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Use of simulation in the industry 4.0 context: Creation of a Digital Twin to optimise decision making on non-automated process

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ABSTRACT
The advent of new technologies brings a significant impact on systems management. The Industry 4.0 looks for increasingly automated, integrated, and digitised processes. We highlight the use of simulation as a Digital Twin, a virtual and intelligent copy capable of mirroring real processes and optimise decision making. This paper analyses the applicability of the Discrete Event Simulation as a Digital Twin in a non-automated process, a challenging scenario on the implementation of Industry 4.0 solutions. Amethod for conducting simulation projects of this nature was proposed, considering its integration with the process data, as well as its constant updating due to changes in the real environment. To verify its applicability, the method was used in a real study object. The proposed approach proved possible from the present research. We also present some discussions related to the use of simulation as Digital Twins, highlighting the main characteristics of such an application.

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Industry 4.0; Discrete Event Simulation; Digital Twin; optimised decision making

1. Introduction

Computer simulation has been consolidated over the last decades as a valuable tool for analysis and decision support (Rodič, 2017). In general, the simulation extended its application among many sectors, including hospitals, military applications, services, and logistics. However, the tool's most significant outcome relies on manufacturing environments application (Negahban & Smith, 2014). In this case, several advantages are arising from the use of simulation, such as the possibility of investigating the behaviour of complex systems, conducting "what if" experiments, and the possibility of evaluating changes in real systems, without interfering in them. (Banks et al., 2010; Greasley & Owen, 2018). However, despite the vast applicability of simulation, it is noted that exposure to high velocity and volume of changes directly impacts the way that systems and processes are managed, and, in this context, the use of simulation is also vulnerable to such changes. Mourtzis (2020) reports that the simulation is transforming the current industrial environment, making it possible to use more complex analysis models, synchronisation, and monitoring of physical systems through its data, advanced graphic resources, and constant support for decision making. More specifically in the manufacturing field, simulation is no longer a limited analysis tool but it is a fundamental and constantly used tool in the context of the so-called Industry 4.0 (Rodič, 2017). The term Industry 4.0, referring to what would be the fourth industrial revolution, refers to a new industrial age based on intelligent companies and processes, which aim to increase their efficiency through the integration of real and virtual environments with the use of emerging technologies (Wan et al., 2015). Furthermore, Industry 4.0 represents a global goal for the modern industry, intending to integrate and virtualise industrial systems for a fully automated, integrated, and connected era of production (Rüttimann & Stöckli, 2016; Uriarte et al., 2018).

In the global economic scenario, there is a growing need for a reformulated industry, which will allow an increased level of digitisation and computerisation in order to raise efficiency and competitiveness. In this case, the development and technological advances will allow the viability of several growth solutions for the industries. This fact can be seen by the increasing number of areas that have been making progress from the benefits from Industry 4.0, through the digitisation and creation of intelligent interfaces for decision making (Xu et al., 2018). The pillars of this new industrial age, in addition to the well-known Information Technology (IT), include solutions such as the Internet of Things (IoT), Big Data, and Cloud Technology, which make it possible to connect multiple processes and equipment, large-scale and variety of processing data, as well as data and information flows without physical resources, respectively. Another important pillar is the Cyber-physical System (CPS), which represents the virtualisation of real processes

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and systems from smart digital copies (Zhong et al., 2017). When considering virtual copies of real systems, the Digital Twin (DT) term appears as a reference to the digital aspect of CPS (Zhuang et al., 2018). In this case, DT is understood to be a virtual copy that represents the physical systems and which is automatically supplied with real data, as well as answers instructions or commands with a certain degree of autonomy. Thus, a DT aims the optimisation of such real systems through an intelligent interface (Kunath & Winkler, 2018; Vachálek et al., 2017).

When referring to operational decisions in the industry process, DT has stood out due to its ability to assist in decision making on the shop floor (Tao & Zhang, 2017). The authors add that adopting the DT will be an inevitable tendency to solve problems and improve the management of industrial processes. It is precisely in the DT context that simulation becomes remarkable in the Industry 4.0 scenario. As Digital Twins refer to intelligent virtual copies that aim to optimise the decision-making, the simulation can be used as an alternative in designing such twins (Rodič, 2017). Mourtzis (2020) highlights that simulation as a DT is among one of the main trends in the Industry 4.0 era, standing out as a powerful decision support technique. Moreover, to differentiate traditional simulation use with the new DT concept, Wright and Davidson (2020) reveal that traditional digital models can provide a snapshot of physical behaviour at a specific time, but when using this model as a DT, it is necessary to extend its use to time scales over which the physical system will change significantly. Ashrafian et al. (2019) report that, within the transformation scenario driven by Industry 4.0, simulation combined with graphical interfaces and data from operations has become the basis of DT. Thus, based on data from sensors, IoT devices, and information systems, we can automatically adapt the simulation model according to the modifications of the real system, enabling more efficient and effective decision making. Finally, Alam and Saddik (2017) conclude that the DT can be used to support operational decisions from three approaches: (1) diagnostics, aiming to evaluate decisions from previous analyses; (2) monitoring, in order to observe and control the process; (3) prognostics, aiming to anticipate and predict behaviours and, consequently, guide decisions. Therefore, the characteristics of DT will depend on its application and scope of action.

Despite the benefits of the new industrial age, we noted that the pursuit of adapting processes and systems to the precepts of Industry 4.0 represents a challenge for companies and organisations. In this case, one of the most significant challenges is related to technical issues, since today's business infrastructure is not yet ready for the digitalisation era, which may require high investments (Xu et al., 2018). Moreover, Eyre et al. (2018) point out that, although the implementation of DT is increasingly accessible due to emerging technologies, the system must present significance and industrial value in face of its investments. This fact is due to the cost related to DTs implementation through the various options of software and commercial platforms available (Mourtzis, 2020; Terkaj et al., 2019). Furthermore, such difficulties regarding DT implementation are even clearer when it comes to companies with non-automated processes. In this case, Mieth et al. (2019) highlight that monitoring and control are more difficult compared to automated processes, which impacts the implementation and operation of Digital Twins. In this context, simulation appears as a financially viable and versatile tool to adapt systems and processes to some of the precepts of modern industry, such as the DT (Grube et al., 2019; Terkaj et al., 2019; Uriarte et al., 2018). Moreover, among the various types of simulation that can be used as DT, the Discrete Event Simulation (DES) stands out as the most popular simulation technique to support decision making in manufacturing systems (Uriarte et al., 2018). Therefore, the objective of this paper is to analyse the applicability of DES as a DT in a non-automated process. From now on, for the sake of simplicity, DES will be designated simply as "simulation". Figure 1 illustrates the simulation's position as a DT in the Industry 4.0 context, as proposed in this paper.

In the literature, there are research opportunities to explore the implementation of DT in real environments, since most research in the area still has a theoretical nature (Kritzinger et al., 2018; Zhuang et al., 2018). Moreover, Zhuang et al. (2018) report some key issues that will guide researches in this area, including the need to systematise the creation of DT and its integration with physical systems. In this case, such a need is even more evident when considering the use of simulation as DT, lacking research focused on structuring steps to create models of this nature. Furthermore, Murphy et al. (2020) complement that another challenge related to the creation of DT is regarding the availability and acquisition of data from productive operations. Since DT is updated using data from physical systems, it is essential to ensure that this information is available correctly and on time for decision-making (Zhuang et al., 2018). Therefore, when considering the use of simulation as DT, attention should be paid to important issues such as the creation of data update routines according to changes in the physical system; integration and synchronisation of the simulation model with data from physical systems; creation of user-friendly interfaces aiming at the wide use of DT and allowing the data updating and decision optimisation easily and intuitively. Finally, another point to be explored in the

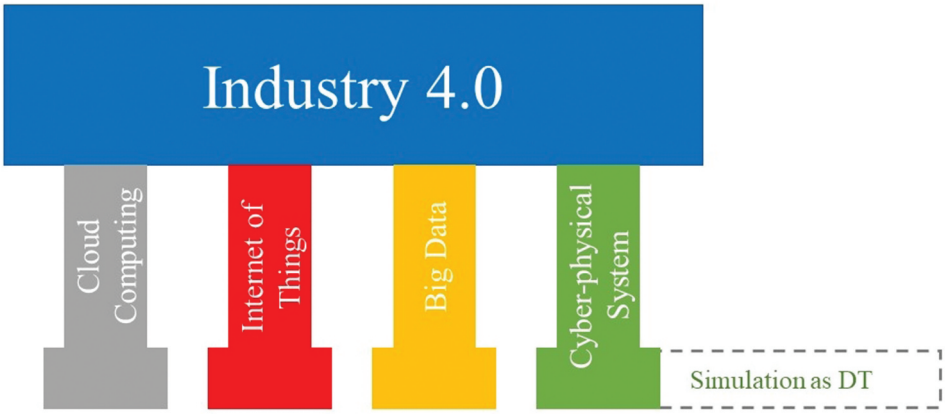

Figure 1. Simulation role as a Digital Twin in the Industry 4.0 context.

literature is related to the current difficulties in the implementation of the Industry 4.0 concepts, including the DT. In this case, research involving alternatives, as proposed in this paper, can assist in the transition of different segments of the industry towards more intelligent and efficient processes.

Therefore, given the aforementioned research opportunities, this paper aims to analyse the possibility of implementing a DT and its main characteristics, through the use of simulation, more precisely from DES, in a non-automated process. In this case, we intend to evaluate the main characteristics and requirements of DT, highlighting the role of simulation as an alternative for its creation. Furthermore, when referring to DT implementation in a non-automated process, we intend to highlight the simulation as a facilitating agent in adapting processes to the Industry 4.0 precepts. To pursue the objectives, this paper presents a review of the literature on the topics to be worked on, approaching the use of simulation as a DT in the Industry 4.0 context, as described in the Introduction section. Then, the Method section presents the method used for the development of the work, which indicates all the necessary steps for conducting the simulation project as a DT. The Results and Discussion section presents an application, according to the described method, in a real study object, to analyse such applicability, as well as to verify the theoretical and practical aspects involved in it. Finally, the Conclusions section presents the conclusions of the work.

2. Method

2.1. Available methods in the literature for conducting simulation projects

Several works in the literature approach methods for conducting simulation projects. Such methods present sequences of steps that guide these projects conduction, which helps establish logical flows to assist the responsible ones for implementing such projects (Montevechi et al., 2015). Law (2009) suggests a seven-step method, ranging from problem formulation to results presentation. Sargent (2013) describes a method with three main steps called Problem Definition, Conceptual Modelling, and Computational Modelling, as well as other intermediate steps, which concern the validation and verification of the main steps. Another method widely used in the literature is proposed by Balci (2012), which is composed of eleven main steps and which are interspersed by validation, verification, and analysis phases for their quality. This allows intermediate evaluations throughout the project. Finally, Montevechi et al. (2010) propose a method divided into three macro phases, called Conception, Implementation, and Analysis, which are composed of a total of twelve main stages.

Montevechi et al. (2015) compared the methods described above and others available in the literature and, considering the level of details approached by the method and its robustness, they stand out the methods proposed by Montevechi et al. (2010) and Balci (2012). Considering the level of detail, this paper will use the method proposed by Montevechi et al. (2010) as a basis for structuring the research. This method is structured in three major phases, and each of them is composed of several stages, as shown in Figure 2.

2.2. Method adaption to the context of industry 4.0 and Digital Twin

Some modifications are necessary to adapt the method to this paper. The use of simulation has gone through some changes with the advent of the Industry 4.0 and DT concept. In this context, Uriarte et al. (2018) point out that simulation is no longer a limited and isolated analysis tool and has to be able to connect and integrate with several data and sources. In this case, simulation as a DT is used to continuously support the decision-making process. Furthermore, models that require the assistance of specialists tend to be replaced by models which can be operated by any user, without

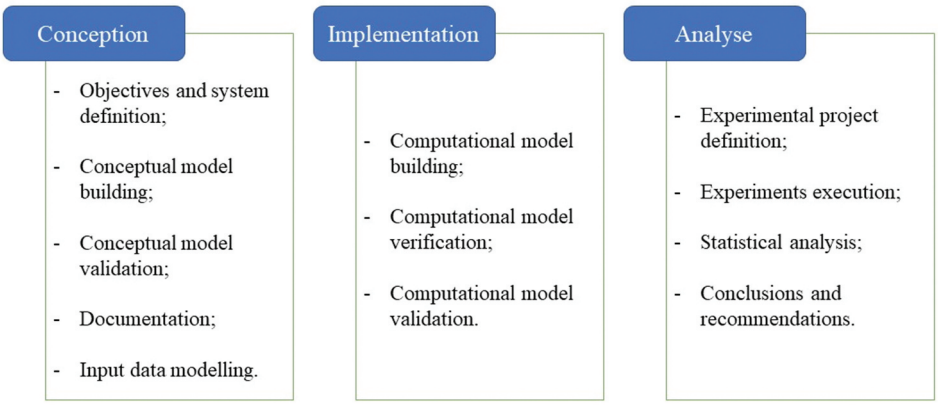

Figure 2. Structure of the method proposed by Montevechi et al. (2010)

previous knowledge of the model and simulation software (Rodič, 2017). Finally, some other characteristics that should be presented in simulation models as DT include a connection between the simulation model and sensors, IoT devices and management systems; model adaptation in real or near real-time due to changes in real systems; connection with analysis and optimisation tools; constant support in decision-making; among others (Alam & Saddik, 2017; Tao & Zhang, 2017; Uriarte et al., 2018).

Given these considerations, we proposed some modifications to the method in order to make it suitable for the present application. The following changes were required at each phase:

(1) Conception

This phase stages have not changed. However, a new nomenclature for this phase is proposed, aiming for a better representation of its activities. Therefore, the first phase of the method is called "Conceptual Modelling".

(2) Implementation

Regarding the use of simulation as a DT, data is sent from the real system to the digital model. Then the digital system is simulated, and the computer instructions direct the results from the digital model to the physical environment again (Kunath & Winkler, 2018). Thereby, two new steps were introduced in the method, called "Model update data and desired responses definition", and "Interface structuring with the real process". Moreover, the phase nomenclature has also changed, being called "Computational Modelling." Given these modifications, it is intended to answer the following questions:

- *What are the necessary parameters for updating the simulation model, in order to reflect the physical system?*

- *What information should the simulation model return to the physical environment?*

- *How will the connection and interface be made between the simulation model and the physical process, in order to allow the exchange of data and information between them?*

(3) Analyse

Finally, in the Analyse phase, we proposed three new stages, which will replace the stages proposed by Montevechi et al. (2010). These steps are called "Future scenarios definition", "Periodic scenarios execution", and "Analysis and decision-making". The phase nomenclature has also been changed to "Operational Modelling". From the proposed changes, we intend to answer the following questions:

- *Which scenarios should be tested considering the desired model responses already defined in the Computational Modelling phase?*

- *How often should the model be executed given the decision-making needs?*

Figure 3 illustrates the method after the modifications.

3. Results and discussions

The proposed method was applied to a real study object. Thus, we intended to analyse the main characteristics, advantages, and challenges of this application, besides the viability of its use.

3.1. Study object

The study object of this paper is a process of supplying materials of an aeronautical industry. The company is composed of four production lines located in different spots of the plant and which have independent demands. Each line has an intermediate on-site stock, called "kanban station", allowing materials to be placed close to production lines. As these materials are consumed, they should be periodically replaced for the correct operation of production lines. These kanban

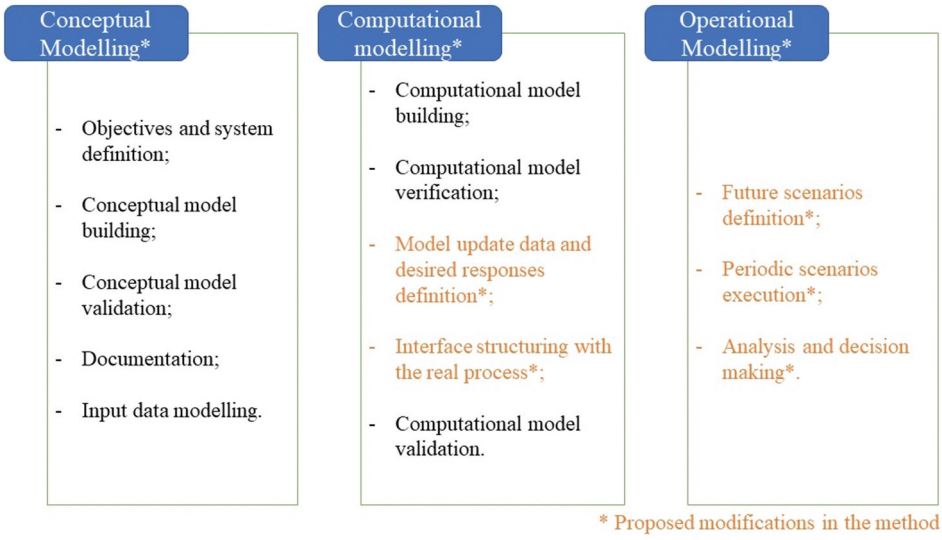

Figure 3. Method structure for using the simulation as DT.

stations are filled with materials present in the warehouse. The plant has a relatively sizeable built-up area, which is a common feature for industries in general, allowing the logistics team, responsible for the supply, to choose from one of many possible supply routes. In this case, the choice of the best supply route is often related to the team's experience, and we cannot guarantee that the chosen route is the most efficient choice. Furthermore, it is a mostly manual process. The materials consumption of each kanban station is recorded in the operation's Enterprise Resource Planning (ERP) and the logistics team is responsible for manually replenishing such stations. The presented scenario constitutes a common problem in industries from the most different segments and justifies the contribution of this study. In this case, the objective is to optimise the logistics team's decision making regarding the best supply route. Figure 4 illustrates the kanban stations in the plant.

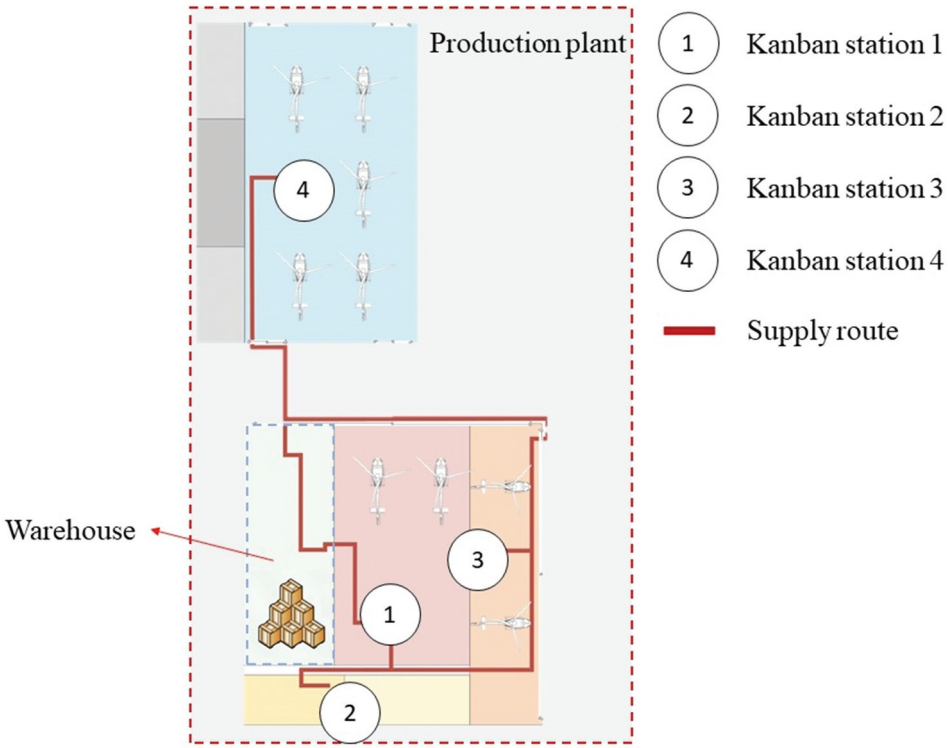

Figure 4. Production plant illustration.

3.2. Application

3.2.1. Conceptual modelling

Initially, we defined the objectives and definitions of the system, considering the general objective of this research. The first objective of the simulation model is to provide the most efficient route in terms of the distance travelled by the logistics team. Moreover, it is necessary to keep in mind that it is not always possible to supply all kanban stations in just one working day, as production lines may vary in their material consumption pattern and may require a high replacement volume, overloading the supply process. In this case, the choice of the supply route directly impacts the supply of kanban stations. Furthermore, the second objective of the simulation model is to provide the most efficient route in terms of the amount of materials daily supplied. In this case, the logistics team should supply as much materials as possible on the day.

To achieve these objectives, the simulation model should be able to understand the supply demands of each kanban station, simulate possible routes and provide the best route to follow, considering the shortest distance and the greatest amount of materials delivered. Moreover, we built an interface between the simulation model and the real process, allowing the integration of both and making the virtual model a reflection of the real system, acting as a DT. The purpose of the interface is to ensure that as the real process changes its demand for materials, the model is updated periodically. This structure makes decision-making possible based on the model results, interfering again in the real process, and closing the decision cycle. Figure 5 illustrates the proposed approach.

After defining the system objectives, it is possible to build the conceptual model. Chwif and Medina (2015) point out that, to represent the real process, it must start with a suitable technique to represent simulation models. For this, we used the IDEF-SIM modelling technique, developed by Leal (2008), which uses logic elements adapted to simulation projects. The use of IDEF-SIM allows conceptual modelling closer to the computational model requirements, helping to reduce the time spent during the execution of this phase (Montevechi et al., 2010). The supply process is divided into two stages: (1) Receiving and storage and (2) Kanban replenishment. The first stage includes the arrival of the materials at the warehouse, and the second one consists of the kanban stations replenishment, which covers from the consumption of materials by the production lines to the materials supply by the logistics team. Stage 2 is the main study issue since all the analyses will be done based on this scope. Figure 6 presents the process conceptual model.

The materials arrive at the warehouse in boxes. Boxes of type 1,2,3 and 4 related to the materials of kanban stations 1, 2, 3, and 4, respectively. Type "O" boxes contain other materials that are stored in the warehouse. After going through the "Receiving & Inspection" operation (performed for a "Receiving CT" period), the kanban materials are stored in the warehouse, in a specific location, where they are waiting to be collected later. From the consumption of materials at the kanban stations, the logistics team is responsible for checking the demands and collecting new materials at the warehouse. In this case, the process first passes through the "Picking point", where the materials are collected and identified (for a time "Picking CT"). After being prepared, the materials are transported to the "Delivery point", where the materials are separated into "packs", according to the kanban station to which they will be destined. Finally, the packs are transported to each kanban station, where they are allocated for a "Delivery CT" period. All transport is carried out manually and at a "Travel speed".

The conceptual model was validated by the research team and the process managers. Regarding the model's input data, three parameters are essential: "Picking CT", "Supply CT" and "Travel Speed". We have considered the Supply CT as deterministic data (30 seconds). For the other parameters, data were collected through sampling, analysed using descriptive statistics, and linked to probabilistic models. The times were associated with normal distributions (95% confidence level). For Picking CT, we have a normal distribution of N(176.10, 26.77) seconds, and for Travel Speed, we have a normal distribution of N(1.10, 0.26) m/s.

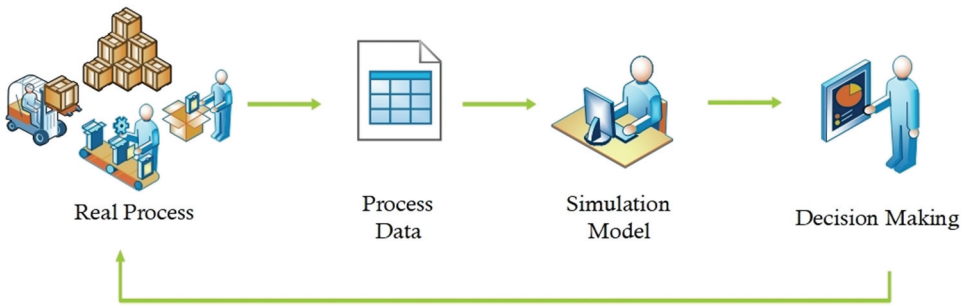

Figure 5. Proposal for using simulation as a DT for decision making.

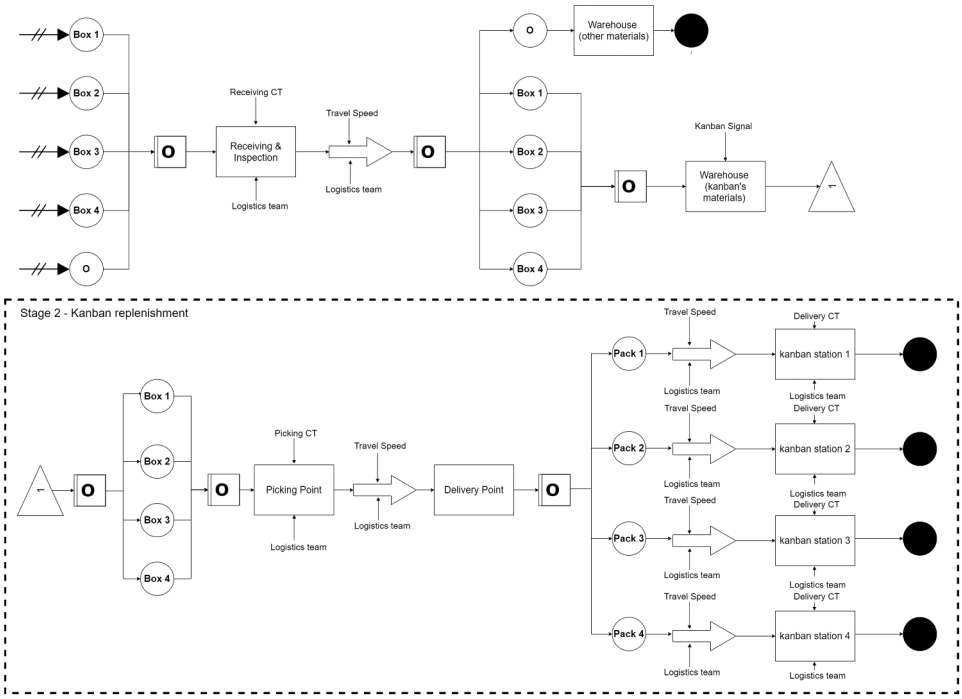

Figure 6. Conceptual model of the material supply process.

3.2.2. Computational modelling

The next step was to build the computational model. Rodič (2017) points out, among other features, the high graphic resolution of the computational model, the high level of detail, and the low level of abstraction as essential features for the adequacy of the simulation as DT. Thus, we decided to use the FlexSim® software and Figure 7 shows the 3D model.

The computational model verification should focus on the model's functions analysis, such as the simulation logic, times, and activity flows (Sargent, 2013). Thereby, the computer model verification was performed using two techniques suggested by Chwif and Medina (2015): (1) Modular implementation, which is based on the construction and testing of the model in parts, and (2) Graphical animation, where it seeks to identify and correct errors through the model visual monitoring during the simulation.

3.2.2.1. Model update data and desired responses definition. As the demand for materials at each kanban station is a crucial factor for changes in the real process, we chose it as the data needed to update the simulation model. Thus, the simulation model was programmed to periodically receive a list of all materials consumed in the different kanban stations and,

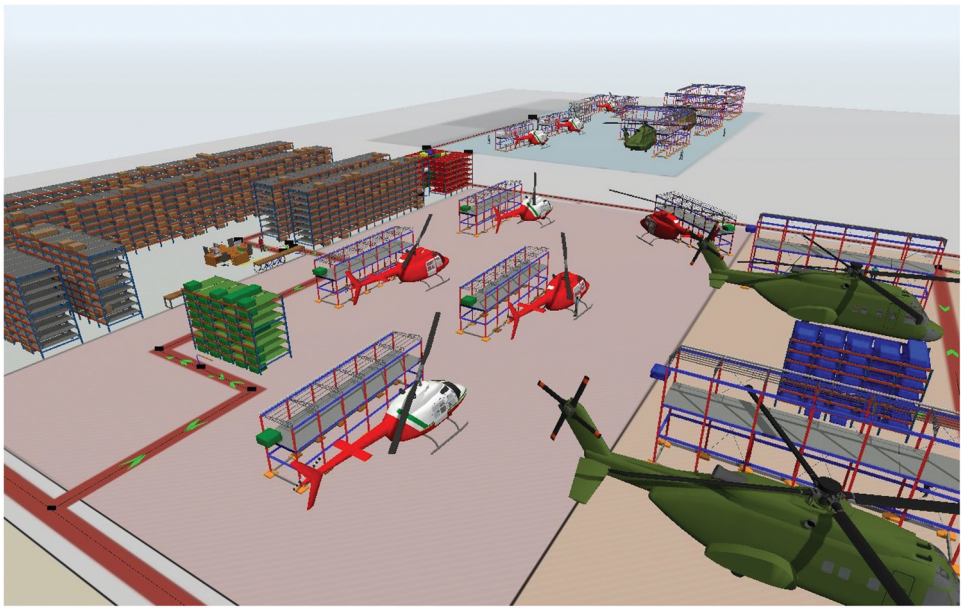

Figure 7. 3D view of the computational model.

upon this entry, the model adapts itself to reflect the real process. Therefore, it is a proposal for a near real-time DT. Regarding the desired response for the real process, we defined it as the most efficient supply route. In this case, the distance travelled by the logistics team is considered, as well as the amount of materials supplied in the period. Equation 1 illustrates this relationship and Table 1 summarises this step.

$$\textit{Most efficient route} = f(\textit{travelled distance}, \textit{supplied amount in the period}) \quad (1)$$

3.2.2.2. *Interface structuring with the real process.*

The interface that establishes the connection between the real process and DT can be implemented in different ways, depending on the characteristics of the simulation software and the connectivity between the real and the virtual systems. Skoogh et al. (2012) point out that simulation software has increasingly developed communication tools with external sources, reducing the need for intermediate systems. However, it is noted that direct connections are still tricky, mainly because data need to be prepared before being inserted into the simulation model. This fact explains why intermediate systems and interfaces have been widely used (Barlas & Heavey, 2016).

For the interface creation, we used a "Control and Management Dashboard", built from Microsoft Excel® software. Furthermore, we used a programming language already present in this software, the Visual Basic for Applications (VBA), used to automate the dashboard commands. Such choices are justified by the versatility of the software, widely used in the world, and which has secure connectivity to the company's ERP and Flexsim®. The dashboard initially functions as a database, importing reporting material demands that come from the operation's ERP. It then allows the virtual model to be updated and simulated automatically, with the operation data. Finally, the dashboard allows obtaining the results from the simulation, enabling the subsequent decision-making. This entire process is performed semi-automatically, merely selecting the corresponding button to the desired option in the dashboard. Figure 8 illustrates the dashboard created, followed by its main elements.

Dashboard I, II, III, and IV elements play a fundamental role in system operation, as described below.

(I) Dashboard Control Buttons: through these buttons, the user interacts with the system;

(II) Route panel: after exporting the simulation results, the dashboard will present the three best routes;

(III) Comparison Charts: the dashboard displays the route comparison charts;

(IV)Route map: indicates the supply order of the kanban stations to guide the decision making.

Finally, we highlight that the dashboard and the simulation model do not necessarily have to be in the same physical space as the operation since the data obtained from the ERP reports can be inserted in the simulation model through cloud technology. Figure 9 illustrates how DT interacts with the real system through the decision making

For the computer model validation, we opted for the "Formal Quantitative" procedure, where statistical tools help to determine operational validity (Chwif & Medina, 2015). The parameter chosen was the Unit

Table 1. Model update data and desired responses.

Model update data	Desired response
Demand for materials at each kanban station	The most efficient supply route

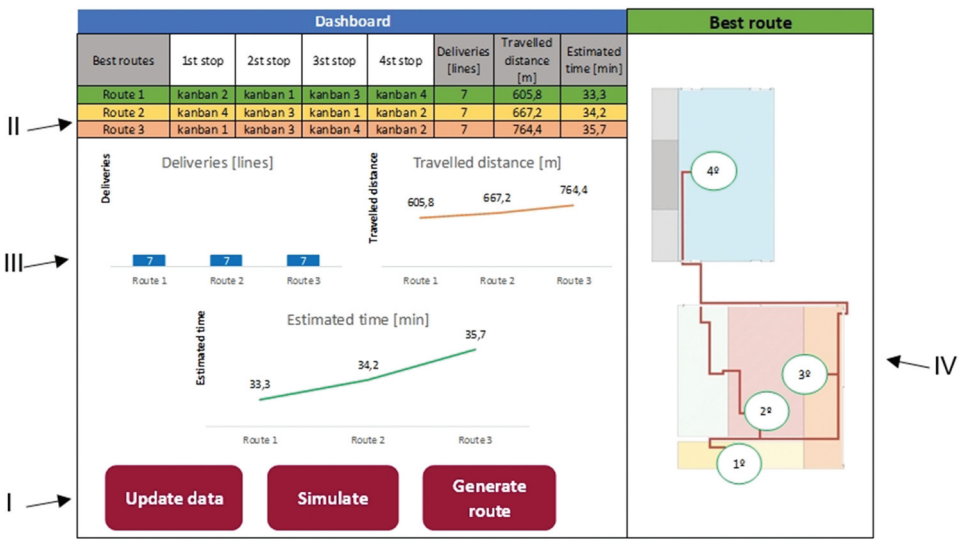

Figure 8. Interface dashboard that links the real process to the simulation model.

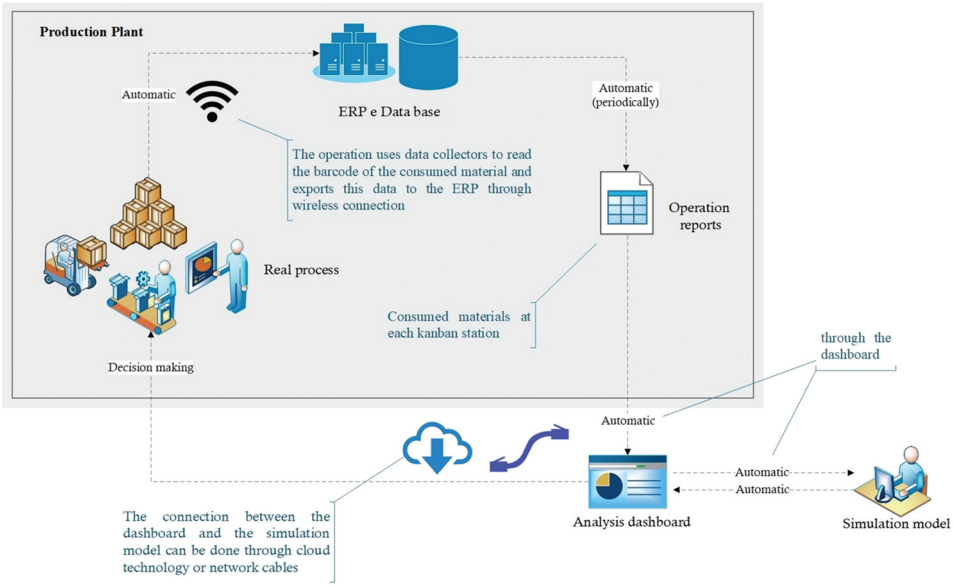

Figure 9. Data and information flow architecture between the real system and the simulation model.

Supply Time (UST). To obtain the UST, the total time of each supply round was divided by the amount of supplied materials. Thereby, we chose the variance ANOVA test to compare the real system data with the results of the model's replicates. In this case, the simulation model was programmed to run 17 replicates in each round, in order to provide the accuracy of one minute and the 95% confidence level (Chwif & Medina, 2015). 15 supply rounds were considered for the test. The ANOVA test shows that it was not possible to prove significant differences between the real and simulated data (p-value = 0.584) with a 95% confidence level, validating the model (Montgomery & Runger, 2011). Figure 10 shows the boxplot that compares the real UST with each model replicate.

3.2.3. Operational modelling

In the operational modelling phase, the simulation model is already validated and ready to be used. Thereby, it is possible to explore the benefits of using the simulation as a DT.

3.2.3.1. Future scenarios definition. For scenarios definition, we opted for the optimisation via simulation approach. The scenarios were defined to test the possible supply routes and obtain the ideal route based on travelled distance and material replenishment. As an optimisation parameter for the software, the travelled distance should be minimised while the amount of materials supplied in the period should be maximised. Equation 2 illustrates the objective functions considered.

$$\begin{aligned} Objectives: Minimize\ (Travelled\ distance) &= \sum_{i=1}^{4} x_i \\ Maximize\ (Material\ replenishment) &= \sum_{i=1}^{4} y_i \end{aligned} \tag{2}$$

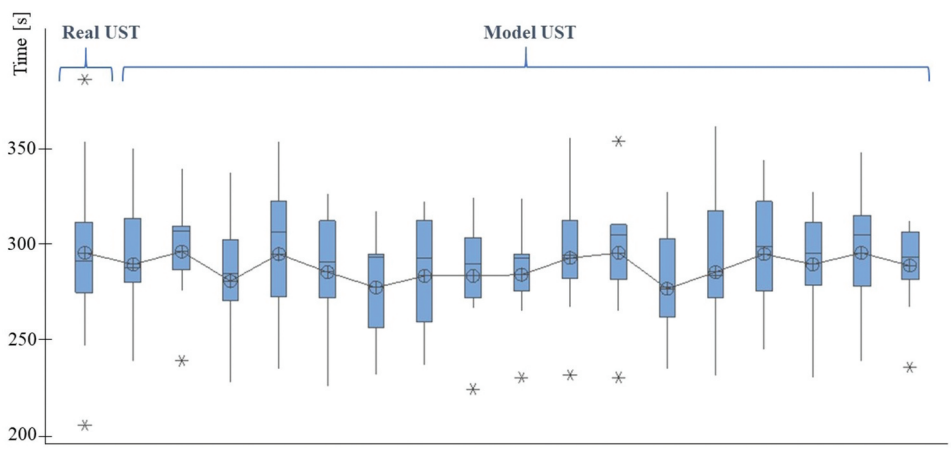

Figure 10. Boxplot comparing the real UST with simulation results.

In which x_i is the distance travelled from a previous point to the kanban station i and y_i is the amount of materials replenished at the kanban station i, both considering one supply round at a time.

Subject to: $\sum_{i=1}^{4} y_i \geq$ *The total amount of materials consumed at each kanban station* (there are cases where the minimum batch to be replenished is greater than the consumed amount).

After carrying out the experiments, the model classifies each of the routes in a ranking where the optimum presents the best result combining the response variables. In this way, the results are recorded in a database and imported to the control and management dashboard. It is worth mentioning the possibility of defining other scenarios to be tested, according to the decision-making needs. Issues related to workload analysis, task redistribution, layout changing, and other common shop floor problems can be solved using this approach.

3.2.3.2. Periodic scenarios execution. The periodic model execution is one of the main characteristics of DT. Tao et al. (2018) underling that DT must be integrated and synchronised with the physical system in order to represent it accurately and realistically through communication between them. Therefore, the simulation model should be executed at predetermined periods to represent the real process in its main characteristics. Therefore, it is possible to build a virtual system that reflects the real system through its data, enabling the simulation model to be adapted and modified according to the physical system variations, aiming to predict and optimise decisions for the real system (Rodič, 2017).

Moreover, the time interval between model runs should be chosen in a way that allows decision making on time. Uhlemann et al. (2017) point out that the virtual model must be updated with a minimised delay after data collection. Kunath and Winkler (2018), complement that DT's results need to be as fast as possible so the decision will not be hampered, which would disturb the real process. Therefore, in the case of near real-time DT, it is necessary to consider the characteristics of the process under analysis when defining the time between model updates. The material supply process is carried out during the entire working day and, when a supply route is completed, the process starts again, with a new decision making. Consequently, at the end of each route, the operator must make a new decision for the next route. For this new route, the simulation model will be updated and executed, assisting in decision making.

3.2.3.3. Analysis and decision-making. The decision-making frequency will depend on the consumption of materials by the production lines. We expect working days that only one supply round will be carried out, and others where several rounds will be necessary, demanding different patterns of DT use. Figure 11 presents a flowchart summarising the decision making from the perspective of the team responsible for the supply process.

Previously, the decision on which route to take was based only on the team's experience. In this scenario, cases such as job rotation and drastic changes in demand resulted in inefficiencies in the material supply process. From the proposed DT, despite being a manual process, it was possible to optimise decision making, since the team's experience and variations in demand do not affect the performance of the process.

3.3. Discussions

After implementing DT through simulation, we can analyse the proposed approach, considering some points covered in the literature. The DT concept, although it was defined almost ten years ago by Shafto et al. (2010), it has gained more relevance in recent years, becoming one of the key terms in the Industry 4.0 context. In its first definition, Shafto et al. (2010) defined DT as a virtual copy of a real system, which is based on the analyses of its data and able to optimise the decision making. However, despite being a broad concept, present in several works, there is still some confusion regarding DT characteristics (Kritzinger et al., 2018). Wright and Davidson (2020) report that DT features may vary according to the application area and even within the same area there may be variations. Issues such as the degree of autonomy and reaction time can be discussed to define essential requirements for a DT.

Regarding reaction time, it is important to mention that data collection and DT reaction are independent activities that may occur at different times. In this case, Tao et al. (2018) and Kunath and Winkler (2018) report that data collection from physical systems must be performed in real-time to allow the DT updating when necessary. However, the DT reaction does not necessarily have to be in real-time but must occur when there is a need to make decisions. This fact allows some flexibility to DTs and, therefore, the near real-time approach is reasonable (Alam & Saddik, 2017; Onggo et al., 2018). On the other hand, it is also important to analyse issues related to the degree of autonomy of DTs. In this case, the literature presents some examples of autonomous DTs, where decision making is associated with automatic systems and without human intervention (Beregi et al., 2018; Donhauser et al., 2018). However, the DT's response, according to its definitions, can be characterised by recommendations and guidelines for decision making, involving the figure of the decision-maker (Alam & Saddik, 2017; Lu et al., 2019; Vijayakumar et al., 2019).

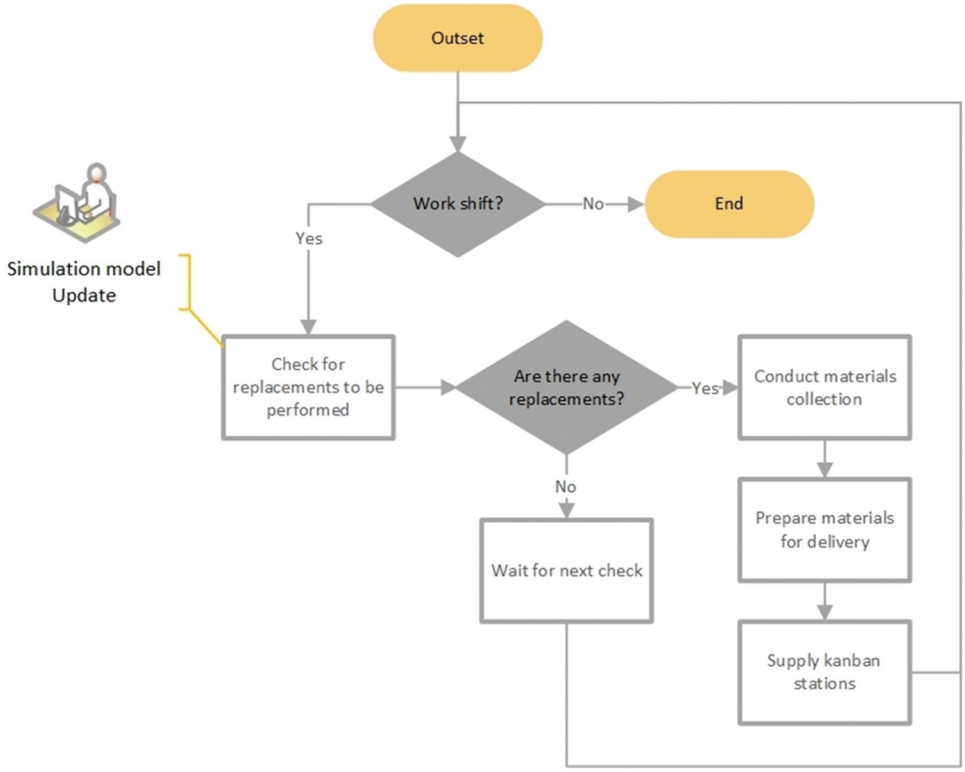

Figure 11. General flowchart for the material supply process.

Therefore, the degree of autonomy of the DT will also depend on the characteristics of its application and both autonomous and semi-autonomous approaches may be considered.

Given the above considerations, the proposed approach meets the requirements of a DT when considering its implementation through simulation. The operation's ERP is updated in real-time according to material consumption at kanban stations. When decision making is required, the simulation model is updated with the information from ERP and provides guidelines to decision-makers responsible for the supply process. Moreover, we noted that the use of simulation as DT expands its application possibilities, allowing to solve difficulties and challenges experienced by traditional approaches, as well as evidencing the compatibility of the simulation with the precepts of Industry 4.0. From the integration of simulation with real systems, we can build intelligent models, capable of adapting to real behaviours and supporting the decision more effectively.

To compare the decision making based on the experience of the logistics team and based on the DT guidelines, an experiment was carried out with twelve supply rounds. The DT was updated each round, but the supply routes were determined traditionally, without consulting the DT results. Thus, it was possible to estimate the potential gain of the proposed tool. Each supply round considered had a low and similar supplied amount. We observed an average travelled distance of 704.3 metres per round, compared to an average of 563.9 metres considering the routes provided by DT. This represents a potential reduction of approximately 20% in the unnecessary movement of people, a non-value-adding activity. Figure 12 shows the boxplot that graphically presents the differences in the travelled distances. Moreover, a Two-sample t test was performed, showing that the difference between both is statistically significant, with a 95% confidence level (p-value = 0,00).

It is important to highlight that this work has some limitations. Regarding the type of simulation used as DT, besides DES (Lu et al., 2019; Vijayakumar et al., 2019), there are works in the literature that also use Agent-Based Simulation (ABS) and hybrid approaches, as proposed by Beregi et al. (2018). However, the focus of this paper was not to address each type of simulation but to provide a practical guide for the creation of DTs through DES, as well as demonstrating its applicability in a real non-automated process, discussing the characteristics and requirements for this approach. The DES choice justified because it is the most used simulation technique in manufacturing decision making (Uriarte et al., 2018). Furthermore, due to the study object characteristics, we did not consider the creation of several DTs working in a synchronised way and acting in decision optimisation in a wide scope of the process. Such considerations represent opportunities for future research.

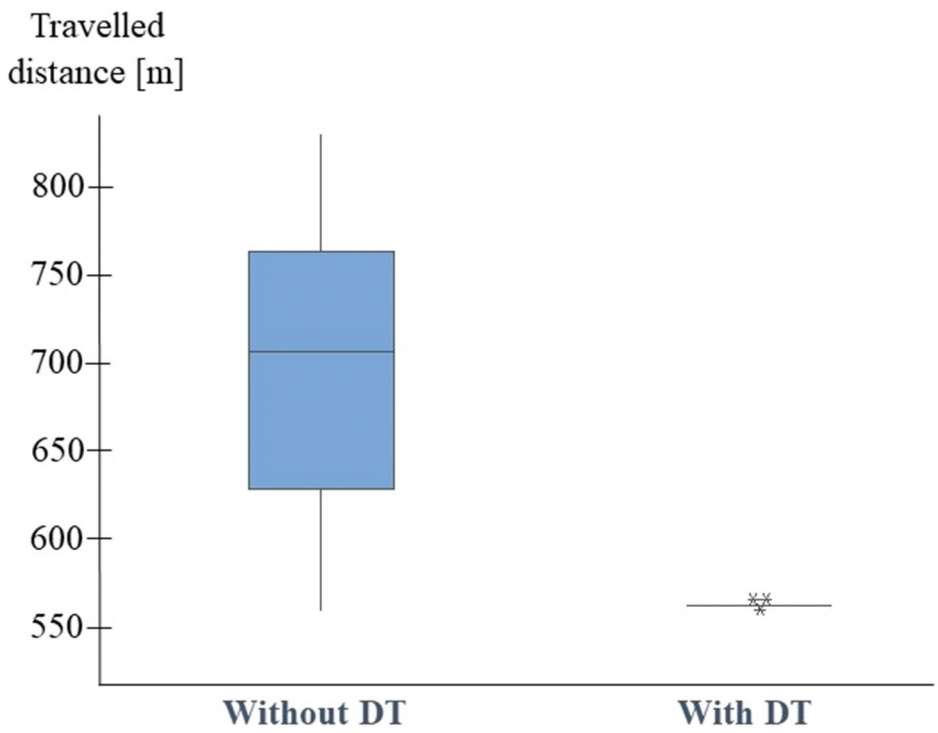

Figure 12. Boxplot comparing travelled distances in supply rounds.

Table 2. Simulation in traditional applications vs. DT.

Features	Traditional approaches	Simulation as DT
Data collection	Manual	Automatic[a]
Model update	Manual	Automatic and periodic[a]
Time perception	Analyses with historical data	Real-time or Near Real-time analysis[a]
Scope	Limited[a]	Embracing
Main goal	Punctual Analyses	Constant aid for decision making[a]
Complexity	Need for Experts	Friendly interface[a]
Integration with real processes	No	Yes[a]
Degree of autonomy	None	Autonomous or semi-autonomous[a]

[a]Features present in the proposed DT

Finally, we can compare the main characteristics of simulation projects considering its traditional and DT applications, as shown in Table 2.

4. Conclusions

The use of simulation, more precisely from DES, as DT in a real non-automated process proved possible from the present research. Although the adoption of Industry 4.0 solutions is linked to high investments and adjustments by the processes, it is noted that challenges can be reduced by using versatile tools, such as simulation. First, to adapt the use of simulation in this context, a method for conducting simulation projects of this nature was proposed. In this case, steps were considered related to the integration of the simulation with the process data, as well as its constant updating due to changes in the real environment, making possible its use in the day-to-day decision-making. The proposed approach was used in a real study object in order to verify its applicability.

The study object refers to an aeronautical industry logistic process. It is a process of supplying materials at kanban stations and, through the proposed DT, it is possible to optimise decisions related to supply routes. From the integration of the simulation model with the operation's ERP and the creation of a friendly control and decision-making interface, we obtained a model capable of updating itself according to the changes occurred in the physical environment, simulating scenarios, and providing directives for more efficient decision-making. Finally, the work also addressed some discussions related to the use of simulation as DT. In this case, we highlighted characteristics such as reaction time and degree of autonomy of the DT, in addition to the comparison with traditional simulation projects, with emphasis on the advantages of using it as DT. It is worth mentioning research opportunities related to the creation and integration of several DTs in the same operation, aiming at making decisions in a broader scope of action trough simulation.

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