35th European Modeling & Simulation Symposium
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0029 © 2023 The Authors.
doi: 10.46354/i3m.2023.emss.032

Implementation and integration of a Digital Twin for production planning in manufacturing

Michela Lanzini[1,*], Nicola Adami[2], Sergio Benini[2], Ivan Ferretti[3], Gianbattista Schieppati[4], Calogero Spoto[5], Simone Zanoni[3]

[1]Department of Mechanical and Industrial Engineering, University of Brescia, Brescia, Italy
[2]Department of Information Engineering, University of Brescia, Brescia, Italy
[3]Department of Civil, Environmental, Architectural Engineering and Mathematics, University of Brescia, Brescia, Italy
[4]Neosperience S.p.A., Brescia, Brescia, Italy
[5]Fabbrica d'Armi Pietro Beretta, Gardone Val Trompia, Brescia, Italy
[*]Corresponding author: michela.lanzini@unibs.it

Abstract

The aim of this paper is to discuss the theoretical concepts and the preliminary steps required for the implementation of a Digital Twin for a manufacturing company that would integrate data from a Manufacturing Execution System (MES) with Discrete Event Simulation (DES) to improve production planning. The Digital Twin would aim to represent material flows in the production department, in order to improve the monitoring and the control of production scheduling, allowing the timely identification of deviations from the plan and a more responsive and informed management of any delay alerts; the final goal is to provide a conceptual framework to improve the synchronization of material flows and enhance punctuality towards the final customer. This contribution also discusses the level of integration required among the following enterprise systems, with which the Digital Twin would interface: the MES (Manufacturing Execution System) for constant updates on production status and order progress; the ERP (Enterprise Resource Planning) for resource planning data; the PLM (Product Lifecycle Management) regarding products design and their production cycle; the GPS (Global Planning System) regarding order scheduling. These data streams, following adequate data preparation steps, will feed into the Discrete Event Simulator (DES)

Keywords: Digital Twin, Industry 4.0, MES, Discrete Event Simulation, Dataflow

1. Introduction and literature review

In recent years, the term Digital Twin (DT) has been increasingly mentioned not only in the literature related to Industry 4.0, but it has also started to appear more frequently in conversations within large companies, particularly in the IT and digital sectors. The fact that the term "Digital Twin" is very evocative and, although in an approximate and undefined way, sufficiently self-explanatory, has two effects: the first is that the concept has gained popularity across various application fields, transcending the boundaries of the areas in which it was initially developed, i.e. aerospace engineering, robotics, manufacturing sector, and IT (Negri et al., 2017); the second is that there is no agreement on the exact definition of what it actually is, or on what the "minimum requirements" are to be able to talk about it.

As shown in Fig. 1, the publications indexed on Scopus featuring "Digital Twin" in the title have increased markedly over the past few years, exceeding 5000 in 2022 (and over 10,000 in 2022 on Google Scholar). It is also possible to note that approximately 17% of the publications indexed on Scopus are not inherently related to the traditional application fields of the Digital Twin, that is, the production-engineering and Computer Science (CS) areas. Some of the other most common fields are the medical, chemical, energy, biological, and agricultural sectors. This transversality of application makes DT a very flexible tool, but as mentioned, this entails a general lack of agreement on an exact definition, thus difficulties to identify the requirements.

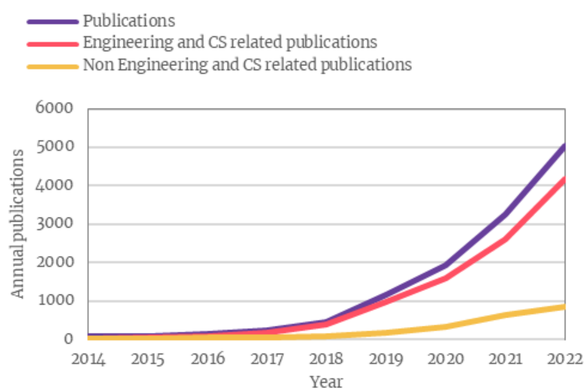

Figure 1. Number of Scopus publications per year that contains "Digital Twin" in their title.

For the preliminary work to implement a Digital Twin in a manufacturing company, the following elements of the literature have been taken as reference, in order to outline the characteristics required for this technology.

Formally, the first to present the concept underlying the DT was Grieves, who, within the scope of product lifecycle management, presented the idea of a real space and a virtual space, connected/interconnected by bidirectional flows of data and information. The idea was named "mirrored space models" (Grieves, 2005).

The first actual definition of Digital Twin, including its nomenclature, can be found in the final release of the NASA Modeling, Simulation, Information Technology & Processing Roadmap (2010 and 2012) where it is described as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin. It is ultra-realistic and may consider one or more important and interdependent vehicle systems."

In subsequent periods other terms were identified to express the concept just expressed or to read variations of the same: it is relevant to mention the Digital Surrogate, the Digital Shadow, and the Virtual Twin to provide the reader with references and possible directions for comparison and deeper understanding. It is in fact relevant to clarify that the nomenclatures presented may refer to a system that has many features assimilable to those of a Digital Twin, or a system with few substantial differences, in which however both the thought behind the system described by Grieves, that is a real world and a virtual world connected by a bidirectional flow of data and information, and the concept of Nasa's ultra-realistic multi-scope simulator are maintained. The key functionality of a Digital Twin, according to the NASA publication, are prediction, monitoring, and analysis of unpredicted disturbances.

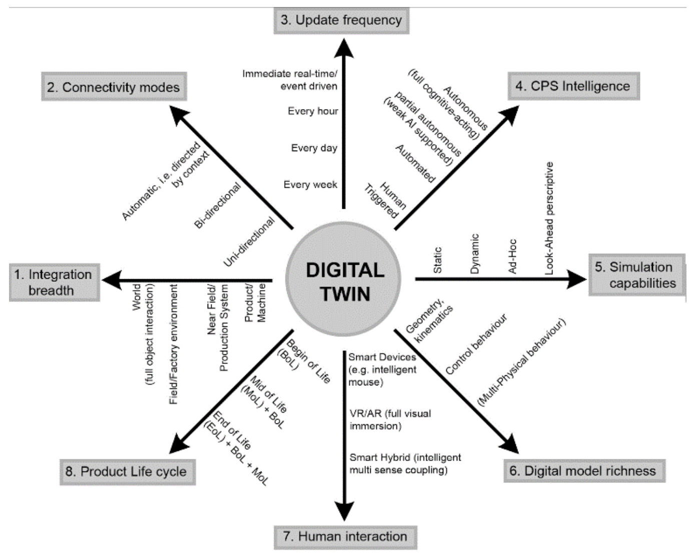

Figure 2. The "Digital Twin 8-dimension model", Stark et al., 2019

Turning to a more application-oriented standpoint, the insight of Rosen and Borschen (Boschert and Rosen, 2016; Rosen et al., 2018; Rosen et al., 2019) is particularly relevant. They describe the Digital Twin as a unification of relevant digital information (design data, operational data, lifecycle data) integrated with models that can adequately describe the behavior of a system. The DT must therefore integrate the concepts of system engineering, based on models, and extend them coherently to the operational and service phases. By this structure, the DT is configured as the "next wave of simulation, by means of seamless assistance along the entire life cycle". These concepts are central to Industry 4.0: it is possible to use DT to create a system that can provide new and faster information, allowing the decision-maker to intervene in the real system while being confident that the system will not react inappropriately.

Finally, Fig. 2 shows the list of the 8 dimensions with which a Digital Twin can be classified (Stark et al., 2019); the author specifies that a higher level in some dimensions does not necessarily correspond to a more desirable situation, but simply to a different state of study. In conclusion, this brief analysis of some of the most relevant sources shows how ambiguity of definition, combined with transversality of application, makes the concept of Digital Twin circumstantial and complicated to manage.

Regarding the manufacturing field, it is possible to find some interesting applications of the digital twin, such as the digital twin for an experimental assembly system (Židek et al., 2020) and recently, (Eunike et al., 2022) a DT was also implemented for an adaptive scheduling process for the assembly of a component on four stations.

In general, a framework that presents how a DT can be integrated with enterprise information systems in order to support the planning process is not widely present in the literature yet.

The purpose of this paper is to start developing such a framework in case the DT needs to capture the multidimensionality and complexity of a large number of processes, which will need to be simulated with a discrete-event simulator. The connection with the MES is subdivided into two conceptual phases: in the first one, there will be the analysis of historical MES data, and in the second one would be monitoring the production with the MES data, but with a higher frequency. in this way, historical MES data will lead to statistical distributions to be fed into the DES for the simulations and the predictions, and with the day-to-day date it will be possible to monitor and control the progress.

The paper will be structured as follows: in Section 2, the interrelationships of business information systems will be presented; in Section 3, the integration of DT within business information systems will be discussed; in Section 4, the advantages over traditional solutions will be presented; conclusions will then follow.

2. Standard manufacturing information systems

Having provided the starting definitions, it is now possible to delve into some possible real applications of the DT: the ultimate goal of this research would be the implementation of a Digital Twin focused on production and internal logistics, in order to improve the current method of production planning and to better the monitoring the operational processes, with the ultimate goal of being able to improve the customer service and, in particular, to be able to improve the delivery time estimate and improve the punctuality indices. In a dynamic environment, punctuality management strategies are of extreme interest, because in companies it is common practice to overestimate delivery times in order to make them easier to meet.

The purpose of structuring a Digital Twin is not only to support planning activities, but also to enable more in-depth, advanced, and reactive analysis in the face of the scenario presented. An example of this analysis is simulation optimization: with a suitable Digital Twin structure, it would be possible to accurately evaluate the rescheduling options when a disruptive event occurs, such as prolonged machine stops, numerous defectiveness in lots previously synchronized for assembly, supplier delays in input; even the optimization objective could vary: it could be marked as the objective to minimize inventory accumulations or the minimization of subsequent delays to the final customer. The benefits of the Digital Twin are therefore those of trying to aim at the stability of the planning performances under unforeseen circumstances and to propagate disruptive events along the entire internal process if they cannot be corrected. The project thus aims to cover a series of subsequent and transversal needs concerning the series of operations.

Fig. 3 shows the main information systems in a manufacturing company and their interrelationships, which are very important factors to evaluate in order to understand how a digital twin can fruitfully connect with previous information systems.

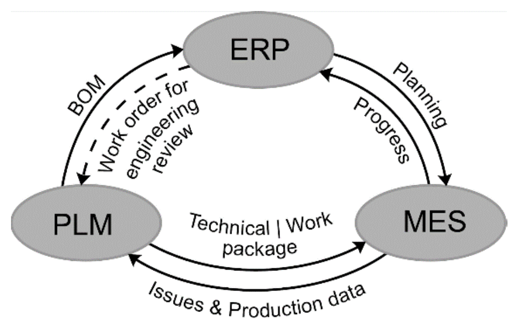

Figure 3. main Information systems in a manufacturing company and the main data flow among them

Typically, in a manufacturing company, the main three information systems are ERP, MES, and PLM; enterprise resource planning (ERP) is a management software that integrates all business processes and all relevant business functions, e.g., sales, purchasing, inventory management, finance, or accounting. It integrates all business activities into a single system to better support management. Through such a system, data from multiple parts of the company are collected and managed centrally; applications have been developed to help business managers implement this methodology in business activities such as inventory control, order tracking, customer services, finance, and human resources. Usually, as a business starts to grow, an ERP is one of the first information technologies bought.

The manufacturing execution system (MES) refers to a computerized system whose main function is to manage and control the production of a company. The management involves the dispatch of orders, quantity and time advancements, deposit to stock, as well as a direct connection to machinery. So, a MES is a software system that is applied to manage a company's production process in an integrated and efficient way, through both direct connections to machines (PLC/SCADA) and/or manual declarations of the operators who are working on a specific machine. This information from the floor shop, about progress in work orders, is collected in real-time, even though the data extraction activity can be quite time-consuming, and is fed into the ERP, from which the ERP receives the production planning.

Product lifecycle management (PLM) is a strategic approach (as well as information technology) to the management of data and information, processes, documents, drawings, and resources to support the lifecycle of products and services, from their conception, development, production, support, and retirement. PLM communicates with both ERP and MES. In terms of MES, it provides the technological cycle of the products, receiving as input the processing performed on the floor level; in terms of ERP, PLM provides information required to manage the entire production side, such as bills of materials, and receives information about any revisions and reengineering of products from ERP.

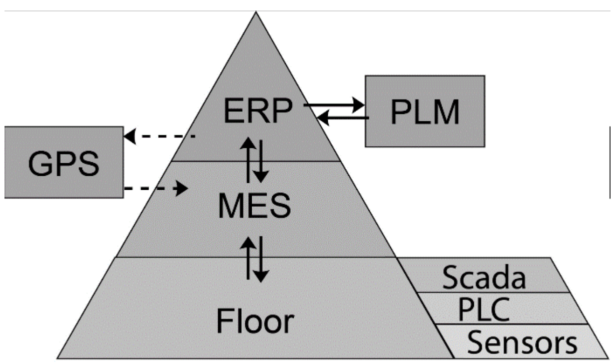

Figure 4. Pyramid of Industrial Automation as per ANSI/ISA95 standard

Often, the communication between these three elements is not seamless and requires some effort to acquire, extract, clean, and transfer data to make it usable. This is frequently done at times when the plant is at its productive minimum (e.g., overnight). However, these three systems are not the only information systems that aim to manage, control, organize, and simplify production: Fig. 4 depicts the "Pyramid of Industrial Automation," as defined by ANSI/ISA95 standards. The Industrial Automation Pyramid is a hierarchical illustration of the various levels of automation and control accessible in the industrial production process.

As shown in Fig. 4, the ERP is the information system that operates at the enterprise level, and the other systems are hierarchically dependent on it; at the second hierarchical level, we have the MES, which, as anticipated, operates at the management level. The supervisory, control, and field levels are represented by SCADA, PLCs, and sensors beneath the MES; structured DT concentrates on the higher hierarchical layers of this automation pyramid.

Although the ANSI/ISA 95 standard was designed to address a critical industrial business issue, namely standardizing integration procedures between disparate enterprise and control systems, and although this standard is widely accepted and implemented, it cannot be assumed that data flows are completely seamless in the operation of the individual enterprise; on the contrary, it is not uncommon to find at the industrial level fragmentation and proliferation of local information systems, which creates difficulties in managing data flows

For the company under consideration in this case study, for example, the flow of data from the ERP to the MES, which includes production planning, goes through another enterprise planning support system: the Global Planning System (GPS); the automation pyramid also lacks an important previously discussed element, represented by PLM.

Another aspect of the pyramid representation that is not explored in depth is data collection from the production department: depending on the level of automation implemented on the individual machine and on the production floor, data collection can take place in two ways:

- automatically, by utilizing specially placed and designated systems to collect and pre-process data, which is then fed into appropriate hardware and software facilities, from which it will be extrapolated and analyzed at a later stage. (Peterson, Daily, 2016)
- manually, for activities with a low level of automation and/or that are poorly automatable and where human presence is and will remain an incompressible or uneconomical factor for an indefinite amount of time.

Other data flows, despite the Industry 4.0 manifesto and the industrial automation principles, are neither instantaneous nor real-time: the multitude of systems that must be integrated, combined with the varying levels of automation already found in the same departments, represents the big data challenge applied to manufacturing. In any case, each level in the hierarchical chain exchanges information with the levels preceding and following it, and changes in one decision-making plan will result in an influence or change of the plans in other decisional levels.

3. Proposed Framework

After having described the peculiarities of the system in question and taking into account the set goal as far as this DT is concerned, i.e., to be a valuable support for production planning through simulations, with an additional focus on monitoring the progress resulting from the ESM, it is possible to represent the conceptual framework of the work to be developed as depicted in Fig. 5.

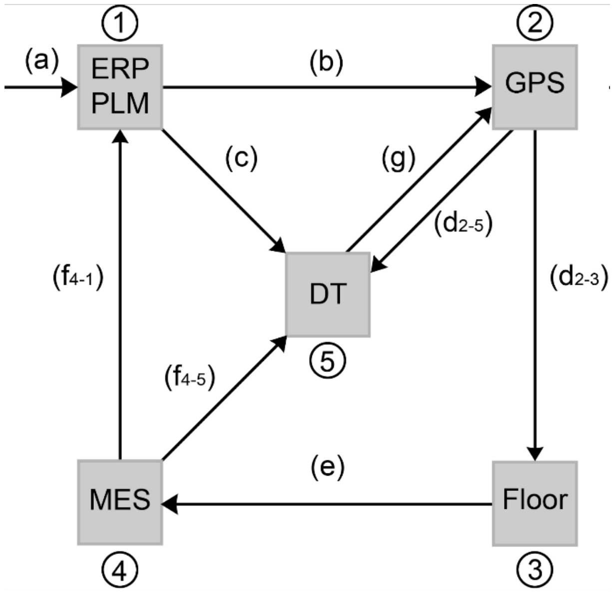

Figure 5. Framework of proposed DT structure and integration

Two different groups of elements are identified from the figure: nodes, which represent the different representative systems of the factory; and arcs, which indicate the dataflows.

Regarding the nodes:

1. ERP PLM: indicates the highest hierarchical level of information systems and manages the highest level of information,
2. GPS: is the production planning and scheduling system, which is interposed as an intermediate level, as previously shown.
3. Floor: transposes through the MES the plan established by GPS; represents the actual production level, characterized by the various levels of automation presented earlier.
4. MES: an information system for operational management, which collects data from the floor and operates an initial unification and systematization
5. DT: the digital twin is configured as an autonomous architecture, characterized by various components: the core is the simulation system, specifically a discrete event simulator (DES) was chosen, which allows a level of detail on inputs and effects that were deemed necessary in order to provide adequate decision support.

Regarding the arcs, which represent the dataflows:

(a) Represents the starting point of the production system i.e., incoming orders. In node 1, this information will be combined with inventory levels, technological cycles, and bills of materials.

(b) Represents the net production requirements

(c) Represents data appropriately processed to identify relevant boundary information to the DT simulations: particular attention should be paid to incoming orders, production cycles, bills of materials, inventory levels for semi-finished and finished goods, procurement times for raw materials, and required components.

(d_{2-3}) Represents the production plan made by production decision-makers.

(d_{2-5}) Represents the transmission of the plan to the DT, to enable control and monitoring analyses and possible deviation analyses on planned and actual production.

(e) Represents the data flow of the production department, which will then be merged and organized in node 4 (MES).

(f_{4-1}) Represents data on production advances and progress.

(f_{4-5}) Represents one of the most critical and delicate points for the implementation of DT: data from the MES properly preprocessed will be the basis of the statistical distributions as input to the discrete event simulator (DES) within block 5 (DT). Given the multitude of data and given their possible heterogeneity, it is critical to pay attention to how these data are processed and analyzed.

(g) Represents the final output of the DT: that is, an appropriately selected set of information that can be received by decision-makers in the production department not only to monitor production progress but also possibly to be able to take timely action in the face of certain warning signs (e.g., a high probability of delay on one or more orders, or an order deemed as crucial).

With reference to Fig. 6, it is possible to see a much more streamlined representation of the general operation of the DT, similar to that proposed by Grieves.

Beginning in the physical world, specifically at the production site, the logical process continues with updating the production systems, specifically with - but not limited to - MES data. This data is then piped into a data flow that leads to the system's virtual representation. The first step is to prepare the data that will allow simulation and prediction of the physical system's performance. To ensure that these operations are conducted correctly and optimally, the data must be properly prepared by filtering and pre-processing.

After the simulation, all data deemed useful will be represented in a manner suitable for decision-makers, so that these analyses can provide relevant information for business decisions, guiding them to seek a global optimum for the entire production chain, rather than a local optimum, or a solution only good if a single order, a machine or a production line is evaluated.

Once this information is received, choices will be made and these decisions will guide subsequent production, thereby resuming the cycle.

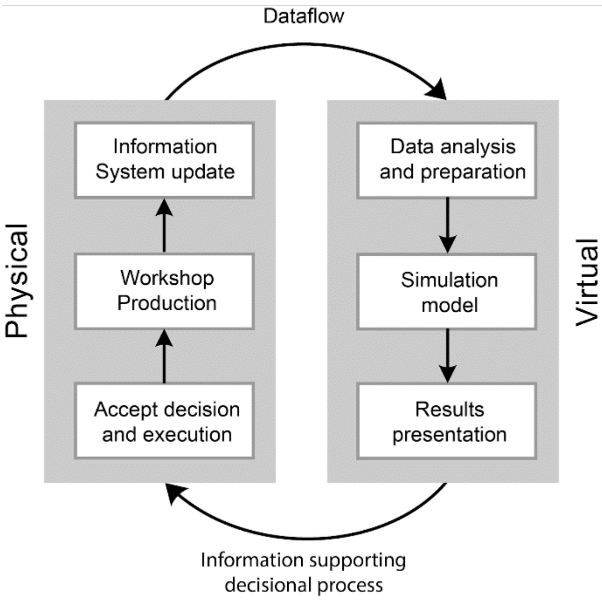

Figure 6. Synthetic overview of DT framework

The DT, therefore, is presented as an autonomous architecture that collects, processes, and derives information from the operational data and behaviors of the simulation models implemented within it. It must have access to all the data necessary to establish reasonable boundary conditions. It will be possible, if necessary, to add new simulative models so that later decisions can be supported.

It is also important to emphasize that DT alone cannot replace the information systems in the enterprise: integration with these is certainly a crucial point, but it is equally certain that production planning and control systems will not be replaced by this technology, which serves as a hub for collecting and unifying the various data sources.

4. Discussion

In order to enable these analyses, an adequate deployment of energies and commitment is needed in structuring the Digital Twin, which must, on one hand, be based on an explicit and mathematically structured model, and on the other hand, refer to the historical data of what happens in the production department, as close as possible to real-time; in addition to the structure of a discrete event simulator, the historic data of the MES must be added for the most constant monitoring possible, the data of the ERP and PLM for a reasonable update regarding bill of materials, order status, and stock availability, and the plans derived from the GPS, in order to be able to evaluate the goodness of the output data by monitoring the adherence index of the production department. Despite it being beyond doubt that the Digital Twin must support the production planning decision makers, it could be of interest to provide dashboards with progress indicators of the batches, to also enable the line managers or non-specialists to perceive the deviations of actuals compared to the planned activities, to allow the timely detection of discrepancies and targeted and functional interventions.

Concerning the indications of Stark (2019), for an analysis of the requirements of a digital twin, we can summarize the project framework explaining some of the most peculiar characteristics of this DT framework as follows:

- Integration breadth: the level of integration focuses on the entire manufacturing department, with adequate information and boundary conditions regarding business data, which will not be the decision variables in the optimizations. In the context of DT in manufacturing, the most implemented solutions tend to be related to the individual product or the individual machine/robotic island (Zheng et al., 2019), and solutions that manage the entire production department, with downstream and upstream linkages, are still scarcely studied. Compared with previous literature, the scope of action of this DT is broader.
- Connectivity mode: the interconnection between real and virtual will have to be bidirectional, although it is assumed that, for the first period of use, any information gleaned from simulation and forecasting will be screened and filtered by people knowledgeable about the system. The goal for this dimension is to gradually lean toward an increasingly automated mode of connection.
- Update frequency: Although close to the Industry 4.0 philosophy, a fully real-time data flow is currently not feasible and would have an excessive level of detail to support planning. The update frequency is primarily determined by the time it takes to extract data from the MES system. It is reasonable that data update and analysis related to order progression be monitored daily, and any corrective decisions be dosed appropriately over time, in order to avoid an excessive number of interventions, which have the potential to be detrimental if too many.
- Simulation Capabilities: discrete-event simulation is a specific technique for modeling stochastic, dynamic, and discretely evolving systems, which

means the simulation will not only be dynamic in nature, but will also allow timely deviation analysis of production progress, and allow a better overview to identify the causes. In addition to evaluating deviations, it will be able to simulate various order distributions to enable more comprehensive optimization concerning business objectives and overall service levels.

The proposed work may raise the question of whether implementing a new technology, such as a DT, is actually necessary to enhance production planning as opposed to using existing technology. To answer this question, it is important to keep in mind that the entire order process, from the customer's order to the final delivery, lacks transparency in manufacturing companies, especially small and medium ones. One of the reasons for this phenomenon is that information systems are frequently insufficiently digitized, coordinated, or integrated, and the update of the data is often not frequent enough.

Moreover, other process characteristics, such as unanticipated machine failures, intermittent and irregular orders, or changing client requirements, are also producing additional disturbances in the order management process. In this uncertain environment, a lot of manufacturing businesses are investing in production process optimization and control. However, while optimizing, usually the problems are treated locally by ad hoc solutions, without considering the influence on subsequent stages of the order management process. The fundamental difficulty in solving these problems brought on by disruptive occurrences is identifying appropriate solutions that support nearly all corporate goals and enhance the overall performance of the production system, rather than obtaining a local optimum (Kunath, Winkler, 2018).

It should be noted that the quality of any solution is determined by the decision maker's experience and the available information. Employees with more experience may predict the impact of their actions more easily than employees with less experience, nonetheless, regardless of expertise level, the accuracy of manual computation and prediction of event probability is quite poor (Takemura, 2014).

As previously mentioned, there is still a need for integrated decision support that can actively anticipate the effects of potential solutions on the system and the effects on the downstream linkages. The ability to simulate various scenarios will enable a traceable and transparent decision-making process and should limit the selection of locally optimal solutions that, however, may have significant effects on the overall system. This should lead to a preference for solutions that enhance overall synchronization and synergies at the expense of solutions that are only locally beneficial.

Moreover, the use of a DT in this environment provides a highly versatile tool for various types of 'what if' analyses: it is useful not only for production planning, but also for potential machine repositioning to minimize internal transportation times or for maintenance intervention scheduling.

5. Conclusions

The complete digitization of production processes is a critical component of the Industry 4.0 concept: appropriate technology must be employed for rapid digitization, data transport, data storage, and, lastly, data mining. Regarding the potential for digitization, the industrial sector has undergone a significant transformation, and it is well known that major companies like Siemens and Microsoft are launching numerous initiatives aimed at a large-scale implementation of Digital Twins.

The DT thus emerges as an innovative and promising system, not only to be able to integrate various business information, but also and most importantly as a tool to be able to work with more useful information in dynamic environments where unforeseen events occur: the ability to simulate will allow control not only in feedback, but the analysis of scenarios will allow to be able to see what are the global effects of the possible decisions that can be made at the time of planning.

Critical factors in this innovation will involve technologies for transmitting and managing data at the enterprise level, as well as finding appropriate technologies to pretreat data from information systems so that it is valid for use in simulation systems.

The paper has proposed the framework of a DT that will actually be implemented in a production environment, so it is possible that some assumptions or solutions may be reevaluated or revised. The key challenges during the implementation of the DT will be:

- validate the statistical robustness and significance of the MES data as a source for historical data to be fed into the simulator.
- find an adequate aggregation for the presentation of the result to the decision-makers.
- build the appropriate infrastructure for the dataflows, allowing an automatic synchronization that balances a reasonable closeness to the “real-time” and the feasibility of the synchronization itself.
- finding the optimal frequency of data update, which will be characteristic for each and every source of data (namely: MES historical data statistically pre-treated and analyzed, MES updates, PLM information, ERP information, GPS plans).

The results that will be obtained within and after the implementation of this framework will be the focus of future works.

References

Boschert, S., & Rosen, R. (2016). Digital Twin—Boschert, S. and Rosen, R. (2016) 'Digital Twin—The Simulation Aspect', in Mechatronic Futures. Springer International Publishing, pp. 59–74. doi: 10.1007/978-3-319-32156-1_5.

Cimino, C., Negri, E., & Fumagalli, L. (2019). Review of digital twin applications in manufacturing. Computers in Industry, 113. https://doi.org/10.1016/j.compind.2019.103130

Daily, J., & Peterson, J. (2016). Predictive maintenance: How big data analysis can improve maintenance. In *Supply Chain Integration Challenges in Commercial Aerospace: A Comprehensive Perspective on the Aviation Value Chain*. https://doi.org/10.1007/978-3-319-46155-7_18

Eunike, A., Wang, K. J., Chiu, J., & Hsu, Y. (2022). Real-time resilient scheduling by digital twin technology in a flow-shop manufacturing system. Procedia CIRP, 107. https://doi.org/10.1016/j.procir.2022.05.043

Grieves, M. W. (2005). Product lifecycle management: the new paradigm for enterprises. International Journal of Product Development, 2(1–2). https://doi.org/10.1504/ijpd.2005.006669

Grieves, M. (2014). Digital Twin: Manufacturing Excellence through Virtual Factory Replication - A Whitepaper by Dr. Michael Grieves. White Paper, March.

Kumbhar, M., Ng, A. H. C., & Bandaru, S. (2023). A digital twin based framework for detection, diagnosis, and improvement of throughput bottlenecks. Journal of Manufacturing Systems, 66. https://doi.org/10.1016/j.jmsy.2022.11.016

Kunath, M., & Winkler, H. (2018). Integrating the Digital Twin of the manufacturing system into a decision support system for improving the order management process. *Procedia CIRP*, 72. https://doi.org/10.1016/j.procir.2018.03.192

Min, Q., Lu, Y., Liu, Z., Su, C., & Wang, B. (2019). Machine Learning based Digital Twin Framework for Production Optimization in Petrochemical Industry. International Journal of Information Management, 49. https://doi.org/10.1016/j.ijinfomgt.2019.05.020

Shafto, M., Conroy, M., Doyle, R., Glaessgen, E., Kemp, C., LeMoigne, J., & Wang, L. (2010). DRAFT Modelling, simulation, information technology & processing roadmap - technology area 11. National Aeronautics and Space Administration, November.

Shafto, M., Conroy, M., Doyle, R., Glaessgen, E., Kemp, C., LeMoigne, J., Wang, L., & A. (2012). Modeling, Simulation, Information Technology & Processing Roadmap-NASA. National Aeronautics and Space Administration, 1–38.

Negri, E., Berardi, S., Fumagalli, L., & Macchi, M. (2020). MES-integrated digital twin frameworks. Journal of Manufacturing Systems, 56. https://doi.org/10.1016/j.jmsy.2020.05.007

Pan, Y., & Zhang, L. (2021). A BIM-data mining integrated digital twin framework for advanced project management. Automation in Construction, 124. https://doi.org/10.1016/j.autcon.2021.103564

Park, G., & van der Aalst, W. M. P. (2021). Realizing A Digital Twin of An Organization Using Action-oriented Process Mining. Proceedings - 2021 3rd International Conference on Process Mining, ICPM 2021. https://doi.org/10.1109/ICPM53251.2021.9576846

Ricondo, I., Porto, A., & Ugarte, M. (2021). A digital twin framework for the simulation and optimization of production systems. Procedia CIRP, 104, 762–767. https://doi.org/10.1016/j.procir.2021.11.128

Rosen, R., Boschert, S., & Sohr, A. (2018). Next Generation Digital Twin. Atp Magazin, 60(10). https://doi.org/10.17560/atp.v60i10.2371

Rosen, R., Fischer, J., & Boschert, S. (2019). Next generation digital twin: An ecosystem for mechatronic systems? IFAC-PapersOnLine, 52(15). https://doi.org/10.1016/j.ifacol.2019.11.685

Stark, R., Fresemann, C., & Lindow, K. (2019). Development and operation of Digital Twins for technical systems and services. CIRP Annals, 68(1). https://doi.org/10.1016/j.cirp.2019.04.024

Takemura, K. (2021). Behavioral Decision Theory. In *Behavioral Decision Theory*. https://doi.org/10.1007/978-981-16-5453-4

Uhlemann, T. H. J., Lehmann, C., & Steinhilper, R. (2017). The Digital Twin: Realizing the Cyber-Physical Production System for Industry 4.0. Procedia CIRP, 61. https://doi.org/10.1016/j.procir.2016.11.152

Zhang, C., Xu, W., Liu, J., Liu, Z., Zhou, Z., & Pham, D. T. (2019). A reconfigurable modeling approach for digital twin-based manufacturing system. Procedia CIRP, 83. https://doi.org/10.1016/j.procir.2019.03.141

Zheng, Y., Yang, S., & Cheng, H. (2019). An application framework of digital twin and its case study. Journal of Ambient Intelligence and Humanized Computing, 10(3). https://doi.org/10.1007/s12652-018-0911-3

Židek, K., Pitel', J., Adámek, M., Lazorík, P., & Hošovskỳ, A. (2020). Digital twin of experimental smart manufacturing assembly system for industry 4.0 concept. Sustainability (Switzerland), 12(9). https://doi.org/10.3390/su12093658