Perceptions of a Digital Twin Application Case in the Auto Industry

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Abstract. Reality shows that, despite promises to facilitate the analysis of manufacturing systems, the use of state-of-the-art tools and techniques may become a challenging effort. Reliable data can drive significant analyses to help companies understand underlying issues and plan actions to improve processes. Digital Twins (DT) are models that could monitor production parameters and possibly run cause-and-effect-like investigations and future project events once fed with real-time and reliable data. In an attempt to bring light to recurring issues present in the daily lives of those who work on the implementation of Industry 4.0 projects in production lines, this article presents insights obtained from the case of a Digital Twin model fed with near real-time in the auto industry. It also proposes a minimum structure necessary for capturing, reading, and sending data and presents users' perceptions from several functional units within a given company to build and test the developed model. Preliminary results show that companies should prepare for unexpected problems and limitations that span from the inadequacy of legacy hardware to obstacles related to human behavior in real-life implementation projects.

Keywords: Digital twin · Manufacturing system · Near real-time data

1 Introduction

Industry 4.0 is related to the subject that involves current technologies, presenting implementation strategies [1] in fundamental objectives such as the implementation of systems, regularity of engineering involvement throughout the product life cycle, and new infrastructures for the work environment systems. With these contexts presented, the digital twin is related to Industry 4.0 from the involvement with objects to larger machines and devices [2], being considered as fundamental assets and the need for assistance from specific software to automate production processes.

Cited by some authors, this Industry 4.0 era can be called the DT era [3], as it presents a trend towards the progressive use of digital models when involved with 4.0 themes [4]. As a synonym of manufacturing or smart factory for involving the concepts of computer-integrated manufacturing, flexible manufacturing, circular economy concepts and encompassing the management of a high amount of data ingested by the DT model,

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thus enabling the integration of tools and technologies related to the Internet of Things (IoT) [5].

Related to Industry 4.0, its level of maturity must also be analyzed. The Acatech model, developed by the National Academy of Science and Engineering to define the basic steps for a factory to reach its Industry 4.0 maturity, is also known as the Industry 4.0 Maturity Index. The model is formed by a scale composed of 6 items, starting with Computerization, followed by connectivity, which these two items are essential for digitization. Following the scale and introducing Industry 4.0, the third item is visibility, next is transparency, next is prediction, and finally, adaptability, as shown in Fig. 1.

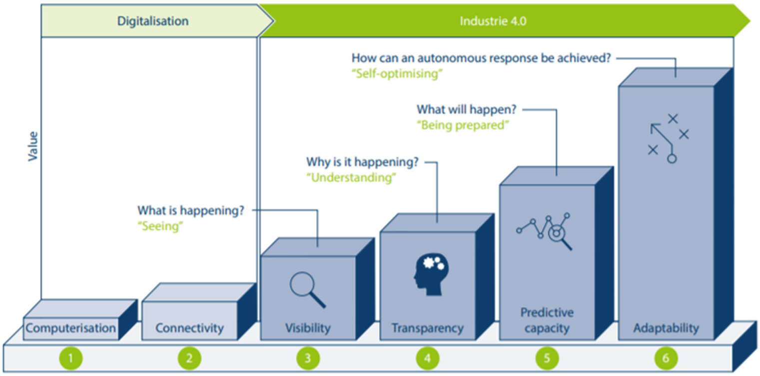

Fig. 1. Acatech scale [6].

Based on these concepts and this approach, this article presents the perceptions of the use of the DT in the automotive industry, with its stages and characteristics for applying the model. The article is structured as follows; in Sect. 2, some methodological aspects are presented, moving on to Sect. 3 with the information and description of the application case. In Sect. 4, the first perceptions of the first users of the DT model are presented, and finally, in Sect. 5, the conclusions and future work.

2 Overview

Many concepts are presented in the theories about the DT, and through the concept of Industry 4.0, the possibilities of using this model to aid decision-making, for example, and production planning, are spread [7]. The early diagnosis and resolution of conflicts and unexpected failures in a production line or process [8] and all the dissemination of knowledge between the parties involved, such as developers, executors, leadership, management, and executives [9].

Research involving DT models is progressive, and their implementations are still being passively applied. Proposals for implementations and small applications involving additive manufacturing are the most commonly found, but papers that demonstrate the step by step of its application in an industrial environment emerged as a gap and focused on the development of this application case.

When talking about DT models, therefore, there is a link with the monitoring of systems in real-time. Terminology related to the question of the term in real-time also makes an alert because to be considered the collections of data in real-time, they must be processed immediately to be valid, which in the current models, this processing involves a slight delay and thus can be considered as near-real-time data collection.

There are few applications with real-time systems in industrial environments [10]. There are several studies relating simulation optimization with industrial environments and human activities, but presented as future works, such as maintenance systems [11], industrial production lines [12] and new product development [13].

The following section presents the procedures and information about applying the DT model in a wheel production line in the automotive industry. All aspects were studied and applied by the authors in the physical environment and the procedures, minimum requirements, and difficulties encountered during the application.

3 Application

3.1 Infrastructure

For the development of the DT model, some points need to be evaluated first, as the need for basic infrastructure is essential so that the virtual model represents the physical model as close as possible to reality. For the construction of the DT, the object or process to be represented must count on the participation of a minimum of technologies with essential roles to succeed in the analysis of the model. Some technologies that can be mentioned include the choice of simulation software, data related to the object or process, and the Internet of Things (IoT) involvement.

Internet of Things is understood as the entire involvement of connecting the data generated by the manufacturing process, remote access for follow-up and monitoring, and the presence of sensors to capture movements and data, in general, to keep everything connected. In the case of the application presented in this article, the DT model was implemented at a point on the wheel production line of an automotive company. Initially, the criteria for this possible implementation were analyzed, including what already existed in the line and what would be necessary to request, implement and change to be compatible with the digital model.

The implementation of a physical computer was necessary at this first moment to capture and transform the data to be ingested into the digital model. The computer must have a minimum of internal capacities such as memory and processing to support running the necessary applications following the needs of the software used.

For the remote access of the model, it was necessary to install another network card in the computer for reasons of reliability required by the company since a network input present on the computer would be connected to the PLC panel to capture the line data and another network input would be connected for remote computer access. The need to have two independent inputs was necessary so that the line data (sensor data, times, alarms, among others, which will be better explained in Sect. 3.2) could not be accessed by the network external to the company.

3.2 Data

To select the data used in the digital model, what was possible in the line was analyzed. After this analysis, meetings were held to survey the needs of each user and the wish lists for the use of the DT model. After these meetings, the crossing of this information and data selection was obtained.

In the case of application, the data selected for ingestion in the digital model were the sensor data as active and non-active, being true and false, the alarms related to that stretch of the line, such alarms as zone blocking, non-engagement of the line or preventive maintenance necessary as well as activation by a defect of some part such as an actuator, frequency inverter, and sensors.

Other data obtained are from all sensors and actuators present in the machines for actuation and movement of the parts, being boolean (true or false). The section selected for the demonstration and application of the DT model were the first machines on the wheel assembly line.

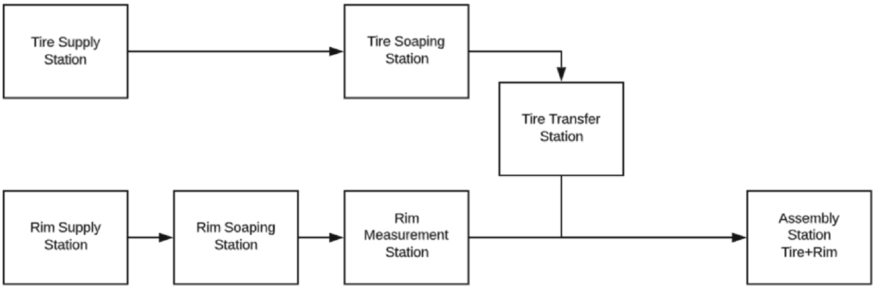

Fig. 2. Production line.

Starting the process as shown in Fig. 2 by the tire feeding station and in parallel with the rim feeding line, the tires are sent to the soaping station, then heading for transport and transfer. In parallel, the rims are fed into the production line, going to the soaping station, and subsequently measured to verify compliance, that is, if the rim in that position matches the appropriate size for the tire that will be mounted.

The next station is the tire assembly on the rim, where the fitting of the two occurs so that in the subsequent stations, the air is filled in the wheel, through the inflator, then the balancing and calibration of this set. The wheel is understood as the already assembled set of tire and rim.

In addition to the status data of the sensors and actuators present in the line, other data are ingested in the digital model, such as the wheel identification number, in the case described as PJI, being numerical values and captured each one, the P, the J and o I separately. Other numerical data related to the diversity of the set are the set number, in this case, a number representing the tire plus the rim, and the test plan number to be used later in the calibration and balancing of the wheel.

Finishing the data captured from the line, the operating times of each operation of the stations will also be used, such as the soaping time of tires and rims, the transport time of tires, and assembly time of the set, the cycle time of the entire station will also be used in ingesting data for the digital model.

3.3 Design

It is not necessarily necessary for a DT model to have a 3D drawing of the process, but it is known that its understanding and subsequent analysis are better interpreted when animations and digital representations are presented.

For the construction of the digital model, software was chosen that could serve as a simulation model and, at the same time, accept the ingestion of data in real-time. With these firsts, we opted for the Infinite Foundry software, starting the construction of the model design through a laser scan, transforming this scan into a cloud of points of the physical environment, and later generating the digital simulation model.

First, a laser scan is performed inside the factory to capture all items, objects, machines, dimensions, arrangements, and layout. Then the designs of the 3D model are made from the scanning and, finally, the design of the model of the production equipment. When there is any change in the layout or any other point, the 3D model needs to be updated, perform this scan again with the scanner, and then the scanned model will be updated.

After performing this scanning and design of the 3D model, some adjustments are made to better conform the digital model with the physical model. This is how the design of the 3D model of the DT is generated, making it possible, even without data ingestion, to visit the company virtually, for example, by suppliers, the study layouts, and the physical validation of the insertion new work stations.

3.4 Software

The choice of Infinite Foundry's software was fundamental for the development of the DT because, among the various simulation software found on the market today, few have the possibility of ingesting external data in real-time. For specific reasons for the project, the application case presented in this article counts on the ingestion of data practically in real-time, having a minimal delay.

The data is generated on the production line and captured by the Node-Red tool to transform signals into data in JSON format—the action required to ingest the data into the Infinite software. In addition to this language transformation, the data is also scaled so that they are all read and that some data is not read because it was ingested at the same time as other data. The software initially monitors the process in question, in this case, the wheel production line, connecting the 3D model with the physical equipment through Node-Red. The Node-Red tool generates a file with the data values and updates this file whenever there is a change in some data value.

This file is read every 0.02 s, sending this information to the simulation, thus animating the digital model, as it takes this short reading and sending time to generate the animation that the authors chose to consider reading data practically in real-time.

With the ingestion of data in the simulation model, the software represents the physical model with movements and actions that occur and are captured by the sensors and actuators present in the line. In addition to all the simulation and animation present in the software, other data can also be seen in its interface, data such as the PJI number of the wheel being produced at that moment, production data such as the number of pieces produced, the number of times they occurred line stop and time that was stopped. In Fig. 3, it is possible to visualize the interface of the software chosen for the model.

Fig. 3. Steps for the digital twin model.

Other fields found in the software interface, which were created based on the needs demonstrated by the twin users, are operating information, machine alerts, maintenance history, and planning, as well as the associated and expected time for each one, all obtained from ingesting data from capturing and transforming signals from the production line.

3.5 Systems Integration

To capture and ingest the signals from the sensors and actuators present in the chosen production line in the DT, initially, the mapping of the PLCs was carried out, as well as the mapping of other variables that can add value to the model. Later these variables are captured by the Node-Red tool that performs the interaction between some devices.In Node-Red, programming was done in JSON (JavaScript Object Notation) to read all the selected variables, and the processes are grouped in a flow to fulfill their objective: to generate a file in.json format so that the digital model performs its ingestion. In total, this programming has 441 mapped and transformed variables. The structure developed for the construction of the DT starts with the data from the machines present in the line, whether coming from the PLC or from the sensors and actuators, followed by the transformation of this data into JSON format to be ingested in the digital model.

The next step is to ingest the data into the digital model and update it when necessary so that the model can be simulated practically in real-time. After the simulation, there is monitoring, observation, and analysis of the systems so that predictions of possible scenarios can be carried out, impact resource savings, quality, and efficiency, optimize processes, and reduce non-value-added activities.

4 First Perceptions

Once the steps for constructing the DT model have been carried out, implementation and use with the first users begin. Users related to maintenance, quality, IT, and engineering were chosen; all were consulted at the beginning of the project to indicate their objectives and wish lists using the DT.

After the beginning of the development of the stages, the models built were presented and how they were working for these same users, and their opinions were very favorable for the use of the twin. Among the main observations, it is possible to mention the opinion of the IT user, citing the fact that the use of the model is fundamental to providing a dynamic view providing cost reduction.

From the point of view of maintenance users, some criteria were raised, such as the prior identification of problems and providing greater equipment availability. Moreover, from the engineering and projects side, the use of the DT implies the visualization of data in practically real-time, being that from the user's side, it is considered as real-time, making the work and decisions more agile, raising the extreme importance in an environment in the which is always seeking to add value and gain a competitive advantage over other companies.

Among the benefits of the DT model, we can mention that it integrates systems by mapping and selecting different data from different areas and ingesting them into a single system for its simulation and analysis. Another factor contributing a lot is the dependence on machines, with no need for human interaction to carry out this entire data reading, extraction, import, and simulation journey, thus transforming technology as a necessity and no longer a simple differential.

The ability to improve with other mechanisms, devices, and systems makes the DT model even more effective and meaningful in an industrial environment, whether in a single process or a complete production line. Companies that use the model can offer more efficient and aligned products according to the needs and demands of their customers, as they will be more actively involved in the production processes, testing, and approving or improving their quality.

5 Conclusions

With this first implementation of the DT, some preliminary results can be highlighted, among them the fact that companies that desire to achieve the twin must be structurally prepared and skilled in the workforce.

The need for an essential structure for its implementation from network and internet points that are sufficient in terms of data transport capacity, a computer with good memory and processing, and even implementers and users who can make correct use of the twin are critical to the success of the DT model.

Ingesting data practically in real-time makes the twin a tremendous competitive advantage for companies from different sectors that use this type of technology. Its use has a solid predictive feature, making it possible to identify the points that need more attention in a production line or process, making it possible to detect failures and future risks more efficiently.

When analyzing the maturity scale in Industry 4.0 of the project in question, it can be said that the model reaches level 4 but still lacks some requirements to reach level 5, despite already presenting transparency demonstrating what is really happening in the line and the predictability effect in alerting users to possible future problems and thus being prepared to solve them.

In the following steps, the authors will disseminate the DT model project to other users and improve the number of variables to be ingested in the digital model; the more variables are ingested in the twin, the more faithful it will be to reality.

Thus, every digital transformation that everyone seeks to update and improve is already constant in the industrial environment. The use of DT models clarifies how technology helps improve people's lives and daily activities in the industrial environment. Not only in the industrial environment but a DT model can be applied in any process of daily life, as long as they involve minimum criteria for its development. The fact is that to oppose a reality that everything is advancing technologically is to miss the opportunity to highlight the company and leverage on a competitive advantage.

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