and virtual workshop in real-time. Three factory floor disruption scenarios are listed, namely, the arrival of a new service, a change in the due date, and a change in the processing time. Decisions for optimizing resources are based on data received from the physical part and information shared by other twins. Two scheduling rules are compared to provide the sequence of alternative services in each twin: EDD (Earliest Due Date) and GA (Genetic Algorithm). Although there are indications that the developed model can be used in a large-scale system once it uses computers with parallel processing, there is a challenge involving processing time and data transmission, which may compromise real-time decision-making. The results of the experiments confirm that the DT system was able to establish a process scheduling that finds rapid changes in real-time.

The authors developed a DT to simulate the consumer, as well as a pseudocode to illustrate how it was programmed. Although Python was used for programming, it is not clear which libraries and/or programs were used, turning it difficult to make an affirmation about the algorithm speed and performance. Good results were achieved, but for small processes involving few machines and few services. Finally, as stated in the article, the scalability of the project is a challenge.

5.2.14. Article: Shop Floor Digital Twin in Smart Manufacturing: A Systematic Literature Review

In [26], the applications of digital twins in production logistics were reviewed using a systematic literature review approach. The paper discusses the state-of-the-art concerning the technology and establishes some common definitions in the field, as it states a lack of them within the theme. Firstly, an introduction to the history and development of DTs is given, and then it is explained how the study was conducted, with 93 studies identified by the tool Scopus, of which only 28 were selected for the review.

Next, in the results, several types of analyses were conducted on the chosen articles, sorted by: (1) Descriptive Analyses; (2) Content Analyses; (3) Definitions of Digital Twin; (4) Systematic Evaluation of the Identified Literature; (5) Case Study Analyses. In (1), the main addressed points were: appropriateness, number of publications by year, top publishers, authors, and countries, number of collaborators per paper, affiliation, and backward reference search. In (2), the 28 works were displayed in a table and categorized by the type of digital twin definition used, virtual model, type of the study, and application domain. In (3), the authors identified different definitions of DT used and discussed them individually. The definitions were given by Grieves ([27]), Glaessgen and Stargel ([28]), and Tao et at. ([29, 30, 31, 32]), with this last being by far the most used. However, some of the papers didn't follow those three main models and, thus, were classified as "other". In (4), the evaluation considered: enabling concepts, areas of operation and state of development, virtual model creation, enterprise information systems, decentralized applications, and machinery prognostics and maintenance management. In (5), the digital twins were rated considering their fulfillment of the model proposed by Tao et al. Also, in (5), the different modeling technologies were identified, and so were the targeted objectives and application areas.

In the discussion, the authors identified some common definitions and basic concepts, though details and focus areas differed. It was also spotted that most of the studies used laboratory production lines, with automotive, electronics and metalworking in the sequence. Regarding the technology involving the Virtual Models (VM), the DES (Discrete Event Simulation) was recognized as the most used one, though real-time functions are still scarce. Later on, the paper compares itself with articles reviewing digital twins, and, after stating the existence of different methods of using them in production logistics, the authors affirm no paper have systematically surveyed the theme in the context of industrial logistics.

5.2.15. Article: State of the Art and Future Directions of Digital Twins for Production Logistics: A Systematic Literature Review

[3] explored the application of DTs in production logistics systems within the context of Industry 4.0. The authors acknowledge the lack of a unified understanding regarding the constitution and usage of DTs in this area and aim to address this gap. They conduct a systematic literature review to examine definitions, characteristics, and functionalities of DTs, as well as current developments and implications of state-of-the-art implementation approaches.

The authors conducted the review by applying the systematic literature review approach using the Scopus database to analyze the state-of-the-art development of digital twins in production logistics processes. The search strategy focused on logistics and DTs, limiting the document types to articles and conference papers in the engineering and business management subject areas. The search timeframe was set from 2015 to 2021. The initial search for "Digital Twin" yielded 2689 results, and after narrowing it down to "logistic", 93 relevant publications were identified, showing also the final search input given to Scopus. The PRISMA method was applied to perform the review. Hence, after the filters were applied, 28 out of the initial 93 articles were selected for the study, rating the papers accordingly to their appropriateness and analyzing the full text of the ones defined as high appropriated.

The article provides an overview of the key concepts and features of DTs, highlighting their potential to enhance the competitiveness of manufacturing enterprises. By evaluating a set of DT case studies, the authors analyze the practical implementation of DTs in production logistics. They also identify research gaps and suggest potential directions for future initiatives in this field. Regarding the gaps, the paper indicates that the exploration of Digital Twins in production logistics is still in its early developmental phase, and there is a lack of substantial industrial applications. In terms of suggestions for future work, the authors highlight the need for research that combines theory-based exploration of logistics systems with empirical research methods.

Regarding the results, the authors showed the analysis of the articles in many categories. Some examples are appropriateness rating; the number of publications by year; publication sources; the number of authors per study; the number of publications of the top researchers; publications by country and authors' affiliation; backward reference search; assessment of the papers included in the review; definition of digital twin used; fulfillment rate of the DTs considering the five dimensions' model; the virtual model used; objectives by implementing the digital twin; application areas, etc.

Overall, this article serves as a comprehensive introduction to the application of DTs in production logistics within the context of Industry 4.0. It offers a valuable review of the existing literature, presents real-world case studies, and provides insights into current developments and future research directions. The information presented in the article can be beneficial for researchers, practitioners, and decision-makers interested in leveraging DTs to improve production logistics in manufacturing enterprises.

The conclusion of the article highlights the current developments and approaches to Digital Twins (DTs) in the context of production logistics. The authors provide an overview of the definitions, implementation concepts, and technologies used in DTs for production logistics. They analyze case studies to identify application areas and objectives addressed by different DT implementation approaches. The conclusion acknowledges that research in the application of DTs in production logistics is still in its early stages, with a lack of profound industrial applications.

This serves as motivation for future research initiatives aiming to combine theory-based explorations of logistics systems with empirical research methods.

5.2.15. Article: Synchronizing physical factory and its digital twin through an iiot middleware: A case study

[13] presents a potential solution to help companies in the challenge of applying the appropriate software infrastructure that allows the synchronization of the physical plant and its DT. The solution is based on an Internet of Things (IIoT) middleware, which is implemented in a fully dual synchronization between the physical and virtual worlds. A case study was conducted to investigate the possibilities of implementing the solution to demonstrate the correctness and validity of the approach, and the tests were conducted in the laboratories of Tallinn University of Technology. The DT was used in different conditions to allow various operations on the factory floor, as well as to simulate and evaluate the performance of the industry. The authors focus on specific applications of the Digital Twin in the management and control of manufacturing systems, particularly in the field of industrial robots. Four main points are established for the realization of the DT: (1) data acquisition; (2) detailed configuration of synchronization; (3) use of the model to represent the real industry and its performance; (4) synchronization between the real and virtual plant. Thus, the work focuses on the software infrastructure to constantly synchronize the physical components and their digital representations.

A list of necessary points for a good 3D digitalization of the company's equipment was made. The DT was complemented with VR (Virtual Reality), allowing researchers to test the robot online while all together in the same virtual environment, also granting the ability to monitor the equipment and collaborate in real-time, even from remote locations. After the implementation of the DT, three criteria were used to evaluate the solution: (1) latency; (2) capacity to measure according to performance; (3) ability to control the DT from remote locations. Benefits derived from the proposed infrastructure exploration are also listed. In summary: (1) it is possible to work with the system remotely in real-time; (2) support for multiplayer mode and remote collaboration; (3) possibility to create simulations, thus allowing to go back to an arbitrary point in time and identify failures or analyze system actions; (4) DTs take efficiency to a new level.

6. CONCLUSION

Based on the articles studied during the composition of our study, it is possible to affirm, to the best of the author's knowledge, that the current scientific literature has limited works focusing on the implementation of digital twins in industries. As observed in Section 5, few articles utilized real factories as a basis for their studies, while others relied on laboratory tests or simulations to validate the theory. Additionally, some articles presented no validation as they were frameworks, theoretical studies, or literature reviews.

The limited implementation of digital twins in the industrial context can be attributed, in part, to the immaturity of the technology. Developing and implementing a useful digital twin requires significant financial resources and expertise in the field, creating barriers such as a lack of these elements or even the perceived risk of investing in a technology with uncertain returns, usually restricting its usage to large companies.

Despite these challenges, the reviewed articles proved to be valuable in terms of acquiring expertise in the field of digital twins. Each paper contributed unique insights into the theoretical foundations, practical applications, and potential improvements of digital twins in various industries. By examining and analyzing these articles, the authors gained a comprehensive understanding of the current state-of-the-art in digital twin research and its implications for manufacturing industries.

The theoretical studies provided a solid foundation for understanding the underlying principles and concepts of digital twins, while the case studies and practical implementations showcased real-world applications and the potential benefits that can be achieved. Additionally, the frameworks and literature reviews helped to consolidate and synthesize existing knowledge in the field, highlighting gaps and future research directions.

In particular, the case studies and practical implementations presented in the reviewed articles offered valuable insights into the potential optimizations that can be applied to the digital twin of the large automotive parts manufacturer in Brazil. These optimizations encompassed various aspects, including data integration, real-time monitoring and control, predictive analytics, and decision support systems. Each article was carefully examined and evaluated individually to identify the specific contributions and applicability to the manufacturer's digital twin.

It is worth noting that the findings from the literature review provide a starting point for enhancing the existing digital twin. However, further research and implementation efforts are necessary to tailor and customize these optimizations to the specific requirements and challenges of the manufacturer's production processes. The digital twin should be continuously monitored, evaluated, and iteratively improved to ensure its long-term effectiveness in supporting the manufacturing operations and achieving the desired outcomes.

Future work involves exploring the application of the digital twin for production scheduling in the examined manufacturer, using the concept of APS (Advanced Planning and Scheduling). However, since the literature still does not have studies using digital twin shop floor to solve complex scheduling issues, an APS software is being developed and will be integrated to the DT. The plan is to use the real-time data available on the DT to reschedule the production plan based on events occurring in the production line. The ongoing research aims to assess the feasibility and effectiveness of leveraging data integration and modeling capabilities to proactively identify scheduling conflicts and make timely adjustments. The objective is to improve overall efficiency, minimize the number of setups, optimize resource utilization, and streamline the production process. The study seeks to implement a practical solution that addresses production scheduling challenges and enhances coordination.

In conclusion, while the implementation of digital twins in industries is still limited, the reviewed articles have provided valuable insights and knowledge for advancing the understanding and application of digital twins. The theoretical studies, case studies, frameworks, and literature reviews collectively contribute to the growing body of knowledge in this field. By leveraging the findings and optimizations proposed in these articles, the digital twin of the automotive parts’ manufacturer can be enhanced, possibly leading to improved productivity, efficiency, and competitiveness.

AUTHOR CONTRIBUTIONS

The contributions of each author are given as follows: Pasianotto - writing, reviewing, editing, and draft preparation; Junior - writing, methodology, supervising and reviewing; Valle, Deschamps e Santos - reviewing.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] Xin Ma, Jiangfeng Cheng, Qinglin Qi, and Fei Tao. Artificial intelligence enhanced interaction in digital twin shop-floor. volume 100, page 858 – 863, 2021. doi: 10.1016/j.procir.2021.05.031. URL https://www.scopus.com/inward/record.uri?eid=2-s2. 0-85107885361&doi=10.1016%2fj.procir.2021.05.031&partnerID=40&md5=c084c24281618f3b26fc5411f6c3b8e2.

[2] Carlos Henrique dos Santos, Renan Delgado Camurça Lima, Fabiano Leal, José Antonio de Queiroz, Pedro Paulo Balestrassi, and José Arnaldo Barra Montevechi. A decision support tool for operational planning: a digital twin using simulation and forecasting methods. *Production*, 30:1 – 17, 2020. doi: 10.1590/0103-6513.20200018. URL https://www.scopus.com/inward/record.uri?eid=2-s2. 0-85101094714&doi=10.1590%2f0103-6513.20200018&partnerID=40&md5=812bf65095976460e48d21b3a67e1895. Cited by: 12; All Open Access, Gold Open Access, Green Open Access.

[3] Alexander Kaiblinger and Manuel Woschank. State of the art and future directions of digital twins for production logistics: A systematic literature review. *Applied Sciences*, 12(2), 2022. ISSN 2076-3417. doi: 10.3390/app12020669. URL https://www.mdpi.com/2076-3417/ 12/2/669.

[4] Agustina Eunike, Kung-Jeng Wang, Jingming Chiu, and Yuling Hsu. Real-time resilient scheduling by digital twin technology in a flow-shop manufacturing system. volume 107, page 668 – 674, 2022. doi: 10.1016/j.procir.2022.05.043. URL https://www.scopus.com/ inward/record.uri?eid=2-s2.0-85132286450&doi=10.1016%2fj.procir.2022.05.043&partnerID=40&md5=4631c9299ce9d9b56636d2c613a8f89a. Cited by: 3; All Open Access, Gold Open Access.

[5] Fei Tao, Weiran Liu, Jianhua Liu, Xiaojun Liu, Qiang Liu, Ting Qu, Tianliang Hu, Zhinan Zhang, Feng Xiang, Wenjun Xu, Jun-Qiang Wang, Yingfeng Zhang, Zhenyu Liu, Hao Li, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, Fangyuan Sui, and Hui Cheng. Digital twin and its potential application exploration, volume = 24, journal = Computer Integrated Manufacturing Systems, doi = 10.13196/j.cims.2018.01.001. 01 2018.

[6] Fei Tao and Meng Zhang. Digital twin shop-floor: A new shop-floor paradigm towards smart manufacturing. *IEEE Access*, 5:20418– 20427, 2017. doi: 10.1109/ACCESS.2017.2756069.

[7] Fei Tao, He Zhang, Ang Liu, and A. Y. C. Nee. Digital twin in industry: State-of-the-art. *IEEE Transactions on Industrial Informatics*, 15 (4):2405–2415, 2019. doi: 10.1109/TII.2018.2873186.

[8] Flavia Pires, Bilal Ahmad, Antonio Paulo Moreira, and Paulo Leitao. Digital twin based what-if simulation for energy management. page 309 – 314, 2021. doi: 10.1109/ICPS49255.2021.9468224. URL https://www.scopus.com/inward/record.uri?eid=2-s2. 0-85112395893&doi=10.1109%2fICPS49255.2021.9468224&partnerID=40&md5=2e1195dc7eca76d78e97399cd7e9ce2a. Cited by: 8; All Open Access, Green Open Access.

[9] Vladimir Kuts, Martinš Sarkans, Tauno Otto, Toivo Tähemaa, and Yevhen Bondarenko. Digital twin: Concept of hybrid programming for industrial robots – use case. volume 2B-2019, 2019. doi: 10.1115/IMECE2019-10583. URL https://www.scopus.com/inward/ record.uri?eid=2-s2.0-85078760988&doi=10.1115%2fIMECE2019-10583&partnerID=40&md5=b4701f42634b294598b15da65037cd74. Cited by: 17.

[10] Alem Čolaković and Mesud Hadžialić. Internet of things (iot): A review of enabling technologies, challenges, and open research issues. *Computer Networks*, 144:17–39, 2018. ISSN 1389-1286. doi: https://doi.org/10.1016/j.comnet.2018.07.017. URL https://www.sciencedirect.com/science/article/pii/S1389128618305243.

[11] Anis Assad Neto, Elias Ribeiro da Silva, Fernando Deschamps, Laercio Alves do Nascimento Junior, and Edson Pinheiro de Lima. Modeling production disorder: Procedures for digital twins of flexibility-driven manufacturing systems. *International Journal of Production Economics*, 260, 2023. doi: 10.1016/j.ijpe.2023.108846. URL https://www.scopus.com/inward/record.uri?eid=2-s2. 0-85151011335&doi=10.1016%2fj.ijpe.2023.108846&partnerID=40&md5=5c3c0c012d0841ca9381b7357252a1bc. Cited by: 0.

[12] Sze-jung Wu, Nagi Gebraeel, Mark A. Lawley, and Yuehwern Yih. A neural network integrated decision support system for condition-based optimal predictive maintenance policy. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 37(2): 226–236, 2007. doi: 10.1109/TSMCA.2006.886368.

[13] Vladimir Kuts, Gianfranco E. Modoni, Tauno Otto, Marco Sacco, Toivo Tähemaa, Yevhen Bondarenko, and Ruxin Wang. Synchronizing physical factory and its digital twin throughan iiot middleware: A case study; [füüsiline tehas ja selle digitaalse kaksiku sünkroonimine tööstusliku nutistu vahevara kaudu: Juhtumi uuring]. *Proceedings of the Estonian*

Academy of Sciences, 68(4):364 – 370, 2019. doi: 10.3176/proc.2019.4.03. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85074654014&doi=10.3176%2fproc.2019.4.03&partnerID=40&md5=d380f1445671cadd677f43e0a209c39a. Cited by: 26; All Open Access, Gold Open Access.

[14] Aidan Fuller, Zhong Fan, Charles Day, and Chris Barlow. Digital twin: Enabling technologies, challenges and open research. *IEEE Access*, PP:1–1, 05 2020. doi: 10.1109/ACCESS.2020.2998358.

[15] M. Sommer, J. Stjepandic, S. Stobrawa, and M. Von Soden. Automated generation of a digital twin of a manufacturing system by using scan and convolutional neural networks. In *Advances in Transdisciplinary Engineering*, volume 12, pages 363–372, 2020. URL https://www.scopus.com/record/display.uri?eid=2-s2.0-85092798079&doi=10.3233%2fATDE200095&origin=inward&txGid=fc9dec37796349412ea310e3002cf678.

[16] M. Sommer, J. Stjepandic, S. Stobrawa, and M. Von Soden. Improvement of factory planning by automated generation of a digital twin. In *Advances in Transdisciplinary Engineering*, volume 12, pages 453–462, 2020. URL https://www.scopus.com/record/display.uri?eid=2-s2.0-85092759053&doi=10.3233%2fATDE200105&origin=inward&txGid=1ed0a2928d10448d9fb4b0dbbbcab7f2.

[17] Lilan Liu, Kai Guo, Zenggui Gao, Jiaying Li, and Jiachen Sun. Digital twin-driven adaptive scheduling for flexible job shops. *Sustainability (Switzerland)*, 14(9), 2022. doi: 10.3390/su14095340. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85129841365&doi=10.3390%2fsu14095340&partnerID=40&md5=98592a2539dab97fc5dca66b077668e5. Cited by: 4; All Open Access, Gold Open Access.

[18] Michael Grieves. Digital twin: manufacturing excellence through virtual factory replication. *White paper*, 1(2014):1–7, 2014.

[19] Fei Tao, Meng Zhang, Yushan Liu, and A.Y.C. Nee. Digital twin driven prognostics and health management for complex equip- ment. *CIRP Annals*, 67(1):169–172, 2018. ISSN 0007-8506. doi: https://doi.org/10.1016/j.cirp.2018.04.055. URL https://www.sciencedirect.com/science/article/pii/S0007850618300799.

[20] Jay Lee, Moslem Azamfar, and Behrad Bagheri. A unified digital twin framework for shop floor design in industry 4.0 manufacturing systems. *Manufacturing Letters*, 27:87 – 91, 2021. doi: 10.1016/j.mfglet.2021.01.005. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85100980468&doi=10.1016%2fj.mfglet.2021.01.005&partnerID=40&md5=186eb8d455edddead0c951a1894d4907. Cited by: 15.

[21] Werner Kritzinger, Matthias Karner, Georg Traar, Jan Henjes, and Wilfried Sihn. Digital twin in manufacturing: A categorical literature review and classification. *IFAC-PapersOnLine*, 51(11):1016–1022, 2018. ISSN 2405-8963. doi: https://doi.org/10.1016/j.ifacol.2018.08.474. URL https://www.sciencedirect.com/science/article/pii/S2405896318316021. 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018.

[22] Cunbo Zhuang, Jianhua Liu, and Hui Xiong. Digital twin-based smart production management and control framework for the complex product assembly shop-floor. *International Journal of Advanced Manufacturing Technology*, 96(1-4): 1149 – 1163, 2018. doi: 10.1007/s00170-018-1617-6. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85041548794&doi=10.1007%2fs00170-018-1617-6&partnerID=40&md5=95207b340f6af35279e8aeb39aa5137e. Cited by: 352.

[23] Khalil Tliba, Thierno M. L. Diallo, Olivia Penas, Romdhane Ben Khalifa, Noureddine Ben Yahia, and Jean-Yves Choley. Digital twin-driven dynamic scheduling of a hybrid flow shop. *Journal of Intelligent Manufacturing*, 2022. doi: 10.1007/s10845-022-01922-3. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85126214952&doi=10.1007%2fs10845-022-01922-3&partnerID=40&md5=2c3e9e2d1c7a916da989899494ab449b. Cited by: 6.

[24] Romão Santos, João Basto, Symone G. S. Alcalá, Enzo Frazzon, and Ame´rico Azevedo. Industrial iot integrated with simulation -a digital twin approach to support real-time decision making. Number July, page 816 – 828, 2019. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85079487305&partnerID=40&md5=73b313993562bcdb727ab57b26729ff4. Cited by: 9.

[25] I. Graessler and A. Poehler. Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system. volume 2017-December, page 289 – 293, 2018. doi: 10.1109/IEEM.2017.8289898. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85045258714&doi=10.1109%2fIEEM.2017.8289898&partnerID=40&md5=92d7e0001842aa8301d766f9b07b70f5. Cited by: 42.

[26] Angelo Corallo, Vito Del Vecchio, Marianna Lezzi, and Paola Morciano. Shop floor digital twin in smart manufacturing: A systematic literature review. *Sustainability (Switzerland)*, 13 (23), 2021. doi: 10.3390/su132312987. URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-85119964111&doi=10.3390%2fsu132312987&partnerID=40&md5=3cc38be0937c03718507d7627ca8d8cc. Cited by: 11; All Open Access, Gold Open Access.

[27] Michael Grieves. Product lifecycle management: the new paradigm for enterprises. *International Journal of Product Development - Int J Prod Dev*, 2, 01 2005. doi: 10.1504/IJPD.2005.006669.

[28] Edward Glaessgen and David Stargel. The digital twin paradigm for future nasa and u.s. air force vehicles. 04 2012. ISBN 978-1-60086- 937-2. doi: 10.2514/6.2012-1818.

[29] Fei Tao, Jiangfeng Cheng, Qinglin Qi, Meng Zhang, He Zhang, and Fangyuan Sui. Digital twin-driven product design, manufacturing and service with big data. The International Journal of Advanced Manu- facturing Technology, 94, 02 2018. doi: 10.1007/s00170-017-0233-1.

[30] Qinglin Qi, Fei Tao, Tianliang Hu, Nabil Anwer, Ang Liu, Yongli Wei, Lihui Wang, and Andrew Nee. Enabling technologies and tools for digital twin. Journal of Manufacturing Systems, 58:3–21, 03 2021. doi: 10.1016/j.jmsy.2019.10.001.

[31] Fei Tao and Qinglin Qi. New it driven service-oriented smart manufacturing: Framework and characteristics. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 49:81–91, 01 2019. doi: 10.1109/TSMC.2017.2723764.

[32] Rodolfo Elias Haber Guerra, Ramon Quiza, Alberto Villalonga, Javier Arenas, and Fernando Castaño. Digital twin-based optimization for ultraprecision motion systems with backlash and friction. IEEE Access, PP:1–1, 07 2019. doi: 10.1109/ACCESS.2019.2928141.