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MODULAR, SCALABLE AND GENERIC DIGITAL TWIN APPROACH FOR DYNAMIC MANUFACTURING PROCESSES

Matheus Antonio Nogueira de Andrade
Universidade Federal da Bahia, Av. Adhemar de Barros, s/nº - Ondina, Salvador - BA, 40170-110
matheus.andrade.lp@gmail.com

Herman Augusto Lepikson
Carlos Alberto Tosta Machado
Senai Cimatec University Center, Orlando Gomes Avenue, 1845 - Piatã, Salvador, BA, 41650-010, Brazil
herman.lepikson@fieb.org.br; carlos.tosta@uol.com.br

Abstract. *Digital twins are commonly referred as the virtual copy of a physical asset. But there is no common definition regarding this term that is widely adopted. Alongside with other terms in the industry 4.0 context, digital twins are being discussed more and more. The creation and development of a digital twin depend on the physical counterpart that is being mirrored. Products, services, industrial processes and physical phenomena are some of the instances being digitized towards digital twins. Dynamic manufacturing processes are the focus of this work. The potential of digital twins has led to the creation of working groups in associations to develop standards for digital manufacturing environments that can evolve to support the foundation for digital twin implementations. These recent efforts highlight the need for developments of generalizable and scalable solutions for digital twins. This article proposes a modular, scalable and generic structure for the development of digital twins based on the concept of multi-agent systems to support the specificities of different industrial processes in a single configurable constructive structure. Intelligent cooperating agents can perceive the environment in which they are and react appropriately to it, ensuring the modular characteristics of this structure. The ASTM E3012 standard proposes a modular approach for manufacturing processes dividing them into Unit Manufacturing Process (UMP) that can be understood as the smaller part of an industrial process that can perform a significant changing of shape, condition or property to the raw material. The UMP concept was useful in this paper to help understanding how entire industrial processes can be divided into smaller pieces. UMP and multi-agent systems concepts can also help to achieve a scalable objective. As a case study, the digital twin dynamic model of an essential oil steam distillation plant was created to demonstrate the proposed methodology. Essential oils are extracted from plants through several methods. In the steam distillation process, the steam acts as a mean of transportation to the oil. Steam distillation extraction are performed in batches using distillers with discrete quantities of plant material. As a batch process, it presents both continuous and discrete dynamics. This way, the essential oil extraction process is a good demonstration of a generic digital twin. The proposed concept of digital twin can be the basis for the creation of several others.*

Keywords: *digital twin, manufacturing process, multi-agent systems, essential oil*

1. INTRODUCTION

In the era of the fourth industrial revolution many new different technologies are being discussed. One promising technology that arises within the industry 4.0 context is the digital twin. The term is relatively new, being used for the first time in 2002 during a presentation about Product Lifecycle Management (Grieves and Vickers, 2017). However, it only started to be a more solid part of discussions related to industry 4.0 in 2010, when NASA (National Aeronautics and Space Administration) addressed the concept. The first digital twin mention, in 2002, was composed basically of three components: Physical space containing the physical object, the virtual space in which the virtual object exists and the connection between both objects enabling the data flow from the physical world to the digital world and vice versa.

The digital twin constantly brings the idea of a virtual copy of a physical asset. Since 2002, many definitions of digital twins were proposed and can be found in the literature, as stated by Negri et al. (2017), Liu et al. (2020) and Jones et al. (2020). These definitions are not equivalent, showing that there is no widely used definition adopted for the term. Digital twins can be defined as a tool to support Product Lifecycle Management as He et al. (2018) and Madni et al. (2019) discuss. For Söderberg et al. (2017), the digital twins are correlated with the optimization of products and systems. There are also authors who define the digital twin as an individual replica of a physical counterpart as Schluse et al. (2018) and others like Rosen et al. (2015) bring the concept that digital twins are very realistic models of an entire process. Some papers bring the simulation to the digital twin definition, as in Gabor et al. (2016), Wang et al. (2019) and Vachálek et al. (2017). In addition, there are some definitions that are very connected with the context in which they are developed, as in

Tuegel (2012) and in Reifsnider and Majumdar (2013), both of them have an understanding of the concept that is only applicable to vehicles. Some authors emphasize the necessity of a real time connection with the physical counterpart, as Brenner and Hummel (2017) and Fotland et al. (2020).

According to Kritzinger et al. (2018), there is an important misunderstanding concerning the level of integration between the physical and digital entities in the academic literature. They divided the digital twins in three categories. The first one is the digital model, a digital representation of a physical object, which does not use any type of automated data exchange with the physical counterpart. The second one is the digital shadow, a step further in comparison with the digital model, it has a way of exchanging data automatically with the physical object without the intervention of an operator, but the data only comes from the physical world to the digital world. The third one can be actually named digital twin. Due its higher level of integration, the data exchange happens in both directions. Changes of states noted by the sensors are reflected in the digital object and the digital object is also capable of changing the state of the physical counterpart through the actuators.

Considering this categorization, in the literature it is common to find different digital models and shadows being called twins contributing to the lack of a common definition. Shadow and model twins do not have the third element proposed in 2002 when the term was coined. It is evident that digital twins are in their infancy and it is still necessary to reach a higher level of maturity in order to create a proper definition as Zhang et al. (2017) and Fuller et al. (2020) say. The digital twin proposed in this paper achieves the highest possible level of integration according to the classification made by Kritzinger et al. (2018).

The type of the physical counterpart in which the digital twin is focused also contributes to the lack of common definitions as it can be a physical product, an entire manufacturing process, a system, a system of systems or just a simple part of a machine. In order to create proper models that could represent different physical entities, different approaches should be chosen. If an object is being digitalized, information about geometry and topology gains more relevance. For an industrial process, the main focus of this work, information about scheduling, and the complete production line are indispensable. To digitalize a manufacturing phenomenon, machine vibration, forces and temperature should be measured, as discussed by Ullah (2019) and Bao et al. (2019). Therefore, a definition used to digital twins of complex production systems may not be applicable to smaller instances. Figure 1 illustrates how the digital twin of a dynamic manufacturing process works, with the sensors, actuators, data exchange between physical and digital worlds and data analytics.

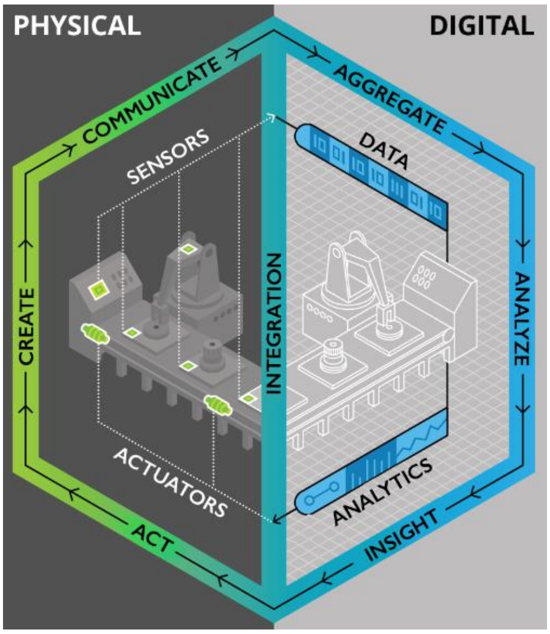

Figure 1. Dynamic Manufacturing Process Digital Twin. Source: Adapted from https://www2.deloitte.com/cn/en/pages/consumer-industrial-products/articles/industry-4-0-and-the-digital-twin.html

According to Figure 1, the sensors are responsible for collecting information about the current state generating a historical database. The data comes from the sensors combined with the data that the company makes available, such as stock information. The integration between the physical and digital parts aims to reproduce digitally as faithfully as possible, with the data transmission happening in real time, what actually happens in both sides. Data analysis techniques are the part responsible for interpreting this data through simulations, producing a set of actions to be executed. The actions are then transmitted to the physical world through the control systems that interact with the actuators. Thus, there is a digital twin that works by joining the real and the digital in a cyclical way.

A system can be modeled using a white-box or black-box approach. White-box modeling is based on principles and physical laws that describe the system indicating its behavior. The black box model is obtained with the use of real data from the process using some computational analysis technique to create the model (Sohlberg and Jacobsen, 2008). Trying to model a complex system with physical principles and laws can be a hard task while the data-based modeling can be easier using AI (Artificial Intelligence). In the Industry 4.0 scenario, in the era of IoT, machine learning in conjunction with big data analytics can be a very supportive tool for digital twins (Min et al., 2019). According to Liu et al. (2018), thanks to the ability offered by the Internet of Things to acquire a large amount of relevant data, the data union will evolve towards approaches based on machine learning or induced by real-world evidence. Machine Learning can be used to automate complex real time data analysis to adjust the current behavior of a production system with minimal supervision maximizing the desired outputs. Besides, the combination of IoT and digital twins can enhance preventive maintenance and analytics-based optimization of the physical assets (Madni et al., 2019).

Garretson et al. (2016) carried out a discussion of terminology to assist in the characterization of industrial processes. They divided the processes in continuous, discrete and batch processes taking the definitions of Duflou et al. (2012) and Hopp and Spearman (2011) as a basis to the division. Duflou et al. (2012) presented the concept of continuous processes as a production system in which the output can be measured continuously represented by a mass or volume flow, being a variable that grows continuously with time. Discrete processes were defined as processes in which the outputs are measured in discrete units that, unlike continuous processes, do not show continuous growth over time. Hopp and Spearman (2011) define batch processes as the processes in which the raw material is processed in discrete volumes, being quite common in some industries such as chemistry. Bähner et al. (2020) say that when it comes to simulation, batch processes are more challenging because they present dynamics of both discrete and continuous systems. The intention of this paper is to propose a generic framework that could be applied to any manufacturing process.

One of the most used approaches to simulate processes with purely discrete dynamics is known as discrete event simulation (DES). Varga (2001) define DES as a system in which events occur generating discrete changes in state over time. But many systems do not change based on discrete events and discrete times. Generally, these systems involve mechanics, electricity, thermodynamics and hydraulics that present continuous dynamics over time. To simulate such systems, simulations in which variables constantly change over time are used (Tang et al., 2019).

For systems that combine discrete and continuous dynamics, the DES and continuous simulation can’t be used and the agent-based models can be a way to simulate them. According to Macal and North (2005), it is an approach to model systems composed of autonomous agents that interact with each other based on simple rules of behaviors. The dynamics of the system then emerge as a result of the individual modeling of each agent and their interactions. Agents are entities who perceive the environment in which they are inserted and decide what action to take at a given time based on the state of their environment and their own state and rules that guide their decision-making process. The central idea of agent-based models can improve the behavior of many real-world phenomena and systems (Nguyen et al., 2020).

When two or more agents coexist in the same environment, it consists of a multi-agent system. Alkhateeb et al. (2010) define multiagent systems as a system composed of multiple intelligent agents to solve problems that are very difficult or impossible to solve with a single agent or a system without divisions. The distributed logic that the multi-agent systems provide helps in solving tasks of the most diverse types by taking into account the specific nature of each application. This distribution of tasks among agents facilitates the system modeling process, which becomes increasingly challenging as complexity and proportion increase. Multi-agent systems contribute to the implementation of distributed control systems in addition to enabling the use of AI by agents (Xie and Liu, 2017). Kavak et al. (2018) defend the idea that agent-based models can achieve a higher level of performance when using databased modeling to guide agents' decisions. Models created from machine-learning data can be used so that agents make decisions based on knowledge about some real-world phenomenon. The multi-agent systems approach proposed by this paper is the alternative chosen to create a generic framework that can be used in several manufacturing processes due to the possibility of simulating various complex systems.

Modularity is a concept from software engineering, widely used for the construction of computer systems. Parnas (1972) discusses the importance of modularity when creating a system. He points out some advantages, such as flexibility to change the system, ease of understanding its functionalities and faster development when applying a modular approach. Modularity is an important concept that must be taken into account when creating digital twins leading to greater efficiency in production processes. Flexibility is a positive consequence achieved by modularity (Rosen et al., 2015). Other authors who stress the importance of building modular digital twins are Zhang et al. (2019). They applied the concept of modularity to the development of the digital twin to meet the necessity that some industrial processes have to be reconfigurable. Digital twins, when applied to industrial processes that undergo constant changes, also have to be reconfigurable saving time to make the changes.

Another important concept for the construction of a digital twin framework is the scalability, defined by Bondi (2000) as a capacity that a system or process has to deal with an increasing number of objects, processing large volumes of work in an acceptable way and being susceptible to eventual growths. Qi et al. (2019) support the idea that digital twins must be scalable to meet the growing demands of industrial processes and that when building modular digital twins, characteristics such as flexibility, reusability and scalability are more easily attainable. Schleich et al. (2017) also demonstrate the concern with creating models that are scalable and can be adopted for simple and complex systems.

Shao and Helu (2020) defend the idea that the creation of digital twins should be supported by a framework that can be reusable for other applications, also needing to be modifiable and generic so that it can be applied to several case studies regardless of the application. Some organizations are mobilizing for the creation of norms and standards that serve as a basis for the construction of digital twins as is the case of the ISO (International Organization for Standardization), that created a standard with this objective (Shao and Helu, 2020). According to Barnstedt et al. (2021), eight organizations have been created since the beginning of 2020 with the aim of building bases that will support the creation of digital twins in the future. Some of these organizations have digital twins as their main focus, as is the case with DTC (Digital Twin Consortium) and IDTA (Industrial Digital Twin Association). The fact that there are so many organizations proposing to create norms and standards with this theme is proof that the development of generic frameworks can be a valuable contribution.

2. THE PROPOSED APPROACH

A digital twin can be developed for creation and development of a product, for monitoring and optimizing a process, to analyze the failure of a device, for predictive maintenance of one or more equipment, among other applications. The aim of this work is to develop a creation method for digital twins that is modular, scalable and generic with a focus on dynamic manufacturing processes. This work refers to manufacturing processes in an extensive way, encompassing all types of industrial processes, whether discrete, continuous or batch processes. The dynamic aspect refers to industrial processes that continuously change over time.

For the context of this work, digital twins are a set of intelligent modules capable of perceiving the current state of the industrial process and acting on it through control systems or operators, in order to obtain better results. Due to the fact that there is no clear definition of digital twin, this approach was chosen. With this definition, the aim is to implement the data flow in both directions, from the process to the digital twin and back to the process, reaching the highest level of integration as discussed in the previous chapter.

Industrial processes can be very complex with multiple workstations and raw material transformations. This can become a problem when trying to create and maintain a digital twin. For this reason, this work brings a modular approach to industrial processes based on the concept of UMP (Unit Manufacturing Process). UMPs are the smallest element or sub-process in a manufacturing system that adds value by transforming the shape, structure or property of the raw material, according to ASTM E3012 - 20. The standard establishes that more than one raw material transformation process can take place in a single UMP if it is necessary to perform two transformations on it.

Taking this approach, it is possible to overcome the complexity of an industrial process with multiple steps and transformations of raw materials that could overwhelm the computer on which the digital twin is running. The division of the process into smaller units helps to achieve the goals of modularity and scalability, as the digital twin is now seen as productive units that can be linked to each other through their inputs and outputs as stated in the standard. The UMP concept can be applied to industrial processes of any nature, whether continuous, discrete or batch, facilitating the generalization of the proposed digital twin model.

Multi-Agent Systems (MAS) is another concept introduced in order to build a modular, scalable and generic model. MAS consist of a set of intelligent entities that are able to perceive their environment and react based on the perceived state and the rules that govern their behavior (Nguyen et al., 2020). Agents become an interesting approach to the proposed model due to their ability to deal with discrete and continuous variables. The MAS approach can be used to model various complex systems and its dynamics come up as a result of the modeling and interactions of each agent (Macal and North, 2005).

Each of the modules of a UMP must be able to communicate with other modules, if necessary, in order to receive information that will be used by it. Each module must be responsible for executing a single task so that the UMP is properly modular. The digital twin is inserted in the context of industry 4.0, in which the industrial processes are properly automated with the use of sensors, actuators and controllers. Therefore, for the creation of the digital twin, it is necessary to have actuators capable of acting in the process and sensors that can measure the variables in which the actuators will interfere and measure the effects of their actions. For discrete events that occur during the operation of a UMP, it is necessary to have some way to identify the occurrence of these events so that the digital twin understands which stage the UMP is performing and proposes coherent modifications.

This work proposes five classes of modules to represent all the components involved in an industrial process: sensors, actuators, operators, conveyors and storages modules. These five classes were proposed to represent some of the most common entities in an industrial process, although it might be useful to create other classes and subdivisions to represent the particularities of a specific industrial process. The sensor modules are responsible for establishing communication with the physical process in order to obtain data regarding the current state of the process and communicate with all the other modules to inform what is happening in the UMP. The actuator modules are responsible for communicating with UMP's actuator control systems, proposing changes of parameters in their operation. This module class is subdivided into two other classes, the discrete and continuous actuator modules. This subdivision was designed to cover the differences in functioning that exist between discrete and continuous variables. Discrete actuator modules exist to assess the state of discrete actuators that work by receiving binary signals, such as on/off, energize/de-energize, high/low, or actuators that receive only discrete instructions from the control systems as pre-set levels of operation. This class evaluates the state of the discrete actuator and proposes a change if necessary. Continuous actuator modules have as attributes the operating point at which the actuator is located or the control parameter it is responsible for evaluating, such as the system gains of a PID (Proportional Integral Derivative) controller. This type of class must evaluate the condition under which the controller is operating and propose new control parameters.

The conveyor modules are responsible for monitoring the transport actions that take place in industrial processes. The transport modules must monitor the items being transported, the quantity of those items, the origin and destination of the transport. Transport actions in an industrial process are generally responsible for taking the outputs of an UMP to be used as inputs in other UMPs or for stock or even bringing raw materials. This class will monitor the receipt and delivery of items, proposing transport actions that are more effective for the UMP they are part of. Conveyor modules are divided into two other classes, fixed and mobile. This subdivision was created to cover the differences that exist in the dynamics of these two types of transport. Fixed conveyors are those that remain fixed and transport takes place on them, such as conveyors, in which its speed will define their transport capacity. Some actions that fixed conveyor modules can take are to stop, move or change the speed at which it runs. Mobile robots are instances of mobile conveyor modules that are capable of performing transport functions with freedom of movement by loading or pulling the transported items. Mobile transport modules can perform functions such as suggesting optimized transport routes for the robot or requesting it to wait for some time until new items that must be transported are produced.

The operator modules are responsible for requesting some action from an operator or informing them about some relevant forecast, for example, informing about the need for raw material or estimated process time. Some industrial processes are the result of constant collaboration between humans and machines. Therefore, this class of module is necessary due to the need to understand operators’ actions during the UMP's operation.

Storage modules are responsible for monitoring and managing storage stations. This class is divided into two subclasses, which are warehouse and management. Warehouses are responsible for monitoring and managing local stock stations, such as silos, tanks and pallets that fulfill the function of storing raw materials and products from one UMP before being sent to the next when there is no continuous flow between two consecutive UMPs. The management class, on the other hand, fulfills the function of making analysis and forecasts related to the stock, such as verifying if the raw materials necessary for the UMP are available.

A relevant point that must be taken into consideration about the digital twin model proposed by this work is the communication between the process controllers and the digital twin. OPC UA (Open Platform Communications Unified Architecture) is currently one communication medium that has become industry 4.0 standard due to its ability to connect the most diverse types of devices through different communication protocols allowing scalability (Braune et al., 2008). Therefore, the OPC UA is the adopted communication medium for a generalizable and scalable digital twin model. Figure 2 shows how the integration between the digital twin and the process controllers works.

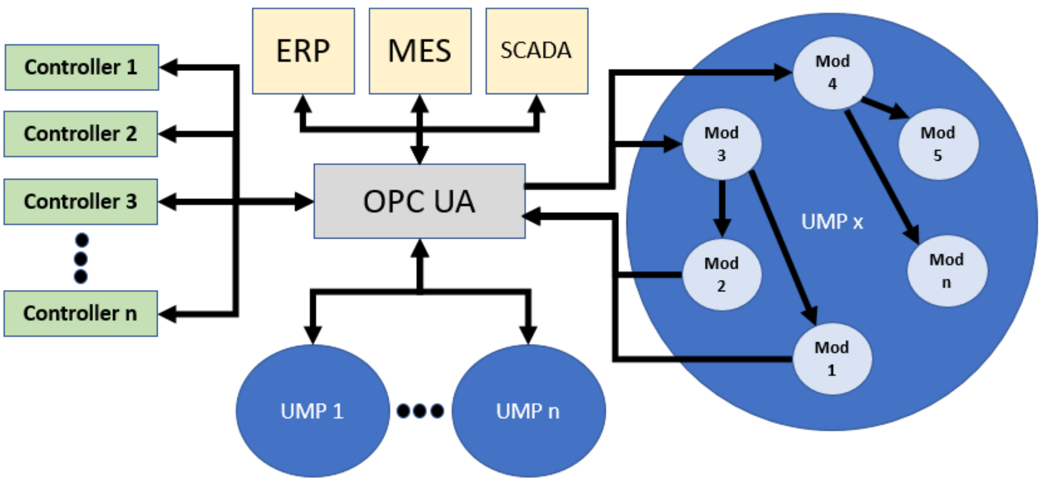

Figure 2. The Proposed Model for Dynamic Manufacturing Processes. Source: Authors.

As illustrated in Figure 2, process controllers, regardless of type, must be able to communicate through the OPC UA protocol making the data available so they can be accessed by the digital twin. The sensor modules, represented in the figure by numbers 3 and 4, will communicate with the server in order to obtain data about the current state of the process and pass it on to the other modules so they can perform their functions. Modules 1 and 2 represent modules that need to communicate with the server in order to propose some modification to improve the UMP's performance, such as actuator, storage or transporting modules. Modules 5 and n represent the modules that receive data from other modules and don’t have to communicate with the OPC UA server. With this model of communication between the digital twin and the physical process, the data flow happens in both directions automatically without the need for a person to intervene.

Figure 2 also shows that the model considers that the digital twin of industrial processes has to communicate, through the OPC UA, with physical systems to use their available data for analysis purposes, such as data from SCADA (Supervisory Control and Data Acquisition), MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning). In addition, the model allows communication between different UMPs, also through the OPC UA, to exchange information between different UMPs when necessary.

The digital twin model is designed to be executed following a time-oriented simulation logic. It must analyze the current state of the UMP at constant time intervals. For continuous processes, the simulation model based on time is already applied without causing major problems for the implementation of the proposed model. For discrete processes, concurrency of events must be understood by the digital twin so that it can identify in which stage the UMP is in the present time in order to be coherent and not trigger actions that could compromise the proper functioning of the UMP. The processes that have hybrid characteristics have their continuous and discrete variables being evaluated at each time interval, taking into account the occurrence of events so the modules can decide how to act.

Regardless of the type of process, the digital twin must perform its analysis in real time and be as fast as it needs to be. Processes that undergo large variations over short periods must have a digital twin that is equally fast in order to contribute effectively. The time interval between two analysis must then be consistent with the variations that the process presents.

The proposed digital twin model, as shown in Figure 2, foresees the communication of the UMP's digital twin with other systems in the organization via OPC UA. The exchange of information with these systems provides the ability to improve the functioning of the UMP by using higher-level data to perform predictions and optimizations. The UMPs must also have the ability to exchange information and interact with other UMPs before and after the processes in order to connect the process inputs and outputs as ASTM E3012 – 20 proposes. Depending on the production pace of the previous or subsequent UMP, it may be convenient to increase the production of some UMP, for example. In real industrial processes, they are arranged in parallel or in series. This arrangement must be respected in the construction of the digital twin to represent accurately the dynamic manufacturing process.

3. THE CASE STUDY

The case study that will serve as a way to demonstrate the method and concept developed in this work is based on one UMP of essential oils extraction by steam distillation. In this process, the steam is generated by a source of heat, passes through the plant material inside the distiller and carries the essential oil to the condenser to be turned into a two-phase liquid that gets separated by density difference as they are immiscible. At the base of the distiller there is a water reservoir that is heated to generate the steam used in the process. A low-level switch is positioned at the base of this water reservoir to ensure the heater always have water, avoiding the heating element burn out. Also, a level control valve ensures that the proper amount of water enters the system. The extraction plant is instrumented according to Figure 3, which shows the sensors and actuators available to generate data and interfere in the process dynamics.

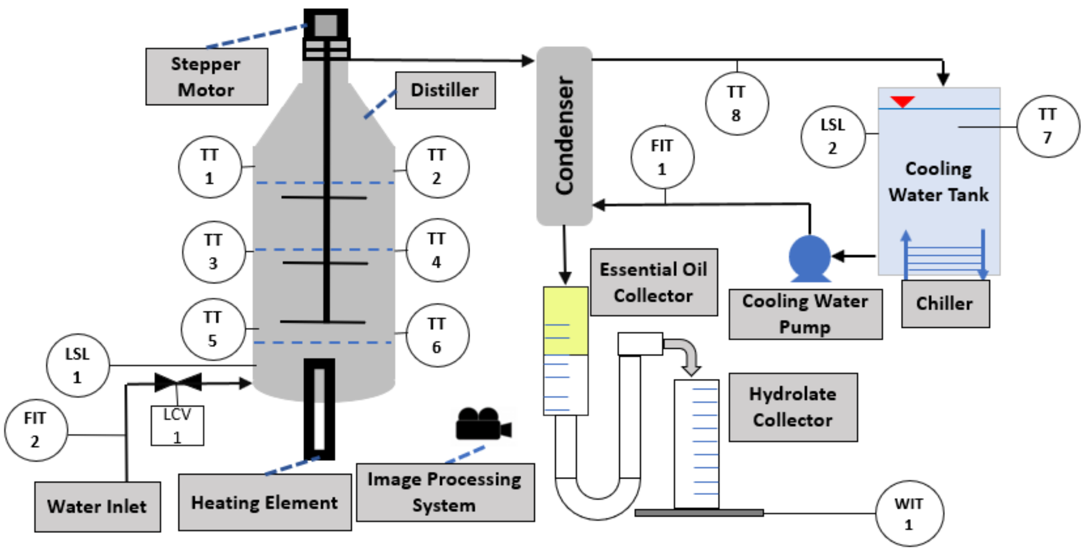

Figure 3. Essential Oil Extraction Process P&ID. Source: Authors

Temperature transmitters are positioned inside the distiller, as shown in Figure 3, to verify if the steam is flowing equally through all the plant material in order to deal with a phenomenon called channeling, which is the formation of preferential and unwanted channels of steam flow inside the vegetable mass. Channeling can cause excessive degradation of part of the vegetable mass while another part may contain essential oil that will not be extracted, compromising the quality of the extracted essential oil, with the presence of impurities generated by the excessive burning of the raw material, and the quantity of the final product in the batch.

Leaving the distiller, steam goes towards the condenser. Cold water is pumped into the condenser to exchange heat with the steam in order to condense it. A flow sensor measures the amount of chilled water pumped. In the water-cooling system, there is a sensor to measure the temperature of the water into the condenser. In addition, there is also a level switch to gauge how much water is in the cooler. The liquid leaving the condenser is separated into hydrolate and oil by density difference, as the two liquids are immiscible. A weight balance is placed to measure the amount of hydrolate produced. The most relevant product of the process is the essential oil, but the hydrolate also has commercial value and therefore both amounts produced shall be monitored. The cold water leaving the condenser is measured through a temperature sensor.

One camera measures the amount of oil extracted from the batch being processed capturing the image of the oil column. The image processing system is composed by a Raspberry Pi 3 Model B+ controller and its camera Module V2. The algorithm was developed in Python language, using the OpenCV computer vision library.

With the exception of the camera that works together with the Raspberry, all other sensors and actuators work through two PLCs (Programmable Logic Controller) from Altus, models Nexto Xpress XP340 and XP 315. A SCADA software, called Blueplant, also from Altus, operates the essential oil extraction plant together with the two PLCs, which are connected with SCADA and the digital twin using Modbus TCP (Transmission Control Protocol) protocol to establish communication. In this case study regular OPC was used to establish communication between PLCs and supervisory systems, as Modbus TCP meets the needs of the pilot plant. However, for larger applications, the OPC UA is the ideal solution, as discussed in the previous chapter.

The data that was used to create the digital twin AI models was acquired through a process historian that reads the inputs and outputs of the PLCs and Raspberry at regular time intervals and stores these values in a tabular form for later use in the construction and training of the models. The software chosen for the construction of the digital twin was MATLAB/Simulink, as it has all the necessary functionalities for the construction of the digital twin of the process of extracting essential oils by steam distillation according to the model discussed in the previous chapter. MATLAB offers several functionalities that can be used through a programming language based on the C programming language that can be easily transported to its integrated simulation environment, called Simulink, through blocks that allow the creation of functions by the user.

In addition, Simulink has other blocks that can perform specific functions and assist in the construction of the digital twin. Simulink is a programming and simulation environment that presents a graphical diagram interface made up of blocks that facilitates the implementation and visualization of the modularity desired by this work. Figure 4 shows the agents and how they are divided in the classes presented in the previous chapter.

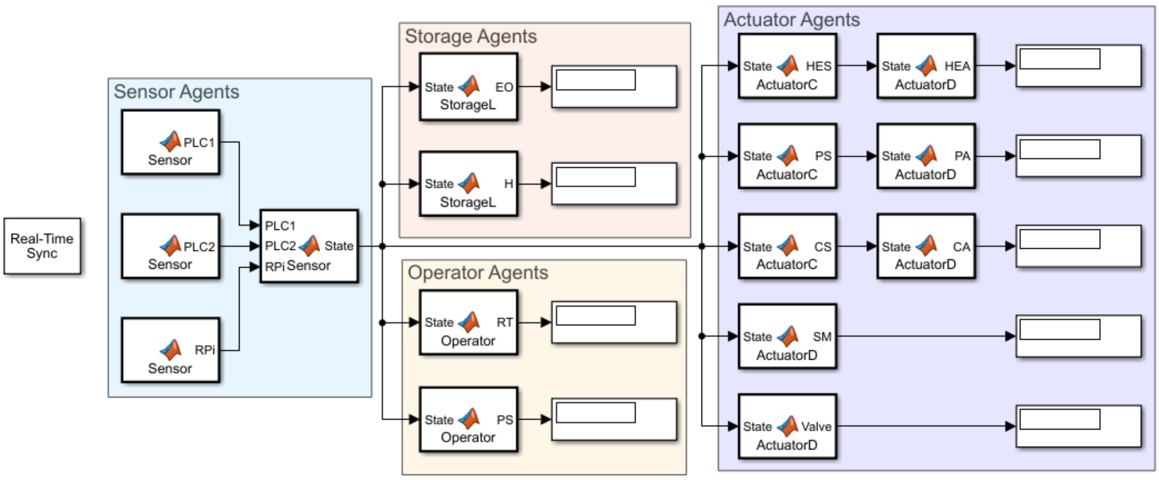

Figure 4. The Essential Oil Digital Twin. Source: Authors

The sensor agents are the ones responsible for communicating with the two PLCs and the Raspberry. One more sensor agent was placed after the first three to unite all the data from the previous sensor agents for better organization. The storage agents are responsible for the essential oil and hydrolate local storage. The operator agents are responsible for informing the remaining process time and the process stage to the plant operator. As a typical batch process, there is a ramp up, when the temperature inside the distiller is increasing, a ramp down, when it is decreasing, the stationary state when the essential oil is continuously running out of the condenser and other possible states as the lack of water state, for example, when the heating element should be turned off. There are three continuous actuator agents responsible for defining the best setpoint for the temperature inside the distiller, the pump flow and the chiller. The discrete actuator agents are responsible for deciding if the heating element, pump, chiller, stepper motor and valve should be activated of not. One real time synchronization block and several display blocks were used to run the model in real time, control concurrency and to show the actions the agents are taking.

4. DISCUSSION AND EVALUATION

MATLAB/Simulink presented the main components necessary for the construction of the digital twin according to the proposed model. MATLAB offers several ways for industrial communication with PLCs and other controllers and systems, such as Modbus TCP that was used, within the Simulink simulation environment, together with machine learning tools to create the desired multi-agent architecture.

Solanki and Schulz (2005) also used the MATLAB function block to implement agents in Simulink. One of the strengths pointed out by them that also contributed to the choice of software is the ease of adding blocks to represent new agents and reconfigure the system. Some points were raised by Solanki and Schulz (2005) as possible problems for the implementation of multi-agent systems with Simulink, like the difficulty of working the blocks in parallel due to the single-thread nature of the program's operation.

Another relevant limitation is the ability to exchange messages between blocks within the same simulation step, since each block is executed only once within each step. To overcome these problems, they chose to use a Java language-based application called JADE (Java Agent Development Framework) in conjunction with Simulink. Using JADE it is possible to build more complex communications between agents, such as competitions and bargains that are very common in multi-agent systems in general, being an interesting option to overcome the problems mentioned above.

Another relevant point to be discussed about the case study is the Modbus TCP used as the communication protocol. Modbus TCP presents some scalability problems that make its implementation difficult for more complex systems with a larger number of sensors, actuators and process controllers. The migration to OPC UA with enhanced communication protocol is a possible future work for the built-in digital twin. As with the case study, some digital twin applications in legacy system may use previously implemented architectures to communicate with controllers or have reduced dimensions and no growth prospects. For applications with these characteristics, Modbus TCP, for example, may be a satisfactory alternative.

As this is an academic project with limited resources, some possibilities for improvement were not explored in the pilot plant, which could generate a more complex and refined performance of the digital twin. Actuators in the plant are working with an on/off control logic that is very simple and limited. Alternatively, PID controllers should be considered for better results. The classes presented in the previous chapter are a simplified division of the types of agents that can be present in a digital twin of an industrial process. The purpose of creating these classes was to present a possible classification for agents in the industry, seeking to contemplate all the possible and most common agents. However, for complex industrial processes that demand greater detail, other classes can be created.

One possibility for digital twins that was not explored in this work is the presence of a CAD (Computer Aided Design) model that represents in three dimensions the industrial process and can be used in some process simulators for better visualization, as present, for example, in the works of Zhang et al. (2019) and Malik (2021) that used CAD models in simulations. The focus of this work is to propose a digital twin model that can interfere in the real world. Providing a visualization interface for the user was not considered an essential requirement. However, especially for processes where there is movement of some component of the production unit, it may be interesting to have a CAD model and a simulation environment that represents it.

Just like a CAD model, other things that were not explored by the case study can be incorporated to expand the functioning of the digital twin using some industry 4.0 technology. One technology that can work in conjunction with a CAD model is virtual reality. According to Qi et al. (2019), virtual reality can be a strong ally to improve an operator's understanding of a complex physical process or entity. Industrial systems pose some security risks for businesses. The data generated by an industrial process is very valuable from several perspectives. Through a digital twin, it may be possible to interfere in the process to cause some harm to the company in question. So, cybersecurity can be an important aspect of implementing a digital twin. As explained by Hearn and Rix (2019), a digital twin can be the perfect gateway for a hacker as it is connected to several industrial systems and represents the industrial plant as a great source of information that can be used in different ways. Both cybersecurity and virtual reality can be addressed by future works.

The digital twin modularity provides the capacity of changing the essential oil digital twin as it needs according to the physical process. With the addition of a new sensor, its data can be aggregated to the digital twin being captured by the sensor agents and used by other agents for their decision making. New agents representing the action of a new actuator can be added as it needs. Also, operator agents can be added to the digital twin to communicate other relevant information to the operator. This model can also be applied to an essential oil extraction industrial plant that produces bigger amounts of essential oil just creating new AI models to support the digital twin actions with new data, proving its scalability. The model can also be applied to other industrial processes as discussed before. Agents can be designed to take discrete and continuous actions as it needs.

5. CONCLUSION

As an emerging technology from industry 4.0, digital twins are gaining more and more attention. Their capabilities to enhance manufacturing processes' productivity is one of the main reasons for that. However, there is still a lack of studies concerning digital twins and its application is on its infancy. This paper intends to contribute to the discussion about this topic proposing a framework for manufacturing processes' digital twins.

Modular, scalable and generic are three important characteristics to have in mind to create the basis for digital twins. And this paper proposes an objective and simple way to build digital twins for industrial process with these characteristics. Once there is a known model, many other digital twins can be created based on it, achieving the highest level of integration, as discussed by Kritzinger et al. (2018).

The case study brought in this paper is an interesting approach to prove the developed model capabilities. Using AI to support the agents' decision making, plant productivity can be optimized considering the core aspects of the process. As a typical batch process containing also both discrete and continuous dynamics, the case study shows that the presented model can be the basis for many other industrial processes. In the close future, these digital twin models will be tested to show its capabilities for productivity enhancement.

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