DIGITAL TECHNOLOGIES REVIEW FOR MANUFACTURING PROCESSES

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ABSTRACT

It is apparent the industrial processes transformations caused by industry 4.0 are in advance in some countries like China, Japan, Germany and United States. But, in return, the developing countries, as the emergent Brazil, seem like to have a long way to achieve digital era. Considering manufacturing processes as the starting point the rise of industry 4.0, this research aims to show a review about the most important technologies used in smart manufacturing, including the main challenges to implement it at Brazil. The papers were collected from Web of Science (WoS), comprising 114 articles and 2 books to underpin this study. This exploratory research resulted in the presentation of some challenges faced by Brazilian industry to join the new industrial era, such as poor technological infrastructure, besides lack of investment in technologies and training of qualified people. Even though the primary motivation of this research was to present a panorama of smart manufacturing for Brazil, this study results contributes to the most of emergent countries, bringing together general concepts and addressing practical applications developed by several researchers from the international academic community.

Keywords: Smart manufacturing; Industry 4.0; Manufacturing Process; IoT.

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1. INTRODUCTION

Digitalization of data is a reality today and has been growing more and more in the technological age, due to its great importance for factories, in which this way it is possible to exchange data and interoperability between the smart equipment of a factory, thus allowing the implementation of the Smart manufacturing approach (Santos et al., 2017; Liu et al., 2020; Sahal, Breslin & Ali, 2020).

Today's factories constantly deal with large demand for goods with a high degree of diversity, which makes it difficult to manufacture products in small batches (Lu, Xu & Wang, 2020). In the midst of this great difficulty in serving consumers with smaller and more personalized batches, manufacturers begin to enter a new era, in which product customization, integration of machines in virtual environments and the use of artificial intelligence (AI) becomes necessary to obtain profits and maintain the company's competitiveness in the market. Such an era is known as the fourth revolution, popularly called industry 4.0 (Lu, Xu & Wang, 2020; Tortorella et al., 2018; Tang & Veelenturf, 2019; Da Silva & Almeida, 2020).

Industry 4.0 has been growing rapidly, despite difficulties in implementing it. Some of the obstacles encountered are technological changes that lead to changes in layout and design in industries (Müller, Buliga & Voigt, 2020). In order for the fourth industrial revolution to be implemented, it is essential to redesign the manufacturing process, so that smart manufacturing production lines are inserted in the industry (Moktadir et al., 2018).

Some techniques/methodologies can be considered as a fundamental part of the fourth revolution paradigm when they are related to manufacturing (Yadav et al., 2020). Techniques such as Internet of Things (IoT), Big Data, Blockchain and Machine Learning are used to improve the manufacturing process in industry 4.0. (Souza et al., 2020).

Data virtualization has been increasing in recent years in the industry (Müller, Jaeger & Hanewinkel, 2019), with this the IoT gains strength, connecting an entire manufacturing process, making it fully automated and exchanging information between machines (Kerin & Pham, 2019; Shah & Wang, 2020). One of the benefits that IoT can bring to the manufacturing process is the ability to produce varied products with minimal or no workers operating the machines (Fox & Subic, 2019).

This research aims to show a review about the most important technologies used in smart manufacturing, including the main challenges to implement it at Brazil. The research carried out has its relevance focused on the dissemination of knowledge of the difficulties found in the Brazilian scenario in relation to industry 4.0, analogous to the scenario of other emerging countries such as India and South Africa that are in the initial stage of implementation (Menelau et al, 2019).

In general, the research contributes to a relevant and notorious topic in the academic community, considering the other publications of renowned authors who carry out research and develop solutions applied to intelligent manufacturing. According to the bibliographic review, it was found that industry 4.0 has numerous challenges to be overcome, mainly in Brazil, such challenges can be summed up in two major aspects, investment in technologies and training of qualified people to work in this new era.

2. CONTEXTUALIZATION OF MANUFACTURING PROCESSES

Since antiquity, human beings have learned to create tools, the act of creating is what makes possible a process that determines a product (BI et al., 2017). Over time came the need to evolve, and with that Industrial Revolution emerged, which allowed the involvement of numerous experiments and case studies that enabled researchers to new methods of optimization in manufacturing processes (Ćwiklicki et al., 2020; Takezawa et al., 2020).

In the literature, the concept of process is defined by the raw material that gives rise to the finished product (Ozkan-Ozen et al., 2020), a process is carried out according to the need for a product or tool, the raw material is intrinsically important for to obtain manufacturing, through well-organized goals and plans that enable the best productivity in a company (Lin et al., 2020).

With the implementation of continuous improvements (Xia et al., 2020; Moktadir et al., 2018) and the optimization of time waste in lean manufacturing processes (Tortorella & Fettermann, 2018), the process classification was developed, which are related to the functions due to the type of process, energy involved, working temperature and working voltage (Kiss & Grievink, 2020).

The types of processes such as mechanical forming, casting, welding, powder metallurgy, machining and others, are specific in the creation of metallic materials (Mokhtar & Nasooti, 2020). Those that are driven by techniques and tools such as turning, milling,

drilling, planning, abrasive jet, EDM (Electrical Discharge Machining), laser, plasma, lamination, extrusion, stamping and many others, for each type of technique a group is formed that makes up the type of process (Nwankwo et al., 2020).

In addition, there is a classification of the types of energy involved that deal with mechanical, metallurgical and intermediary processes (Moon et al., 2020). Another classification is given by the working temperature, with an analysis by means of variables such as cold and hot, with this the phenomena that lead to the production of the material for the finished product are considered (Buswell et al., 2020). Finally, the working stress classifies the process through the deformation or removal of stress in materials that lead to the shape of a product (Liu & Shi, 2020).

Smart manufacturing has been evolving according to the need to optimize processes, dependent on technologies that increase productivity and reduce costs, making possible methods previously not practiced, allowing greater reach in the analysis of investment, productivity and business performance (Kusiak, 2019).

Thus, the implementation of industry 4.0 model brings high expectations regarding the ease of information, through data processing, internet of things, data analysis, information security and artificial intelligence (Mittal et al., 2019; Moeuf et al., 2018), resulting in large investments and greater complexity in the use of resources and training of qualified people.

Due to the inclusion of technologies that include a communication facility, there is transparency between the processes, where it does not make explicit how the digitization method is performed (Jones et al., 2020; Zhuang et al., 2020), only allows the use and guarantees the integrity of the data through smart techniques and ways of applying smart manufacturing in practice (Gupta et al., 2020).

In this way, factories become intelligent and embrace innovative resources with regard to technology (Kusiak, 2019; Kusiak, 2018). The manufacturing process, which is an extremely important step towards the finalization of the product, is seen as a great concentrator of methodologies that minimize the gaps in time and process of a product (Walheer & He, 2020; Ghayour et al., 2020).

With the advent of intelligent manufacturing, failure projections are minimized considerably (Kusiak, 2019), this is done by methods such as Deep Learning and Machine Learning (Tortorella et al., 2020; Romeo et al., 2020), which are techniques of computational
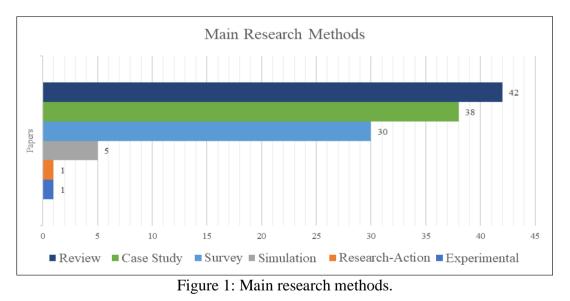
intelligence that approach and simulate machine learning through trial and error, often through inferences and others with predetermined meta-heuristics.

In addition, there are also the pillars of the IoT, considering the best data processing through a distributed architecture that offers security in anonymity. The use of algorithms and techniques like Blockchain are notoriously studied, applied and improved by scientists who develop more and more new solutions, allowing scientific advancement of industry 4.0.

3. PAPERS COLLECTION

For the development of this study, an exploratory search was carried out on the Web of Science database through the Science Direct and Google Scholar platform, in which the following keywords were used: "Industry 4.0", "Smart Manufacturing", "Manufacturing processes", "Blockchain", "Robotic", "Challenges of Brazil in smart manufacturing", "Smart manufacturing on process industry", "internet of things and its pillars", "robotics in industry" and "intelligent manufacturing processes". 114 articles from 69 journals and 2 books from 2 publishers were used.

Figure 1 shows main research methods used by authors, showing that "Review" is the method chosen for the most of papers (42), followed by "Case Study" (38).

Figure 1: Main research methods.

The following lists all the techniques and technologies found in the cited articles: Cylinder Detection, Artificial Neural Networks, Computed Tomography, Cloud Computing, Big Data, Space Industry, Mathematics Paradigms, IoT, Detection Network, Digital Fabrication, Linear Programming and Multi-Objective Optimization, Embedded Systems, 3D Printing, Digitization, Delphi-Based Scenario, Health Systems, Augmented Reality,

Optimization, Cyber-Physical Systems, Cloud Computing, Robotics, Technique Additive Manufacturing, Web Framework, Robots, Delamination, Virtual Reality (VR), Digital Twin, Blockchain, Process Systems Engineering (PSE), Data Mining, Automated Manufacturing Systems, Digital Manufacturing, Artificial Intelligence, Graying, Binarization Methods, Total Factor Productivity (TFP), Internet of robotic things (IoRT), Deep Reinforcement Learning (DFL), Imitation Learning (IL), Analytical and Optimization Tool, Automation and Manufacturing Digital Thread, Descriptive Analysis, Technology Foresight, Automation Construction Robotics, Bibliometric, Simulation,Decision Support Tool, Best-Worst method (BWM) and Smart Technology, Method based on the Integrated and Normalized Cross Power Spectral Density of the Background Noises, Research, Digitization in Wood Supply, Triple Bottom Line, fuzzy, TOPSIS Multi-Criteria Method, Deep Learning Techniques, GPU Virtualization and Serverless Computing, Economic Analysis, Integrated Process Safety Management System (IPSMS) Model, Fuzzy Analytic Network Process (ANP), Analytics-Statistics Mixed Training (ASMT), Developed Technology Computer-Aided Design (TCAD), Text Mining, Digital Twin, Radio-Frequency Identification (RFID), Smart Sensors, Machine Learning (ML), Decision Tree, Bayesian Filter, Stream Processing, Semi-Autonomous Programming, Optimization Algorithm and Metaheuristic Algorithms, Cyber-Physical Human Systems (CPHSs), Real-time Embedded Computing Systems, Interval type-2 Fuzzy Sets, NSGA-II, Sequential Inherent Strain Method and Sensitivity Analysis, Drones, Framework-New IT Driven Service-Oriented, Smart Manufacturing (SoSM), Organizational Learning (OL), Multivariate Analysis and Lean Production (LP), Data Envelopment Analysis, Computing Fog Based, Industrial Cloud Robotics (ICR), Cloud Service, Robust Best Worst Method (RBWM), Autonomous Car and Intelligent Robot, Structure Entropy Model and Structural Order Parameter .

4. APPROACHES AND TECHNOLOGIES USED IN SMART MANUFACTURING

Among the technologies that involve manufacturing processes are additive manufacturing, virtual reality, augmented reality and robots (Mittal et al., 2019; Moeuf et al., 2018). Digital Twin was conceptually proposed for a future vision for smart manufacturing, representing reality in a digital perspective (Tao et al., 2018). Digital Twin is a production methodology that allows a reconfiguration or simulation through decision making in manufacturing strategies (Grieves & Vickers, 2017; Tao & Qi, 2017), one of the great

benefits of this technology is the mirroring of processes through computational models and simulators, allowing real-time management (Qi & Tao, 2018).

In the study of Xia et al. (2020) and Zheng and Sivabalan (2020), the methodology presented and applied to minimize the gap between the physical and the digital is the Digital Twin, allows the use of intelligent manufacturing.

Figure 2 illustrates the conceptual model of the Digital Twin in a practical example of virtualization or digitizing data and machinery for the virtual environment, thus generating its digital twin.
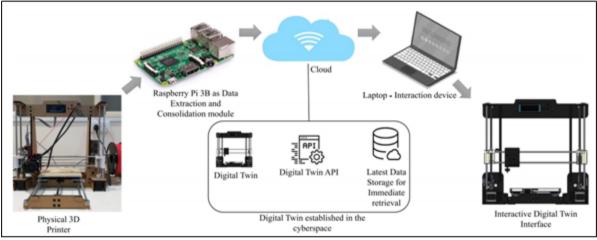

Figure 2: Conceptual model of Digital Twin.
Source: Zheng and Sivabalan (2020).

Another technology to be highlighted that is being used a lot in the manufacturing process in the industries is the IoT, if the Digital Twin takes the real to the virtual, the IoT connects the machines and allows "conversation" between them. In the articles by Hang, Ullah and Kim (2020) and Souza et al. (2020), IoT is used in conjunction with another methodology, blockchain, allowing connectivity and data security in the manufacturing process. The blockchain in the manufacturing process allows product traceability in all logistics, thus keeping a block of important product information (Pólvora et al., 2020).
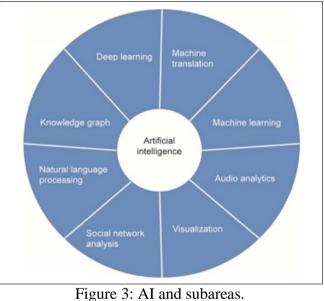
With the connectivity and integration of IoT and Digital Twin, another technology comes to further strengthen smart manufacturing, popularly known as artificial intelligence (Azouz & Pierreval, 2019; Mana et al., 2018), which has N optimization and prediction algorithms. In the case of the work by Ruiz-Sarmiento et al. (2020), the prediction technique called Artificial Neural Networks is used to assess the health of assets in a stainless-steel industry.

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Another AI (Artificial Intelligence) technique used is Fuzzy Logic, the article by Shukla et al. (2020) exemplifies the use of such a technique. With the great growth of industry 4.0, industrial plants began to spend more energy due to the connectivity provided by the IoT, and to alleviate energy consumption by industrial plants, Shukla et al. (2020) applies fuzzy logic with Genetic Algorithm (AG).

Figure 3 illustrates artificial intelligence and its subareas, totaling 8 intelligent techniques that are used in the model of integration of technologies in smart manufacturing, which allows synchronization through real-time systems and data processing that generates information useful for decision making.

Figure 3: AI and subareas.
Source: Mao et al., (2020).

To be applied IoT, Digital Twin, and AI it is necessary to automate processes in factories, and industries must have robots that play a fundamental role in various sectors, becoming indispensable for intelligent manufacturing (Yan et al., 2017).

Over the years, strategies for improving manufacturing processes have been developed and continue to evolve constantly, seeking results of excellence and greater profitability for the industry (Parashar et al., 2019; Fox & Subic, 2019; Craveiroa et al., 2019), the concepts of the new industry model, smart manufacturing, arise, that is, an intelligent industry that accommodates a cluster of techniques and technologies that cooperate with each other through methodologies to carry out the least effort and highest productivity in the industry (Wu et al., 2018).

With these operations, the idea of cyber-physical systems arises, which are characterized by collaborative control, in addition to other technical terms known as connectivity, interoperability, real-time communication, among others, that make the difference in working together with the information worked on (Sharpe et al., 2019; Zheng & Sivabalan, 2020). This type of sector is constantly challenged by the temporal structures of the machines, with different times for each machine working in parallel or dynamically.

Due to the need to optimize technologies and processes characterized in the industry, which is one of the sectors with a high rate of profitability and productivity, research related to the theme is triggered, generating numerous contributions in the academy and in the sectors that work directly with automation in the manufacturing processes (Catalá et al., 2016; Moreira & Correa, 1998).

For Raj (2020), it was possible to identify the needs to apply an intelligent model in the manufacturing processes, considering the Brazilian scenario as model:

- Enter into the dispute of the technological productive sector allowing negotiations with other countries, besides strengthening a professional relationship between qualified scientists;

- Increase the employment rate and amplify the course market focused on industry 4.0;

- Moving working capital and allowing economic development in the states;

- Products with high added value when using high performance equipment and higher manufacturing quality;

- Increase in work efficiency with accurate and qualified productivity with statistical content of analysis.

In accordance with the factors presented, the industry 4.0 model consists of equipment with high performance and highly qualified professionals, the technologies and services that consolidate the pillars of intelligent manufacturing, for Kusiak (2018) are: manufacturing technologies and processes; materials; data processing; predictive engineering; sustainability; sharing resources and networks.

According to Kusiak (2019), for the application of manufacturing processes, some technologies are necessary, such as additive manufacturing, virtual reality, augmented reality

and robots, with these elements the basic structure for an intelligent manufacturing process is obtained.

4.1. Additive Manufacturing

In the perspective of industrial evolution, the smart industry model has been preparing for a stage with great challenges and innovative principles (Lins & Oliveira, 2020), with the concept of additive manufacturing and elements such as 3D printing (Klockner et al., 2020; Benitez et al., 2020) will be commonly used in several sectors acting mainly in the production stage, allowing a greater reach in certain situations.

With mass production using this technology, there will be a guarantee of an accurate precision in the development of parts or finished products, through computational software it is possible to determine the characteristics of the element such as: color, dimension, thickness, depth, height, type of material, size and others that are previously configured (Robinson et al., 2019; Maresch & Gartner, 2020).

With this type of work that can be on a large scale, processes such as machining are easily exchanged, or even in civil construction where machines build houses using the 3D printer (Craveiroa et al., 2019).

For Den Boer et al. (2020), in his research on "advantages and challenges in the spare parts supply chain", it is possible to identify some advantages of using this method that are listed as follows:

Speed: Manufacture in high definition and quality of a product or part, being able to be distributed or supplied in several sectors, being a prosthesis used in surgeries or even large-scale constructions with heavy materials and large machines, in addition to enabling prototyping fast;

Cost: Measurable control of the quantity of elements produced, without limitations regarding hardware or machinery, expanding new forms of the market;

Design freedom and complexity: With qualified and qualified professionals in the subject, you get the freedom to customize a certain product at a low cost, in view of the customer's needs and even the rate of evolution in production, obtaining greater results in the supply and manufacture;

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Customization: Through the use of specialist or proprietary software created by a development team, it allows the use of legal and personalized form in the creation of plans and models of objects and elements of the project to be printed;

Sustainability: Control the use of raw materials and high-cost materials, in addition to avoiding energy costs and manufacturing waste.

For some authors like Dev et al. (2020), Bauza et al. (2018) and Mittal et al. (2019), the management of additive manufacturing using 3D printing is used in 3 stages, making it possible to carry out the planning, simulation and production of the part or product:

3D Modeling: Created in computer software such as AutoCAD;

Sizing in layers: With the definition of some parameters, the slicing process will be performed, in this way a file in g-code format is generated;

Production process: The generated file is sent to the 3D printer which, after reading and interpreting the code, will print using the coordinates established by the producer, depending on the object to be printed, the manufacturing time can vary from hours to days.

Thus, the expectation of using 3D printing in various sectors of commerce and industry is high, directly impacting the local economy, in addition to influencing the supply of raw materials for the manufacture of finished products (Dev et al., 2020; Pacchini et al., 2019; Culot et al., 2020).

4.2. Virtual Reality (VR)

Another important technology to be highlighted is the virtual reality characterized by the generation of environments simulated by computer, this tool becomes necessary mainly in the presentation of objects or environments through interfaces rendered in high definition allocated in hardware with transmission capacity, as is case of 3D glasses (Roldán et al., 2019; Chiarello et al., 2018). In addition to simulating the production environment through this equipment, it also brings great benefits and facilitates communication, increasing the focus on business (Masood & Sonntag, 2020).

Thus, in the near future it will be possible to immerse the user in virtual reality, through sensors, actuators and neuro-computational connections, which allow the use of the senses, bringing in fact reality resulting in bodily phenomena such as pain, anxiety, fear, anger, joy and others (Mittal et al., 2019).

Thus, it is worth emphasizing expectations regarding the use of this innovative resource as an element of work in industry 4.0, one of the applications is the realization of practical training, reducing costs in team trips to seek knowledge and technical qualification, another important point is the cheapness of the process, with the use of virtual simulators, allowing greater security and increasing the operational efficiency of training (Pejic-Bach et al., 2020; Kerin & Pham, 2019).

Cases in Brazil related to the use of VR are presented in international magazines and Brazilian blogs, as is the case of automakers in Minas Gerais where Fiat car models are simulated several times by virtual simulators, avoiding errors in the manufacturing process and increasing the degree of quality in details unnoticed through predicted calculations, thanks to the simulation model.

According to Pallavicini et al. (2016), some of the applications of virtual reality also involve areas such as: workplace safety; training and capacity building; industrial maintenance; maintenance of processes on the production line.

Through the factors presented it is possible to identify a leap in production and manufacture of new technologies with these resources, among which there is the game market that evolves as new intelligent computational techniques are developed (Xia et al., 2020; Zheng & Sivabalan, 2020).

Just as it was with the concept of AI in virtual stores, embedded systems, autonomous systems of supervision, prediction and data collection, in addition to technologies that virtualize environments for people with visual impairments, attitudes like these bring the real essence of science in creating technology which benefits not only in the manufacturing processes in an industry, but also in the best condition for an employee to carry out operating tasks within the manufacturing environment (Santos et al., 2017; Kerin & Pham, 2019).

4.3. Augmented Reality

The industry will also be able to invest in technologies that support augmented reality (Müller, Jaeger & Hanewinkel, 2019), with a higher expectation in relation to the other, having the user's vision in a real environment as a major characteristic, an example would be the projection of a person in another distant location through a hologram, or even a technical visit to a distant company through virtualization in the environment, the possibilities are diverse (Fox et al., 2020).

Using computing, numerous technological solutions are possible, through the analysis of variables and the development of mathematical models, augmented reality has great expectations and benefits in several sectors of the industry (D'anniballe et al., 2020; Tao et al., 2019).

According to Van Lopik et al. (2020), this technology becomes versatile and allows a range of applications in view of the industrial scenario, such as:

- Training, with activities carried out by means of intelligent simulators, achieving greater productivity and control of the processes;

- Visualization of the exact locations in which several items must be arranged, allowing better conditions for performing tasks in the operator's process;

- Recognition of parts and patterns;

- Overlay images of the internal hardware of industrial machines to assist technicians' work, allowing fault identification and parts exchange with ease.

- Among the most diverse uses of augmented reality in Brazil there are:

- Development of applications and software that scan machine data and illustrate or describe through interfaces the stages of maintenance of the same by a technician while performing it;

- Accident prevention, where employees are able to walk with their cell phones around the factory while interacting with the protective equipment required in each sector, with this method the training experience has become better, in addition to avoiding expenses with the construction of specific safety rooms in the factory;

- Quality Inspection with the use of glasses with augmented reality technology like Glass from Google, assisting in the inspection of tractor assembly.

As mentioned by Lovreglio and Kinateder (2020), and Wedel et al. (2020), research is carried out in several countries, with exploratory research, action research and even qualitative and quantitative ones, analyzing and identifying ways of improving technologies such as augmented reality, through computational intelligence that it is possible to expand horizons in models of industrialization in manufacturing processes.

According to research by Porpiglia et al. (2020), with Artificial Neural Networks (ANN) or even Genetic Algorithms (AG), formation improvements in image frames and virtualization in real environments are possible, the construction of pixels may change according to the mathematical model used (Naranjo et al., 2020), this allows an optical variant of the user, such as people with low degree of vision, or even considering the level of brightness of the environment (Li et al., 2020).

Some computer scientists constantly develop research related to optimized search algorithms (Shabani et al., 2020), that are applied in cases like this that present problems of rendering images with binary blocks of pixels (Fernando et al., 2020; Bu et al., 2020), several models are developed as research to improve the optimization of image rendering, which depends on the need for use.

4.4. Robots

The greatest technological invention after the first computer is in fact in the area of automation with the emergence of the robot (Syed et al., 2020; Pekkarinen et al., 2020), it allows and if it has great futuristic expectations, several films are produced about the theme that they discuss about the future of humanity with robotic interaction, in the industry it is not different and the applications with the use of robotic arms and complete robots are diverse (Franklin et al., 2020; Lee et al., 2020).

One of the examples to be cited is the robotic arm used in a production line, capable of making decisions and identifying parts using variables such as size, thickness, depth, color and type of material (Yun et al., 2016; Xu et al., 2020). With the evolution of technologies and research on the subject, new models of robots were built, among them the robot builder that is already a reality in German industry and in other countries (Melenbrink et al., 2020; WANG et al., 2020).

With 3D printing it is possible to develop customized robots, with the material specified in specialist software and the trained professional to develop the robot's construction plan (Petrick & Simpson, 2013), another important point to be highlighted is about the research addressed by Xia et al. (2020), he explains about the processes of using the digital twin to train a deep reinforcement learning agent for factories in a factory environment with interfaces and computational intelligence.

In his research, it is reported the way of programming robots using the Digital Twin, through control modules where a sequence of commands is digitized and executed through programmed actions to only then start the simulation process. This procedure in a developer's view can be determined as an input of unit events that resemble PLC programs, having the input and output signals controlled by an intelligent and autonomous signal system, with a high level of programming, its application may vary from small and medium-sized companies (Xia et al., 2020).

Another application of robotics is the construction of Drones (Hang, Ullah & Kim, 2020), with a high level of performance in relation to the autonomous systems used in mobile vehicle networks, besides including specific hardware to perform certain tasks, it also has algorithms such as learning machine learning and deep learning that are widely used in heuristic decision-making methods. The inferences of data are through a specific technical infrastructure acting with the sending of data to the cloud and a client module capable of interpreting and processing the data, thereby generating useful information for the administrators and managers of sectors that work with these technologies. (Yan et al., 2017).

5. CASES AND PRACTICAL APPLICATIONS

Intelligent manufacturing can be applied in various sectors and applications, such as Steelmaking industry; Energy efficiency; Factories in general; Training of workers; Civil Construction and Automation of processes intelligently using robots.

The stainless steel industry, as stated in the article by Ruiz-Sarmiento et al., (2020), the authors discuss the machines used in the manufacture of steel sheets with a high level of quality, in which they propose a way to minimize the damage to these machines through prediction, made by Machine Learning which is a branch of AI.

Industry 4.0 values the integration of all machinery so that the application of IoT and AI is possible, however, the integration of all machines means that industrial plants consume more electricity in each plant, to solve the difficulty it is necessary to find the shortest time and the lowest energy consumption to perform a task (Shukla et al., 2020). Having the problem, the authors Shukla et al., (2020), applied multi-objective AG and fuzzy logic to have a balance between the time to be fulfilled in the manufacture and the amount of electrical energy, achieving an optimal result. It is noted that, to achieve the digital technology present in industry 4.0, AI must be heavily worked on.

In addition to AI techniques, another methodology that has many applications is Digital Twin, which can be applied not only in the manufacturing process, but also in the supply process. According to Lu et al. (2020), Digital Twin can be applied in factories in general, creating a virtual model of the real model, so there can be simulations with real data in an external environment to the production, which can bring benefits such as optimization of manufacturing processes, identification of problems in the production line, among others.

A practical application of Virtual Reality that brings many benefits is the training of people for manufacturing processes that involve manufacturing and assembling products (Roldán et al, 2019), as is the case with IC.IDO which is a tool to display processes of machining through a computer-aided logical interface and virtual reality (Giannuzzi, Papadia & Pascarelli, 2020) or even in cases where VR is used in highly dangerous projects as shown in the research of nuclear devices, where it is used in all phases of the project, including investigating plasma geometry, stability, the scraping layer and the discharge process and conducting an engineering analysis of its electromagnetic, thermodynamic and structural characteristics. (Wang & Chen, 2020).

In civil construction there are examples of intelligent construction, in which additive manufacturing is used. In the article by Craveiroa et al. (2019), it is demonstrated how civil construction makes use of this resource of industry 4.0, which in the specific case is Construction 4.0, the article shows that construction is taking an important step in evolution, building houses, buildings and monuments fully automated and with 3D printers, accelerating the construction process.

Amid so many technologies and methodologies used in smart manufacturing in this fourth Industrial Revolution, one of which stands out is intelligent automation through connectivity and exchange of information in real time (Yan et al., 2017). One of the uses of this process is the interaction of data in the cloud as is the case of the approach based on a robust linear time circle detection algorithm that discards outliers, allowing the manipulation of data sets with different levels of density and noise while uses a variable and relative inferences model, and with this projecting the data in the cloud, this technique was compared with state-of-the-art methods and it was found to be superior in terms of precision and robustness that directly impact noise while maintaining an execution time competitive. (Araújo & Oliveira, 2020).

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Table 1 shows the scenario of some advances regarding the implementation that confirms the industrialization 4.0 model in Brazil.

Table 1: Industrial technological advances.

Company	Description
Romi	Launch of a machining machine capable of molding metal parts by removing or adding layers, being able to register and receive data on processes, an element similar to additive manufacturing with IoT.
Birmind Automação	It works with preventive inspection and monitoring software, providing factory equipment cost data, pointing out any flaws that may have an impact on the company's productivity.
Automatsmart Tech	It works with an industrial maintenance data management platform, based on computational intelligence working with preventive analysis and data storage in IoT cloud.
Autaza	It works with an industrial inspection system using Computer Vision, with the capture of images by cameras on the production line, the system evaluates the quality of the product produced by means of computational intelligence.

Source: Adapted from Nazaré et al. (2018).

6. STATE OF DIGITAL MANUFACTURING AT BRAZIL AND OPPORTUNITIES

The Brazilian industry scenario advances slowly with small contributions related to the theme, a fact that is mainly explained by the regional economy, although several studies are being carried out that directly imply the consolidation of this industrial revolution.

In their research, Nara et al. (2020), addresses the impact of industry 4.0 technologies on sustainability, based on economic factors, using the Triple Bottom Line perspective for sustainability. As a result, it was shown that the Internet of things, cyber-physical systems, sensors and the Big data implementation is a determining factor for sustainable development. In addition, the authors highlight the negative impacts of robots on job creation and the low influence of cloud computing and the integration technology system for sustainable development.

Thus, edge technologies in the context of smart manufacturing show the importance of synchronism and interoperability between the other components that make up the industry (Ren et al., 2019). Bringing to the context of the manufacturing process, there is a decrease in the gaps that are modeled and analyzed in each case of industry, considering variables such as production time, maximum production capacity, in addition to others that may or may not impact the final manufacturing performance.

According to the literature review carried out by Teixeira et al. (2019), where the paths of industry 4.0 in Brazil in the steel sector are investigated, the results indicate that there is a need to update the industry, as well as the teaching centers to prepare the future

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manager and engineer for new technologies and integration in the industrial processes, with many challenges related to the change in mentality that directly impact the socioeconomic scope. It is more than a matter of moving forward, it is about being prepared or not or preparing for the necessary changes (Evans, 2018).

In Brazil, the application of increasingly complex intelligent technologies (technological clusters) impacts transformations in industrial lines, as well as in organizational structures, in addition to better security, however there is a need for high qualification of manpower for the technologies brought by industry 4.0 (Teixeira et al., 2019). For Rampasso et. al. (2020) one of the major difficulties in implementing industry 4.0 in the brazilian scenario is related to a strengthening in the training of professionals, with this through a systematic review of the literature it was possible to verify that out of 10 competencies analyzed in a database, only 6 were identified as a research target, leaving aside: people management, service orientation, negotiation and cognitive flexibility.

According to Souza and Vieira (2020) the great challenge of implementing industry 4.0 is strongly focused on the creation of public policies for science and technology and investment in professional education, for Brazil to consider itself one of the countries that make industry 4.0 a the flagship of the development process will need to prioritize public policies for industrial and technological development, reaching models of strategy in the state with an important role in the realization and articulation of programs with other actors and agents (Souza & Vieira, 2020).

The country invests approximately 1.27% of its GDP (Gross Domestic Product) in R&D (Research and Development) with public and business spending, which makes it much less than the average of OECD (Organization for Economic Cooperation and Development) countries, where investment represents 2.38% of GDP, however, it is above countries Latin American countries, such as Mexico and Argentina, and even countries such as Spain or Portugal (Negri, 2018, p. 23). With these data it is possible to understand that investment in professional education is important and it becomes a strong ally to the creation of public policies in the scope of science and technology making this a structuring factor for the country.

In addition Nazaré et al. (2018) states that the difficulties and challenges are not limited only to these factors, but also due to the lack of investments in technologies and equipment prepared for the specific tasks that allow the integration of industry 4.0 model,

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change and alteration in layouts, modification in production chain, in addition to the high investment in tools and intelligent systems that allow the processing of data and the transformation of this into decision information autonomously.

Soon, the industry will have a greater expectation in the service segment, molding professionals able to act in the context of the smart industry, more and more technical knowledge will be required to manage the other processes of the company or industry, from the acquisition of raw material to finish goods, be it a service or even a measurable product.

For Bogle (2017), some challenges should be highlighted regarding the implementation of technologies in the scenario of manufacturing processes, considering professionals in the area of Process Engineering, among them is highlighted: flexibility and uncertainty; responsiveness and agility; robustness and security; prediction of properties and functions of the mixture; new paradigms of modeling and mathematics.

This model aims to link disruptive technologies to manufacturing systems, combining intelligent operations and supply chain management (Zhang & David, 2020), some challenges are shown in Table 2 for the implementation of intelligent manufacturing in some industry segments in Brazil.

Table 2: Challenges for the implementation of industry 4.0 in Brazil.

Authors	Challenges of for industry 4.0 in Brazil
Brito (2017)	There is no high competitiveness among companies for the adoption of industry 4.0 in the manufacturing process, besides the small amount of products with a high rate of innovation.
Da Silva, Vasconcelos and Campos (2019)	In the Brazilian territory, the implementation of industry 4.0 suffers with some difficulties, among them the question of technology developed in the country that is not of the first world.
Teixeira et al. (2019)	Some of the challenges encountered by Brazilian industry in the transition to the fourth industrial revolution are the new paradigms, the socioeconomic impacts and the change in mentality that must exist.
Vello and Volante (2019)	One of the most impacting factors in the challenges regarding the implementation of the fourth industrial revolution in Brazil is the lack of qualified labor, lack of technological infrastructure that can meet all the integration that the new era needs and a factor that should be mentioned which is the lack of government support.
De Moura Souza and De Castro Vieira (2020)	The difficulties of having the full potential of industry 4.0 on Brazilian soil is directed at qualifying labor for Smart Manufacturing.

According to the study by De Moura Souza and De Castro Vieira (2020) and Storolli, Makiya and Cesar (2019), in the new industrial era, countries such as Germany, Japan, the United States and China are investing heavily in the digitization and integration of industrial processes, so countries that do not have the same momentum in the virtualization and

connectivity of the machines, it will have difficulty following the global market, and Brazil is one of them.

Based on the article by Brito (2017), Brazil has great challenges to overcome in order to implement industry 4.0, mainly in the manufacturing process. Based on this statement, the country needs to reformulate public policies related to industry and trade that enable business models and the exchange of knowledge with suppliers of accessible technologies in the market.

According to Gonçalves (2018), one of the ways to improve and implement smart manufacturing in Brazil is through logical systems of partnerships that allow a solid relationship between supplier and company, in addition to contributing with technological resources, investment in qualified professionals who are prepared for the adversities in a factory environment, with a high productivity rate and thus allowing the incorporation or development of new technologies supported by the industry 4.0 model.

Analyzing all the work, a research opportunity to be explored is the study of mechanisms that can minimize the difficulties that Brazil has in the implementation of industry 4.0, without involving the government, since all the obstacles that result in the country's non-development are linked to government investments and the qualification of professionals to work in this new industrial age.

The problem of professional qualification can be solved through training using VR, as previously mentioned, as it is a consolidated technology in the Brazilian market. A possible resolution would be the adequacy of the large multinational industries in the fourth revolution, this would generate a disparity in relation to competitors, then, they would have to adapt to industry 4.0 to remain competitive in the labor market, not only national, but also global.

7. CONCLUSIONS

The present research had as main objective to present the main digital technologies in the manufacturing process, considering the Brazilian scenario that presents a slow advance in relation to developed countries, in addition to listing some of its challenges, which was achieved through a literature review that includes 114 articles classified as having a high impact factor from the Web of Science (WoS) database and 2 books.

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In general, the research contributes to the academic community, considering the other publications of renowned authors who carry out research and develop solutions applied to intelligent manufacturing. According to this review, it was found that industry 4.0 has numerous challenges to be overcome, especially in Brazil, such challenges can be summed up in two major strands, investment in technologies and training of qualified people to work in this new era.

Among the difficulties pointed out for the implementation of the intelligent model of industry in Brazil, is the precarious technological infrastructure, which is responsible for supporting the execution and accommodating integrated resources that make the manufacturing processes viable, for example the speed of the internet is a great influence o work of the pillars of industry 4.0, in view of the synchronism of the information that will be necessary to generate indicators and reports that assist in decision making and promote new forms of process optimization.

Another important factor to be highlighted is the formulation of public science and technology policies for greater investment in the educational base, allowing the development of qualified professionals and expanding the scope of new research in the industry, which makes new models of strategy and articulation of feasible. programs with other actors and agents.

This research was successful in explaining the panorama of intelligent manufacturing in Brazil, where it was possible to highlight contributions to most emerging countries with the enrichment of the theme, especially in relation to Brazil, gathering general concepts, weaknesses found in Brazil and addressing practical applications developed by several researchers from the international academic community. In addition to providing readers with easy-to-understand content with technical details on the main technologies used in Smart Manufacturing, a systematic literature review is suggested, comprising a larger database to encourage the strengthening of the theme and adherence to the smart model of industrialization by countries emerging.

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