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COB-2023-1226 - A SYSTEMS ENGINEERING BASED METHODOLOGY FOR DIGITAL TWINS IMPLEMENTATION

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Abstract. *The Industry 4.0 movement is supported by a technology revolution converging to the Cyber-Physical Systems concept, with mainstream interest in the Digital Twin (DT) concept. A DT is commonly defined as a virtual representation of a physical object or process, allowing ultra-realistic simulations of physical models, capturing historical data, and real-time processing/monitoring. Different levels of abstraction offer varied views of industrial systems, equipment, processes, and products. Given its complexity and multi-technological composition, its implementation is quite tricky. In this context, we propose using a methodology based on Model-Based Systems Engineering (MBSE) to support a model industry's technological evolution, aiming to implement its DT. Using the ISO 23247 standard for DTs, we modelled the system at several levels with the MBSE Arcadia method through the free tool Capella. As a result, we reached the Final System Architecture, indicating the actors involved in the scenario, their functionalities and the interaction flow between all the components. The resulting model provides us with correlations among indicators of different abstraction levels, generating the basis for implementing a multi-scope DT. Therefore, the principles used to construct this work result in an innovative methodology by allying MBSE's tooling support to the efficient implementation of Digital Twins.*
Keywords: *Arcadia; Digital Twin; Industry 4.0; MBSE*

1. INTRODUCTION

Industry 4.0, or the Fourth Industrial Revolution, emerged in Germany in 2011 and designated an entire sector innovation process. Berger (2014) defined this movement as the evolution of productive systems through the integration of new technologies of industrial automation (IA) and information technology (IT). According to Lu (2017), the Fourth Industrial Revolution is the integration of machinery and devices through sensor networks and software aimed to enhance prediction, control, and plan outcomes. Therefore, this is a new era of connectivity among machines, workpieces, and systems along a company's value chain. This industry concept relies on several Enabling Technologies capable of driving radical changes in processes, culture, products, and services (RÜßMANN et al., 2015). Obtiko and Jirkovsky (2015) have listed those technologies: Big Data, Internet of Things (IoT), Autonomous Robots, Simulation, Horizontal and Vertical Systems Integration, Cybersecurity, Cloud Computing, Cyber-Physical Systems, Additive Manufacturing, Artificial Intelligence, and Augmented Reality.

Based on technologies such as Cyber-Physical Systems, Simulation, Internet of Things (IoT), and Big Data, the concept of Digital Twins (DT) has gained momentum. When applied to manufacturing, a DT can be defined as a virtual representation of a production system and is characterized by synchronizing virtual and real systems through intelligent devices that enable real-time data communication (NEGRI et al., 2017). As a result, it becomes possible to conduct simulations, tests, and analyses in a virtual environment before implementing them in the real world. These characteristics ensure process optimization, problem identification, and predictive maintenance, enhancing operational efficiency and product quality (JONES et al., 2020).

The benefits of a DT are significant, but challenges such as high costs and the level of complexity involved are a drawback. There is no widely adopted reference model to support DT adoption, which poses a need for industry consensus. The lack of standardisation adds difficulty to its implementation and impacts the number of systematic research studies on the subject. To contribute in addressing DT development, this research proposes a simplified framework supported by the Model-Based Systems Engineering (MBSE) approach to guide the implementation of Digital Twins in manufacturing systems. A case study of a Model Factory illustrates the issue and how our approach supports DT development.

This work is structured to provide initially a state-of-the-art overview of the key concepts involved: Digital Twins and MBSE. Subsequently, it presents the development process by contextualizing the selected Model Factory for the case study, indicating the method and tools used in system modelling, and then introducing the referenced framework for Digital Twin implementation. Finally, the work discusses the main results and proposals for future improvements.

2. STATE OF THE ART

2.1 Digital Twins

The first mention of Digital Twins occurred in 2003 when Grieves introduced the concept during courses taught at the University of Michigan. At the time, the definition could have been more precise. However, it established that a Digital Twin has three components: a physical product, its corresponding virtual representation, and the data that connects both. It is worth noting that the virtual representation of the product was immature, and data collection from the physical product was minimal and manual (Grieves, 2005). From this initial mention until 2011, only some studies appear in the literature on the subject. Starting from that point, with the development of technologies such as the Internet of Things (IoT), big data, and simulation technologies, Digital Twins gained momentum, particularly in the aerospace industry, where they are extensively explored (Tao et al., 2018).

In 2012, Glaessgen and Stargel introduced a widely recognized and used concept. They defined the Digital Twin as a multi-physics, multi-scale, and probabilistic simulation integration that, through sensors, can mirror a physical product in its virtual twin. According to the authors, based on this conception, a Digital Twin would possess the following characteristics: real-time synchronization, interaction and convergence between the physical and virtual models, and the ability to self-evolve by implementing continuous improvements based on collected data.

According to Chen in 2017, the Digital Twin can be understood as a computational model of a physical element or system that represents all its functionalities through data integration. In 2018, Liu, Meyendorf, and Mrad advanced this concept by categorizing the Digital Twin as a living representation of an object or system, as it constantly adapts and updates through continuous online data collection. They also emphasize that the Digital Twin should possess some level of predictability of the future state of the physical element due to these characteristics. This view is similar to Madni and Lucero in 2019, who describe the Digital Twin as a representation of a physical system continuously updated with data on performance, maintenance, and health status throughout the lifecycle of that physical entity.

Enriching the concepts presented, Stark and Damerau proposed in 2019 that the Digital Twin would be an active digital representation of a product (object, machine, service, or intangible asset) or a system (a product and its related service) that faithfully captures its characteristics, properties, and behaviours through informational models and data collected throughout its lifecycle. Fuller et al. (2020) summarize the Digital Twin as a complete integration of data between the physical and virtual systems, where the flow of information occurs constantly and bi-directionally. They emphasize that, despite the absence of a universal concept, a fundamental requirement characterizes a Twin: the automatic flow of data between the systems. According to the authors, this would ensure that the virtual representation is a twin that accurately reflects the real state of the physical counterpart and, in turn, enables self-regulation. It is important to increase the level of abstraction when considering the concept, applications, and benefits of a Digital Twin. As previously mentioned, the Digital Twin is not limited to a single object, product, or machinery. The concept can extend to the system level. Considering the industrial context of Manufacturing, Tao et al. (2017) present an interesting definition considering the representation of a shop floor: the Digital Twin Shop Floor (DTS). A DTS consists of the physical ecosystem, its virtual twin, and the entire environment's data. Thinking at this broader level makes the scope of the Digital Twin more complex in its application.

Since 2018, the use of this technology in industries has gained traction due to advances that enable the process and greater maturity of the concept. With the increased adoption of Digital Twins, there arises a need for defining a framework specifically tailored for their implementation. Considering its inherent complexity, such a framework is an effective way to guide the entire process. It facilitates the understanding of the architecture and practical introduction of Digital Twins. Moreno et al. (2016) proposed a five-step process for creating a Digital Twin model, including 3D modelling, behaviour data extraction, modelling of entity interactions, operation modelling, and simulation. Also in 2016, Schroeder et al. suggested an architecture based on five levels (device, user interface, web service, query, and repository) to manage Digital Twin data. They also introduced a system based on Augmented Reality for displaying real-time information. Regarding the exchange of information between physical and digital systems, they indicated a modelling method using AutomationML, which consists of three stages: model creation, model definition, and information system development.

Stark et al. (2019) developed "The 8-Dimension Digital Twin Model" to assist in scoping Digital Twins. Each dimension has a specific number of achievement layers: Integration Level, Connectivity, Update Frequency, Cyber-Physical Intelligence, Simulation Capability, Digital Model Richness, Human Interaction, and Product Lifecycle. The authors concluded with the need for a unified view regarding the Digital Twin framework. Tao et al. (2018) emphasized that after reviewing over 50 papers and eight patents, it became clear that there needed to be a standard model in place. They even urgently highlighted the need for further research on this subject. Other authors share the same view, such as Liu et al. (2020), who also stated that they could not identify a widely accepted reference model in the industry, thus hindering its implementation and systematic research on the topic.

The ISO 23247 series, published in 2021, emerged to address this gap by proposing a standardized framework for Digital Twins in Manufacturing. ISO 23247 outlines the following applications of Digital Twins in manufacturing: Real-time control, Offline analysis, Predictive maintenance, PHM (Prognostics and Health Management), Engineering design, and Production control. Thus, Digital Twin in manufacturing is the digital representation of an observable manufacturing element with synchronization between the physical element and its representation. The standard also states that the Digital

Twin can exist throughout the product lifecycle, leveraging aspects of the virtual environment (high fidelity, external data sources, among others), computational techniques (virtual testing, optimization, predictions, among others), and aspects of the physical environment (historical performance, customer feedback, costs, among others) to improve the performance of the manufacturing system.

The ISO standard certainly supports the process of implementing a Digital Twin by providing a standardized framework for its architecture. However, it still needs to reduce the complexity of such a project. For this reason, some studies suggest integrating this development with Model-Based Systems Engineering (MBSE).

2.2 Model-Based Systems Engineering (MBSE)

Systems Engineering (SE) is the science that seeks to understand socio-technical systems' complex and interdisciplinary universe, ensuring successful implementations. The concept began to be utilized around the 1970s and gained prominence with applications in the U.S. military. Since its introduction until the present day, its definition has evolved, and the approach to systems has become more holistic (Ramos, Ferreira, & Barcelo, 2012). The International Council on Systems Engineering (INCOSE) 2007 indicated that SE is a field of study focused on identifying customer/user needs, translating them into requirements, and subsequently into functionalities. As part of the scope, this information is documented and used to guide the design and validation processes of the system.

McGee (2016) presented one of the most popular models in Systems Engineering that help to understand this discipline, the "V-model". It summarizes the key phases in SE, proposing a top-down design and bottom-up verification approach. Figure 1 provides a detailed depiction of this model.

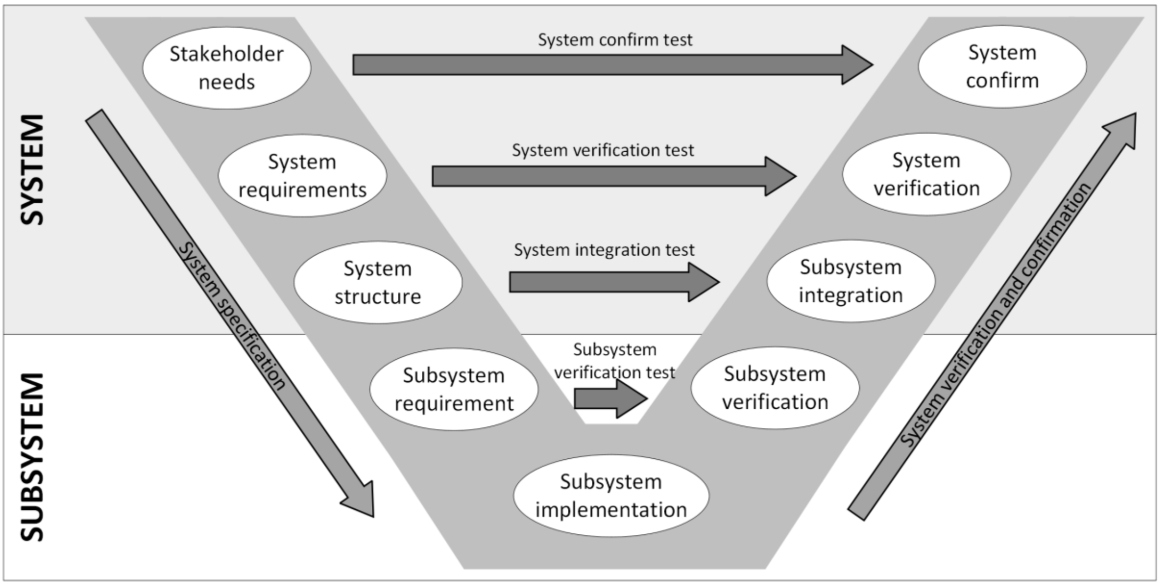

Figure 1. The V-model of Systems Engineering lifecycle. Source: Adapted from McGee (2016)

Based on the model and various studies, such as Bickford et al. (2020), the key processes involved in systems design in SE encompass the following stages: requirements analysis, system specification, system design, implementation, testing, and operation/maintenance. Estefan (2007) indicated that system descriptions and expressions can be conveyed textually and through digital models and graphics to support this entire lifecycle. According to Bonnet et al. (2016), using models enables a better understanding of complex systems, allowing for the pre-verification of solutions before their development. The models provide a detailed specification of requirements for conducting low-level simulations.

The complexity of systems relying on various combined technologies increased with the rapid technological advancements and accelerated development of software and information infrastructure. This complexity represents both business and technical challenges. To enable this reality, new methods of work and development are emerging. It is in this context that Model-Based Systems Engineering (MBSE) gains strength. Wymore (1993) introduced the term MBSE as a series of mathematical concepts, such as the mathematical theory of system coupling, algebraic relationships between systems, and the mathematical structure of requirements. Delligatti (2013) indicates that MBSE methodology has three basic elements: a modelling language, a modelling method, and tools for modelling. Madni and Sievers (2018) understand that MBSE defines system requirements and structure, performs system function decomposition, indicates data flows and software and hardware behaviours, and enables testing activities. The adoption of MBSE addresses the complexity of modern systems by providing a systematic approach to modelling and designing systems, facilitating requirements definition, system decomposition, and behaviour specification. MBSE enables effective communication, collaboration, and verification throughout the system development process by leveraging modelling languages, methods, and tools. It is a powerful framework to manage the intricacies of interconnected technologies and ensure the successful implementation of complex systems.

MBSE is a descriptive technique that reflects the functionality and architecture of a system, along with its rules (Huldt and Stenius, 2018). However, the authors concluded that, the term needed an internationally standardized definition, leading to vague concepts that allowed for broad interpretations. Another perspective indicates that MBSE is an area of study focused on supporting the key stages of the design process according to systems engineering (requirements analysis, system specification, system design, implementation, testing, and operation/maintenance) based on models (Bickford et al., 2020). This approach was endorsed by (INCOSE, 2020), which defines MBSE as the application of diagrammatic models to support system needs, design, analysis, verification, and validation activities. The support begins in the conceptual design phase and extends throughout the development and other phases of the system lifecycle. Then the benefits of adopting MBSE, including centralizing all system information in a single repository, optimizing product lifecycle management, increasing the ability to manage complex projects, reducing costs and schedules, standardizing languages involved, defining clear requirements and methods, improving communication among stakeholders, product quality, and knowledge management. MBSE provides a structured and systematic approach to systems engineering, utilizing models to enhance the design, analysis, and validation processes, and offers numerous benefits contributing to more efficient and effective system development and management.

Considering the benefits involved and some of the key applications of MBSE - using system modelling to support requirements definition and decomposition, analyzing models to assess whether an architecture meets the identified requirements, employing models throughout the system lifecycle to ensure its health, reliability, maintenance, and performance - it becomes possible to draw a strong parallel between this area of systems engineering and the enabling technology of Digital Twins.

2.3 MBSE and Digital Twin

Bickford et al. (2020) perceived a relationship between the topics of MBSE and DT, as they understood that an integrated modelling environment using MBSE could become a Digital Twin of a given OME (Object of Managed Elements). According to the authors, MBSE establishes standards and norms that can be adapted into an appropriate framework to guide the development of a Digital Twin. The Digital Twin is an operational instance of the various system models defined throughout a lifecycle. By evaluating the concepts presented thus far and the perceived advantages of employing the MBSE approach, two major contributions of this association to the Digital Twin emerge: the fluidity in defining its architecture and the support for decomposing stakeholder requirements. Madni and Sievers (2018) summarized the main objectives of the MBSE methodology and, in doing so, contextualized the stages of its process: Defining the scope of the models; Establishing a connection between the system domain and entities in the model; Managing the model repository to enable information visualization, simulation, and analysis.

It is important to highlight that various artefacts can be used in this methodology, and their selection is derived from the defined modelling language. Huynh and Osmundson (2006) point out that SysML is the most commonly used language in MBSE, mainly due to its effectiveness in specifying systems' requirements, structures, and functional behaviour. As mentioned, the adopted language impacts the grammar, types of diagrams, modelling method, and, ultimately, the modelling tool used in the MBSE approach. Considering the objective of this study and the various alternatives available, we selected the Arcadia method (Architecture Analysis and Integrated Design Approach) for this research. This software and systems engineering method is oriented towards operational analysis and architectural design. It draws inspiration from various modelling language standards, such as NAF4, DoDAF4, and SysML (Huldt and Stenius, 2018).

The decision to base this study on the Arcadia method (using the Capella tool) was driven by comparative results from various studies. Alai (2019) points out that this method allows for highly efficient modelling of the architecture of complex systems with multiple domains and overcomes several implementation challenges observed when using SysML. For example, it enables intuitive and simplified mapping of functions and the creation of a functional architecture. Some other advantages that influenced the choice include the Capella tool's good usability; a user- and system-focused approach that addresses real needs; less complex and more comprehensive diagrams and syntax; integration between system structure and behavioural aspects. However, it is important to note some of the main limitations of Capella/Arcadia, such as limited interoperability with other engineering tools, the inability to control flow between functions, and the lack of parameter analysis capabilities.

3. DEVELOPMENT

This section provides the context for applying this research, which focuses on using the Arcadia/Capella methodology in implementing Digital Twins in a factory model. Initially, the factory model will be introduced by describing its business model, infrastructure, and needs. Next, creating models for the factory model within the Arcadia/Capella system will be demonstrated at different levels of abstraction and detail. Finally, the implementation project for the Digital Twins will be presented based on the Arcadia/Capella methodology and the ISO standard.

3.1 The Factory-Model: LAB

The "Laboratório Aberto de Brasília" (LAB) is Factory Model to solve real-world problems through product and service development and prototyping (Zimmermann, 2018). The LAB engages in project development and offers tools for prototyping, primarily through 3D Printing, to students, professors, entrepreneurs, and other institutions interested in developing new products or prototypes. The 3D Printing cell is the area of interest within the LAB Factory-Model, being managed byt two teams: the management team and the operations team. The management team handles orders (service requests), validates budgets, ensures data governance for operations, coordinates production, and manages other administrative tasks. The operations team execute the service orders, manufacture parts, and monitors key production and product metrics.

There is a need for greater control over production and information within the factory, a more accurate sizing of the team and inventory, and the definition of an optimized process for machinery maintenance. Being an ecosystem immersed in the advancements of Industry 4.0, there are already projects in the Laboratory for developing digital twins of the printers, partially addressing the challenges identified in this study. Therefore, considering a higher level of abstraction, the objective is to implement a Digital Twin of the entire factory floor.

3.2 Applying MBSE to the LAB Factory-Model context

The project's first stage involves the macro modelling of this manufacturing system using the Arcadia method and the Capella tool. The following activities were carried out for this purpose: i) data and information collection regarding the key processes in the area, ii) mapping of the "Order Processing - 3D Printing" flow using the Bizagi Process Modeler tool and iii) system modelling at a high level of abstraction in Capella. The Capella tool is fully aligned with the Arcadia method. Therefore, its modelling stages are the same:

1. Operational Analysis, which focuses on defining stakeholder needs and the system context.
2. System Analysis, where system requirements are formalized.
3. Logical Architecture, focusing on the system, its components and functions.
4. Physical Architecture, where the system physical architecture is developed.

Figure 2 provide a concise overview of the key artifacts used and a description of each modeling phase.

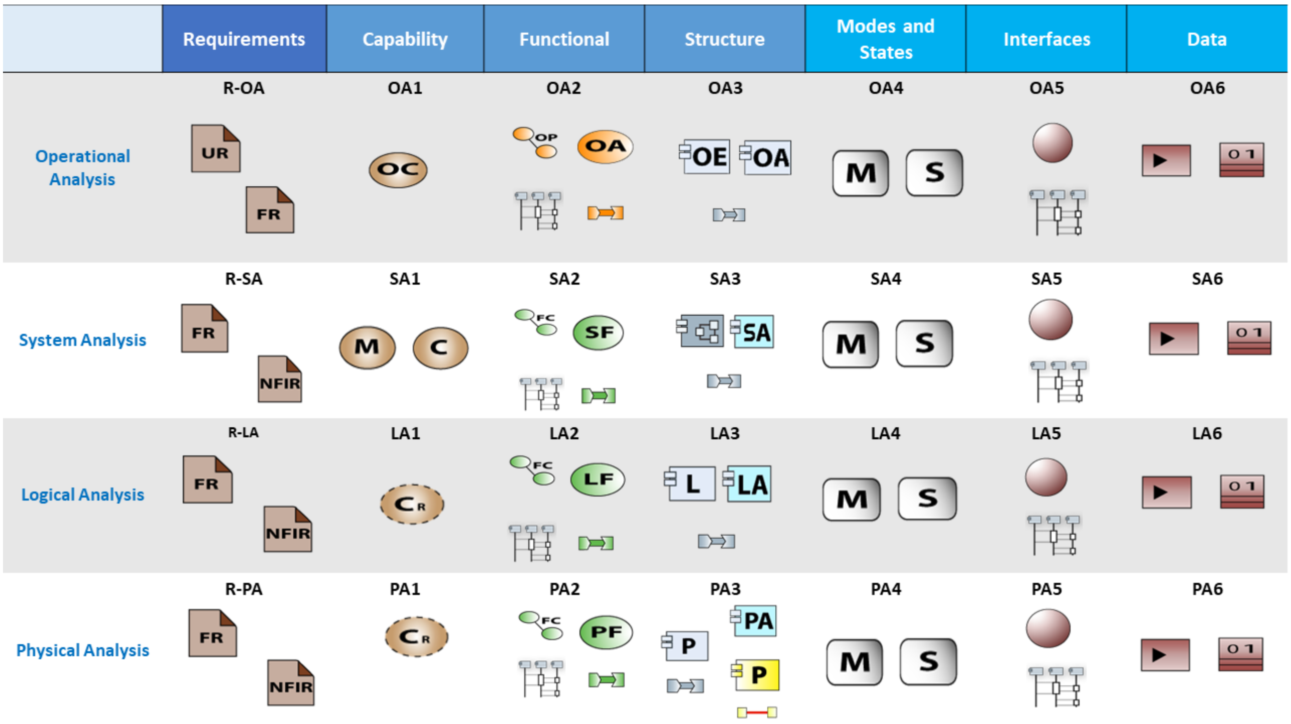

Figure 2. MBSE with Arcadia activities matrix. Source: Castro (2023)

The requirements gathering stages were carried out, and it was possible to define the functions of this system, as indicated in Figure 3. A macro structure of the "3D Printing Cell" system was also established, as represented in Figure 4.

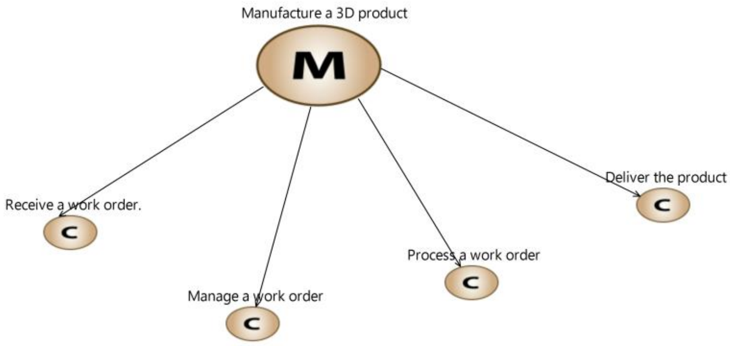

Figure 3. Functions of the system. Source: Author

The diagram in Figure 3 summarizes the functionalities expected to be found in the analyzed manufacturing cell system: "Receive work order," "Manage work order," "Process work order," and "Deliver product".

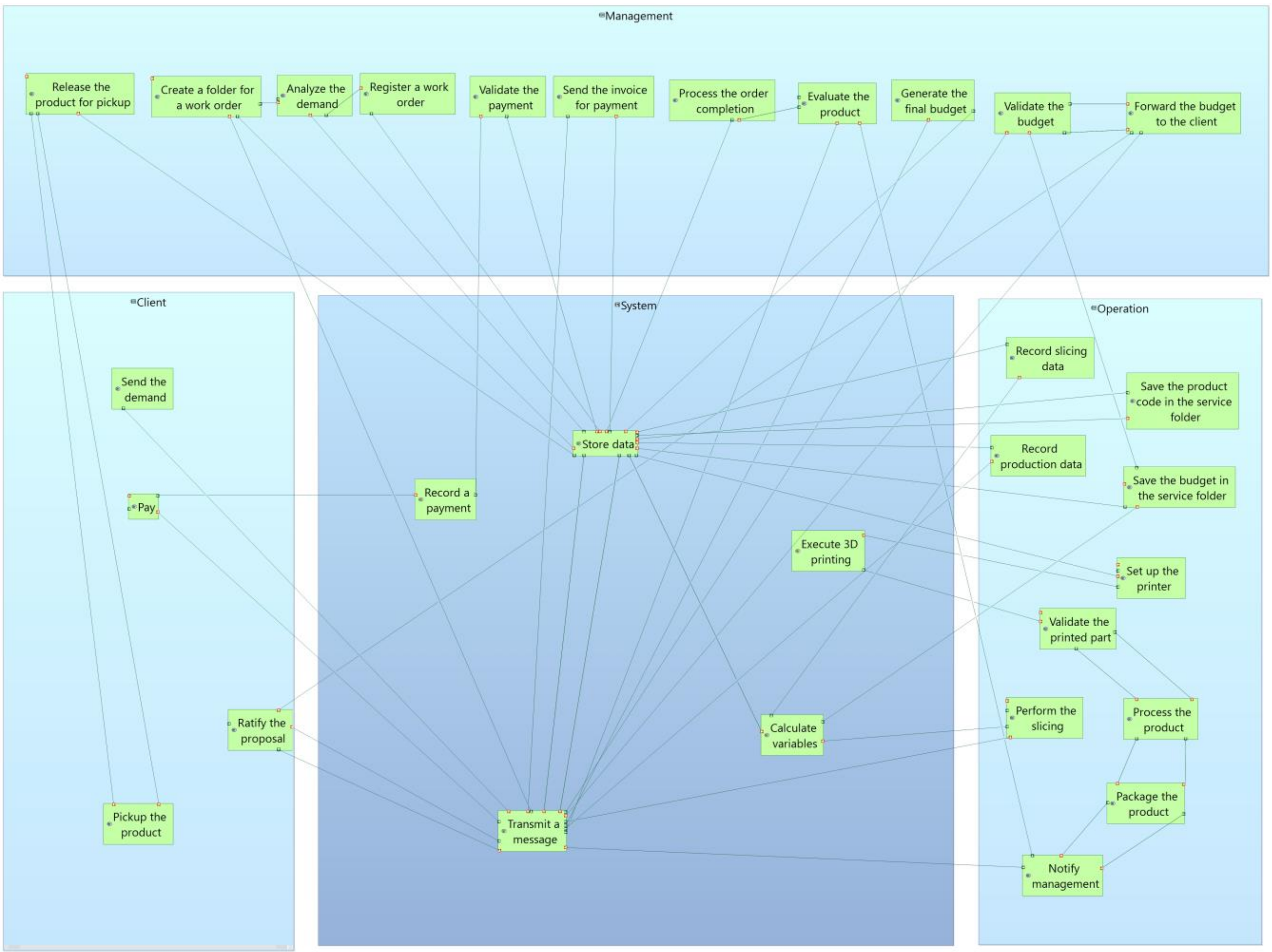

Figure 4. System: 3D Printing Cell. Source: Author

This view presents the system's functions, interactions with actors/entities, and processes involved. It also reinforces one of the advantages of modelling using tools like Capella: having a robust repository of system documentation. The last two phases of the modelling process indicate how the system will function and how it will be developed and constructed. In the context of this work, it would make sense to relate these final stages to the definition of the final architecture of the DT. However, it goes beyond the scope of this research and was not explored here.

As the next steps, it would also be interesting to explore the feasibility of integrating the Capella tool with other systems that could bring intelligence to the models, such as simulators, data acquirers, databases, and management tools. The current findings suggest some limitations in Capella's interoperability with other systems. However, some viable possibilities exist, such as the DESS (Dynamic Execution and System Simulation) simulation extension by Pu Gou Mountain, the SysML bridge extension by OBEO, and the Python-4-Capella extension by OBEO.

These examples demonstrate that certain integrations could already be made directly or indirectly to ensure a more comprehensive modelling of systems and thus enable the implementation of the Digital Twin referred to in this project.

3.3 Digital Twins in the Factory-Model

Industry 4.0 has stimulated the pursuit of intelligent and connected production systems. With this, the need for a framework to support this process became evident. In this context, the RAMI 4.0 (Reference Architectural Model Industry 4.0) emerges, providing a conceptual framework for defining a standard architecture and guiding the integration and interoperability of different system components in an industrial environment.

This reference model consists of a three-dimensional system divided into three main axes: hierarchy, architecture, and life cycle. The hierarchy defines the interconnection of all production elements, including data, users, and equipment. It should be flexible, interoperable, and distributed across all hierarchical levels. The architecture defines six layers of data flow verticalization, their interfaces, interdependencies, and usage in the production process. These layers are the business layer, function layer, information layer, communication layer, integration layer, and asset layer. The life cycle axis is related to the entire product process cycle, from planning to development (GOTZE, 2016; CHUANG, 2016). Figure 5 illustrates the graphical representation of the model.

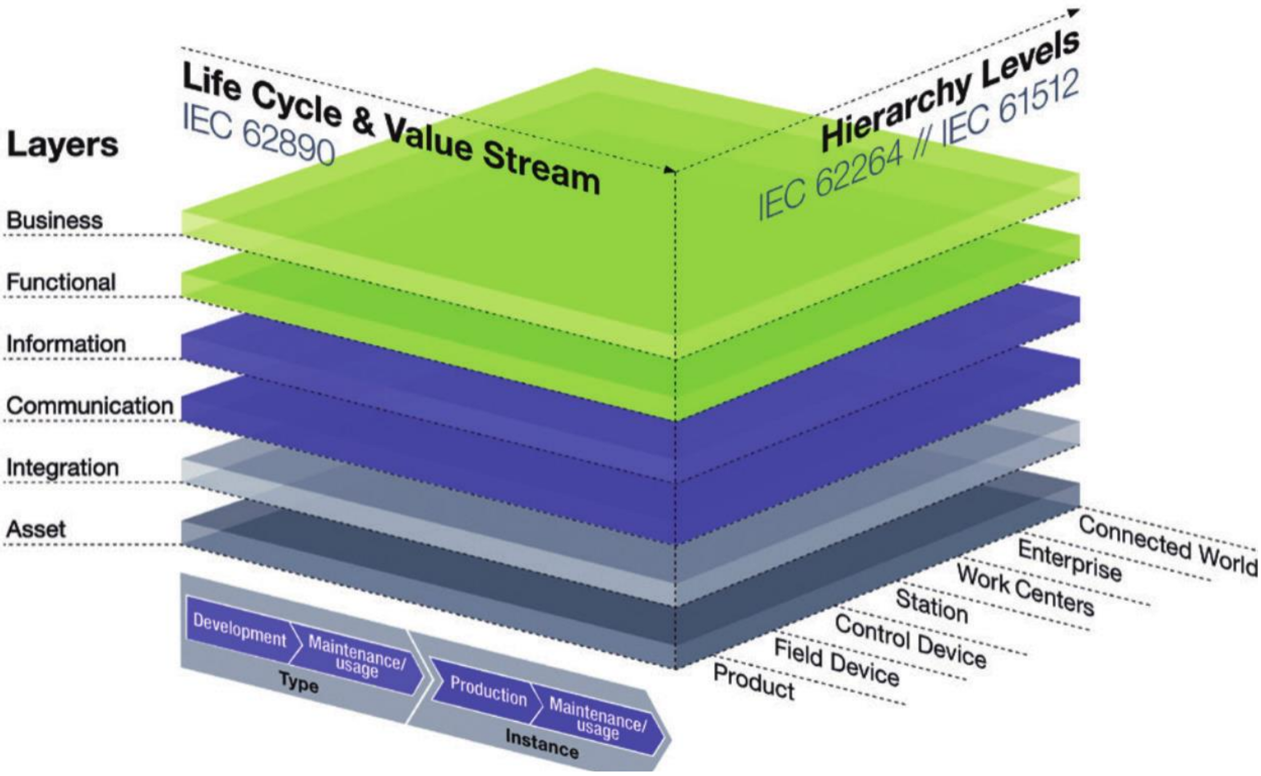

Figure 5. System: 3D Printing Cell. Source: Hankel and Rexroth (2015)

Developing systems based on the Reference Model makes it possible to standardize the description of complex interactions and fundamental requirements among associated elements in architecture. Understanding the Digital Twin as a system of the Fourth Industrial Revolution, it makes sense to draw a parallel between Rami4.0 and ISO 23247, which presents its architectural reference for manufacturing. Figure 6 shows a high-level relationship between the references, and from it, one can infer the alignment between the ISO and the connectivity requirements of RAMI 4.0.

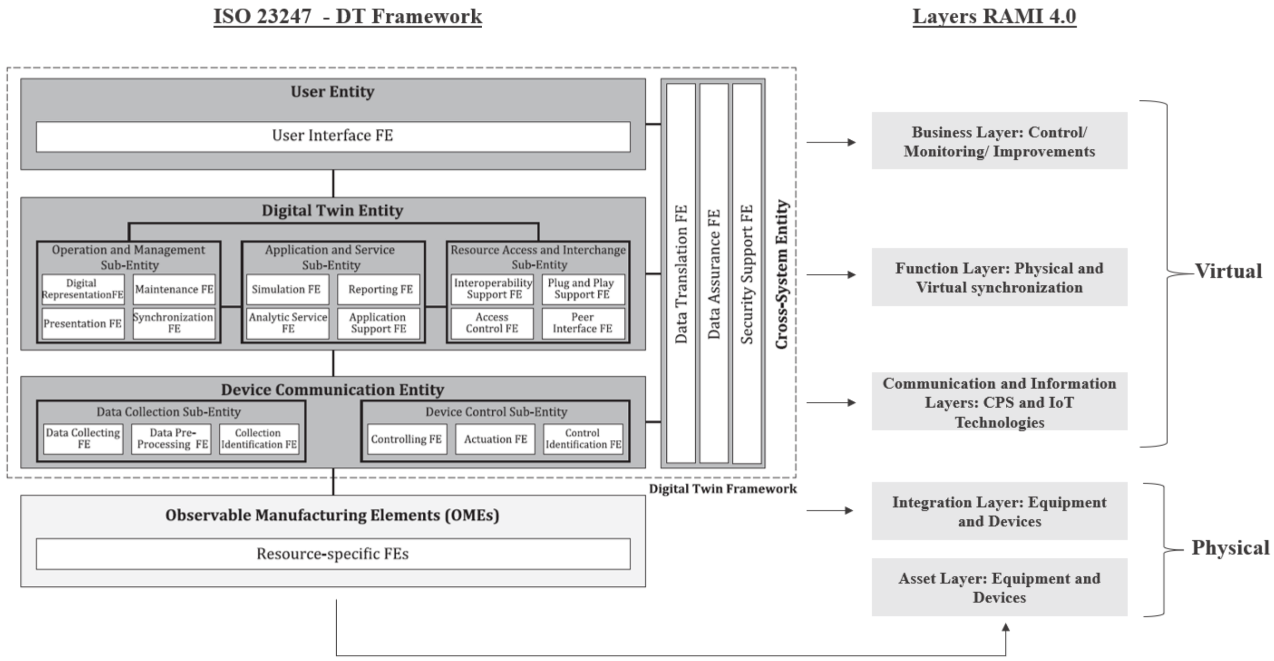

Figure 6. ISO vs. RAMI 4.0. Source: Author

The linkage becomes more precise with the identification of the technologies involved in each domain of the DT, but this study will present a different level of detail. Other interesting analyses would include correlating: i) the entities and requirements proposed by ISO 23247, ii) the technologies used for DT implementation, and iii) the Architecture and the Hierarchy of Rami 4.0. To support this process of specifying the DT architecture, the suggestion of using MBSE is brought up. This approach facilitates the definition of its scope, functions, and interactions. Furthermore, if the modelling tool used encompasses the main entities specified by ISO 23247, the model will become a digital twin. Inspired by the proposal of Bickford et al. (2020), Table 1 presents a preliminary framework.

Table 1. DT Framework. Source: Author

LIFE CYCLE	CONCEPT EXPLORATION	PRELIMINARY DESIGN	DETAILED DESIGN	IMPLEMENTATION	TEST	MAINTENANCE
MBSE EFFORT	Operational Analysis System Analysis Logical Architecture	Physical Architecture	Performance Models System Models Lifecycle Models	Detailed Lifecycle Models Final Interface Diagrams	Final Performance Models System Models Lifecycle Models	Lifecycle Models Performance Modelling
TOOLS	**Capella**	**Capella**	**Simulation Tools** Ex.: MapleSim; extendsim; Matlab&Simulink; DESS	Ex.: Computerized numerical control (CNC); CAD/CAM/CAI; Data base; API; Service network	Ex.: Computerized numerical control (CNC); CAD/CAM/CAI; Data base; API; Service network	Ex.: Computerized numerical control (CNC); CAD/CAM/CAI; Data base; API; Service network
DT DEVELOPMENT PROCESS	1) Identify DT Primary purpose	5) Define DT Architecture	10) Map Data Elements to Sensors	14) Collect Sensor Data, verify DT Operability	18) Collect Data	22) Deploy/Integrate DT with Physical Asset
	2) Identify DT Algorithms	6) Identify System sources of data	11) Develop Digital Twin Software Models	15) Begin Data set collection, develop Algorithms	19) Near-Real time use of DT during T&E	23) Integrate DT with Shore support, Logistics Communities
	3) Identify DT Data input types	7) Identify Data storage	12) Integrate Disparete DT Models	16) Validate performance Models T&E	20) Retrain/Modify DT Algorithms as necessary	24) Continue to build DT System Model Data Sets
		8) Define DT Digital Thread				25) Leverage DT for Reliability, Performance, Maintenance, Support decision making
	4) Identify DT location	9) Integrate DT Requirements into Physical Design	13) Test DT with dummy Data	17) Integrate DT with Physical Asset	21) Leverage DT to support performance verifications	26) Retrain DT as necessary

Delving into the context of LAB, it was possible, through modelling in Capella, to define the scope of the DT and the data monitoring needs. As a result, this system needs to emulate the following processes: receive work orders (manufacturing request), manage work orders, process work orders (manufacturing process), and manage the delivery of the product. Regarding informational needs, the following items were identified:

- Order tracking: Order ID; customer data; order details; order deadline; quotation data; payment information; delivery status.
- Production control: Inventory data; production lead time; data about the manufacturing process; Operator ID; error data.

To specify the remaining stages of the DT development process, it is necessary to dig into the architecture of this system and the identification of associated technologies.

4. CONCLUSIONS

In light of this study, the need for LAB to implement a digital twin of its factory floor has been identified. This arises from the desire to enhance control over the manufacturing system, collect real-time data, apply simulations for better inventory and resource management, and also improve the quality of the produced parts.

Considering the complexity involved in the development process of a Digital Twin and the relative novelty of the abstraction level addressed in this research, we sought to rely on the MBSE approach, as well as ISO 23247, to develop the proposal for a framework that guides the process.

Supporting the proposed framework, it is possible to identify compatibility between this model and the integration levels of RAMI 4.0, a reference in connectivity. Therefore, it is considered that the main objective of the study has been achieved, as there is a plausible proposal to meet LAB's need.

To do so, it is necessary to explore the elaboration of this framework in future work, including the system's architecture, the technologies involved in its implementation, and the informational requirements required.

Furthermore, it is important to conduct a more in-depth investigation into the Capella tool, chosen to support the DT modeling process, as this study remains inconclusive in confirming its suitability. This is due to its significant limitation in integrating with other systems/technologies and its lack of a native simulation module.

As a result, there is a plan to model/analyze the manufacturing system at lower levels, explore other tools for modeling complex systems, research tools that enable the construction of the digital twin, and verify compatibility between the chosen tool and Capella or another analogous software that better meets the requirements.

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