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Industrial Insights: Evaluating a Hierarchical Digital Twin in an Industrial Production Setting

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Abstract

This paper evaluates a prototypical hierarchical digital twin (HDT) for industrial production environments, addressing the gap in practical evaluations of digital twin concepts. The HDT integrates data from various production levels, offering a comprehensive virtual representation of the physical production environment. A qualitative interview study was conducted with 14 practitioners from different industrial sectors to assess the HDT's utility and gather feedback. The study identified key data classes, performance indicators, and functions necessary for effective HDT implementation. Results indicate that the HDT provides significant benefits in monitoring, simulation, and control of production processes, aligning with scientific perspectives while highlighting practical enhancements. This evaluation informs future HDT development and implementation strategies in industrial settings.

Keywords: Hierarchical Digital Twin, Industry 4.0, Industrial Production Environment, Design Science

1. Introduction

Industrial production must meet increasing customer requirements, e.g., individualized products, while products should be produced quickly and cost-efficiently (Lasi et al., 2014). To meet these requirements, companies are relying on increasing production automation. Machines and sensors distributed in production, continuously generate data from the production environment (e.g., process data) and manufactured products (Bauernhansl, 2014). Thus, companies must determine how they can use the data to increase efficiency, e.g., use of resources. An approach to this challenge is integrating cyber-physical systems (CPS) that map the production environment in real-time (Pistorius, 2020). However, mere data collection with CPS does not yet create benefits. The data must first be processed and then prepared for presentation to decision-makers involved in the production process, e.g., managers in production planning (Freier & Schumann, 2020).

Digital twins (DTs), which create virtual images of physical objects based on their corresponding data, are suitable for processing the collected production data (Grieves & Vickers, 2017). These DTs allow to obtain information about the physical object and make predictions regarding the object's future behavior through simulations (Glaessgen & Stargel, 2012; Tao et al., 2019). In industrial production, DTs are used for particular machines to monitor machine functionality and to predict the next maintenance date with simulations avoiding sudden machine failure (Aivaliotis et al., 2019). Although a DT allows individual objects to be digitally mapped, production managers do not make decisions based on individual machines' isolated information but require cross-machine and factory-wide information (Finke et al., 2023). From a technical point of view, the required data is often split across several interdependent systems (e.g., enterprise resource planning, manufacturing execution), making it difficult to access factory-wide information (Raptis et al., 2019). Therefore, a holistic approach is required to combine the individual DTs and enable an aggregated provision of information throughout the different factory's hierarchy levels. An approach is a hierarchical digital twin (HDT). The HDT aggregates the collected production data creating a virtual, hierarchically structured image of a production environment. On the one hand, this allows the display of the relationships between objects (e.g., machines), on the other hand, decision-makers can access information from various production levels (e.g., machine level, factory level) and carry out simulations covering the entire factory (Finke et al., 2023).

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Though some previous research discusses approaches for linking individual digital twins, evaluating those concepts in practice is necessary to specify the benefits for companies (Oettl et al., 2022). Hence, we aim to address this gap by conducting a qualitative interview study on the HDT concept and prototype evolved by Finke et al. (2023). Therefore, we examine two research questions:

RQ1: *How do practitioners assess a hierarchical digital twin for industrial production?*

RQ2: *How do the assessments from practitioners regarding hierarchical digital twins for industrial production correspond to the scientific perspective?*

To answer these questions, the research paper is structured as follows: Section 2 presents the basic concepts of industrial production and HDTs for a common understanding and introduces the evaluated HDT. Section 3 outlines our methodological approach containing the qualitative interview study according to Myers and Newman (2007). The results of the interview study are shown in section 4. Then, section 5 compares the scientific perspective on HDTs for industrial production to the practical perspective. Section 6 discusses the findings and concludes the research paper.

2. Theoretical Foundation and Evaluation Object

This section provides the theoretical foundation to establish a common understanding. Therefore, we initially introduce the organization of industrial production. Subsequently, the description of a (H)DT follows and the evaluation object is presented.

2.1 Organization of Industrial Production

Industrial production is “the part of an economy that produces material goods which are highly mechanized and automatized.” (Lasi et al., 2014). However, production environments are not standardized and depend on the company. The environment may differ based on batch sizes and product individualization. Furthermore, it can be characterized by the organization type, e.g., shop floor or line production. Regardless of these variations, Jiang et al. (2021) identify a hierarchical production structure. Production components can be described by subordinate systems and units that are part of a higher-level system from the opposite view.

Consequently, Finke et al. (2023) use this approach to describe different production hierarchy levels (Figure 1). The top level is the factory, which contains the machine groups and sensors present in the factory as subordinate elements. The arrangement of machine groups may depend on the type of organization. Each machine group contains individual machines and sensors. Again, the machines can be subdivided by machine components, i.e., sensors. This hierarchical structure provides the core model for the HDT, which we explain in more detail in the next section.

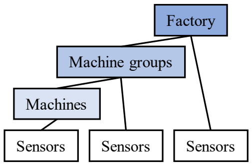


Figure 1: Hierarchical structure of HDT

2.2 (Hierarchical) Digital Twin

According to Tao et al. (2019), a digital twin consists of three components. The first component is the physical object that (potentially) exists in the physical space. The second component is the virtual image representing the physical object in the virtual space. Finally, the bidirectional connection between the physical object and the virtual image builds the third component. The object’s generated data serves to create the virtual image. Subsequently, conclusions about the object can be drawn in the opposite direction using the information obtained from the virtual image. For this purpose, the collected data is analyzed and used in simulations to predict the object's future behavior (Glaessgen & Stargel, 2012).

With the increasing performance of computer systems, virtual imaging is no longer limited to individual objects; instead, the goal is to map entire production lines and factories virtually while establishing the relationships and dependencies between the digital twins of standalone objects. The hierarchical structure of production outlined above can be applied to describe those relationships and dependencies so that the digital twins are grouped and arranged in a hierarchical order (Figure 1). This construct, which considers the different hierarchical levels of the production environment, is referred to as HDT (Finke et al., 2023). Besides providing information, it allows simulations to be carried out across all hierarchy levels (e.g., determining throughput times and bottlenecks).

2.3 Evaluation Object

The HDT of Finke et al. (2023), which we evaluate in this paper, addresses 13 functional core requirements in the four areas *monitoring & data display of the physical model*, *management of the digital model*, *simulation functions*, and *control functions*. However, we do not evaluate the area *management of the digital model* as it only has a minor impact on operational production. Table 1 lists the functional requirements under evaluation.

Table 1. Core requirements (R) of the HDT

	Monitoring & data display of the physical model
R_1	Display basic information of the individual hierarchy levels
R_2	Display current status, metrics, and performance indicators
R_3	Display historical data of the individual hierarchy levels
R_4	Switch between hierarchy levels
R_5	Display data in real time as needed
	Simulation functions
R_6	Simulate digital models
R_7	Setting options for simulation
	Control functions
R_8	Control the order flow
R_9	Control the hierarchy levels

Area (1) **monitoring & data display of the physical model** contains six core requirements implemented in prototype views for the various HDT levels: The HDT should display basic information on each element of the four hierarchy levels, such as the ID, object name, and operating time (R_1). In addition, current status information (e.g., the machines' operating status), measured values (e.g., temperatures, pressures), and performance indicators (e.g., processing time, throughput) should be shown for the individual objects to quickly identify both technical and economic deviations in ongoing production (R_2). Apart from the current values, the HDT should also display historical data for each object to track issues and identify patterns relevant for predicting future issues (R_3). Navigation between the different hierarchy levels (e.g., switching from a machine group to a machine) should be simple and clear enabling users to view the needed information quickly (R_4). The HDT is updated according to the hierarchy level's needs (e.g., in real-time) to provide decision-makers with the latest information (R_5).

Area (2) **simulation functions** contains two core requirements: The HDT should be able to perform simulations on the digital models to draw predictions about the production environment (R_6). For this purpose, the user should configure the simulation's options (e.g., specifying a production order, adapting the production layout) and hence virtually view the effects of different scenarios and decision alternatives (R_7).

The information gathered in simulations can be used to influence the physical production environment. This leads to two core requirements in area (3) **control functions**. On the one hand, the HDT should process and control production orders (e.g., machine sequence planning) to improve the production process (R_8). On the other hand, controlling production facilities across the various hierarchy levels should be possible (e.g., switching off machines) to limit or avoid production failures (R_9).

3. Research Design

To address the two research questions, we conducted a qualitative interview study adapted from Myers and Newman (2007) using a specific application scenario. The scenario depicts an industrial company specializing in the manufacturing of customized bicycles. The production is spread across two factories and includes 16 production units. This application scenario is used to present the HDT to experts from corporate practice. To get a diverse sample of experts, we selected practitioners varying in, e.g., job positions and related companies' industry sectors. With their expertise, practitioners can assess what benefits the HDT can achieve in today's production environment, and which adjustments are necessary to improve HDT support. Therefore, the HDT prototype's functionalities are presented extensively during the interview. We chose a semi-structured interview to ensure that the application scenario is covered in full and allow the interview's adaption to the interviewed practitioner. The interview follows a four-section script recommended by Myers and Newman (2007) and contains six use cases in the main section (Table 2):

- **U_1**: Monitoring machine's functionality,
- **U_2**: Monitoring of production steps in quality management,
- **U_3**: Monitoring at machine group and factory levels,
- **U_4**: Production control,
- **U_5**: Scheduling a priority order, and
- **U_6**: Testing an adapted production layout.

Table 2: Interview use cases (U)

	Short description / questions
U_1	• questions on company situation: machine monitoring, necessary analyses, required data, and data visualization • live presentation: machine overview page
U_2	• questions on company situation: analyses of quality issues, recorded product data • live presentation: production and sensor overview page
U_3	• questions on company situation: required analyses, and KPIs • general view on production hierarchy levels (top-down or bottom-up) • live presentation: machine group and factory overview pages
U_4	• questions on company situation: intervention in event of target-performance deviation • HDT intervention suggestions • live presentation: automatic correction of target-performance deviation
U_5	• questions on company situation: priority order scheduling • live presentation: simulation of priority order
U_6	• questions on company situation: production layout planning • live presentation: simulation of adapted production layout

Those six use cases are selected to cover the various requirements in the three areas **monitoring**, **simulation**, and **control** defined in section 2.3 (Table 3). The use cases U_1-U_3 focus on monitoring, U_4 on control, and U_5-U_6 on simulation.

Table 3. Requirements (R) covered by use cases (U)

	Monitoring					Simulation		Control	
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9
U_1	✓	✓			✓				
U_2			✓						
U_3	✓	✓	✓	✓	✓				
U_4		✓			✓			✓	✓
U_5						✓	✓		
U_6						✓	✓		

All use cases adhere to the same structure. Each use case starts with a short introduction, followed by questions on how the company has acted in the specific use case capturing the current situation in practice to derive requirements for the HDT. Then, the interviewee receives a live demonstration of the prototype showing the HDT's support in the use case. Finally, the expert is asked about the estimated benefits of this support based on expertise from daily production as well as any necessary adjustments and suggestions for improvement of the prototype. The full interview script can be found in the online appendix:
https://hdl.handle.net/21.11101/0000-0007-FE14-5

4. Results of the Interview Study

A total of 14 practitioners took part in the interview study. The interviews were conducted partly by video call and partly in person at the premises of the respective company in 2023 with an average duration of 70 minutes. As described in the research design, the practitioners' job positions (e.g., CEO, production manager, and machine worker) and the companies' industry sectors (e.g., industrial engineering, paper, and pharmaceuticals) vary to gain a comprehensive overview. A qualitative content analysis according to Kuckartz and Rädiker (2022) is carried out to evaluate the interviews. The study results for the requirements and the HDT prototype are presented along the six specified use cases in the following two subsections.

4.1 Evaluation of the Requirements

The results for **monitoring the machine's functionality** (U_1) can be categorized using the data to be recorded and the way recording takes place. The practitioners identify seven data classes to be recorded (Table 4): operating status, productivity indicators, quality indicators, malfunction data, maintenance data, configuration data, and sensor values.

Table 4. Data for monitoring machines

Data class	Key findings
Operating status	• examples: operation, set-up process, or malfunction state • states should be color-coded making it easier to differentiate them • advisable to adapt the color scheme to an existing color scheme (e.g., a physical light system)
Productivity indicators	• examples: overall equipment effectiveness (OEE); flow rate; average processing time; throughput • continuously compared with target values • certain indicators are derived from the operating status (e.g., ratio of downtimes to operating times) • particular observation periods must be considered (e.g., hour, shift, day)
Quality indicators	• examples: waste parts count; ratio of waste to yield; first time quality • allow for determining the machine tool's replacement date
Malfunction data	• examples: malfunction type, and duration • in practice, often recorded by employees at the machine • storing a fault list in the HDT's user interface suggested • employees may select from predefined fault types (to standardize the failure recording process)
Maintenance data	• examples: maintenance type, reason, and time; responsible employee • documented to prove compliance with maintenance plan • analyzed to predict next maintenance date
Configuration data	• examples: equipped tools; configuration parameters • combined with maintenance data, analyses about suitability of tools (or parameters) for certain product types are possible
Sensor values	• examples: temperature, pressure, or vibration metrics • allow monitoring of production parameters • ensure products meet the defined requirements

The results for the **monitoring of production steps in quality management** (U_2) can also be categorized according to the information and data to be recorded. In total, the practitioners mention four data classes (Table 5): quality specifications, product data, resource data, and process data.

Table 5. Data for monitoring production steps

Data class	Key findings
Quality specifications	1. Product specifications: target properties that a product must fulfill to pass quality check (e.g., target dimensions, and target weight) 2. Process specifications: description of production steps (e.g., specific torque for screwing elements), and parameters (e.g., temperature) 3. Inspection specifications: guidelines and instructions for inspection process (e.g., inspection interval, and sample size)
Product data	• concrete product characteristics to compare with product specifications • examples: actual dimension; actual weight
Process data	• concrete process characteristics to compare with process specifications • examples: temperature, pressure
Resource data	• resources (e.g., machines, materials, and employees) involved in the manufacturing process • examples: used machine and tool; consumed material; operator

In the use case (U_3) of **monitoring at the machine group and factory levels**, the general perspective proposed by the experts can be examined first. The majority of experts suggest an approach from the factory level to the sensor level (top-down). The practitioners justify this by arguing that the factory level initially offers a good overall view of production and therefore provides a good starting point for more in-depth analyses at sublevels. The top-down design also has the advantage that the visualization remains the same when changing areas (e.g., from factory 1 to factory 2) enabling the employee to quickly adapt, as the structure is uniformly specified from above. In contrast, some experts suggest building the HDT from the sensor level to the factory level (bottom-up) and justify this view with an incremental approach. Initially, it must be ensured that the requirements (e.g., data availability and quality) are met at the lower hierarchy levels. Then, the structure can be gradually extended to the hierarchy levels above. However, these two approaches are not necessarily contradictory: One expert suggests the top-down design for data visualization and operation but recommends the bottom-up approach for deploying the system to ensure the mentioned data quality.

In addition to their preference for a particular approach, the experts were asked which analyses they would like to carry out and which KPIs they expect at the machine group and factory levels. Three classes of analyses and their associated KPIs can be identified (Table 6): productivity, quality, and costs.

Table 6. Analyses for monitoring machine group and factory

Analyse class	Key findings
Productivity	• example KPIs: OEE; throughput; speed • aggregated metrics from machine level data • compared continuously with target values • support identifying bottlenecks and viewing order completion progress
Quality	• example KPIs: waste; yield • assess differences in the quality of machines (for similar products) • assess differences in the quality of products (for similar machines) • allow to improve quality and prevent quality issues
Costs	• example KPIs: malfunction frequency, and types • determine downtimes and repair times • allow conclusions about machines' reliability and maintenance costs

The results for the **production control** in the event of target-performance deviations (U_4) can be categorized by four phases the interviewees describe: fault detection, root cause analysis, impact analysis, and application of necessary adjustments. The HDT support and resulting benefits for companies in these phases are listed in Table 7.

Table 7. Functions for controlling production

Phase	HDT support (•) and companies' benefits (→)
Fault detection	• detect faults based on the data automatically • detect emerging fault patterns automatically before the fault occurs • react to deviations by automatically adjusting machine settings → sudden faults can be avoided → more flexibility in scheduling maintenance
Root cause analysis	• locate the cause of fault • recommend actions for troubleshooting → troubleshooting process can be accelerated
Impact analysis	• provide relevant information (e.g., fault type, and severity) • notify further departments (e.g., maintenance, and production planning) → cross-department information asymmetries can be reduced → faster impact analysis and decision about troubleshooting
Application of necessary adjustments	• reschedule the order flow (i.e., reroute orders affected by fault) → delays can be avoided → employees can concentrate on troubleshooting

The final two use cases focus on simulations for short-term (U_5) and long-term (U_6) decisions. The practitioners consider **scheduling a priority order** (U_5) as a manual process. First, the sales department receives the priority order from the customer. Then, a decision about the acceptance or rejection of the order is made with the involvement of other departments, e.g., purchasing, and production. Finally, the production plan is adjusted and the priority order is executed.

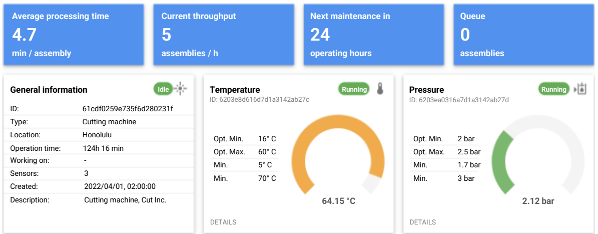
The HDT can provide automation to this process as follows. A priority order can be entered into the simulation component of the HDT. The simulation component can generate scenarios with various order flows and display the resulting impacts. After selecting a suitable scenario, the HDT can apply the necessary adjustments in the physical space (e.g., reschedule the order flow).

Similar to U_5, the experts describe **testing an adapted production layout** (U_6) as a manual process. When it comes to expanding the shop floor as long-term decision, historical data on the utilization of existing machines is considered (e.g., count and impact of utilization peaks) to discover improvement potential. In addition, managers draw forecasts about sales and available budgets estimating the break-even for a new machine. The replacement process of an old machine that has reached the lifecycle end is corresponding.

A HDT simulation may support this process showing the impacts on the production processes that result from the purchase of a new machine. Possible applications arise in the display of bottlenecks in the production layout and the visualization of impacts on those bottlenecks by integrating an additional machine. Therefore, different scenarios can be analyzed and then, one scenario is selected and applied to the physical space.

4.2 Evaluation of the Prototypical Hierarchical Digital Twin

When **monitoring the machine's functionality** (U_1), the general presentation of the machine overview in the HDT prototype (Figure 2) is perceived as useful, detailed, and comprehensive because all machine information (e.g., upcoming maintenance) is available on one page. Shift and plant managers rate the displayed information as valuable for decision support.



Average processing time
4.7
min / assembly

Current throughput
5
assemblies / h

Next maintenance in
24
operating hours

Queue
0
assemblies

General information — Idle
ID: 61cdf0259e735f6d280231f
Type: Cutting machine
Location: Honolulu
Operation time: 124h 16 min
Working on: -
Sensors: 3
Created: 2022/04/01, 02:00:00
Description: Cutting machine, Cut Inc.

Temperature — Running
ID: 6203e8d616d7d1a3142ab27c
Opt. Min. 16° C
Opt. Max. 60° C
Min. 5° C
Min. 70° C
64.15 °C
DETAILS

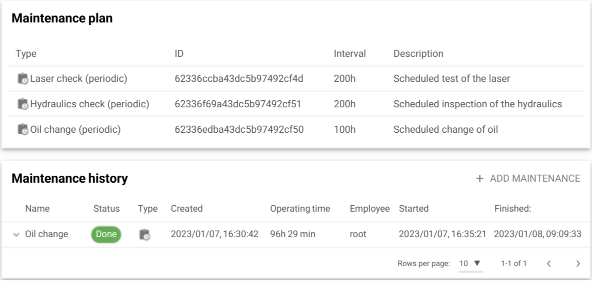
Pressure — Running
ID: 6203ea0316a7d1a3142ab27d
Opt. Min. 2 bar
Opt. Max. 2.5 bar
Min. 1.7 bar
Min. 3 bar
2.12 bar
DETAILS

Figure 2. Machine overview (excerpt)

Considering the individual information shown in the machine overview, the productivity indicators are positively outlined. Employees can understand how many products are manufactured and compare this with the targets. However, there is a lack of the target information in the prototype. Using the historical data, fluctuations can be detected and subsequently analyzed to optimize the processes (e.g., identifying bottlenecks).

Analyzing KPIs is already common practice, but machine times (e.g., operation time, set-up time, maintenance time) are often entered manually in corresponding information systems. In contrast, the HDT creates greater transparency through the automatic recording and digital visualization of the production history. Though, again, the experts note the lack of target values in the figures. In addition, it should be checked to what extent historical data is relevant for the current machine operator. Finally, the majority of experts would add the overall equipment effectiveness (OEE) as a further productivity indicator.

The sensors' visualization is rated positive. It is useful that the employee can set up which sensors are particularly relevant on the machine overview page. This allows a quick and clear overview of the machine's state. In addition, buttons enable the navigation to the detailed sensor view and sensor values are colored to detect problems and deviations quickly providing greater transparency.



Maintenance plan

Type	ID	Interval	Description
Laser check (periodic)	62336ccba43dc5b97492cf4d	200h	Scheduled test of the laser
Hydraulics check (periodic)	62336f69a43dc5b97492cf51	200h	Scheduled inspection of the hydraulics
Oil change (periodic)	62336edba43dc5b97492cf50	100h	Scheduled change of oil

Maintenance history

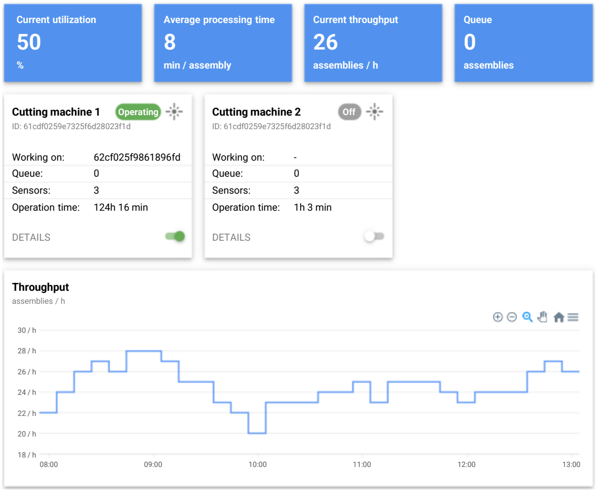
Name	Status	Type	Created	Operating time	Employee	Started	Finished:
Oil change	Done		2023/01/07, 16:30:42	96h 29 min	root	2023/01/07, 16:35:21	2023/01/08, 09:09:33

Figure 3. Maintenance overview

Maintenance data is often stored and displayed separately from other machine data in practice. This separation leads to information asymmetries between production and maintenance employees. Linking the maintenance information with the other machine information in a common overview (Figures 2-3), the HDT creates the necessary transparency and eliminates this information asymmetry. In addition, the experts also rate a maintenance history as useful, as the maintenance work can be documented directly via the user interface with a description of the performed tasks. This enables analyses of the behavior of the machine since the last maintenance.

The interviewees suggest adding further elements to the machine overview. Machine times (e.g., set-up, maintenance) are currently missing. Moreover, faults should be recorded automatically or documented by an employee so that they can subsequently be analyzed. Then, the collected fault data can be used for pattern recognition to detect emerging disruptions earlier.

The practitioners rate the overall **monitoring of production steps in quality management** (U_2) with the help of the HDT positively. Many companies already use enterprise resource planning (ERP) or a similar system to control production steps. Nevertheless, there are some benefits of using a HDT in comparison. The HDT offers a greater depth of detail in product and process information, meanwhile ERP systems often only record the product and its largest assemblies. The HDT can map the product with all assemblies in a hierarchical structure. This enables companies to trace the path of individual assemblies through production. If product issues occur, they can be analyzed top-down and traced back to the specific assembly. Furthermore, this makes it possible to determine the date and cause that led to the product issue. Once the cause has been identified, the HDT allows the detection of other affected products. On the one hand, this prevents faultless products from being incorrectly rejected. On the other hand, defective products can be blocked for further production processes and subjected to a quality check. If the defect is discovered after sending the product to customers, the HDT can be used to check whether the entire delivery or only individual products are affected. Thus, customers only have to sort out the defective products reducing the incurred damage. However, practitioners note that it is impossible to track certain product types such as liquids that way. Liquids must therefore be identified with a unique container or batch number.



Current utilization	Average processing time	Current throughput	Queue
50 %	8 min / assembly	26 assemblies / h	0 assemblies

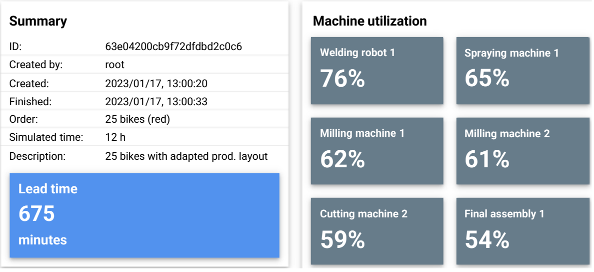
Cutting machine 1 Operating
ID: 61cdf0259e7325f6d28023f1d
Working on: 62cf025f9861896fd
Queue: 0
Sensors: 3
Operation time: 124h 16 min

Cutting machine 2 Off
ID: 61cdf0259e7325f6d28023f1d
Working on: -
Queue: 0
Sensors: 3
Operation time: 1h 3 min

Figure 4. Machine group overview (excerpt)

For **monitoring at the machine group and factory levels** (U_3), the experts state that the overviews (Figure 4) are a good starting point for problem analyses. With the help of the HDT, problems at the factory level (e.g., low productivity) can be tracked top-down to the machine or sensor level. The displayed throughput and average processing time can be used for production planning and determination of bottlenecks. That said, it is mentioned that the machines in a machine group must be comparable to draw meaningful conclusions from those KPIs. If this is the case, practitioners suggest that not only the average productivity of the machine group is displayed, but also the individual values of the machines. As with U_1, the experts complain about the lack of target values and OEE for target tracking.

In the event of target-performance deviations, the experts like the approach of **production control** (U_4) with the HDT. It switches off the malfunctioning machine and reroutes any scheduled products to other available machines. Some experts would have the rescheduling confirmed by an employee considering different prioritization of orders. Furthermore, other resources (e.g., materials, and available personnel) must also be included. Also, the HDT currently cannot find a solution for the case that no rescheduling is possible (e.g., no other machine matches this production step).



Summary

ID:	63e04200cb9f72dfdbd2c0c6
Created by:	root
Created:	2023/01/17, 13:00:20
Finished:	2023/01/17, 13:00:33
Order:	25 bikes (red)
Simulated time:	12 h
Description:	25 bikes with adapted prod. layout

Lead time
675
minutes

Machine utilization

Welding robot 1 76%	Spraying machine 1 65%
Milling machine 1 62%	Milling machine 2 61%
Cutting machine 2 59%	Final assembly 1 54%

Figure 5. Simulation results

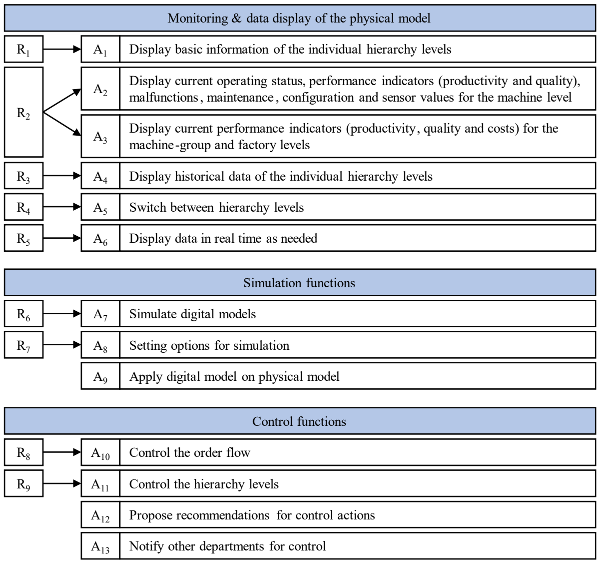
Regarding the **scheduling of a priority order** (U_5), a divergent result emerges. Some experts believe that this use case should not be supported by the HDT, but is part of the functionality of an ERP software. In contrast, some other experts see benefits in scheduling supported by the HDT, as additional adjustments to the production layout can be considered in the HDT simulation options. The presentation of the simulation results (i.e., lead time and utilization of individual machines; Figure 5) is rated as useful. Besides those results, the interviewees also recommend calculating the completion time of the order to cover two-shift and three-shift operations. In addition, the effects on the existing orders (e.g., postponement) should be displayed in the results.

The experts rate **testing an adapted production layout** (U_6) for long-term decisions as useful. Initially, bottlenecks in production can be identified that are not noticeable in daily production, e.g., a machine produces with low performance to avoid queues at downstream machines. To eliminate this bottleneck, the HDT can be used to test, simulate and analyze various scenarios, e.g., whether the queue is cleared purchasing an additional machine or whether the problem is only shifted back some process steps and a new queue is created. Thus, the HDT enables the controller and management to make data-based decisions.

However, to increase the simulation's effectiveness the interviewees recommend adding further simulation inputs. One example is the replacement rather addition of machines (e.g., the replacement of a machine engine with higher performance). This option would provide benefits, especially for plants that have grown over time, as available space is limited. In addition, intralogistics factors must be considered in simulations, e.g., it must be checked what additional space is required for buffer storage or transport systems.

5. Comparison of the Scientific and Practical Perspective on Hierarchical Digital Twin

This section compares the scientific perspective on the HDT with the results from the interview study discussing implications for the core requirements (Figure 6) and prototype (Figures 7-9) of the HDT.



		Monitoring & data display of the physical model
R_1	A_1	Display basic information of the individual hierarchy levels
R_2	A_2	Display current operating status, performance indicators (productivity and quality), malfunctions, maintenance, configuration and sensor values for the machine level
	A_3	Display current performance indicators (productivity, quality and costs) for the machine-group and factory levels
R_3	A_4	Display historical data of the individual hierarchy levels
R_4	A_5	Switch between hierarchy levels
R_5	A_6	Display data in real time as needed
		Simulation functions
R_6	A_7	Simulate digital models
R_7	A_8	Setting options for simulation
	A_9	Apply digital model on physical model
		Control functions
R_8	A_{10}	Control the order flow
R_9	A_{11}	Control the hierarchy levels
	A_{12}	Propose recommendations for control actions
	A_{13}	Notify other departments for control

Figure 6. Adapted requirements (A) for HDT

5.1 Implications for the Requirements

Requirement area (1) **monitoring & data display of the physical model** contains six core requirements. R_1 comprises all hierarchy levels. For the machine level, experts noted that some information may be unnecessary for certain users (e.g., the current machine operator). Similarly, for the machine group and factory levels, the experts explained that information such as the factory's operating time is not required in daily production. Therefore, R_1 is still relevant (A_1), but some information should be hidden for certain employees.

For R_2, the interview results led to seven data classes on machine level (Table 4). Compared with the three data classes defined in the research (Table 1), the *operating status* corresponds with the *status* class. Similarly, the *sensor values* correspond with the *metrics* class. Though, the data class *performance indicators* from research is divided into *productivity indicators* and *quality indicators* resulting in a partial match. The remaining data classes from practice *malfunctions*, *maintenance*, and *configuration* are missing in the core requirements. On the machine-group and factory levels, three classes of analyses and their corresponding KPIs (Table 6) arose in the interview study. Comparing those classes with R_2, the classes *status* and *metrics* only appear in research but not in practice. However, there is a partial match for *performance indicators*, which are distinguished as *productivity*, *quality*, and *cost indicators* in practice. All in all, this leads to the result that R_2 must be differentiated according to the hierarchy level and distinguished indicators. We therefore suggest adapting R_2 to *Display current operating status, performance indicators (productivity and quality), malfunctions, maintenance, configuration, and sensor values for the machine level* (A_2). In addition, for the machine group and factory levels, we suggest a more specific requirement *Display current performance indicators (productivity, quality, and costs) for the machine-group and factory levels* (A_3).

The interview results for R_3 showed, that historical data about the hierarchy levels is needed to enable production control as the results provided various data classes (Table 5). In addition, the historical data of the three performance indicators (Table 6) must be displayed for monitoring at the machine-group and factory levels. Thus, the results confirm R_3 (A_4).

Similarly, the interview statements support R_4 (A_5). The results revealed that the visualization of the hierarchy levels should be top-down because the factory level provides a holistic production overview and is therefore a starting point for problem analyses.

For R_5, the interview results showed, that machine and productivity data is required in real-time to quickly detect and fix faults. Likewise, data from the machine-group and factory levels is needed in real time to identify faults in the entire production chain promptly. The results are therefore consistent with R_5 (A_6).

Simulation functions are requirement area (2) containing two core requirements. R_6 can be confirmed (A_7) based on the results of the interview study, e.g., the HDT can support managers in short-term decisions such as scheduling a priority order using simulations to determine the effects on current production. For long-term decisions (e.g., testing an adapted production layout), simulations can help examine changed processes and perform scenario analyses.

To enable simulations, various parameters are required supporting R_7 (A_8), e.g., for scheduling a priority order, the order must be entered as input to execute the simulation. To test a customized production layout, changes must be made to the machine setup in the digital model.

In addition to the two existing core requirements from research, a third requirement can be identified from the interview results. Once the simulation has been executed and the best scenario is selected, the appropriate actions must be implemented in the physical world. The HDT can provide this, e.g., by applying the simulated order flow to the real production process. We therefore suggest adding the core requirement *Apply digital model to physical model* (A_9).

The last requirement area (3) is **control functions** and encloses two core requirements. R_8 is supported by practice (A_{10}). The HDT should optimize the order flow based on the available information. If disruptions such as a machine failure occur, the HDT should redirect affected orders to other available machines.

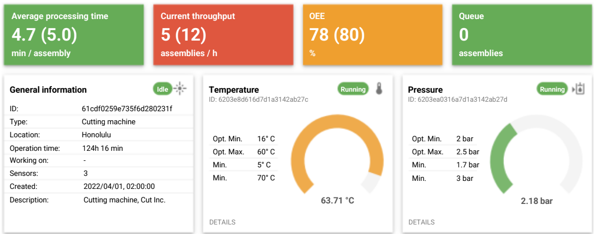
R_9 is also in accordance with practical expectations (A_{11}). The interviewees expect the HDT to enhance a machine shutdown system reacting to faults based on programmable rules, e.g., adjusting machine settings.

Furthermore, the results showed that the HDT can support an employee in controlling the machines suggesting specific recommendations for action. If there is a fault, the HDT could help the employee to rectify the problem using predefined operating procedures and thereby speed up the troubleshooting process. Since this requirement is not covered by research, we suggest adding a core requirement *Propose recommendations for control actions* (A_{12}).

Another requirement that is not mentioned in research, but exists in practice, is informing other departments. The study results showed that in the event of a malfunction, other departments (e.g., maintenance, production planning) are often notified manually by the production employees. The HDT can (partially) automate this process, e.g., notifying an employee to perform electrical maintenance when electrical machine faults are detected. Thus, we propose a further core requirement *Notify other departments for control* (A_{13}).

5.2 Implications for the Prototypical Hierarchical Digital Twin

Based on the experts' assessments of the benefits and potential adjustments, it is possible to draw adjustments to the existing HDT prototype. However, it should be noted that the revisions represent an exemplary and not conclusive concept, as the experts had individual expectations in particular areas, which may not apply to all industrial companies. The focus is therefore on the suggestions that were mentioned by several experts and thus have a higher relevance.



Average processing time
4.7 (5.0)
min / assembly

Current throughput
5 (12)
assemblies / h

OEE
78 (80)
%

Queue
0
assemblies

General information Idle

ID:	61cdf0259e735f6d280231f
Type:	Cutting machine
Location:	Honolulu
Operation time:	124h 16 min
Working on:	-
Sensors:	3
Created:	2022/04/01, 02:00:00
Description:	Cutting machine, Cut Inc.

Temperature Running
ID: 6203e8d616d7d1a3142ab27c

Opt. Min.	16° C
Opt. Max.	60° C
Min.	5° C
Min.	70° C

63.71 °C

DETAILS

Pressure Running
ID: 6203ea0316a7d1a3142ab27d

Opt. Min.	2 bar
Opt. Max.	2.5 bar
Min.	1.7 bar
Min.	3 bar

2.18 bar

DETAILS

Figure 7. Adapted machine overview (excerpt)

On the machine overview page (Figure 2), the experts complained about the lack of target values. These are now shown (Figure 7) beside the current value enabling a comparison to identify deviations. To support the comparison, the productivity indicators are colored differently depending on the deviation direction (positive/negative) and the deviation amount. As a majority of experts also mentioned the OEE as another useful indicator, we added it to the indicator list. Similarly, these adjustments apply to the overview pages on the machine group and factory levels.

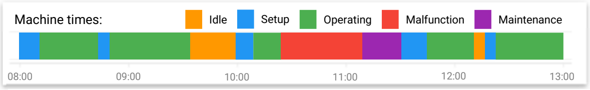
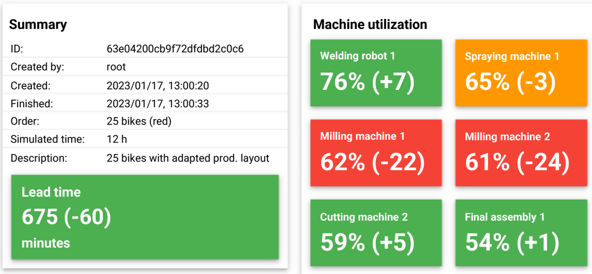


Figure 8. Added machine times

In addition, experts also suggested adding further elements to the machine overview. These include, in particular, machine times. Consequently, we added the various times in a timeline as shown in Figure 8.



Summary

ID:	63e04200cb9f72dfdbd2c0c6
Created by:	root
Created:	2023/01/17, 13:00:20
Finished:	2023/01/17, 13:00:33
Order:	25 bikes (red)
Simulated time:	12 h
Description:	25 bikes with adapted prod. layout

Lead time
675 (-60)
minutes

Machine utilization

Welding robot 1
76% (+7)

Spraying machine 1
65% (-3)

Milling machine 1
62% (-22)

Milling machine 2
61% (-24)

Cutting machine 2
59% (+5)

Final assembly 1
54% (+1)

Figure 9: Adapted simulation results

For the simulation page (Figure 5), it was determined that further simulation results should be calculated in addition to the processing time of an order (e.g., completion date). U_6 also revealed that it is useful to display various simulations and scenarios side by side enabling the comparison of those scenarios. To support this comparison, differences between scenarios can be shown and highlighted in color (Figure 9).

6. Discussion and Conclusion

In this paper, we evaluated the core requirements and prototype of a HDT for industrial production environments from a practice perspective. To achieve this goal, we conducted a qualitative interview study with practitioners containing six use cases in the areas monitoring, simulation, and control. For each use case and area, the results concretized various relevant data classes and/or requirements as well as benefits and possible adaptations of the HDT prototype (RQ1). Then, we compared the interview results with the scientific perspective on HDT deriving improvements and refining the existing core requirements and prototype (RQ2).

The work not only shows the practical assessment of the requirements and prototype of **scientific research** but also provides a detailed overview of, e.g., relevant data classes, analyses, and resulting benefits. We could confirm seven requirements from scientific research and differentiate one requirement into two more precise requirements to clarify the requirements on the various HDT levels. However, three requirements were missing from a practical perspective, so we added them to improve the requirement list and enhance future research. Furthermore, the benefits of the prototype were evaluated and possible adaptations were shown. Thus, the results are relevant for further research in the (H)DT domain such as conceptual modeling and prototype implementations.

Beyond that, the results are useful for **corporate practice**, e.g., companies that have decided to use a (H)DT in production can use the revised core requirements as a foundation for the following development phase. Company-specific requirements can be added to the core requirements to adapt the HDT to the company's needs. During the design phase, the presented prototype can serve as a reference. Regarding this transformation process, the practitioners noted that companies will face different challenges. In particular, as data builds the HDT's foundation, companies must ensure production data availability which is difficult due to machines' heterogeneity. In addition to technological aspects, companies will face organizational challenges, e.g., the employees must be involved in the transformed processes enabling a successful HDT adaption.

Nevertheless, the results of the work are restricted by limitations. The **selected companies** for the interview study differ on various dimensions (e.g., location, sector, company size, and digitization progress). We cannot state to what extent the selection is representative of the industry. However, we took care that the companies differed sufficiently in terms of that dimensions to avoid biases and enable the generalizability of our findings. Similarly, for the **expert sample**, no indication can be given whether the expert's characteristics (e.g., position, work experience) were representative considered. Since the HDT covers multiple company levels, we selected experts from different levels (i.e., production employees to managing directors). Nevertheless, we propose that further HDT studies should aim to include a larger and more diverse sample of companies and experts to validate and expand our initial findings providing a more comprehensive view of the HDT's applicability across different industries.

Further limitations relate to the **selected application scenario**. A fictional industrial company with six typical use cases was selected for the interview study. The practitioners indicated that it was easy to follow the scenario and apply it to their own daily work. However, the simple and general applicability of the scenario leads to shortcomings compared to the complexity of specific, real scenarios, e.g., we could not analyze the HDT's (quantitative) benefits compared to existing solutions in detail. Hence, future research should address this shortcoming and focus on in-depth analyses for specific real-world production settings. For this purpose, the revised HDT concept can be tested and examined in real scenarios across various industries (e.g., as part of field experiment) collecting quantitative data (e.g., production efficiency, cost savings) and thus analyzing benefits of the HDT compared to existing solutions thoroughly. With the data and insights gained, the HDT concept can be further refined and integrated into design science cycles, thereby enhancing the overall applicability of the HDT concept.

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