Advancements in Digital Twin Application in the Metalforming Industry: State of the Art and Challenges

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ABSTRACT

The application of Digital Twin in the metalforming industry has proven promising in enhancing procedural control and predictive maintenance. A Digital Twin is a digital replica of a physical system used to predict behaviors and optimize processes. Key challenges faced include the acquisition and quality of production data, validation of the digital environment and the reliability of results, as well as system automation, which can be hindered by the dynamic nature of physical processes. Thus, the main objective of this study is to develop an architecture that can act in the automation of the DT. This article presents the state of the art of Digital Twin (DT) technology in the metalforming industry, highlighting its growth and diverse applications in intelligent manufacturing, predictive maintenance, and structural analysis. Additionally, it proposes a Digital Twin architecture for fault prediction and process control in the forming industry, considering data acquisition and quality, digital environment validation, and system automation as the main challenges to be addressed. In the proposed architecture, the inferential base distinguishes itself, contributing to the system operating autonomously through four stages: perception, cognition, decision, and execution.

Palabras Claves: Digital Twin, Predictive Maintenance, Smart Manufacturing, Mechanical Forming Industry and Control System.

1. INTRODUCTION

The combination of new technologies that bring forth a series of innovations is referred to as the fourth industrial revolution, shaping Industry 4.0. The technologies involved in Industry 4.0 assist and complement established processes in the industrial landscape, contributing to the efficiency of production control. The convergence of established productive methodologies with new technologies from Industry 4.0 represents a significant challenge for the industrial sector, demanding a shift in policy to adapt and optimize processes through the utilization of available technologies [1,2].

The technologies at the core of this new industrial revolution primarily rely on the use of cyber-physical systems, information and communication technologies, coupled with the integration of artificial intelligence and the "Internet of Things" (IoT). Cyber-physical systems establish the connection between Industry 4.0 technologies and the physical environment through monitoring and automatic control, typically involving feedback cycles and bidirectional information exchanges [3,4]. These technologies enable the development of projects capable of providing autonomy in decision-making and flexibility to the industrial processes that employ them [5].

Industry 4.0 incorporates structures used in specific combinations, depending on the problem to be addressed. These structures include interoperability (the ability of cyber-physical systems to communicate with each other), virtualization (the cyber-physical system's ability to transform a physical system into a virtual system), decentralization (autonomy of the system for decision-making), real-time communication, and modularization (the ability to adapt with flexibility to the proposed problem) [6].

Considering the virtualization present in Industry 4.0 technologies, it can be understood as the creation of a virtual version of a physical model by the cyber-physical system, generating a connection used for data collection, impacting the model [6,7]. From this concept, the "digital twin" (DT) was born, which can be defined as a unified, detailed, and realistic representation of the cyber-physical system, featuring aspects of modularization, autonomy, connectivity, and involving cognitive control processes [8,9]. The digital twin is efficient for process control, performance analysis, and contributes to fault prediction through simulations using real process data and returning predicted parameters [10]. Another aspect that integrates the DT definition is multiscale simulation, dividing the analysis into modules, which enhances the efficiency of information flow [11].

The first definition of DT emerged with Grieves in 2003 [12], presenting it solely as a virtual representation of a physical model. This concept has seen enhancements and new perspectives over the years, as reflected by Tao and Qi [13], who portrayed the DT as precise virtual copies of processes or products sustained by real-time sensor-collected data. IBM [14], in its DT definition, emphasizes the system's evolution concerning the physical environment's lifecycle, highlighting the importance of incorporating techniques such as machine learning, simulations, and data analysis, providing autonomy to the system.

According to GE Digital [15], the DT is a virtual representation of an asset or process used to understand, predict, and optimize its functionalities. Deloitte [16] shares this definition and adds that through the DT, it is possible to quickly simulate conditions and share data to act in the physical environment, seeking the best output scenarios.

NASA [17] and Dufour [18] present the DT concept as a multiphysical, multiscale, and multifaceted integration with different techniques and digital models capable of faithfully reproducing processes, products, or operational systems.

From a productive standpoint, the DT, through its digital representations, can collaborate with other systems and digital twins to achieve comprehensive intelligence that enables decentralized self-control [19]. It also has, as one of its main characteristics, the ability for constant and instantaneous transmission of data and information between the environments, aiming at system optimization and evolution [20, 21].

The DT involves different areas such as collaborative work between humans and robots [22], smart factories [23,24], the telecommunications sector [25], energy generation systems [26], additive manufacturing processes [27], smart agriculture systems [28], among others.

The modularization provided by the DT facilitates productive integration, allowing systemic autonomy that provides the environment with the capacity to respond to problems efficiently, intelligently, and automatically. The closure of this cycle occurs through connectivity that allows the use of past data for future decision-making. Thus, the digital twin is the procedural intermediary that provides the flow of information, generating connectivity between project cycles [8].

The process of virtualization and digitization of the physical model has three facets based on how the flow of information occurs. When data is collected and returned to the physical environment manually, it is a digital model (DM). However, when there is an automatic and unidirectional exchange of information between the physical and virtual environments, with changes in the physical model reflecting instantaneously in the virtual model, it is a digital shadow (DS). On the other hand, when there is a bidirectional exchange of information between the physical and virtual environments, happening instantaneously and automatically, with changes in either model reflecting in its counterpart, it is a digital twin [29].

Furthermore, the concept of a digital twin can be divided into two aspects: the digital twin prototype (DPT) and the digital twin instance (DPI). The DPT uses the necessary information from the physical environment to describe the virtual one, which can include 3D models but is not limited to modeling. The DPI, in turn, resembles the DPT; however, the exchange of information that occurs is constant, making it dynamic [30].

Digital twins provide information considering current, historical, and future data through the prediction of the physical "twin." They are considered the foundation for the future implementation of digital factories (DF), which rely on information flow for decision-making and guidance on the operation of the physical model. For this purpose, digital twins need to evolve into active and autonomous systems capable of detecting and processing their environment, proactively exchanging information, making autonomous decisions that align with their objectives, and integrating with the physical environment to apply determined guidelines [31].

An explanatory diagram regarding the main components that structure the Digital Twin concept is presented in Fig. 1.

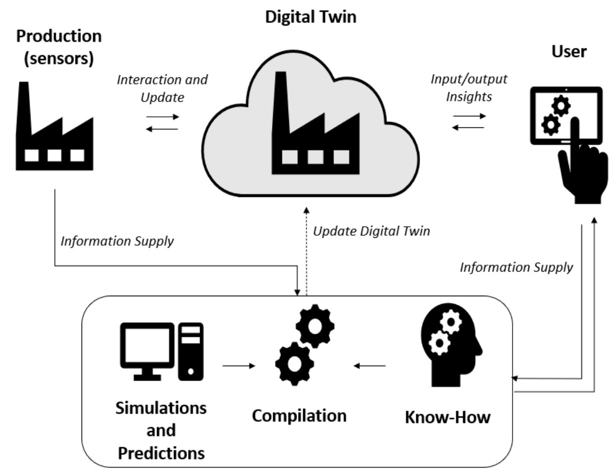

Figure 1 - Schematic Structure of the Main Components of the Digital Twin

Considering the scheme presented in Figure 1, it can be highlighted the constant flow of information, as well as the automatic interaction that occurs among the elements composing the entire system. Thus, the DT can be used for process monitoring, analysis and fault prediction, analysis for process optimization, and even in support of maintenance. It is interesting to note that, in addition to the data collected in the physical process, the know-how of operators and technicians can be considered in the analysis. Figure 1 represents a possibility of DT application in the production environment. It is known that DTs include "ultra-realistic, high-fidelity" integrated models describing the physical behavior of the real system. This may require the integration of various models, such as multi-physics, damage models, models to address randomness, structural analysis (using finite elements), etc., making the system robust enough for the digitization and information flow of complex processes [31].

The first concept of DT, presented by Grieves [12], was developed considering three dimensions for its operation: 1 - The physical entity in physical space; 2 - The virtual entity in virtual space; 3 - Bidirectional data connection and transmission between physical and virtual spaces. However, technological advances and the substantial increase in data generation from modern equipment render Grieves' proposal obsolete. Thus, Tao et al. [32] suggested adding two dimensions to Grieves' model: the data and services modules.

In this new DT model proposed by Tao et al. [32], the data dimension takes a central position in the system, performing the crossing of information, generating insights and controlling the data. The services dimension supports the physical and virtual environment, aiming to promote the optimization of the physical system and maintain the high fidelity of the virtual environment.

The fundamental components for the development of a DT are sensors, data, simulation, analysis, and actuators [9]. Sensors are devices used for capturing data from the physical environment; these data are transmitted through the connection module and stored in a database. The stored data can be analyzed or used for validation of mathematical simulation. This simulation consists of the virtual representation of the physical environment, considering the constituent aspects and interactions between individuals and elements of the system. Through data analysis, it is possible to visualize performance and produce insights about the DT and the real system. Finally, actuators correspond to the mechanical part of the process that receives the analyzed data and acts in the physical environment with the necessary improvements and procedural adjustments.

Therefore, this work aims to describe the state of the art regarding digital twin technology, considering the practical and industrial application of metalforming processes, as well as related areas. For this, a systematic method of selection and analysis of existing works will be followed.

In this article, we will present the advantages and challenges in the application of DT, the state of the art regarding the application of DT for the life cycle of equipment and mechanical components, as well as its application for controlling different forming processes. Finally, a proposal for DT architecture and the study's conclusions will be presented.

2. POSITIVE ASPECTS AND CHALLENGES IN THE APPLICATION OF DT

The application of DT has some positive points regarding control and productivity [33], such as dynamic monitoring of products and services, with high fidelity and in real-time; DT assistance in the development of new products, reducing or even avoiding design errors, and the possibility of providing customers with a virtual experience before the physical product is available; Real-time interconnection between the physical and virtual parts, allowing system operation optimization; Maintenance support through fault prediction and asset control; Possibility of incorporating different technologies, increasing the applicability in different environments.

However, some challenges can be found in implementing DT [33, 9], such as those related to modeling and integration between different software necessary for system development and execution; Provision of adequate communication between sensors and receivers; Storage and manipulation of large amounts of data (big data); Technical level of individuals involved in DT implementation, as it is an emerging technology, and many concepts and techniques are not part of many environments where DT can be implemented; Implementation environment infrastructure and technological capacity of the items that make up the DT may pose obstacles to its execution; Since it is a technology that incorporates various techniques into a single system, support can be a challenge, as several providers are involved; It is a costly process due to expenses with sensing, connectivity, hardware and software for data storage; thus, its application tends to be developed for products or services with higher added value; Insufficient development of the concept and lack of concrete definition, making implementation difficult.

Due to being a diverse and complex ecosystem that allows for various branches, the Digital Twin (DT) faces the challenge of the dynamic functioning of the system, whereby the data collected in the physical environment interacts organically with virtual models, generating insights and an effective control system [34, 35]. Regarding system modeling, the main challenge lies in validating these models, as some systems are highly complex and involve numerous variables, requiring manipulation in the digital model to simplify, which can lead to erroneous results depending on the level of simplification of the system [36, 37].

In addition to the challenge of establishing a system with high fidelity to the physical environment, cybersecurity and the proper handling of data can also be obstacles during the implementation and execution of a Digital Twin. Data analysis is part of the structure of a DT, with most of this analysis occurring through the manipulation of large volumes of data, known as big data, generated primarily through the sensing system during the physical process. Consequently, a challenge to be overcome relates to the quality of this information, as a data control and treatment system may operate complexly. Additionally, another challenge concerns the storage of big data, which incurs hardware costs. This aspect must be carefully analyzed to only store the necessary information to form a relevant history and avoid unnecessary expenses [38].

3. STATE OF THE ART

Given that the digital twin is a methodology that allows for various technologies in its application, it has been implemented to address different demands. These include smart manufacturing [39], predictive maintenance [40, 41, 42, 43], structural analysis [44], performance analysis [45], as well as unmanned maintenance [46, 47]. To address these demands, proposed solutions are incorporating various approaches, such as collaborative operation of the digital twin with the use of Big Data [39], the utilization of historical data analysis along with dynamic data provided by the digital twin [40, 42], the application of machine learning [43], and finite element modeling [44].

3.1 Applications of Digital Twin for Equipment and Component Life Cycle Management

The following provides a brief review of the state of the art in the use of Digital Twin in processes related to the control of industrial equipment and components.

Given that predictive maintenance contributes to high industrial production performance and that multilevel maintenance, involving various parameters for its construction, allows for greater accuracy and robustness for the system, Feng and colleagues [47] developed a Digital Twin for the creation and control of a multilevel predictive maintenance schedule for an industrial plant, focusing on autonomy in decision-making. For this purpose, they created an autonomous system capable of monitoring the operation of various mapped machines through sensory devices. The collected information was processed by a developed algorithm capable of making decisions based on predefined parameters, such as production cycle, number of critical components, equipment costs, available maintenance technicians, number of spare parts in stock, among others. After processing, a maintenance schedule was created and returned to the physical environment, closing the Digital Twin cycle.

To develop a failure prediction system in an industrial plant, Hassan, Svadling, and Bjorsell [48] created a data-based Digital Twin that uses the performance comparison of the physical environment to predict the operating status of the machinery, with discrepancies identified as maintenance points. The comparison between the physical and digital environments was based on process response data and their distances. The model results were classified into three types: parameter configurations, component replacement, and degradation. To evaluate the performance of the digital model, a gray-box technique was used, along with a comparative analysis between the responses of the

Digital Twin and the maintenance records registered by experts. Since a non-autonomous model was developed, the exchange of information between the physical and digital environments did not occur synchronously, leading to some incorrect responses from the Digital Twin.

Industrial autonomy plays a crucial role in reducing errors resulting from human action and providing greater operational flexibility due to possible operator absences. Influenced by the demand for unmanned maintenance of machine tools, Lv and colleagues [49] developed a Digital Twin architecture capable of assisting unmanned maintenance through cognitive support. The developed digital model is based on a cognitive method called LIDA. This method uses four phases: sensory, memory, attention, and execution. The process begins with the capture of information through sensing, storage of this information, inferences about data intersections, and execution of the best decision found. This work resulted in the construction of an autonomous system with potential for evolution without loss of efficiency, utilizing technical and neurosensory aspects without the dependence on experts or human action.

Considering the importance of controlling the lifespan of equipment and its components for the productive environment, Mourtzis, Tsoubou, and Angelopoulos [50] developed a Digital Twin for optimizing the reliability of robotic cells regarding the lifespan of their elements. The system was designed using supervised machine learning with the aim of detecting and classifying the faulty behavior of critical components, in addition to creating a 3D model developed from data obtained from the physical model through sensory devices. All constructed modules were compiled and processed, discussing them with the critical elements raised.

Aivaliotis, Georgoulias, and Chryssolouris [10] also developed a Digital Twin with a focus on determining the lifespan of machine elements. Initially, data was collected by controllers and used as synchronous adjustment parameters for digital models. The analysis results were processed to predict the lifespan of the equipment.

3.2 Applications of Digital Twin in Forming Processes

It is known that quality control ensures the desired product performance; however, technological advances require an evolution of control methods, demanding systems with greater autonomy and improved data acquisition methods. In addressing this issue, Zhu and Ji [51] developed a method for quality control in forming processes that involves Digital Twin technology driven by mathematical simulation of the process and enhanced genetic algorithms. The Digital Twin was established by combining the physical-virtual model with production data processing, compared with process quality indicators. The central control system involves four parts: a real-time data acquisition and processing system, a bidirectional physical-virtual production mapping system, a product quality prediction system using a genetic algorithm, and a dynamic parameter optimization system consisting of evaluation, selection, crossover, and mutation of collected data. The developed Digital Twin can be applied in various production processes due to its generalization, providing efficiency for quality control, as well as quality problem management during production.

Regarding technological advancements to keep pace with manufacturing development, Zhou and colleagues [52] designed a Digital Twin for sheet metal stamping processes using the incremental bending technique. The Digital Twin was based on the development of a digital model of the physical environment and bidirectional information and data exchange. The digital model, through numerical simulation by FEM (Finite Element Method), calculates stamping forces and compression forces on the die. These values are used as a reference in the process and compared with values obtained through data acquisition from the physical environment through sensing. The developed digital model did not have synchronicity concerning data exchange with the physical environment; however, this was not a problem since the processed material could only be verified after stamping.

The need for the development of intelligent manufacturing arises from technological advances and the speed and flow of data transmission. Junqueira and colleagues [53] devised a Digital Twin architecture, using the Python programming language, capable of optimizing the replacement of rolling mill rolls in a wire rod mill. Through a backtracking algorithm, a simulation of roll selection was developed. This automated selection assists in the efficiency of the replacement process, reduces machinery downtime, and provides better control of processing specifications.

Present in all forming processes, wear must be considered to prevent the loss of efficiency in a digital model. In the case of stamping, the die and punch are the elements most exposed to wear and require a well-defined control strategy. Thus, Gan, Li, and Huang [54] designed a Digital Twin based on mathematical modeling for monitoring stamping die wear. The development process of the Digital Twin was based on creating a mathematical model to calculate stamping force and friction coefficient during the process. These data are loaded into the system and processed by an optimization algorithm. Finally, a FEM model is used for quality control of the forming process. The collected data are used as parameters in the wear control process for the stamping die. The system's result is determined by the difference between the stamping force in the physical and digital models, and when the required force exceeds a defined limit, the update algorithm comes into operation and updates the friction coefficient values.

Wang and colleagues [55] proposed a Digital Twin that programmed the ideal amount of water pumping for the cooling system of a hot rolling mill. The cooling process in hot rolling is complex, as, in addition to the excessive amount of water, there is an energy loss from the process due to pumping caused by a lack of control over the necessary water level for cooling. Through iterative optimization, the system was developed by linking machine learning with neural networks, aiming to predict water consumption with a model for optimizing reservoir supply based on consumption prediction, a digital model linking tank water levels with rolling mill speed, and pumping optimization for better energy efficiency. The results were satisfactory, with the system effectively predicting the required water supply levels, optimizing the process.

Zhang and colleagues [56] developed a Digital Twin for the analysis and monitoring of vibration in a strip rolling mill. The Digital Twin has three layers: the first one to describe the geometric parameters of the rolling mill, the second to process vibration data, and the third for the mechanical analysis of the rolling process. The system uses rolling force data to predict vibration and compares the calculated value with actual vibration values. As a result, they concluded that vibrational aspects can be controlled by maintaining a constant rolling force.

4. PROPOSED ARCHITECTURE OF DIGITAL TWIN

The architecture of a Digital Twin (DT) can be structured on demand, based on the problem or proposed analysis. The development of a DT, considering an industrial process, can be based on three stages. The first stage involves constructing a high-fidelity 3D geometric model that accurately represents the dimensions of the physical model. The second stage includes the mathematical modeling of the equipment with the aim of transferring a simple geometric model into a digital model, considering the properties of the physical device. Finally, the third stage consists of synchronizing the physical and digital environments, establishing the flow of information. Thus, by following these three stages, it is possible to build a DT for practical applications to improve production quality and efficiency, as well as assist in predictive maintenance control [57].

Based on the architectures developed by Lv and colleagues [49] and Quin and colleagues [58], a data-driven Digital Twin architecture is proposed in Figure 2, which can be used for failure prediction and process control in the forming industry.

The system depicted in Figure 2 consists of three main modules: the physical environment, the digital environment, and the inference base. The physical environment, composed of machinery, sensors, and experts, forms the basis for DT implementation. Data acquisition can be performed through sensing, expert knowledge, mechanical tests, or other relevant means. It is crucial for the application of the system that the data be transmitted to the digital environment and the inference base synchronously. Information based on expert knowledge can be input into the system to enhance it.

The digital environment is the module that transforms the data and produces responses that facilitate decision-making and processing in the inference base. The digital environment is divided into two stages: the first corresponds to the development of a 3D geometry of the process, facilitating visualization, control, and validation; the second stage concerns the processing of data using statistical analysis and artificial intelligence. Through the second stage, it is possible to model data for fault prediction and process control.

Finally, the inference base is the central module of the entire system, as it captures information from the other modules and processes it for the best decision-making. The resulting decisions and inferences are returned to the physical and digital processes, updating them, thus allowing the system to become autonomous. The inference base consists of four stages: (1) Perception – compilation of received data and storage; (2) Cognition – reprocessing data for decision-making; (3) Decision – decision-making based on information received from the previous stage; (4) Execution – action on physical and digital modules with process support.

It is important to highlight the bidirectional flow of data between the modules. The inference base is responsible for sending small services to the system, which updates constantly, providing dynamism to the entire process.

In Figure 3, a flowchart is represented which exemplifies the scheme of the proposed DT architecture. As the first step of the proposed architecture is the collection of information that will compose the system. Typically, this data is collected through equipment sensing, but the DT can also include other types of information such as equipment data from suppliers, operator know-how, among other types of data.

Data preprocessing is the next stage, and it holds significant importance, as through this stage, it is possible to assess the quality and robustness of the data and prepare it correctly for subsequent stages.

The proposed architecture addresses two types of data processing. The first type is based on the actual analyses, such as statistical analyses, application of computational intelligence techniques, artificial intelligence, machine learning, among other techniques. The second type, which complements the first, is based on the virtualization of the physical environment through its proper 3D modeling. Techniques such as the finite element method, for example, can be used for this task, making the virtual environment robust to mirror the physical environment.

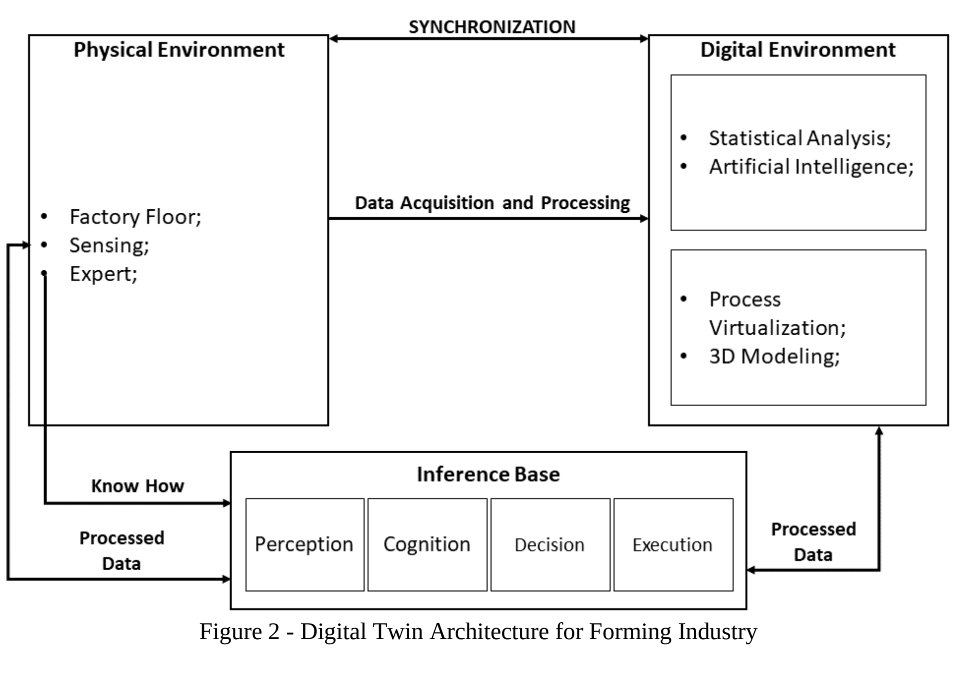

Figure 2 - Digital Twin Architecture for Forming Industry

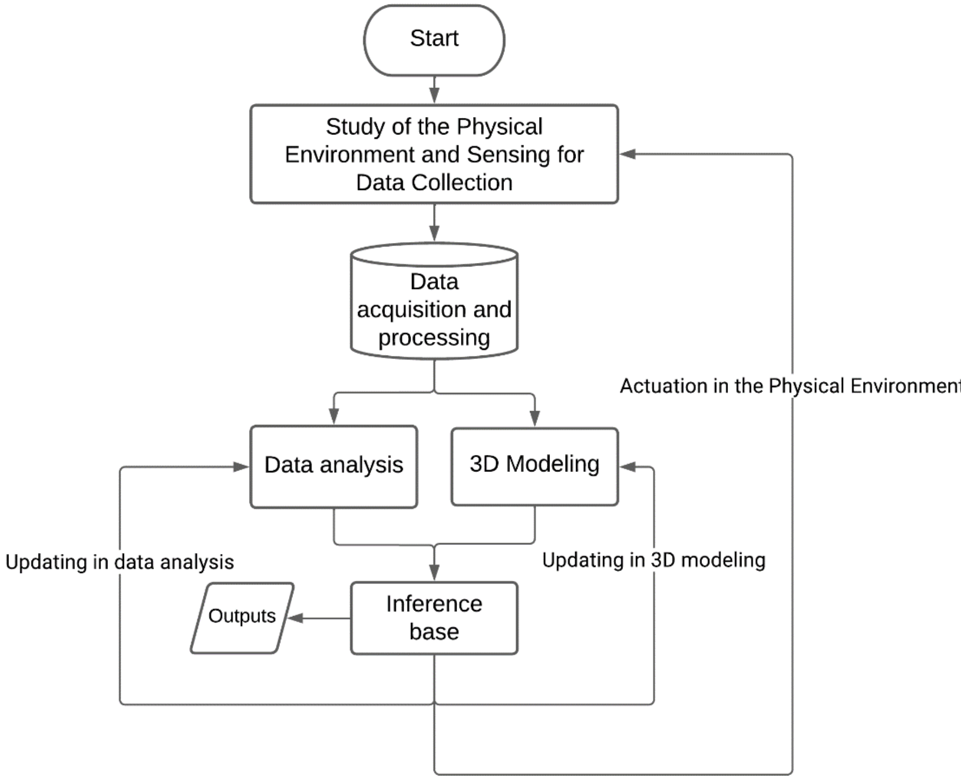

Figure 3 - Flowchart for the proposed DT architecture

The next stage consists of the core of the DT and is based on an inference scheme, aiming for systemic autonomy in decision-making and continuous improvement. This inference base follows a path with the compiled data described in Figure 2. It is interesting to note that this base has three planning stages and a final execution stage, which allows the system to filter the proposed decision and refine it, aiming for the best possible outcome.

Finally, after the inference base, there are three logical outputs that make the DT active and provoke continuous improvement in the system. These three outputs are the outputs that contribute to making the system manageable and keeping the control active, the actions in the physical environment that contribute to continuous improvement and the autonomy of the DT, maintaining process control and updating the generated data, keeping the base robust and the 3D model faithful to the physical environment.

5. CONCLUSION

Influenced by the technological advances in manufacturing, specifically in metalforming processes, and considering the importance of process control and predictive maintenance, the study of the development of the digital twin methodology, derived from Industry 4.0, became relevant. This article highlighted the state of the art of the DT methodology with a focus on processes in the mechanical forming industry. Finally, an architecture for application in this industry was proposed.

The main challenges for implementing DT in the mechanical forming industry can be concluded in three aspects:

(1) Acquisition and quality of production data, since in many processes, collecting some data is impractical due to complexity, requiring the acquisition of secondary data and manipulations for specific purposes.
(2) Validation of the digital environment and reliability of responses. Due to the dynamic mechanisms and unfavorable aspects such as wear in the physical environment, validating the digital environment can be challenging.
(3) Automation of the system may pose a challenge because physical processes lack constancy.

This work aimed at a theoretical review of DT technology applied to industrial mechanical forming processes. Therefore, it is recommended that future studies apply the developed methodology with a focus on system automation, considering the dynamism of the process and physical events that may occur.

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