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Engineering Activities in Digital Twins: A Literature Review

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Abstract: Digital twins are expected to support new service opportunities and leverage product and production engineering to a higher level of precision, e.g. by a predicted compared to a scheduled maintenance approach. After the digital twin paradigm was described, research targeted its definition, approaches for its establishments, its benefits, or security questions. Further understanding is required describing what value-adding activities are carried out by design engineers in or with a digital twin. This article aims to present a comprehensive review of the recent efforts and advances in understanding activities undertaken by engineers interacting in or with a digital twin. A literature-based study is presented as a summarizing high-level activity taxonomy, furthermore tools and roles related to these activities. The paper concludes with directions for further research. Thereby it contributes to the general understanding of the application of digital twins for engineering and design purposes.

Keywords: Digital Twin, Virtual Engineering (VE), Design Activities

1 Introduction

This paper identifies engineering activities that are conducted with or within digital twins (DT). Starting from the research motivation in section 1.1, the approach for the literature review is presented in section 1.2. The results are compiled and presented in section two and the main activities are presented as a taxonomy. Finally, in section three, this paper presents conclusions with respect to methods and tools required in digital engineering.

1.1 Motivation and research target

Digital twins (DT) are understood as one opportunity for improving industrial production and technical system design (Grieves 2022). A DT is defined as “a bi-directional relation between a physical artefact and the set of its virtual models” (Schleich et al. 2017). The twinning, i.e. the relation between one or more virtual entities (master models) and one or more physical objects (shadow data), forms the novel and mandatory technical core of a DT. The data exchange between physical and virtual objects is classified in as partial or full automatic (Kritzinger et al. 2018). Based on this core understanding different IT- architectural set-ups were proposed. The architectures comprise (i) a data collection layer starting from machines and sensors, preprocessing and transferring the signals (Wang et al. 2023) connecting data to various simulation types or business processes in an (ii) application layer (Zhang et al. 2020) and potentially a (iii) human machine interface (HMI) (Rono et al. 2023). The summarized overview of DT architectures with a segmentation in data collection layer, business application layer and user interface layer are further subdivided e.g. into a cyber layer, where the data preprocessing, processing and storage are located (Wang et al. 2023) separated from the data gathering. However, the application and HMI layers support those DT capabilities which are relevant for its value-adding usage. (Wilking et al. 2021) cluster the main purposes of DTs into (i) informing a user, (ii) supporting a user or (iii) acting autonomously. These three main categories mirror in various application examples, such as condition monitoring, optimization of system reliability & performance (Lee et al. 2020), prescription to mitigate future risks and predictive maintenance up to strategic foresight (Li et al. 2022) and many more. Many demonstrations (Iwańkowicz and Rutkowski 2023) and use cases (Rassolkin et al. 2022) of DTs were created with the goal of understanding, improving and teaching (Boettcher et al. 2023) the capabilities and applications of DTs. DT research focusses from an IT point-of-view on processing and calculation location, i.e. edge, cloud or various combinations, data transfer and timing questions, database connectivity, or safety and security. The design methods research so far focused on defining, understanding, or establishing DTs (Stark et al. 2019) describing the technologies applied in a DT, its capabilities and intended use from a business perspective. A discussion of using and applying digital twins from an engineering application view is considered as relevant for a comprehensive digital engineering understanding, i.e. the method and tools view.

Engineering activities are understood as the operations engineers or machines execute, to carry out or instantiate a process following it in a more or less precise manner (Luennemann et al. 2017). The authors state, that the actual value creation is carried out by humans and define the engineering activity with a heuristic *Role XY acts on an engineering artifact or physical item with/without an (IT)- tool*. For the operational part in the activity a set of active verbs is collected. Following this heuristic and the considerations for the DT, three questions guide through the following research:

1. What activities does an engineer carry out in or with a DT beyond the creation and initial deployment?

2. Which engineering roles or users are concerned with a DT?
3. In what layer or tool environment will engineers carry out their activities?

Since there are not many DT installations in industrial environments available for public purpose a literature review has been conducted revealing recent efforts and advances in methods and tool approaches.

1.2 Approach for literature review and research

The expected engineering activities comprise DT types informing and supporting a user and refer to the human machine interface and application layer of a DT. A human machine interface such as a monitoring dashboard is required as information platform, or the DT application layer where the twinning takes place, and proposals or suggestions are formulated by the DT. Obviously data collection and establishing data connectivity towards the application layer is expected during the DT creation phase. Maintenance activities such as exchanging broken sensors or including new ones when a DT function is manipulated are not prioritized in the search, expecting them as an obvious necessity.

Based on the expected engineering activities, the following search terms have been defined: engineering activities & DT, maintenance of DT, decision support & DT, engineering support & DT, analyze/improve product or analyze/improve production or analyze production process & DT. The search terms are applied in the Web of Science database, see also Figure 1. The search for engineering activities and DT lead to 433 papers, DT& analyze product/production process led to over 600.000 papers, only the first 1000 have been considered, DT and decision support lead to 15 papers, maintenance of the DT lead to 30 papers. The extracts were merged into one file and double entries were removed. As valid results paper that have been published after 2014 have been considered, if they are available fully in English language, their bibliography is complete, they are released in a relevant and peer-reviewed journal or conference proceeding. In addition, the title and abstract as well as the name of the journal were manually checked for relevance within the manufacturing industry. These papers have been excluded during the filter and merge step.

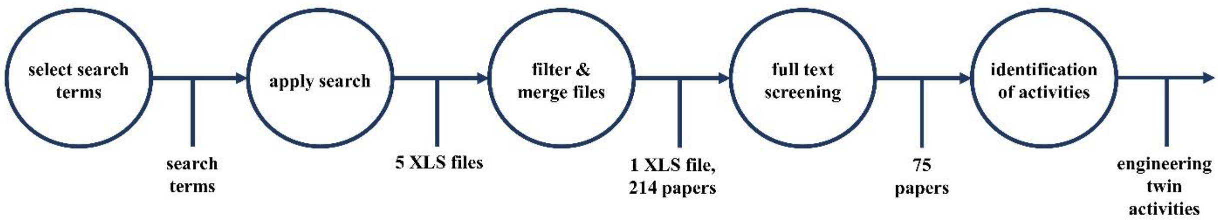

Figure 1: Approach for literature review.

During the full text screening of the 214 papers those with a content deviating from the expected engineering activities area are excluded. Their focus lies on other industries or subjects such as the real estate sector, data connectivity or aggregation methods, computational speed, DT architectures, security, or expecting the DT to act autonomously. Some paper refer to the subject of interest on user interfaces and DT (Newrzella et al. 2022) and explicitly state that an own HMI next to data analytics and simulation environments is required. However, the authors do not explain any detailed functionalities or human activities in this environment. Therefore, this kind of papers are neglected. After removal, 75 papers were considered during the detailed search for activities, tools, and roles.

2 Results and Findings

As main knowledge contribution, this paper presents in section 2.1 a high-level taxonomy of engineering activities with or within DTs as well as an overview of tool supporting the analysis and decision activities in section 2.3. Furthermore, activities are detailed and mapped to business needs, additionally expected roles and responsibilities are briefly discussed.

2.1 Activities

Engineering activities were expected in the DT types (i) informing the user and (ii) supporting the user. Therefore, the papers were reviewed, and sorted the w.r.t. to the capabilities of DT and their intent or expected benefit from a business perspective. For example (Dornelles et al. 2022) collected the improvement of worker safety, the reduction in waste production rate, a resource optimization, the minimization of unexpected disturbance, etc. These capabilities are summarized as (production) process optimization, see Figure 2. Other DTs rather target the improvement of the product or system of interest (SOI), e.g. its quality, the design lead time, the product cost, or sustainability related KPIs etc., see Figure 2. Valuable engineering activities contribute to these business needs. The pure monitoring, i.e. "watching a dashboard moving" is considered a non-added value task and therefore neglected. Therefore, the main engineering activities when acting with or within a DT are analyze or decide on the product or the (production) process of interest.

Analysis here means, the twinning is used to compare two states, situations, or scenarios. For example, the monitored fuel or energy consumption compared to the originally intended fuel or energy consumption, the usual lifetime duration of components collected over time for a fleet vs. the one at hand with a defect, etc. The analyze activity therefore compares two out of three: the past (e.g. historical data and solutions), the presence (often referred to as in-situ or real-time) or the future (named as predictive or preventive subjects). Based on the analyses a conclusion will to be manually taken next to the digital twin. The decide activity refers to present or future events or settings and takes conclusion and action with or in the digital twin.

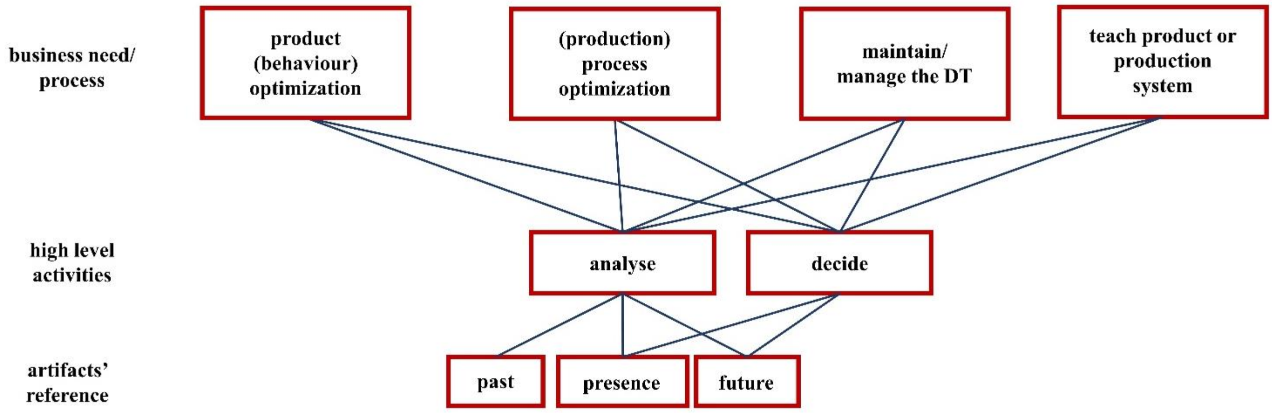

Figure 2: High-level taxonomy of engineering activities in relation to a DT business process.

Several authors report partly significant effort in managing and maintaining the DT (Fuertes et al. 2021), consequently this constitutes the third business need in conjunction with the DT, see Figure 2. The fourth DT business process comprises teaching and training, which supported by the DT reacts more precisely or realistic based on the twinning. Within these four business needs analyzing and deciding are reported as relevant engineering activities. These activities base on engineering artifacts such as data and models, but also on information comprising events, states, or situations. The artifacts refer to past or present information or data; but also have the capability to synthesize into the future.

Most papers considered in this research reported analysis of either the product or the production as the main activity, see lines 1 and 3 in Table 1. Decisions are often executed manually based on automatic warnings or proposals or previously carried out analysis, see also lines 2 and 4 in Table 1. Next to improving a product or (production) process, also the DT itself is under investigation for proper functionality, see line 5 in Table 1. The same activities as for the actual product apply for the DT: analyzing an issue, deciding on a solution proposal, and implementing modifications. Modifications to a process or product are not expected directly from a DT environment, except for those DTs acting autonomously.

Table 1: Summary of engineering activities in or with a digital twin

No.	**Higher-level activity**	**# of papers**	**Relevant activities**	**References**
1	Analyse production	25	• query data, run simulation experiments, • coping with the operational data level in complex systems, • cyber resilience testing, vulnerability management, • create models, • define scenarios, pre-select components, add or change features, components or machines, • perform what-if-scenarios, line-to line comparison • manipulate simulation, components, timing diagrams/parameters, • vary the degree of automation, • vary buffer capacity, • utilize IOT shadow states to instantiate the full [production] state, • use real-time warning of malfunctions,	(Macías et al. 2024), (Li et al. 2022), (Frazzon et al. 2020), (Lima et al. 2019), (Rono et al. 2023), (Alves et al. 2023), (Shao et al. 2023), (Tvenge et al. 2020), (Kandasamy et al. 2022), (Wang and Wu 2020), (Jiang et al. 2023), (Bozhdaraj et al. 2023), (Zhidchenko et al. 2022), (Epiphaniou et al. 2023), (Ghasemi et al. 2023), (Geurtsen et al. 2023), (Lacueva-Perez et al. 2022), (Konstantinov et al. 2022), (Sampedro et al. 2023), (Mathur 2023),

No.	Higher-level activity	# of papers	Relevant activities	References
			• predict machine failure, • analyse phenomena and find root causes.	(Cieply et al. 2023), (Bomström et al. 2022), (Doenhoff et al. 2022)
2	Decide on production settings	7	• decide based on DT proposal, • visualization for energy optimized robot control or settings in a factory, • development of advanced decision-making approaches based on the combination of the capabilities of simulation, • optimization and analytics methods.	(Bhattacharya et al. 2023), (Choi and Seo 2020), (Zhou et al. 2023), (Martinez et al. 2021), (Vatankhah Barenji et al. 2021), (Park et al. 2023), (Pires et al. 2023)
3	Analyse product	12	• perform what-if-scenarios, • use real-time warning of malfunction, • comparing virtual and physical, • learning from history, • correct design mistakes, verify design, • (deploy, maintain, improve): (architecture, look-ahead simulation, online-optimization), • Optimize maintenance activities, advance prognostics, • manage tolerances, modify testbed, • import recommendations, • integrate of environment layout and context information, • balance on product appearance [DT precision via sensory data] and product costs, reliability.	(Damgrave and Lutters 2020), (Tao et al. 2022), (Plachinda et al. 2023), (Macías et al. 2024), (Li et al. 2022), (Jones et al. 2020), (Ogunsakin et al. 2023), (Lee et al. 2020), (Lektauers et al. 2021), (Gu et al. 2021), (Lim et al. 2020), (Lo et al. 2021)
4	Decide on product parameters, behavior	2	• interact directly with customer, • create and explore the design space based on existing physical installations, • co-evolution between physical and virtual product space, • selecting optimal product family configuration.	(Gu et al. 2021), (Panarotto et al. 2023)
5	Manage a DT	13	• establish documentation during DT creation including a data model, • update and/ or expand simulation and DA-models, • maintain twinning, • test/ ensure DT functionality, • define manual interference for maintenance on all DT- architecture layers,	(Harrison et al. 2021), (Nikolakis et al. 2019), (Denno and Kibira 2023), (Xie and Wan 2023), (Heindl and Stary 2022), (Onwubiko et al. 2023), (Lorente et al. 2022), (Jiang et al. 2023), (Bozhdaraj et al. 2023), (Zhidchenko et al. 2022), (Khan et al. 2023), (Werth and Morris 2023), (Cimino et al. 2019), (Fuertes et al. 2021)
6	Training	3	• execute state analysis of production machines, • decide on how to calculate the product performance (outside of DT environment), • create [time series graph when learning DT operation], • narrow down a problem, identify high-priority areas, • modify parameters, components, and configurations in testbed.	(Tvenge et al. 2020), (Kandasamy et al. 2022), (Sato et al. 2023)

Some refernced papers discuss several engineering activities and therefore occur in multiple lines in the Table 1. The listed activities in the table are repeated with the exact words, closed terms such as “adding virtual machines to a scenario” or “including assets into virtual factory” are grouped or summarized, some words or remarks might be added in brackets supporting the understanding or context.

Until now the research focus was on the “act” as well as the “engineering artifact or physical item” from the described activity heuristic *Role XY acts on an engineering artifact or physical item with/without an (IT)- tool*. Consequently, the next sections summarize the findings on users and expected roles and secondly describe the IT tools.

2.2 Roles and Users

Within the scope of the reviewed literature one group of roles refers to the application of DTs in production environments, a second group of roles refers to design environments and the third group of roles refers to the management of DTs. Most of the mentioned roles are found only once.

(Bhattacharya et al. 2023) describe a role for decision making, a role for consuming and executing DT-information on the shopfloor for those DTs applied to improve production processes. Comparably (Bozhdaraj et al. 2023) expect one role for operating a DT based on analysis or delivered data, whereas the operative personnel in the shop floor is supported with decisions or procedural information for the execution of newly revealed insight. Depending on the purpose of the DT authors also mentioned an extension of current role profiles, e.g. (Lacueva-Perez et al. 2022) expect quality managers to consult and use a DT in order to control the quality of product in a real time manner. At the same time new roles appear with the DT paradigm and also potential new business models. In this sense (Sato et al. 2023) describe the need for a data scientist assistant due to potentially missing knowhow in OEM or established industry. This might lead to new service providers with the role production system consultant. (Gu et al. 2021) expect designers and customers to mutually use DTs for product improvements.

With respect to the management and maintenance activities (Liu et al. 2022) describe that each architectural DT layer needs a specialist to take care about it during establishment as well as during the DT- use phase. These are a product manager with an extended responsibility comprising the improvements on a product to be drawn from the DT to be included in the product, a test manager defining the test procedures carried out with the DT, a sensor manager in charge of the data pipeline from the physical entity until the DT-testbed environment, and a resource manager in charge of the physical installation. Similarly, (Doenhoff et al. 2022) expect a system operator in charge for management and updates on models and twinning, an on-site engineer being responsible for physical modifications and an IT-security specialist. Furthermore, the management of DT requires a management of the interdisciplinary dependencies (Harrison et al. 2021).

2.3 Tools

The question what kind of engineering environment is required to efficiently use a DT has several dimensions. Some authors hold the opinion that no extra or new tool is required for engineering activities such as analyzing, testing or simulation (Lima et al. 2019). 51 out of 75 papers do not mention an extra environment or tool, but rather remain in either a simulation tool or a data management tool. In these cases, extra data connections are established and functions for analysis or test activities are created or used based on the tool’s capabilities. For example (Tao et al. 2022) describes a platform for DTs, which supports the user with data connectivity and fusion. Especially on data connectivity and management platforms DT implementations are described with a dashboard functionality (Rubio-Rico et al. 2023). The dashboards are customizable based on already existing tool functionalities and hold a machine learning based analysis environment (Bhattacharya et al. 2023). Other papers describe the need for new or extra tools. In order to carry out analysis, a customizable front end (Jiang et al. 2023) or environment (Harrison et al. 2021) is expected. This might be a web-based user interface with functionalities to trigger prognostic and reactive simulation, create performance views of the product as well as to select and compare relevant KPIs (Park et al. 2023). (Sato et al. 2023) coins the term triplet, when introducing the need for an experimental space. This experimental space is an extra layer above the twinning itself and engineers engage it in problem-solving activities. Also (Bachelor et al. 2020) and (Bhattacharya et al. 2023) expect analysis- problem solving- or training areas on a different architectural layer compared to data analysis and aggregation. When explaining their service layer, the DT user interface, (Liu et al. 2022) describe functions to switch between scenarios and to drive analysis into detail (here an entire production cell or dedicated user interfaces). DTs dedicated to spatial questions propose VR environments as user interface (Damgrave and Lutters 2020). The VR environments are described with self - customizing visualization functions (Rono et al. 2023).

From the perspective of DT management or maintenance activities (Lektauers et al. 2021) describe two tool areas. One dedicated to knowledge management for the preparation of hidden knowhow and another one dedicated to data management. Figure 3 collects and orders the modules, functionalities, and areas from the literature within the human machine interface and DT application layers.

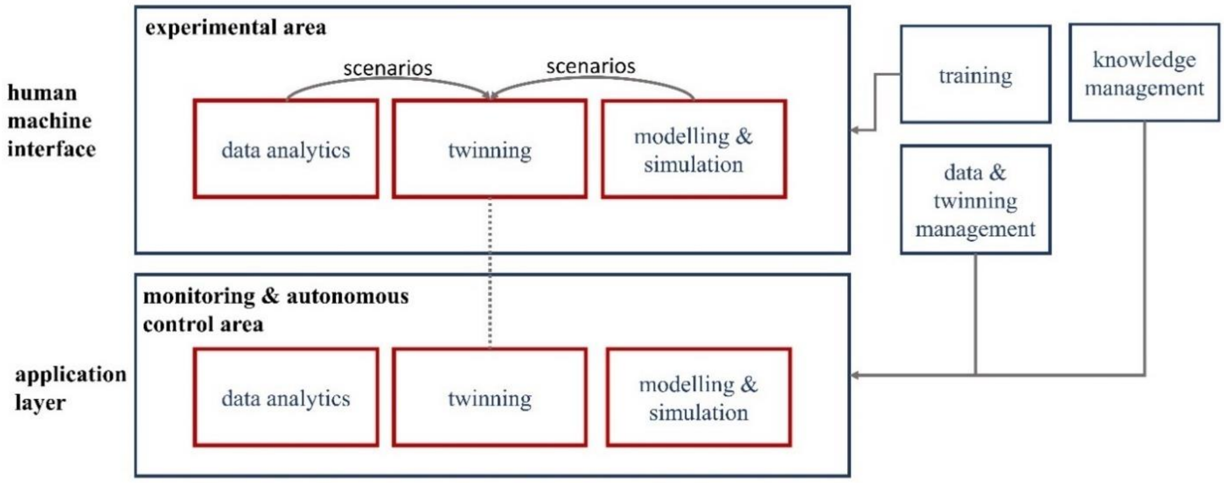

Figure 3: Experimental area of a DT supporting analyse and decide activities.

3 Discussion and conclusions

DTs are characterized by various business needs and strongly depend on the intent of the installation. This paper considers DTs with human interaction and analyses what activities are carried out in or with DTs. The research question 1 asks for what engineering activities are carried out with or in a digital twin. It was found that most engineering activities refer to the improvement of production or production processes (33%), followed by the improvement of products or systems (13%). Taking decisions on the analysis or change settings on the DT installation is occasionally carried out next to the DT environment. Another main activity is the management or maintenance activity on the DT itself, 17% of the papers described detailed activities in this area, stating a significant maintenance effort (Fuertes et al. 2021). However, the reviewed literature descriptions of engineering activities fulfilling the intended business value sometimes lack a concise distinction between human and DT activities (e.g. (Xie and Wan 2023)).

One main contribution of this research is a taxonomy of high-level engineering activities in DTs showing that analyzing and deciding on a product behavior or a production process constitutes the core value-adding activity supporting the various DT use cases. That means DTs will become a powerful tool, if these analysis activities are supported in a customizable manner to the variety of DTs. Also, discipline engineers need to be able to execute the analysis in parallel to the up and running DT installation as well as execute required changes on DTs themselves.

The second research question asked which roles are active withing a digital twin. Answering this question this review revealed four groups. Firstly, one new group of users that is operating the DT for analysis or testing purposes. Secondly, one group of users that is consuming the information and executing decisions. These user group is mostly related to the shop floor and remains therefore with the same task and responsibility but consumes the information from a new source, the DT. Thirdly, a group of uses that is maintaining the DT, comprising different competencies such as IT-Security, data analytics and twinning, or physical installations. The users might be organized according to the different DT layers. Fourthly, a management activity is expected to guide the analysis or relevant updates according to business needs. However, up to now no clear role profile naming and description was observed.

Most papers considered as relevant input for this paper (68%) established their DT with existing tools. Their research contribution focuses on IT-security, data analytics, model building, IT-architecture, or other questions. Only one source (Lima et al. 2019) states explicitly that existing tools constitute a sufficient working environment. Those papers proposing new DT-tools expect firstly a more easy and broad connectivity, preprocessing, and twinning area and secondly an experimental area with customizable analysis functionalities. This paper expects an experimental environment supporting engineers in their analysis activities and serves as decision support, as depicted in Figure 3. Thereby research question 3 is answered with this new application environment.

The focus of this paper is on engineering activities, the conclusions on roles and tools is not exhaustive. Furthermore, the engineering artifacts were nearly neglected during the research and reduced to simulation and simulation models, data analytics methods, and information. Further research is required for a detailed understanding when and where what kind of engineering artifacts are used or might even be created from or within a DT. Only few papers detail activities for product improvement. Further investigation is needed e.g. with an extended search on product quality optimization with data from the production phase, a search if the availability of data from the product usage phase still is a relevant obstacle. However, design activities for product improvement, with a DT are considered a valuable contribution and will be subject to further research.

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