Middle East Technical University
Informatics Institute

A REFERENCE ARCHITECTURE FOR SIMULATION-BASED DIGITAL TWINS

Advisor Name: Prof. Dr. Altan Koçyiğit
(METU)

Student Name: Murat Kandaz
(SM)

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Danışman Adı: Prof. Dr. Altan Koçyiğit
(ODTÜ)

Öğrenci Adı: Murat Kandaz
(SM)

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8. ABSTRACT (MAXIMUM 200 WORDS)

This study investigates digital twins that specifically utilize simulation for various reasons (a.k.a. "simulation-based digital twins") and proposes a reference architecture for those means. To this end, a research methodology is set, and a corpus of existing literature is formed. This also includes landmark and/or highly cited articles, along with review articles on the subject. Several aspects, especially capabilities and metrics are analyzed using this corpus. It is considered that the key outcomes and the main statistics derived from these represent the huge domain of digital twins. Although they can be categorized and structured differently in more granular approaches, capabilities (predictive maintenance, optimization, running what-if scenarios, calibration, simulation model construction, education-training) are based on all identified functionalities and metrics (fidelity, autonomy-intelligence-learning, scalability, maintainability, modularity) are based on all measurable levels in principle. A generic layered architecture is proposed based on these, noticing that simulation, along with data, is ideally at the core of the domain model. Along with this novelty, this study serves as a steppingstone in configuring many real-world implementations of simulation-based digital twins depending on the desired capabilities and metrics.

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1. Introduction

Advancing technology, increasing competition, need for specialization, and specific trends of sustainability and autonomy drives our modern world and products evolve into cyber-physical systems (CPS) with mechanical, electrical, and software components [1]. Within this concept digital twins have a huge potential and is a continuously growing and evolving field since the introduction of the concept [2]. There are quite a lot of definitions of digital twins, but the most common definition is referred as a digital coupling of a physical asset or process to a virtual representation with a functional output [3, 4]. It can also be defined as a digital representation synchronized at a certain fidelity and frequency [5]. Digital twins are being used in many industries already, including manufacturing [6, 7], energy [8, 9], construction [10], aerospace [11, 12], and many others, specifically asset monitoring and predictive maintenance [13, 14, 15].

Digital twins can be based on data, physics, rules, behaviors, and geometry models/features [16]. Together with the conventional data-based approach that has been used for decades, other models that are generally based on engineering simulations allow detection of problems that may occur in components, testing existing or new configurations, and creating and performing what-if analyses. Accordingly, a digital twin consists of two parts as a passive data part and an active program that performs a task [17]. For the purposes of this study, the models associated with physics, rules, behaviors, and geometries form the “program” part for the purpose of simulation. These models are hereinafter called “simulation-based” models and the relevant digital twins that incorporate one of these models are called “simulation-based digital twins” (SbDT). It must be noted that simulations can also be based on data alone in reality, without the incorporation of physics, rules, behaviors, and geometry. Yet it is intended to segregate physics, rules, behaviors, and geometries from the data-based models in this study, as these are heavily incorporated with engineering simulations.

It is also acknowledged that the combination of these models leads to “hybrid” digital twins [16], and almost all examples in literature are based on data-based models and one of the simulation-based models (i.e. physics, rule, behavior, geometry). Hence, the focus of this study is also a hybrid digital twin.

Normally engineering simulations can be majorly associated with physics-based models. Embedded in the relevant asset or run in a cloud-based environment, engineering simulation software can model the life cycle of the asset based on engineering physics, mainly computational fluid dynamics (CFD), computational solid mechanics (CSM), and electromagnetic analysis (EMA). Since real-time mimicking of the conditions by the relevant software requires major computer resources, the related operations are performed with reduced order models (ROM). Again, it is worth mentioning that SbDTs are not solely focused on physics, but also rules, behaviors, and geometry models for the purposes of this study.

In this study, the concept of simulation-based digital twins (SbDT) is elaborated within an architectural perspective. The objectives of the study are to provide improvements and/or novel techniques in defining an architecture for SbDTs. To this end, relevant the literature survey is undertaken in the corpus based on the relevant methodology, and it is proposed to elaborate capabilities and metrics. These two can be associated with functional and non-functional requirements of a product or system respectively. The inclusion of design patterns, abstraction levels, verification and validation concepts are also checked within the corpus, although these are not included in specific keyword searches in literature. With such discussions in hand, a general architecture considering these aspects is proposed.

This study is structured in several sections presenting various aspects. Section 2 presents related work and background of digital twins. Section 3 contains research strategy, scope, methods, and relevant details of the research methodology. Section 4 presents statistical findings based on the literature found via the research methodology. Section 5 and Section 6 explore the corresponding capabilities and metrics. Section 7 is based on the elaboration of architectures based on the outcomes explained in previous sections. Section 8 is the concluding section of the study.

2. Related work

The concept of digital twin has been widely popular since its introduction by Grieves [18]. The number of papers and studies show a stable increase especially in 2010's [19, 20, 9]. As stated, there are many different definitions regarding digital twins, and major disagreements about these definitions are towards bidirectional connectivity and use of cloud and/or IoT. This is mostly because of the lack of establishment of safety and security protocols, mostly towards cybersecurity [3, 21, 22]. Although some resources state that both are required for the system to be classified as a digital twin, most of the studies are inclined to those definitions given in the section above. Various other technologies are also defined as digital models and digital shadows and concepts as product lifecycle management (PLM), simulation, optimization and so on, and their differences from digital twins by Sharma et al. [23]. Harper et al. argue that not all internet of things (IoT) applications will have standard taxonomy, but it will need time for the markets to evolve their own terminologies [24]. Tekinerdoğan and Verdouw also focus on design patterns of and differentiate between digital model, digital generator, digital shadow, digital matching, and several other patterns based on principal design aspects of digitalization [25]. Hu et al. [26] presents a categorization based on level and capacity of updating itself [Rasheed et al 2020], data flow (model, shadow, twin) [27], system lifecycle and degree of updating capability (pre-digital, digital, adaptive digital twin, intelligent twin) [28], abstraction level (twin of an object, process, phenomenon) [29] and aggregation level (discrete, composite, system level) [30].

The originator of the concept, Grieves, together with Vickers, have originally proposed three types, digital twin prototype (DTP) as the main system simulation model, digital twin instance (DTI) as the real time connected copy of the asset, and the digital twin aggregate (DTA) in which DTIs form a network of twins for the asset under consideration with the DTP [31]. They argue that DTP models the generic asset and evolves into a DTI when deployed to each single asset, while being linked to it throughout its lifecycle. So essentially, it is believed that many definitions can be made with many differentiators, and many others will emerge with developing technology in the future, but in this study the core of the technology will be presented making use of these two concepts, i.e., DTP and DTI; any DTP will be considered as a "system simulation model", whereas any DTI will be treated as a "digital twin".

Simulation is defined as the creation of respective set of conditions artificially to study or experience the concept in reality [32]. In our case, it is generally defined as mimicking or emulating a product, process, or system, providing means to improvement of these and/or better decision-making by testing different scenarios. The importance of simulation in DT's is vital and it is perceived as an integral part of DT's [33]. Boyes and Watson [3] argue that collecting and statistically building upon sensor data cannot solely be considered as a digital twin and without simulation it will lead to omission of physics effects or complex features of systems of systems. DT is also defined as a combination of data and behavior descriptions using several simulation models [34]. It is regarded an integrated simulation of an asset to mirror its life, based on multi-physics, multi-scale, and probability concepts [35]. Since DTs contain models and algorithms to mimic the real-life asset, simulation plays an important role in analyses based on DTs [36]. Simulation is also the top theme along with modeling and optimization based on analysis of Jones et al. [37]. With these and many other use cases, the concept of DT has been widely regarded as one of the hot topics in engineering simulation ecosystem in reciprocity [38].

Although there are many studies on the architectures and frameworks about digital twins, the simulation side of the concept has not been well-established. Hence it is aimed to fill this gap by focusing solely on SbDTs. This study will differ from existing research in focusing on the concept of SbDTs in an architecture-centric manner considering various concepts that are explored with the research questions that are described in the next section.

3. Research methodology

Towards tackling the issues in defining an architecture for SbDTs, three research questions are generated to be explored within the scope of this study.

1. How is simulation incorporated in digital twins based on architectural concerns?
2. What are the existing reference architectures for simulation-based digital twins (SbDTs)?
3. Based on numerous applications found in the literature, how can we devise a generic SbDT architecture?

To this end, the following literature searches have been performed, and relevant studies are selected for further elaboration based on the following inclusion criteria:

- in English,
- within context (e.g., “architecture” meaning “software architecture” rather than “building architecture”),
- “digital twin” is associated with the lifecycle per the definitions above,
- containing insights about simulation (e.g., “simulation” term not appearing in only definitions but also providing a study/review/approach with any type of simulation).

First an initial ScienceDirect search was performed as

- *ScienceDirect TITLE-ABS-KEY (“digital twin” AND “architecture” AND “simulation”)*

yielding 71 articles, reducing to 45 with respect to above criteria. It is then checked that the focus of simulation can also be retrieved by a Scopus search with the inclusion of “physics-based simulation”, “engineering simulations”, and “hybrid, based on Tao et al.’s work and analyses in functionalities, applications, and disciplinary fields of use [39], and van Dinter et al.'s work showing a great majority of model representation and simulation efforts come from physics-based and engineering modelling and hybrid modelling – that actually involves physical model, regardless of the type of the approach (deep learning, machine learning, statistical, mathematical, optimization) [20]. Then, the following searches are performed as

- *Scopus TITLE-ABS-KEY ("digital twin" AND "architecture" AND "simulation" AND ("physics" OR "hybrid" OR "engineering"),*

respectively yielding 26, 39 and 1 article(s), which reduces to 7, 1 and 0 respectively after excluding the ones found in the previous searches and within the inclusion criteria above (e.g., mainly "hybrid" term referring to other usages within the specific context of the relevant paper, rather than the intended combination of "data-based" and "simulation-based" approaches).

The relevant papers found with these keyword searches are analyzed based on industry, domain and aim of the usage of the simulation if any, capabilities, metrics, whether the paper proposed an architecture and framework, inclusion of functional components, abstraction levels, and whether fidelity concerns are addressed with validation and/or verification studies. Herein, capabilities and metrics are given special attention as discussed in Sections 5 and 6, whereas others are investigated as side concerns upon which future studies may be built upon. It must be noted that all the relevant analyses are based on the corpus, i.e., papers which consider SbDTs. The relevant body of work and the relevant adjacency matrix based on these criteria are presented in Table 1. Herein the abbreviations adopted for capabilities are,

- O-OM: Optimization (O) in operation and maintenance (OM),
- O-D: Optimization (O) in design (D), i.e., basic/detailed engineering,
- WI-OM: What-if scenarios (WI) in operation and maintenance (OM),
- PM: Predictive maintenance (PM),
- ET: Education and training (ET),
- C: Calibration (C),
- MC: Model construction (MC),

and for metrics, they are:

- Fid: Fidelity,
- AIL: Autonomy, intelligence, learning (AIL),
- Mod: Modularity,
- Sca: Scalability.

The detailed explanations are given in Sections 5 and 6 for capabilities and metrics, respectively.

It must be noted that several papers are also used within the scope of this study that are found mainly by snowballing from major review articles. These majorly consist of referenced articles apart from the ones given in Table 1. These two sets of articles, i.e., found with keyword searches and snowballing, form the corpus of this study.

Table 1: Adjacency matrix for the references found the corresponding keyword search.

Ref.	Industry/subject	Emphasized capabilities	Emphasized metrics	Architecture evaluation / proposal	Design patterns	Abstraction levels / users	Fidelity concerns / V&V
[40]	Manufacturing	O-OM	-	*			
[41]	Manufacturing	O-OM	-				
[42]	Manufacturing	O-OM	-	*			
[43]	Mining	O-OM	-				
[44]	Manufacturing	O-OM	-				
[45]	Energy	O-OM	-				
[46]	Structures	PM	Fid	*			*
[47]	Marine	O-OM	Fid				*
[48]	Robotics	O-OM	-	*			
[21]	Energy	WI-OM	Fid	*			*
[49]	Energy	PM	Fid	*			*
[50]	Autonomous driving	O-OM	Fid, mod	*			*
[51]	Robotics	MC	Mod	*	*		
[52]	Manufacturing	O-OM	-	*			
[53]	Robotics	O-D	Fid	*			*
[54]	Manufacturing	PM	-				
[55]	Manufacturing	O-OM	Fid	*			*
[9]	Energy	PM, O-OM	Fid, AIL	*			*

Ref.	Industry/subject	Emphasized capabilities	Emphasized metrics	Architecture evaluation / proposal	Design patterns	Abstraction levels / users	Fidelity concerns / V&V
[56]	Structures	PM	Fid				*
[57]	Manufacturing	O-OM	-	*	*		
[58]	Manufacturing	O-OM	-	*			
[59]	Manufacturing	PM	-	*			
[60]	Manufacturing	O-OM	-	*			
[61]	Manufacturing	O-OM	AIL	*			
[62]	Energy	O-OM	-	*			
[63]	Industrial	O-OM	-				
[64]	Robotics	O-OM	AIL				
[65]	Manufacturing	O-OM					
[66]	Manufacturing	O-OM		*			
[36]	Industrial	O-OM	Sca	*		*	
[67]	Process	O-OM	AIL	*			
[68]	Process	O-OM, O-D, ET,	-				
[69]	Manufacturing	O-OM	-	*	*		
[70]	Process	O-OM	-				
[71]	Energy	O-OM	-				
[72]	Manufacturing	O-D, O-OM	-				
[73]	Manufacturing	PM, C	-				

Ref.	Industry/subject	Emphasized capabilities	Emphasized metrics	Architecture evaluation / proposal	Design patterns	Abstraction levels / users	Fidelity concerns / V&V
[74]	Manufacturing	O-OM, PM	-	*			
[75]	Port management	O-OM	-	*			
[76]	Manufacturing	O-OM	-	*	*		
[77]	Manufacturing	O-OM	-	*			
[78]	Fusion	O-OM	-				
[79]	Energy	PM	-				
[80]	Energy	WI-OM	-				
[81]	Process	O-OM	-	*			
[82]	Energy	PM, O-OM	-				
[83]	Disaster control	PM	-	*			
[84]	Robotics	O-OM	Fid	*			*
[85]	Energy	O-OM	-				
[86]	Robotics	O-OM	-				
[17]	Robotics	PM	Fid	*		*	*
[87]	Marine	PM, C	-				
[88]	Marine	PM	-	*			

4. Main statistics

Statistical analysis is based on this set of articles given in Table 1. Bearing in mind that these are not the only studies that focus on SbDTs in relevant industries, it is safe to assume that these are almost all the studies that propose/evaluate certain architectures/frameworks in certain level of consideration of details. Hence, although a holistic conclusion about the usage of SbDTs cannot be made based on this summary, a conclusion towards the importance of architecture of SbDTs in these domains with the relevant characteristics can be made.

The very first analysis is the industry/subject of the relevant SbDT as given in Figure 1 and the very first outcome is the very high number of studies conducted in manufacturing industry. This is aligned with the expectations, given that the very first applications are in fact manufacturing and the connection with the product lifecycle management (PLM) around which the term “digital twin” has been coined. It must also be noted that some robotics applications are in fact derived from automation requirements in manufacturing industry – yet categorized under robotics since there is a comprehensive know-how conveyed / focused on the relevant study in robotics. It is considered that CPSs started to evolve with Industry 4.0 that was initiated in manufacturing industry. The one of the very first standards of digital twins are in manufacturing also [89]. The second most popular field is energy, as expected per the usage of predictive maintenance with SbDTs.

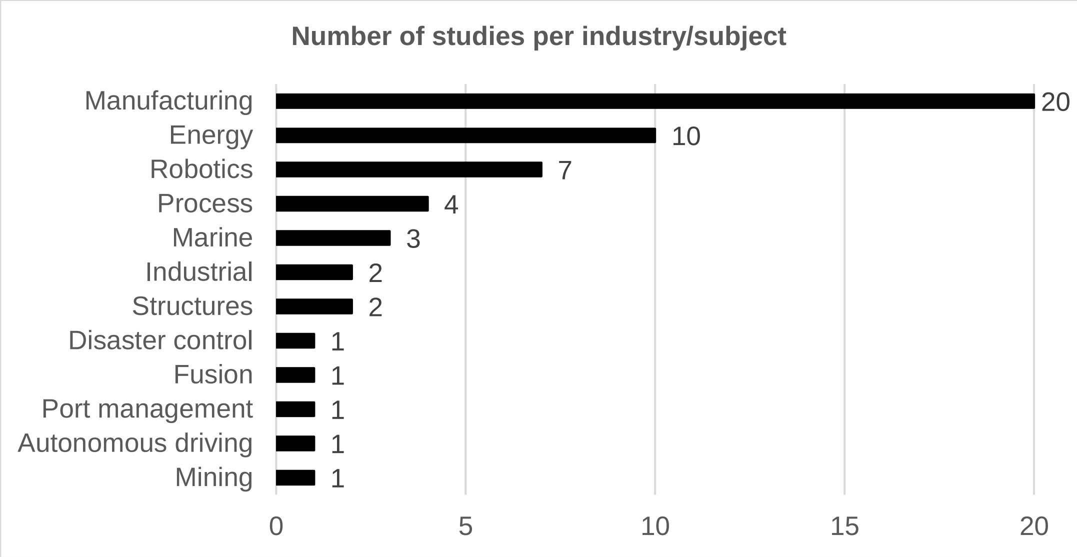

Figure 1: Number of studies per industry/subject

As far as the capabilities are concerned, there is a huge dominance of optimization towards operation and maintenance (O&M) as given in Figure 2. These SbDTs mainly use simulation to predict future operations at a certain time and implement an improvement. The second most dominant capability is predictive maintenance. Figure 3 depicts the industries in which these most dominant capabilities are used, again with the dominance of manufacturing. More than half of the studies in energy are also towards this capability.

The most dominant metric in relevant studies is fidelity per Figure 4. It can be argued that 11 out of 53 studies is relatively a low ratio and fidelity concern is not associated with architectural concerns, however it may also be considered that the quantification of metrics is not quite common in the DT domain given the low standardization in the field regarding maturity. When the capabilities associated with fidelity is investigated it is seen that optimization and predictive maintenance are quite dominant as given in Figure 5, however the industries are quite heterogenous and moreover manufacturing is not the leading industry associated with fidelity as given in Figure 6.

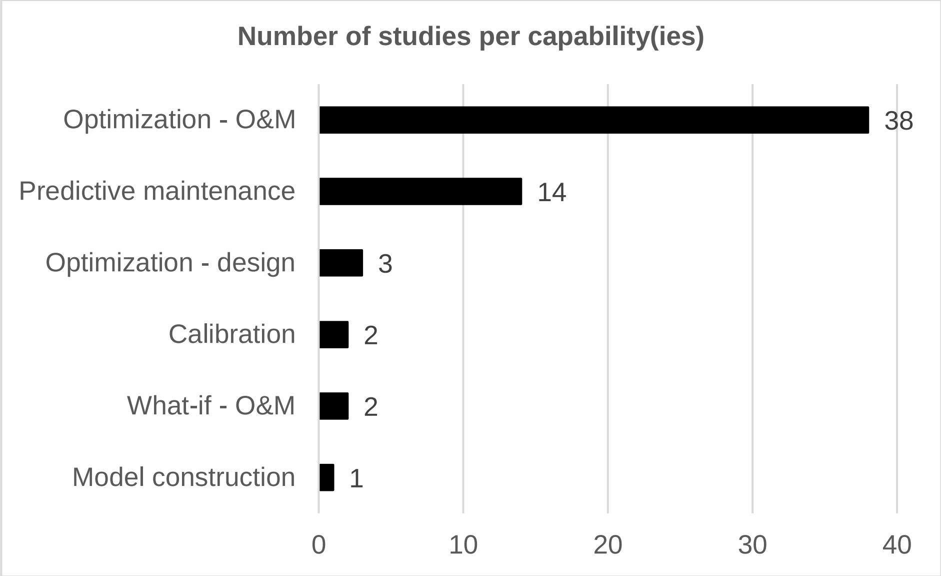

Figure 2: Number of studies per capability(ies)

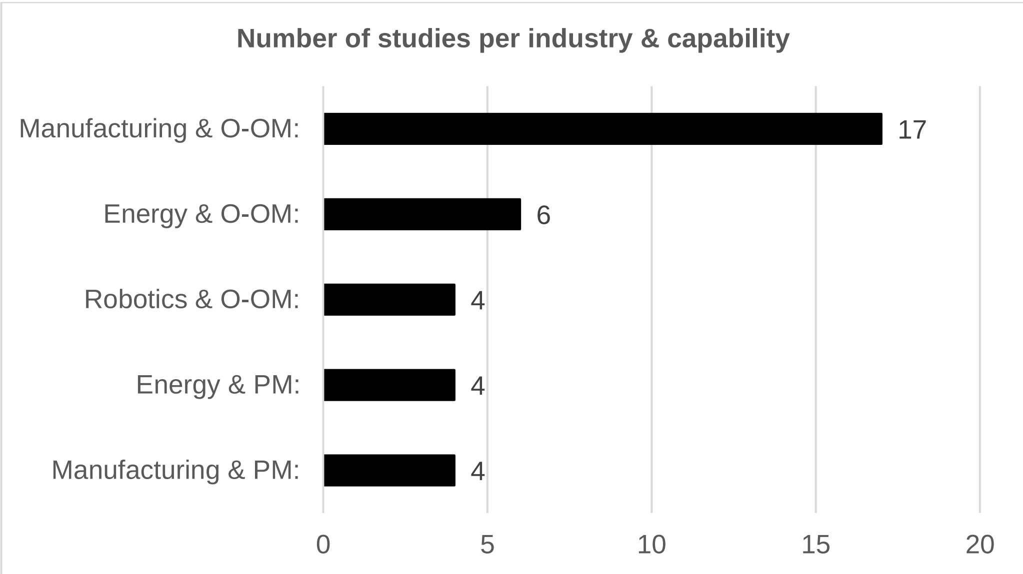

Figure 3: Number of studies per industry and capability

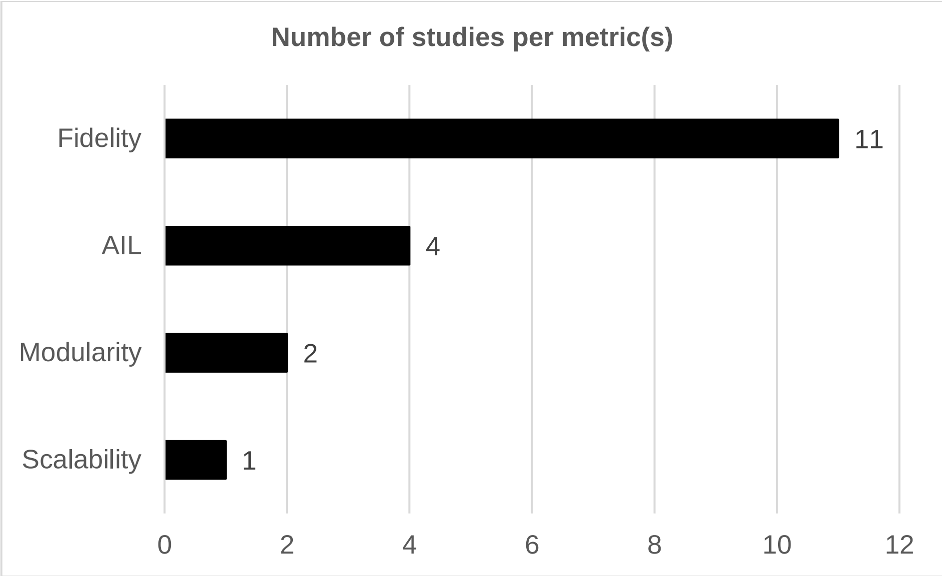

Figure 4: Number of studies per metric(s)

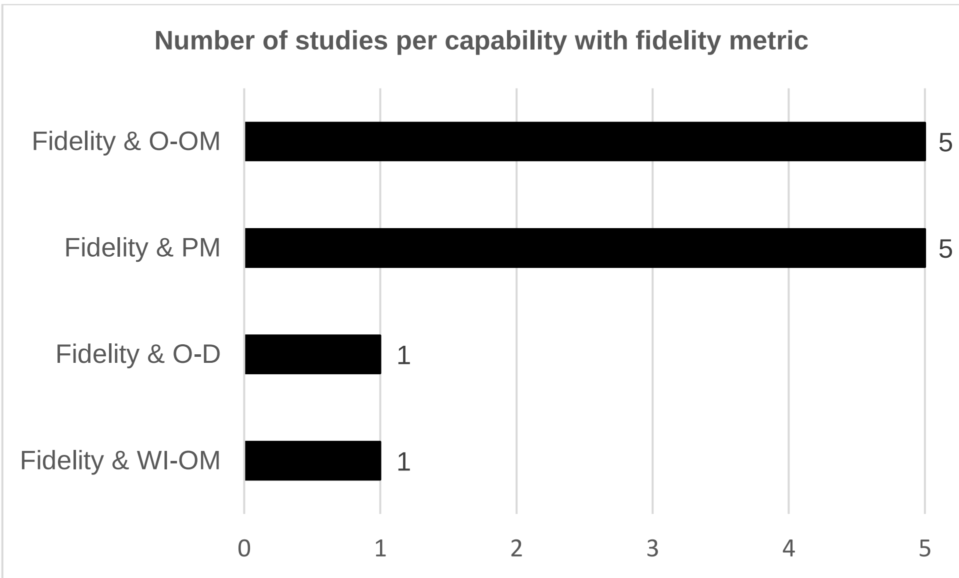

Figure 5: Number of studies per capability with fidelity metric

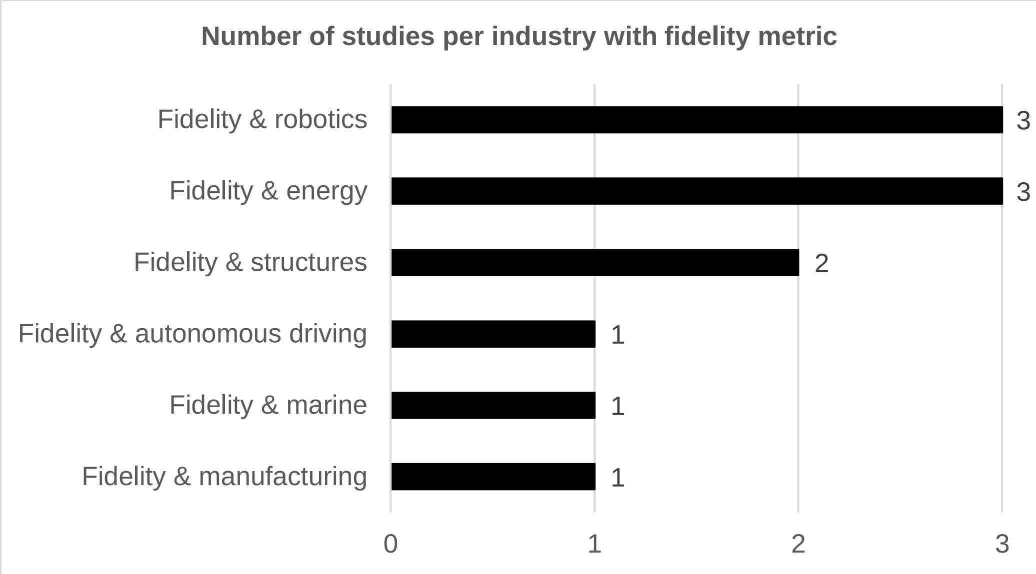

Figure 6: Number of studies per industry with fidelity metric

These outcomes based on popular industries, capabilities and metrics reveal that means and associated costs to construct the SbDTs are feasible for operations in which,

- the relevant asset(s) are relatively costly (manufacturing, energy, robotics, process, marine, industrial, mining, port, and so on),
- an improvement/failure brings a relatively big economic advantage/disadvantage (manufacturing, energy, process, marine, industrial, fusion, and so on)
- human safety and livelihood are of concern (autonomous driving, disaster control, fusion, mining, structures).

Architecture evaluation / proposal is based on the relevant study's presentation of a new/existing architecture or framework, and/or forming the relevant study's outcomes based on architectural concerns, i.e., being architecture centric. The studies which are not marked for architecture evaluation / proposal neither present/evaluate a framework nor are built around such concerns, but still acknowledge architecture as a factor in designing SbDTs.

5. Capabilities

With the drastic popularity increase of the digital twins it is ultimately found that there are DT and/or SbDT studies that even surpass the definitions to the best knowledge of the author. It is hence proposed to analyze SbDTs based on capabilities, and with these, form a correlation with the existing architectures and frameworks and/or propose a new one.

It must be noted that the capabilities given below are the ones encountered in the corpus based on user stories, irrespective of intermediate tasks associated with other capabilities. E.g., communication with other digital twins is not presented as a capability, since it ultimately serves the end-user in one of the capabilities given below. Likewise, machine learning is not presented as a capability since it does not directly serve the end-user. In fact, this is associated with a metric that is commonly used in maturity models [1, 90].

5.1. Predictive maintenance

Predictive maintenance can be defined as the monitoring of assets and performing operations and maintenance actions based on future predictions of health of the assets, operation conditions, fault detection, anomaly detection and so on. As the name implies, prediction of the maintenance activities is essential here and, in this regard, it differentiates from optimization of O&M activities as discussed in the next subsection.

Predictive maintenance can be performed in a data- or simulation-driven manner, via models based on geometry, physics, rules, behaviors, and a combination of these, which are in turn called hybrid models [16]. Simulation can be performed with either of these. This study does not categorize the corpus based on models, yet van Dinter et al. studied in this manner for predictive maintenance digital twins, and it is seen that for SbDTs physics-based models are the most common [20].

Variation of models and requirements for components, systems, and systems of systems may change and this can be handled via abstraction levels. Simulation, at its basic level and especially for physics-based systems, bring challenges regarding computation time [17], which is also handled via federation of and within twins.

5.2. Optimization

This study considers optimization as improving the operation and/or maintenance regime of the asset [85] and improving the design of the future and/or the current asset [91]. Hence both the design engineer and the O&M engineer have different interests and needs associated with optimization. Optimization can be performed by other stakeholders with different levels of know-how and interest, and hence can be subject to abstraction.

It must be noted that optimization of O&M can be associated with predictive maintenance, it is seen that throughout literature there is a concrete line separating the two concepts, i.e., optimization of O&M includes planning, balancing, configuration, and scheduling, whereas predictive maintenance involves an explicit prediction of a repair, change, fault, and so on.

5.3. Running what-if scenarios

What-if scenarios are run majorly for optimization, yet within the scope this study, it is different from optimization in that what-if scenarios are run for other concerns other than the focus of the SbDT – whereas optimization described in Section 5.2 is performed on the asset/system connected with the SbDT. What-if scenarios can also be run by different parties for the purpose of hypothetically analyzing the future operation and maintenance actions and for the design purposes.

5.4. Calibration

Calibration, or in a complete naming convention, calibration of the simulation model or model calibration, is based on data and is crucial in sustaining the fidelity of the digital twin not only during a specific period but throughout its whole lifecycle [92]. It is evident that each SbDT is a unique product slightly different from each other at some point in time [17], i.e., each DTI possessing differences from the DTP or from each other. This needs to be addressed via calibration of each twin, bringing further sophistications which are more often ignored than implemented. Verification of the SbDT is performed within this context.

When the relevant capabilities are closely related with certain level of fidelity, degradation of the assets [93] are the first concern for calibration. Several others may be change/upgrade of a component, change of operation/design conditions, and so on. Hence, calibration in this context is the update of the simulation model either based on data or the initial DTP.

5.5. Simulation model construction

Simulation model construction is the formation of the SbDT model from data when a comprehensive model is not present. In practice, it is performed based on several rules and templates with model-based system engineering (MBSE) approaches and construction of a model from scratch, with AI or ML, is not found in literature. Hence there can be a confusion between model construction and calibration, i.e., when does one starts and the other finishes. In this study the concept of simulation model construction is considered to exist is a piece of the model is missing and needs to be formed with data, whereas in calibration it is assumed that the whole model is complete with all components and upgrades to various model parameters are performed based on data.

5.6. Education and training

SbDTs can be used for education and training purposes, especially for O&M personnel. Whereas simulators are based on DTPs, SbDTs for education and training are based on DTIs. It must be noted that in literature although there are references to education and training based on DTIs, the practice is limited to DTPs.

6. Metrics

There are several established maturity models in literature [1, 90, 91]. It is seen that many studies provide great insight not only for today but also for the future but lack quantifiable metrics. This is majorly since quantification of such metrics via internationally recognized authorities haven't been published yet -and seem implausible while discussions over definitions are continuing still. Yet it is argued that without metric-based evidence it is hard to evaluate DT implementations [23]. It is also seen one-dimensional levels often lack describing relevant DTs capabilities within a certain use case, and hence need evaluation of separate metrics [90]. This section hence discusses relevant metrics -excluding proposing means of quantification- to connect capabilities with the relevant architecture that is to be discussed in Section 7.

It must be noted that metrics in this study represent metrics for describing the SbDT, not metrics for describing the component, system, or system of systems for which the SbDT is created. Some of them are named in terms of quality attributes [94] as below (e.g., modularity, scalability, maintainability), but in fact refer to the actual measures of the relevant attributes.

6.1. Fidelity

Although the meaning of fidelity is extended for the purpose of this report as further explained, the simplest definition of fidelity is the level of accuracy [90]. It is also one of the major concepts in describing a DT and one of the most common dimensions used in literature. In a wider context, fidelity also contains the number of features and abstraction levels by nature [37], which are also metrics and features that are used throughout the literature [95, 20]. In this study, fidelity contains these also and can be defined as a combination of accuracy and abstraction. It is argued that number and type of parameters can be included in abstraction levels and hence fidelity as well.

It must be noted that accuracy also includes time metrics, such as:

- computation time, the time required to construct and deploy the digital twin – in general the higher the computation time the higher the fidelity and vice versa (for a certain number of features) – and,
- synchronization or processing time, the promptness of the change in the digital twin triggered by the physical asset (lag, or delay of the former). Vice versa is not elaborated here – the change in the physical asset triggered by the digital twin is not considered to be a part of SbDTs but rather control systems.

Computation time and especially processing time is inversely proportional to the computational power in which relevant operations are performed digitally. It is hence a good idea to define the required fidelity based on various sensitivity analyses and depending on stakeholder need, maybe creating federated twins based on different fidelities [96] and abstraction levels.

Abstraction levels can be argued to be in SbDTs' capabilities, however, in this study it is included in metrics under fidelity, as many capabilities discussed in the section above can be modified and configured based on different stakeholders' need and the primary modifier here is the number of features that the respective stakeholder uses.

6.2. Autonomy, intelligence, learning

Autonomy, intelligence, and learning are concepts that are encountered in many studies, most often than not theoretically. Gerber et al. separate these three concepts and adding fidelity, present a widely used maturity model for digital twins comprising of four levels [90]. Yet per the discussion above, since this study is focusing on capabilities towards end-users, these concepts are contained in metrics. It must be noted although there is a clear distinction between these three concepts such that,

- autonomy is associated with performing tasks without human input,
- intelligence is associated with human cognition, and
- learning is associated with learning from data without human supervision,

in this study, they are treated under the same category, based on all three are based on mimicking human tasks and/or actions. This categorization is also partly motivated by the fact that even the very few papers which emphasize metrics regarding these either do not present a clear quantitative methodology and/or present a distinction between them while doing so.

The lack of practical and especially commercialized applications with autonomy, intelligence, and learning are considered to become popular in the future but currently there is the issue of placing appropriate safety and security protocols in place.

6.3. Scalability

Scalability is related to the change of the component/subsystem of concern, i.e., research object [97]. In this regard it is also connected to federated digital twins when a change in the fidelity is required for certain reasons [96]. Given the level of fidelity discussed above also includes the number of parameters, scalability in this context also covers interoperability, i.e., switches from data, physics, rule, behavior, and geometry-based models.

6.4. Maintainability

Maintainability is a crucial factor in the lifecycle of the SbDT considering the changes made to the system, in terms of real asset or the digital twin itself, or even the environment of deployment and communication protocols of hardware, sensors, and so on. It directly affects the longevity of the digital twin [98], which must be active for the lifecycle of the asset and even more for the collective data economy. This also includes modifiability that is associated with calibration capability, in which a relevant measure would be the intermittent time that the SbDT would be updated, and no side effects would occur.

6.5. Modularity

The level of modularity is important in terms of reusability in both different DTPs and DTIs. Component or subsystem models in DTPs are generally continued over a large period, with minor changes, until a game changer or disruptive technology renders the model invalid. The same is true for DTIs, for when the relevant asset is upgraded with a slightly improved technology. Modularity also includes the capability to add or remove portions of SbDT models. It must be noted that although modularity is a subcharacteristic of maintainability per ISO25010 [94], it is treated as a separate attribute in this study for the purpose of evaluating SbDT capabilities.

7. Architecture

To define an appropriate reference architecture for SbDTs, firstly the principal concept of the system is presented as given in Figure 7. Accordingly, there is a flow of bidirectional data (regardless of being online-continuous or offline-discrete) between the asset and the SbDT. The dashed line represents the source of truth for the validation of simulation, i.e., the comparison between the data generated by simulation and the operational data generated by the asset.

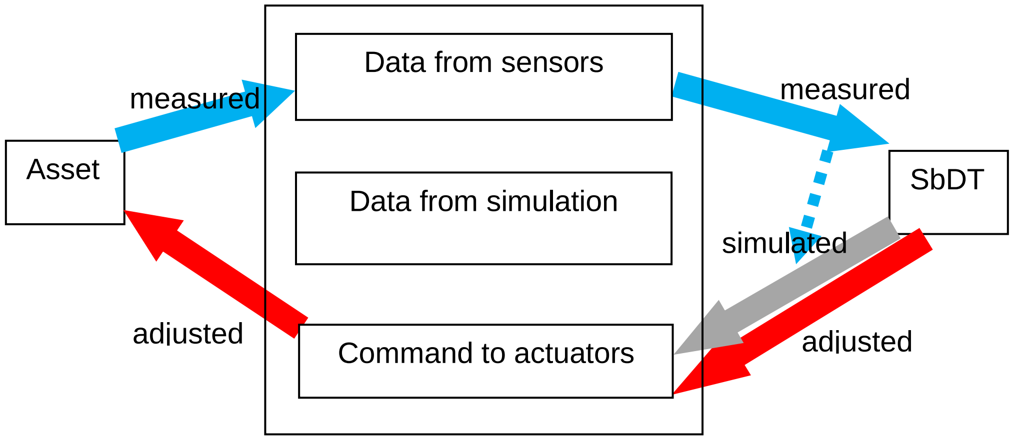

Figure 7: Principal concept of SbDTs indicating measured, simulated, and adjusted data/parameters

Based on this principle, the domain model is created as depicted per Figure 8. The model is given for a domain in which all the capabilities are given in Section 5. It must be noted that since the timestamp / periods are trivial attributes of most, if not all the domain objects, they are not explicitly indicated in the domain model.

The domain objects and their corresponding duties are as below alphabetically.

Actuator: the device responsible for regulating the asset per the adjusted parameters per Figure 7

Asset: the physical asset the replica of which is created via the digital twin

Calibrator: the module associated with performing the relevant calibration capability per Section 5.4

DataSet: collected operational data of the asset

DigitalModel: the model incorporating all the digital data except the simulation model, generally corresponding to all the digital data provided with the asset in addition to the collected operational data

DigitalTwin: the system comprising and/or coordinating all the digital data, model, and programs

FederatedModel: separate models having different fidelities for common components

Historian: the module responsible for storing the operational data

ModelConstructor: the module associated with performing the relevant model construction capability per Section 5.5

OMSafetyProtocol: the module supervising the automatic control of the actuators based on predictive maintenance actions

Optimizer: the module associated with performing the relevant optimization capability per Section 5.2

Predictor: the module associated with performing the relevant predictive maintenance capability per Section 5.1

Sensor: the devices responsible for sensing and collecting measured (operational) data per Figure 7

Simulator: the module responsible for creating the simulation and coordinating the modules to perform the relevant capabilities

Trainer: associated with the relevant education and training capability per Section 5.6

WhatIfAnalyzer: the module associated with performing the relevant running what-if scenarios capability per Section 5.3

The domain model incorporates a business model in which the actors are, alphabetically:

OEMDesignEngineer: the actor associated with the original equipment manufacturer (OEM) responsible for providing the asset, using optimization module for better designs in the new versions of the asset

OMEngineer: the actor associated with the O&M entity, responsible for O&M of the asset

SimulationEngineer: the actor associated with the engineering entity, responsible for creating and improving the simulation module.

In general, CPSs and specifically DTs are built on layered architecture [99]. This study also uses layered architecture specifically inspired by the principle of the passive data part and the active program part [17] which suits SbDTs even better than CPSs and general DTs. Most capabilities and relevant tasks are associated with distinct objects of similar use, which can be present in the same layer. This is extremely beneficial for digital twin components which are not entirely the same but vary with slight changes. To this end, promoting reusability and abstraction levels are quite easy and fast. Also, the central server-client hierarchy makes sense for the collection of data from various assets and combining them in a single location. This will also provide an efficient use of the data security efforts. It is foreseen that module development in the program layer promotes flexibility and collaboration, being in the same layer and having similar access authorities to both data processing and simulation layers. Data latency and inconsistencies during data flows within layers seem to be the most important problem, especially in a real-time performing system as a SbDT. However, it is envisioned that these advantages dominate the general disadvantages of layered architectures.

This proposition is in line with various layered architectures that have been proposed primarily for manufacturing systems that use simulation for optimization of operations and management [91, 74, 76] and for different systems that use simulation for predictive maintenance [16]. Although having different names and numbers, layers serve the purpose of segregating the physical layer, the data layer, the processing layer, and the user interface layer. With this in mind, a 5C architecture proposed by Lee et al. [100] is generally adopted in various studies [16, 76].

Several impacts of this model to the reference architecture can be mentioned as,

1. Simulator is the domain object with most associations as expected from an SbDT, followed by DataSet,
2. Simulator and DataSet objects are not directly associated but the objects executing various capabilities use/are fed by both or either of them,
3. several actors use the same module with different needs and hence different abstraction levels and/or different applications,
4. there is a plurality of the Simulator object when associated with DigitalTwin and Predictor, meaning they can be based on more than one simulation capability,
5. the issue of safety and security between the predictive maintenance module and actuators is treated via either employing an object for a protocol (i.e., SafetyProtocol) and/or this is performed via an actor (i.e., OMEngineer),
6. Simulator also generates data for several other domain objects.

With all the information presented above, the proposed architecture with the layers, modules and connectors is depicted in Figure 9, with the following explanations.

User interface layer: Consists of the interfaces serving the relevant actors – it must be noted that different actors have different interests and requirements from different modules as depicted in the figure. Various abstractions can be used to differentiate these in the program level and the relevant modules. Herein a graphical user interface (GUI) is placed as a module without diminishing the generality of the layer – many other/different modules can be placed depending on cloud/web-based availability of the services.

Program layer: This is the layer involved in the program part of the system and consists of the applications performing the capabilities mentioned under Section 5, except simulation. These also include abstractions to provide the relevant services to the different actors as explained above.

Simulation layer: Simulation module in the relevant layer that generates data for the layer above in line with the data flow model depicted in Figure 7. Simulation module is likely to include a federated model selector that can switch between simulations depending on fidelity and unit/component/system level – this way the federated model object is also contained in the architecture. It is considered that the proposed architecture is like most layered architectures for digital twins except for the placement of the simulation layer as a separate data source upon which the relevant capabilities are performed. Simulations requiring intensive computing resources and parallel processing can be performed via high performance computing (HPC) as indicated.

Data processing layer: Data processing layer includes all functions like the simulation layer, only it handles sensor data rather than simulation data. It can also involve data analytics module at this level for selection of high-quality data ignoring singularities. However, this also can be handled via the programs in the layer above and is not captured in the architectural modules.

Device control and data collection layer: Data and control layer act as the interfaces between the program and the controllers of the asset, and is located in the same layer as in most studies built on layered architecture and the relevant ISO standard [89, 101].

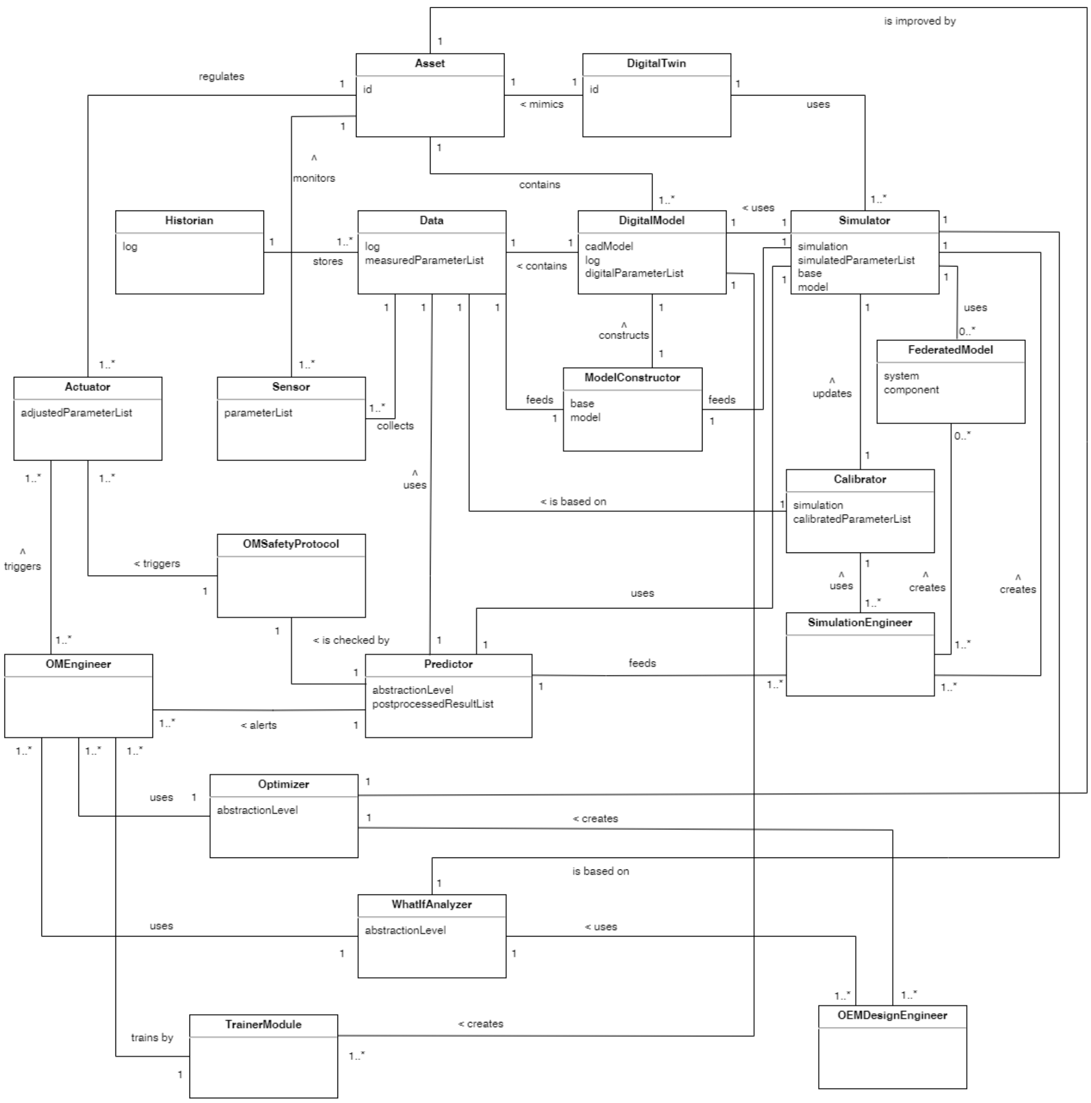

Figure 8: Domain model diagram

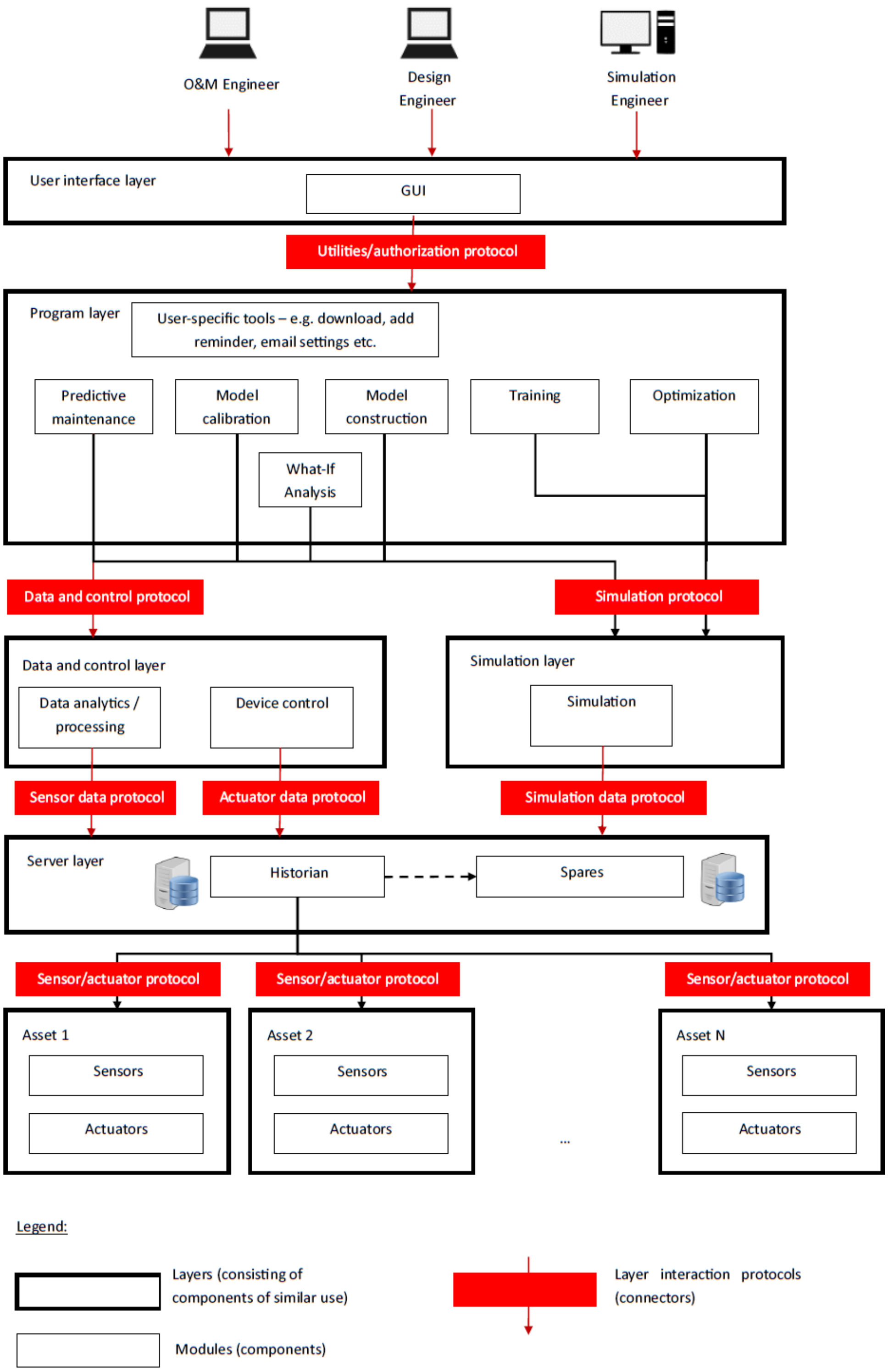

Figure 9: Layers, modules, and connectors in the proposed architecture

8. Conclusion

In this study, the role of simulation in digital twins is elaborated. The importance and impact of architecture are also highlighted. These are performed by first establishing general approaches to both “simulation” and “digital twin”. Although there is a clear consensus on simulation, definitions of digital twin vary, as a natural consequence of the very recent introduction of the concept. This places the concept in the very peaks of the digitalization hype cycle, in which there are very high expectations from the concept of digital twins currently, yet it is being realized that only some of them can be achieved partially, if not fully.

Due to the varying contents of the term, only the most common approaches to digital twins are considered. Once the corpus is formed by the combination of the keyword searches and by snowballing techniques, capabilities and metrics are analyzed in more detail. Again, a basic approach is adopted here so that the categories of capabilities and metrics are consolidated into a few. It is acknowledged that most capabilities and metrics can be further segregated and categorized differently.

As this study focuses on architectural points of view in SbDTs, the corpus mainly focuses on studies that have the terms “digital twin”, “simulation”, and “architecture” in title, abstract, and keywords. Not only the “and” conjunction limits the search results, but also the fact that these and several other linked words can be found in other parts of the studies except titles, abstracts, and keywords, interested researchers are highly encouraged to extend the literature survey. Yet it is of author’s opinion that especially the main statistics given in the relevant section are quite close to those that can currently be found via performing fully fledged surveys, e.g., the dominance of use cases in manufacturing, associated capabilities and so on.

The capabilities and metrics are highly influential in proposing an architecture, along with the relevant domain formed by these and the principal flow of information. This study opts for a layered structure in which the user interface, relevant modules undertaking the capabilities, data and simulation parts, and device control and data processing form the layers from top to bottom, defining the access from the users to assets. As noted, as requirements of the actors from modules change, and these can be implemented by defining different abstractions/authority levels that are not captured here. Safety and security modules are not considered here but obviously these can be utilized especially in program layer, the simulation module-HPC connector and so on.

The novelty in the layered architecture proposed in this study stems from the observation that simulation is the most used domain object in the domain model. Hence it is given a separate layer at the hierarchical level of the data processing layer considering the SbDTs fundamentally consist of data and simulation parts, and most modules undertaking the capabilities use and/or depend on both. This approach helps make the most of the advantages of layered architectures as discussed in the section above. Data latency and performance is a concern that needs to be addressed but can be left to the relevant modules and several workarounds can be found such as using federated models with faster processing with lower fidelity requiring less data transfer performance and so on.

In the future, it is planned to extend the current study with a reference library, relevant sample code, and a sample demonstration of a generic use-case. It is also envisaged to measure impacts of different capabilities with correlations to metrics. Another extension of the study can be towards specializations of the relevant capabilities and metrics which are considered as quite general in this study. Libraries and frameworks specific to SbDTs can also be developed.

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