IMPROVING THE DECISION-MAKING PROCESS BY MODELING DIGITAL TWINS IN A BIG DATA ENVIRONMENT

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Abstract:
Moving to the Industry 4.0 stage. will lead to process automation and implicitly to the change of classical decision support systems with some based on real-time evaluation of processes, on the processing of large and varied volumes of data, in continuous flow and at high speeds, all these elements converging towards automation decision. This involves the creation of virtual models faithful to physical processes and products, models obtained through specific BIG DATA processes. The purpose of this paper is to describe a framework for applying decision support based on the model of digital twins in a BIG DATA ecosystem, the description of the defining elements specific to the decision cycle, the modeling and implementation of this concept.

Keywords: managemet, decision-making processes, BIG DATA, artificial intelligence, Digital Twins

1. Introduction

The technological evolution of sensors, IoTs, cumulated with the emergence of BIG DATA work ecosystems that require distributed computing and stored architectures, has led to changes in the approach to work processes at the enterprise level using technologies specific to the Industry 4.0 era. All this BIG DATA architecture now offers the possibility of management focused on the most detailed production subprocess that can be modeled, the fineness of granularizing the subprocesses and implicitly their modeling offering a virtual image at process or product level very close to the physical process or product. Given the current conditions in which process standardization has led to small differences in production costs between different producers, there is a need to reduce the risks associated with production processes, risks due to variations in production parameters, interruptions or the speed of redesign and implementation of new or versioned products. Decision-making scenarios are becoming very close and the old decision-making support systems need to be adapted to the speed of data flow leading to the automation of production processes and thus the automation of decision-making and the evolution towards autonomous systems. Horizontal processing scaling, offered by parallel computing in BIG DATA ecosystems, offers the possibility of running models with a very large number of parameters in intervals of the order of seconds or minutes.The paper describes the elements of the decision-making process in a BIG DATA ecosystem and defines a decision implementation framework based on modeling production processes using digital twins, which leads to increasing the adequacy of the digital model to the physical one, converging to their identity.

2. AI decision support tools in a BIG DATA ecosystem

2.1. Backgound

The term „decision” has many definitions. (Filip et al. 2017) adopt: *„Decision is the result of conscious human activities aimed at choosing a course of action to achieve a certain goal by allocating the necessary resources and is the result of processing information and knowledge by a person who is empowered to make the choice and is responsible for the quality of the solution adopted to solve a particular problem or situation”.* The term „decision” is defined as a „resolution taken following the analysis of a problem, a situation or a choice of several possible solutions available” (DEX, 2020).

Characteristics of types of decisions by level:

- strategic - determine and pursue the achievement of general objectives and the global allocation of resources;
- operational - determine and pursue the achievement of specific objectives in achieving the general objective are hierarchically dependent and concern the allocation of resources at this level;
- tactics - determine and aim to achieve the final results as well as the economy, efficiency and effectiveness with which the resources involved are used;
- on data, information and knowledge - determines and aims to establish the necessary data, information and knowledge, how to manage, evaluate and transmit them to beneficiaries.

By structure decisions can be classified as follows:

- structured or programmable, with well-established objectives, a solving algorithm and predominantly quantitative elements;
- unstructured or non-programmable, they do not have precise objectives, having a solving algorithm and mainly qualitative elements;
- semi-structured, they do not have precise objectives, having a solving algorithm only for certain parts, and the quantitative elements being preponderant compared to the qualitative ones (this type of decision requires assistance).

As a result, in the context of these three types of decisions, the identification of the problem is of great importance and can have the following types:

- structured or programmable problems - explicit process that allows the processing of information entered in order to choose alternatives;
- unstructured or non-programmable problems - the intuition of the decision maker is used to define the problem, they lead to atypical decisions for the entity and there are no procedures already established for their adoption;
- semi-structured problems - some known procedures can be partially used in order to solve them.

The decision can also be defined as a conscious activity of choosing a certain course of action from several alternative solutions available, the choice made being influenced by the effects generated, so much so that the „decision can be taken by a single person or by a group of people responsible for the choice" (SR EN ISO 9001, 2015), as well as the fact that any successful implementation of a decision also involves the use of resources.

2.2. Decision makers (the decision maker)

The term decision maker is a generic one, it can designate either „an individual decision factor, a role or a person or an entity that is composed of several participants, sometimes called decision group decision maker" (Holsapple and Whinston 1996).

The decision-maker, through his position, has the right to decide and can initiate measures to change a certain situation, acting in an environment that can influence decisively, in this sense being important the processes of continuous improvement of relations, forms of organization and leadership and last but not least, the introduction of modern decision-making methods and the analysis of the results obtained.

2.3. Decision situations

Decision-making situations and associated decision-making issues can be forced or unforced.

Forced situations (sometimes called goals) can be caused by several factors independent of decision makers can be:

- Changes incompatible with the performance of a state or part of the organization;
- changes found or predicted in the decision-making environment;
- new parts or states added to the organizational system.

All of the above cases require reactive decisions that are meant to correct unwanted situations or to exploit perceived opportunities.

Unforced (or subjective) decision-making situations are caused by various decision-makers, such as:

- changing the objectives or levels of decision makers,
- early-warning measures

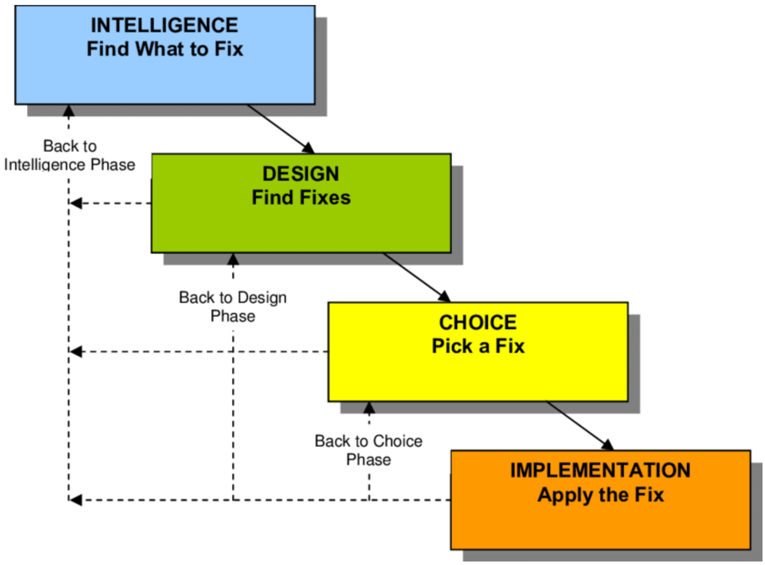
The decision-making alternatives available are variants of action that the decision-maker can have at his disposal to achieve the proposed objectives, the technical and specialization particularities amplifying and refining the necessary economic, technical or social criteria, corresponding to one or more indicators. Strict and accurate knowledge of the reality or decision-making environment is an important requirement for framing decisions in an objective management process, updating information based on scientific basis generating a favorable framework for exploiting the expected consequences, planning operations necessary to be based on an analysis real and complex situation of the past, on the realities of the present and to aim at the situation of perspective.

2.4. The decision-making process

The decision-making process is a set of activities carried out by a person or a group of people who are able to choose a variant from several variants of action, being necessary that the solution adopted corresponds to the objectives and potential of the entity in terms of quantity and the quality of the resources to be involved in the complex of actions to be carried out.

It is significant to highlight here the phases of the decision-making process identified by the renowned American researcher, Herbert Simon, winner of the NOBEL Prize, these phases being non-linear and composed of several stages:

- general information (intelligence) - identifying and classifying the problem and breaking it down into subproblems and establishing responsibilities;
- conception (solutions) - modeling and choosing the criteria for selection, developing mental models, generating alternatives and identifying and evaluating the result of each of them;
- choosing the optimal variant of the decision - using analytical and testing methods to choose the sufficiently good solution;
- implementation (action) - triggering the action and implementing strategies and solutions and identifying technical or human problems that may arise;
- monitoring - depending on the result can return to an earlier phase.



Fligure 1. The decision-making process (Simon 1970)

The efficient management of information and knowledge bases, but also their superior processing cannot be done at the highest standards unless it is joined by the technological support that can be achieved through the convergence of information technology, communications technology and digital content production. Achieving such a synergy is the most important goal to achieve in order to increase competitiveness, the essential goal in the field of military operations being the achievement of superiority or even information supremacy.

2.5. Decision support systems

Decision support systems (SSDs) began to become a field of research in the 1970's, gaining ground in the 1980's and developing tremendously in the 1990's when databases and online analytical processing appeared. Herbert Simon in 1970 defines Decision Support Systems as: "a model based on a set of procedures for data processing and for assisting a manager in decision making (https://en.wikipedia.org/wiki/Herbert_ A._Simon). Analyzing the multitude of definitions expressed by various researchers in the field, it becomes very clear that regardless of the level of decision makers, the support they receive in choosing and adopting decisions consists in the support offered by these systems that can take forms of calculation, visualization, hierarchy, validation, all in order to increase the degree of knowledge extraction to provide decision scenarios as close as possible to the optimal decision. The most appropriate definition is given by Holsapple and Whinston, in Decision Support Systems: A Knowledge-Based Approach (1996), which introduces the five basic characteristics specific to an SSD:

1. contain a knowledge base on the relational ecosystem of the decision-maker's environment (how different activities of the decision-making process are carried out);
2. have the necessary characteristics to acquire and manage various types of knowledge (procedures, rules);
3. be able to present knowledge in a visual or written form in real time or periodically;
4. be able to select and extract a subset of knowledge for visual or written exposure or for processing for further refining;
5. to have a simple interface of direct interaction with the decision maker that allows him to quickly manage possible solutions and knowledge.

The principles that must govern the choice of the decisional variant are the normative and the descriptive one according to which the solutions can be of two types:

- normative models - the chosen alternative can be demonstrated as the best, being presumed in this case that we have the optimal solution resulting from an optimization process;
- descriptive models - it is assumed that in this case we have a good enough solution, being necessary the simulation for several solutions in order to finally adopt the good enough solution.

2.6. The impact of BIG DATA on traditional SSDs

Recent developments in the corporate world, triggered by the increased use of technology and the adoption of data-driven approaches to an organization's defining decisions, have influenced the use of data. Big Data has become an essential component of a competitive organizational advantage. Virtually all stages of operations in modern organizations rely on Big Data to advance and ensure efficiency (Mehner, 2020)

Following the reports of technological trends to large technology companies or those issued by Big Four companies and technology companies (Deloitte Tech Trends 2020 - Deloitte Insights, Ernst and Young Emerging Trends 2020, The Future is Open - KPMG, Accenture - Tech Trend) notice that trends are dominated by data. For example, in the annual Accenture - Tech Trend report for 2020, the five major trends they prioritized are: the experience co-created with consumers, the reimagining of businesses through collaboration between AI and people, equipment from increasingly smart and interconnected, the introduction of large-scale robots, the creation of a business ecosystem based on innovation. All these trends are created around data and technologies for data collection, processing, analysis and visualization. These cognitive technologies support professionals from all fields to understand the growing volume of data, being able to manage both in terms of volumes and complexity what the human mind and traditional methods have failed to do.tools in cognitive technologies can replicate the human response, but they can also improve it and automate the right actions.

Another example, provided by Head (2005), shows that obtaining data insights contributed to the growth of American economic activity in the early 1900s. He mentions Frederick Winslow Taylor, a mechanical engineer considered to be the father of scientific management and efficiency theory, which used a stopwatch and a writing board to measure and analyze the productivity of Midavle Steel Works, a Pennsylvania steel company. In fact, he is the one who founded the theory of scientific management, Taylorism, through which work periods are analyzed and synthesized,being one of the first attempts to apply scientific principles in engineering and management. Taylor is also the author of The Principles of Scientific Management (1911), a volume he wrote in response to President Theodore Roosevelt, who called for increased national efficiency.

In the light of technological evolution, these activities are brought to new standards, their impact being enhanced with each online program or equipment connected to an Internet network. Data collection is closely related to what experts call The Internet of Things (IoT).

Kevin Asthon launched the concept in 1999, the two authors point out, when Ashton was an employee of Procter & Gamble. At the time, the idea that everyday objects could have sensors that allowed them to communicate with each other had been in the market for a decade, called either ubiquitous computing or pervasive computing. The novelty was that regularly used objects, such as a refrigerator, a car or a thermostat, could be connected to the internet, allowing autonomous communication with each of them and with the environment. At present, this connected equipment transmits, compiles and analyzes data on our actions and reactions.

According to the data strategy published by the European Commission at the beginning of 2020 (A European Strategy for Data) a 530% increase in global data volumes is projected in the period 2018-2025. This is an increase from 33 zettabytes to 175 zettabytes. In terms of the value attributed to this data, the Commission anticipates for 2025 in the EU that the data economy would be worth $ 829 billion, up from $ 301 billion in 2018. This upward trend in Big Data could lead to a slowdown in data. data-driven decision-making and can lead to new innovations in all areas.

This is the Big Data era, which Needham (2013) said was the end of computers and technology as we knew them for 70 years.

Theorists Borkovich and Noch (2014) referred to Big Data as a paradigm shift, from the traditional use of data from the last 30 years, such as numerical data and texts to the generation and access of huge volumes of information gathered using technology. and beyond images and data from social media. Traditional media had the ability to store only structurally data made up of letters and numbers, but in the Big Data era there was a growing need to incorporate unstructured data into information management.

For hundreds of years, goods have been produced by hand or with the help of working animals. The change came in the 19th century, with **Industry 1.0** concept and the introduction in the 1800s of machines as a support for production and with this increase in production capacity there was an increase in the structures of the economy that now included owners, managers, employees who serve customers in addition to the old workers.

The emergence of large enterprises, production flows, the record of stocks of raw materials and finished products with the diversification of the economy, consisting of new terms such as: capital, labor, raw materials and energy, with the transition from two categories (producer who consumes its own production and trader who capitalizes on the production surplus) to a multitude of specific categories that respect the principles initiated by the new stage of evolution (standardization, specialization, synchronization, concentration, maximization, centralization) made the data suffer in turn a process of diversification and evolution that followed the process of industrialization. With the emergence of the level of "integrators - who orchestrated the system" - we named here the people who coordinated and determined the populations to respect the principles stated above, appeared the level of leadership both at the enterprise and at society level through the evolutionary emergence of governments - centralizing elements of social systems integrators.

At the level of enterprises, there are two distinct levels, the management level and the operational or execution level, and the data flow is from the execution level to the management level, from where they return in the form of a decision.

The exchange of information between the management level and the production / operational level became in both directions which facilitated the adaptability of the management level and facilitated the implementation at the production / operational level of the **synchronization** principle and at the management level of **concentration, maximization and centralization** .

Thus, there is a need to analyze the internal data and information flows within an enterprise, developing the mode of communication between the management level and the production / operational level but also horizontally between the different production lines for synchronization. The appearance of analog recordings and their storage marks the entry into the first stage of development and quantification of the size of data and information.

Industry 2.0 came at the beginning of the twentieth century, with the introduction of a new energy source - electricity, easier to use than water and steam and allowed companies to focus energy sources on individual equipment leading to increased mobility and production dynamics . This has led to the development of a number of granular techniques for allocating and tracking production that have made it possible to increase the efficiency and effectiveness of production facilities. The standardization of mass production, the use of assembly lines, the specialization and synchronization of workers, where each is part of the total load, have increased productivity with **little effect on data and information**.

Industry 3.0 began at the end of the twentieth century, and the invention and manufacture of electronic devices based on integrated circuits, made it possible to increase the degree of automation of individual machines to complete or replace operators. This period generated impressive amounts of data through the development of computer systems for production planning and management.

The emergence of the "third wave" coincided with **the Digital Revolution** which represents the transition from mechanical and analog electronic technology to digital electronics, which actually began somewhere from the late '50s to the late' 70s, with the adoption and the proliferation of digital computers and the digital preservation of records that continues today (Schoenherr et Steven, 2004).. By implication, the term refers to the radical changes brought about by digital computing and communications technology during (and after) the second half of the twentieth century.

It is the moment when a new level appears within the enterprise, where the analysis processes take place, the data are placed in the context of the enterprise flow, they are associated with the physical processes from the operational level, metrics are measured to measure the efficiency of these processes. of actions lead to achieving the desired efficiency for processes and finally this whole process of adding elements to the initial data set is offered for the choice of the decision makers. This whole process is driven by data and then by associations with this data. We will call information (knowledge, insight in the established terminology of analysis) all these links associated with the data in the sense of the objective of the enterprise (those associations that do not serve the purpose of the enterprise will not be taken into account).

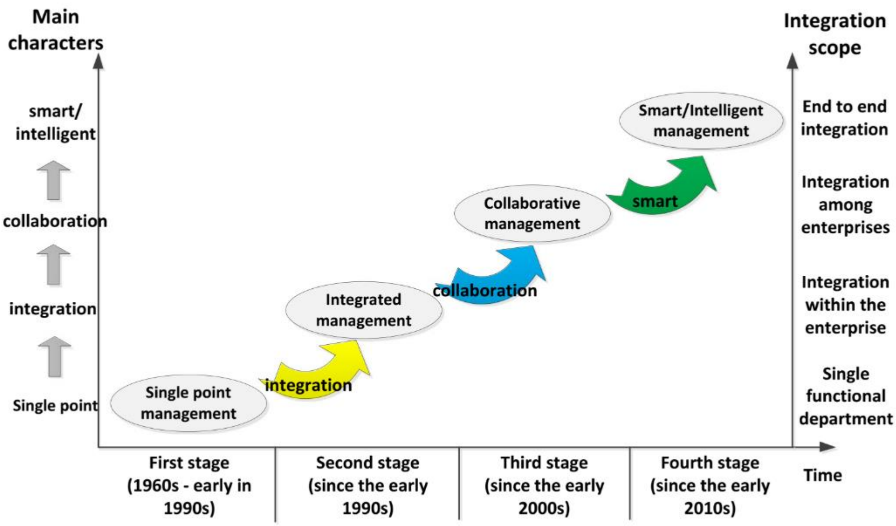
An enterprise in which it is possible that each production element, going down to the machine level and even below to the machine subassembly level to generate raw data that are fully integrated in the flow of the enterprise, along with the rest of the internal data generated by stocks, financial banking, personnel, other internal data) supplemented by the flow of external data (external transactions, quotations of raw materials and finished products, other external data) will be called a data-driven enterprise (**Data Driven Enterprise**)

Stage 1. One-stop production management based on single production flows (1960-1990). The data flow had a single function and a secure meaning for all subsystems being specific to process computers Manufacturing resource planning (MRP / MRPII), Enterprise Resource Management (ERP) and Product Data Management (PDM).

Stage 2. Integrated production management based on MES. The production execution system (MES) appeared in the early 1990s, which had several functions of production management and control (production planning / scheduling, materials delivery / control, quality management, cost control, equipment management and maintenance).

Stage 3. Collaborative production management with network manufacturing technologies (2000). Strategies are taken from the management of information systems that are applied to product life cycle management such as agile production, collaborative, e-production, supply chain management and e-commerce. These strategies have accelerated the integration and collaboration between internal or external components of the supply chain in the manufacturing and assembly process with the effect of increasing competitiveness and efficiency.

Stage 4. Smart management based on smart technologies (2010) The concept of smart production was born in the 1980s, but only in 2011, the Smart Manufacturing Coalition (SMLC) founded in the USA, the concept of industrial Internet was proposed together with the plan action for intelligent production (Coalition SML, 2011). In 2013, was introduced the concept of “Industry 4.0” and in 2015, the Chinese government issued an ambitious plan called “Made in China 2025” which aims to achieve intelligent production in a new round of scientific and technological revolution.



Fligure 2. Development of shop-floor production management and control approach (Zhuang, Liu et al 20180)

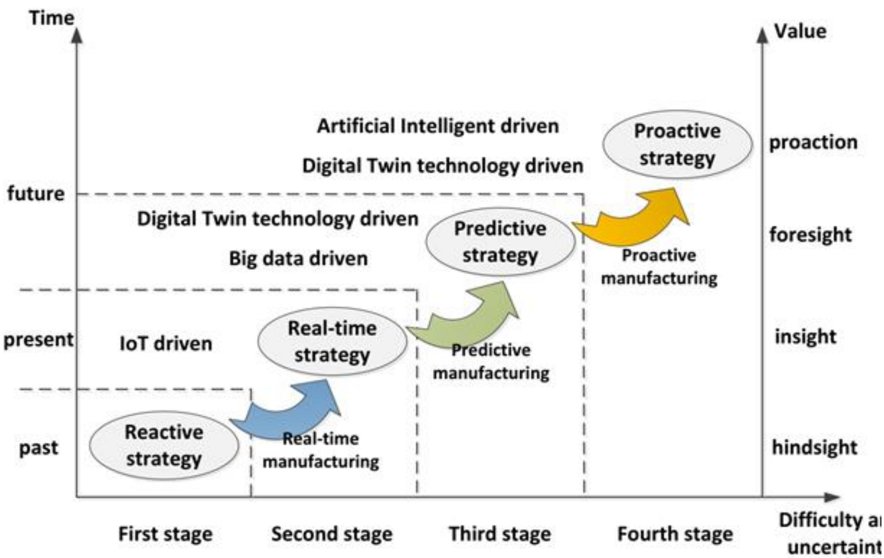


Figure 3. The evolution of shop-floor production management and control strategies (Yao, Zhou et al, 2017)

Industry 4.0 began with the 21st century and the development of the Internet of Things (IoT) along with manufacturing techniques that allow machines to share information, analyze it and use it to guide intelligent actions and then learn from previous phases. The development of smartphones and social networks has led to an explosion in the volume of digital media data by increasing filming resolutions (4K currently, 8K already in prototyping) with these devices, but also the bandwidth required for live transmissions with them. . It is estimated that 85 % of current Internet traffic is occupied by live video broadcasts.

The data and information created within companies and organizations have the greatest complexity and importance, both at the strategic and operational level. This is why it is important to know them and especially how to create and interpret them. In order to understand both the creation of data and information (specific to the classical approach) and the reverse process (specific to BIGA DATA) of structuring a massive amount of data for the desired purpose it is necessary to understand the context and mechanisms of this creation.

The future integrative concept for Data Driven platforms will be based on a two-way correspondence between the company's actual action and its representation at the level of modeled process and at the level of data flow. This presupposes that one of the components of the architecture is a library of models that are then coupled to the data flow through an adaptive mechanism, characteristic of AI that will allow the model to be improved after each cycle. The more cycles will be run, the smaller the difference between the digital model or digital representation and the actual process. Two directions of development appear: one towards the notion of “digital twin” of the enterprise, conceived at unitary level but also the notion of digital organizational sub-structure seen as part of the digital twin, both representing digital model,respectively submodel that can be simulated both integrated and independently.

2.7. Digital twin concept

The introduction of the notion of Digital Twin was made by David Gelernter in the book Mirror Worlds (Gelernter, 1991), the concept being initially introduced in the ecosystems of production assistance and management at the level of production processes. The first presentation of concept and pilot model of a twin digital was introduced publicly in 2002 Conference Company manufacturing engineering of Troy, Michigan by Grieves, of the University of Michigan and the concept of twin had arisen as a model conceptually defines product life cycle management (PLM). The term "digital twin" was introduced in 2010 by John Vickers.

2012 - NASA and the US Air Force Research Laboratory (USAF) presented the digital twins for the vehicles of the future *„and was defined as an integrated multi-physical, multi-scale, probabilistic simulation of a vehicle or built system that incorporated the best available physical models, updated sensor data and historical data to reflect the life and condition of the twin appropriate flyer”*(Tuegel, Ingraffea et al, 2011). In the same year, NASA launched "*Modeling, Simulation, Information Technology and Processing*", and then the term digital twins was widely applied to products or production processes.

In short, the digital twin is *„a virtual model, dynamic in the virtual world, which is fully consistent with its corresponding physical entity in the real world and can simulate the characteristics, behavior, life and performance of its physical* *counterpart in a timely manner”* (Lim, K.Y.H. et al, 2020). Such a concept is also known as the digital model in Germany.

General Electric (GE) sought to perform real-time monitoring, and predictive maintenance of digital twin-based engines.

In Boschert and Rosen (2016) was studied the methods of applying the digital twin in the simulation of complex systems.

Schroeder et al. (2016) proposed a conceptual framework for the digital twin based on a web service.

Grieves (2019) studied methods for predicting and eliminating defects for such a system based on digital technology.

Tao et al. (2017) proposed a new method for the design, manufacture and service of digital twin-based products. Furthermore, three cases have been illustrated for future digital applications in three phases of a product.

Stark et al. (2017) adopted digital twin as a test method in a new approach for next generation manufacturing systems.

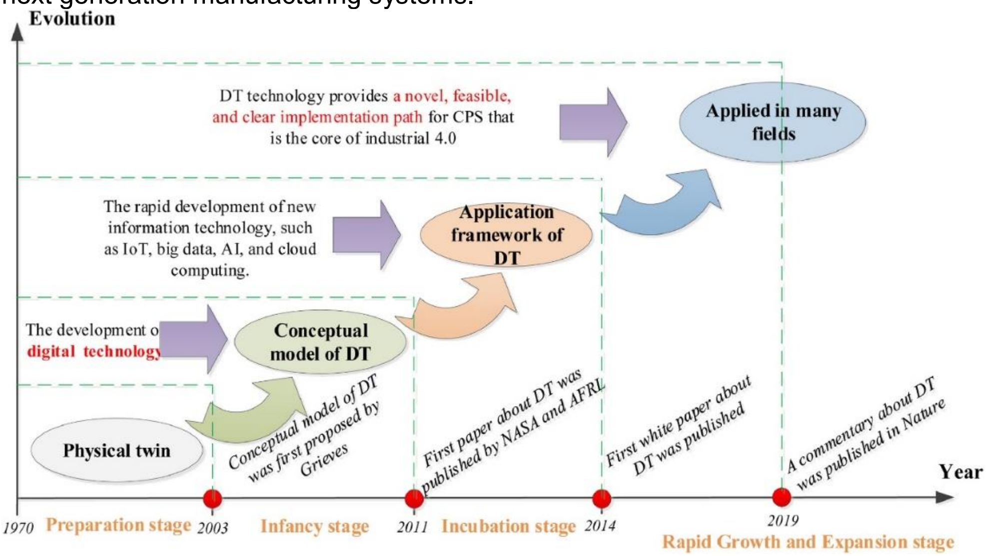


Figure 4. Evolution of Digital Twins (Lim et al., 2020)

The digital twin is structured in three distinct parts: the physical process, the digital / virtual process and the interactions between the two previous components in the form of data flow from the first to the second and in the form of valuable information from digital to physical form.

The digital twin concept consist of 3 stages (Grieves at al., 2016):

1. digital twin prototype (DTP),
2. digital twin court (DTI)
3. digital twin (DTA) (aggregation of the previous two)

DTP represents the design and process analysis phase for the realization of a physical product and precedes it

DTI is the digital representation of each instance of the product in the phases of the production process.

DTA is represented by the aggregation of DTI instances that can be reused in the learning process which can be a simple ML process or can be a DEEP Learning process using Neural Networks and can be introduced both in the initial design phase and in the initial phase. operate.

Grieves and Vickers (Grieves et. al., 2016) extended the study of digital twins into complex production systems by studying the occurrence of nonconformities and how to predict them as actions to prevent and eliminate the inevitable occurrence of their occurrence. Thus Tao et al. performed dynamic updating and data synchronization between the process and the digital twin laying the foundations of PLM with applications in the assisted virtual store. (Tao et al, 2018)

(Zhuang et al. 2018) develop a production management and control platform based on digital data and big data was described.

By granularizing sensor, communication and computing technologies, the digital twin of a process and ultimately of a product becomes a high-fidelity virtual model that simulates, reflects, predicts and improves the life of its physical entity. The key to the fidelity of the representation is the microgranularization of the subprocesses and the possibility of obtaining data from sensors sufficiently "good" to describe and model these microprocesses.

Given that the speed, volume and variety of data transmitted by sensors increase exponentially to achieve real-time monitoring and a feedback loop of "near" real-time monitoring, the characteristics of a BIG DATA ecosystem are reached, a situation in which the increase in bandwidth of their transmission allow the application of horizontal scaling by introducing parallel and distributed computing for the same data stream, which brings the finesse of granularizing the modeling of subprocesses to a level of exponential convergence of iterations of digital twins to real models.

The digital twin model proposed to represent a real model of a life cycle of a product that appears from a production line consists of four levels in which the impact of the "BIG" data transmitted in stream processing, having speed, volume and characteristic BIG DATA variety, are processed in dimensional modeling then undergo distributed and parallel processing, quantified at the last level, that of predictions, followed by the learning stage, resulting in a series of iterations of digital twins converging to the real model. The representation of the logical framework for implementing the process is in figure 5.

The BIG DATA ecosystem interacts with the architecture of a digital twin and defines four layers described in figure 5.

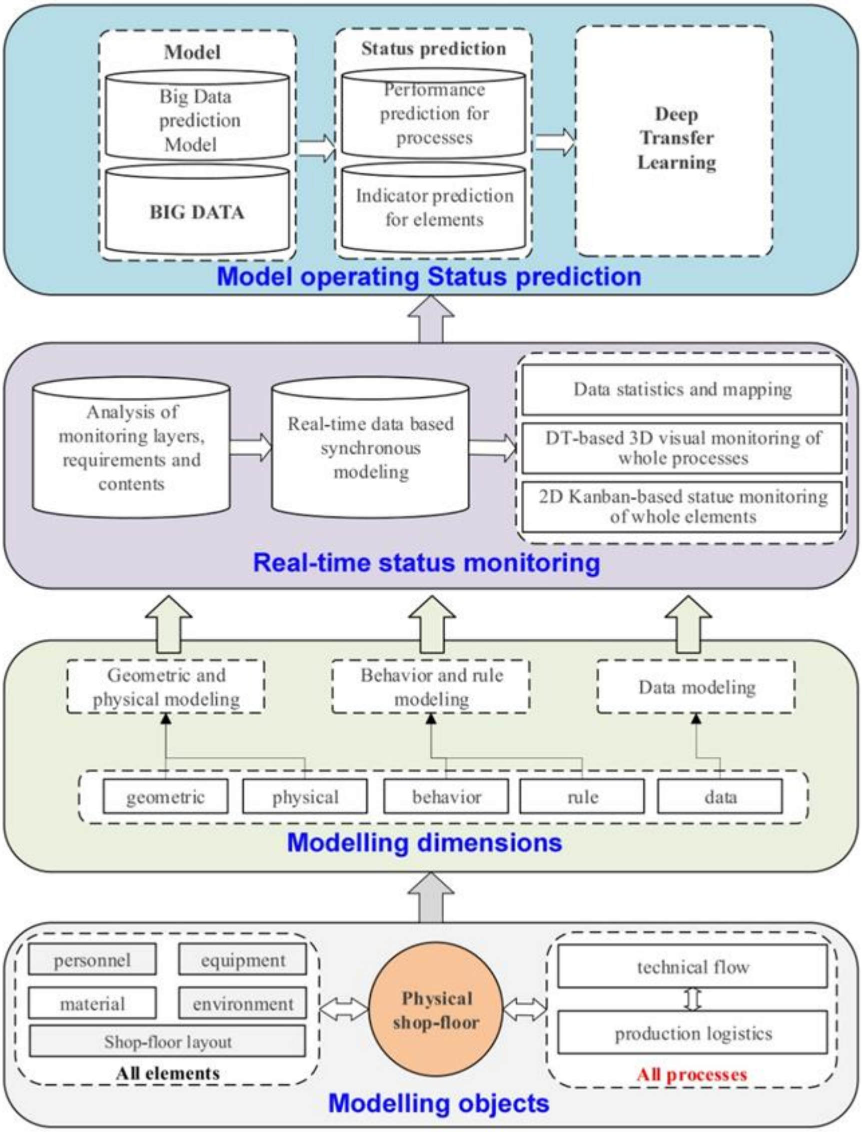


Figure 5. Implementation of the model based on the digital twin in the BIG DATA environment

The logical framework of the implementation is described in figure 5 and has four layers

1. Modeling objects. For the construction of the digital twin, the objects to be modeled must be analyzed in terms of compliance with the requirements of the application - in this case it is a matter of real-time monitoring, prediction of the production process and improvement of the model. Production processes consist of production logistics and production flow and Production elements refer to all physical elements, such as personnel, equipment, material, coordinates

2. Dimensional modeling. It is based on five elements: geometry, physical dimensions, behavior, rules and data. The geometric and physical dimensions are for the construction of a virtual 3D scene that will become the support for the real-time and visual monitoring of the operation state of the production line. The size of the behavior is for the dynamic description of work processes based on the operating logic of the store, which is to reflect the operating status of the store in real time.

The size of the rule includes deduction rules, association rules and constraint rules. The purpose of the data dimension is to build a data organization model for DT so that static and dynamic data management in the store is achieved and provides complete and accurate data for other modeling dimensions.

3. Real-time status monitoring. based on the geometric and physical modeling of the SDT, a real-time modeling of the SDT behavior can be performed. Monitoring content includes real-time synchronous mapping of all production processes and dynamic display of the current status of all production elements. All in-store processes are displayed in real time via intuitive 3D animations

4. The prediction of the state and the improvement of the model is made based on a model in a big data environment but also having a discrete component that uses the time sequences of the operating state. The model is then improved using NN neural networks

The new capabilities introduced by the DT technology generates innovative services within the Business Models (WB) Business Models thus allowing Industry 4.0 to be no longer just a trend but a certainty and a main component of the organizational mission around which the new strategy is outlined and action plan in which DT-based simulation and modeling underpins optimized decisions of top management level.

The introduction of DT increases the competitiveness of the company vertically, by reducing implementation risks, optimizing stocks and sales, reducing production cycles and thus reducing costs. This allows "agile" methods of implementing new production processes for innovative products based on the previous simulation of DT with almost zero risks when implemented in the production environment.

3. CONCLUSIONS

The novelty element introduced by the BIG DATA ecosystem is the horizontal development of competitiveness, in terms of relations with the external environment where the cycle of interaction with external flows at suppliers, financial and customers can be modeled and simulated by evolutionary processes based on both classical data flows. (small data) in the financial accounting field or of the suppliers, especially of the stream flows from the clients' level using the analysis of the social networks. This creates the technological premises to be able to create DT of representation both at the level of micro-communities and at the level of individual client, with obviously higher costs.Direct addressability and obtaining individual customer feedback provided by BIG DATA ecosystems along with the possibility of vertical modeling and simulation within the enterprise, integrated in a digital system will be the next step of a DT that will have integrated digital subcomponents that they will model and simulate the market, production flows, material flows and financial flows.

This ensures the increase of the value of products for the market by increasing the quality, shortening the financial cycle, eliminating non-performing stocks, thus ensuring the increase of capital for investments, reducing the risks of introducing new products on the market, the possibility of introducing "pay as you go" models. on the payment only of the services obtained in the imposed quality conditions.

At the technological level, the NSGA-II and MES type algorithms overlap the DT implementation methodologies over the manufacturing processes and this will allow establishing the necessary type of DT (full, partial or increased) (Kucera et al., 2016) creating future directions of development.

Such a situation is the elimination of the end-of-life stage from the product life cycle by transforming it into a continuous cycle, by introducing in this cycle an innovative remanufacturing component, with DT modeling and simulation and then reintroduction into the cycle. life of the product in the form of a new version, all these iterations of the product versions allowing with the help of BIG DATA tools testing, observation, market influence at the level of the individual customer and then generating the dimensioned production model and with particular product specifications determined for each version in part.

Subsequent developments must take into account several elements that have not yet been standardized and sufficiently implemented:

- Security and quality of data and information transmission from DT to physical model
- A standardized framework for decomposition into reusable, class-standardized submodels, with connection tools that must ensure the interconnection standards at both the submodule and DT levels
- Automation of learning algorithms and integration at the primary level in DT in order to move to real-time simulation and convergence to the optimal model.
- Introduction of VR in DT and AR at the level of the physical model, both based on AI techniques.

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