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ONE4ALL - Agile and modular cyber-physical technologies supported by data-driven digital tools to reinforce manufacturing resilience

Project nr: **101091877**

D2.1 Digital tools specification, architecture and work strategy

Version: 1.0

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ONE4ALL Consortium Partners

N.	Partner	Acronym	Country
1	IDENER RESEARCH & DEVELOPMENT (Coordinator)	IDE	ES
2	INNOPHARMA TECHNOLOGY	INO	IE
3	CRIT	CRIT	IT
4	EXELISIS	EXE	GR
5	UNIVERSITY OF SOUTHERN DENMARK	SDU	DEN
6	AUTOMATIONWARE	AUTO	IT
7	MADAMAOLIVA	MOL	IT
8	HOLOSS	HOLO	PT
9	DORTMUND UNIVERSITY	TUDO	DE
10	ORIFARM	ORI	CZ
11	KARLSRUHE INSTITUTE OF TECHNOLOGY	KIT	DE

Disclaimer

Executive Summary

This deliverable (D2.1 Digital tools specification, architecture and work strategy) is the result of the work mainly done in T2.1 Requirements and specifications of DTs and DSS. Results discussed in this deliverable are primarily the methodology combined with an overview of the project phases in WP2 as well as the data requirements and general architecture for the Digital Twin and the Decision Support System.

The methodology used in WP2 is the inductive approach, where in specific observations and data are collected and analysed to generate overarching theories or generalizations based on patterns and trends identified within the collected information. For example, we created initial simulation models of the manufacturing lines of the two demonstrators and analyse and refine these stepwise.

WP2 consists of four main phases: In phase one the key performance indicators suitable for the demonstrators were researched and defined. From these, the data requirements were derived. The second phase starts with the beginning of T2.2, which supports the model extraction and validation by ensuring the products quality and that the customers demand is met. Shortly after, the third phase starts with the beginning of T2.3 and aims to extract the needed models to create the Digital Twins and enabling the Decision Support System to suggest different courses of actions. Additionally, a process for automating the model validation will be researched and implemented. And finally in the last phase, starting with T2.4, the decision support and optimization are addressed. Currently, the first phase is concluded with this deliverable and phase two is started. From here on, the phases are not strictly sequential as, for example, changes in the model extraction could affect the evaluation on the products quality or if the customers demand is met and vice versa. Lastly, through the whole project there is one omnipresent phase which targets data and information security. This ensures one the hand that the architecture and the system as a whole is secure, minimizing the risk of data or knowledge leaks. On the other hand, guaranteeing that personal data and other sensitive data are handled appropriately. This is build on the knowledge and expertise on the security and data handling set up in WP3.

The data requirements listed in this deliverable target three main goals and objectives: energy efficiency, worker well-being and system reliability. In light of the climate change everybody needs to save energy, in business, this can be leveraged to be a competitive advantage. Thus, the first objective for energy efficiency is to strengthen the understanding of the energy consumption of the factories which later will be expanded enabling the Decision Support System to give suggestions on saving possibilities. The second major functionality that the Digital Twins in conjunction with the Decision Support System will provide is the observation and prediction of worker well-being while not infringing on personal data protection. To do this, several methods are combined with anonymized data to measure worker well-being and enable the Decision Support System to provide appropriate courses of actions. The third goal is the modelling of the system reliability to do so two methods are used: fuzzy fault trees and stochastic Petri nets. The results of both methods will be sent to the Decision Support System enabling it to draw accurate pictures of the state of the manufacturing lines.

The architecture of the Digital Twins and the Decision Support System focuses on two main characteristics: adaptability and plug & play. To achieve this, we introduced a layered architecture that has a single point of contact between the manufacturing line and the digital system, allowing the system to be plugged onto any manufacturing line only requiring adjustments to the connector. Furthermore, a maximum of adaptability is reached through two mechanisms. Firstly, each component is designed in a way that it operates in an isolated manner and provides a standardized interface. Thus, each component is autonomous while defining clear communication channels for the other components. Secondly, the Digital Twins themselves are constructed in a way that allows a

maximum of flexibility during creation and adaption. Here, a hierarchical approach was chosen. Each Digital Twin can have as many sub twins as needed to model the process, machine, etc. as detailed as needed. Furthermore, there are no limitations to the number of Digital Twins on the same hierarchical level. Lastly, all Digital Twins are interconnected to each other on the same hierarchical level, leveraging the strengthened prediction and modelling capabilities of the combination of various independent Digital Twins.

Table of contents

List of acronyms

DMP	Data Management Plan
DT	Digital Twin
DSS	Decision Support System
PMSL	Physical Manufacturing System Layer
CDEL	Communication and Data Extraction Layer
DCI	Device Communication Interface
DCM	Data Centric Middleware
VMSL	Virtual Manufacturing System Layer
API	Application Programming Interface
FMI	Function Mockup Interface
UI	User Interface
DTD	Digital Twin Data
DTO	Digital Twin of an Organization
KPI	Key Performance Indicator
GA	Grant Agreement
IOP	Intelligent Orchestration Platform

List of figures

List of tables

1. Introduction

Work Package 2 (WP2) focuses on critical aspects of the project, aimed at developing and validating key components essential for its success. This work package is centred around the creation and implementation of a data-driven self-reconfigurable Digital Twin (DT) [T2.3] and a distributed self-learning Decision Support System (DSS) [T2.4]. Additionally, it addresses the vital task of defining how product quality will be measured and aligned with customer demands [T2.2]. The ultimate objective is to deliver these modules as "plug-and-play" service packages and adapt them to physical components and end-users for seamless integration into the Intelligent Orchestration Platform (IOP). Furthermore, these developments will be demonstrated in real-world scenarios as part of the activities in WP5. WP2 plays a crucial role in ensuring the success of the project and the efficient functioning of the manufacturing plants in different sectors (food and pharmaceutical) involved in the demonstration.

The objectives of this WP are the following:

1. Develop and validate a data-driven self-reconfigurable DT [T2.3]
2. Develop and validate a distributed self-learning DSS [T2.4]
3. Define how the quality of the product is measured and how it is related to the customer demands [T2.2]
4. Deliver all the modules as “plug-and-play” services packages and determine their requirements, inputs, outputs and interrelation
5. Adapt the DT and DSS to the physical components and the end-users for their further integration with the IOP and the demonstration activities in WP5 [T2.3, T2.4]

Objectives from the GA in T2.1:

- List of requirements and KPIs for the digital twins and DSS, based on the needs of the two demonstrators, i.e., the two manufacturing plants from different sectors (food and pharmaceutical)
- Design of digital tools and suitable algorithms

This document contains the results of the activities performed in T2.1 DATA REQUIREMENTS AND SPECIFICATIONS OF DTS AND DSS. This entails in particular the proposed Digital Twin (DT) architecture as well as its data requirements. While the initial goal of establishing a DT architecture has been successfully achieved, the latter objective is expected to undergo continual adjustments as the use cases of ORI and MOL naturally evolve during the implementation process. Considering this, it is important to recognize that the data requirements outlined in Chapter 3 represent a momentary snapshot and are subject to modification over time.

1.1. Activities Performed

In the following, a description of the activities performed, and the results will be provided.

Activities from GA

Active communication with the demonstrators and stakeholders to define the KPIs and requirements for the DTs. A detailed architecture of the DTs is defined including the methodology to be followed during the development to achieve the innovative objectives proposed. This includes the detail of the technical requirements and the creation of their ontology, further used during the development in T2.3 and T2.4.

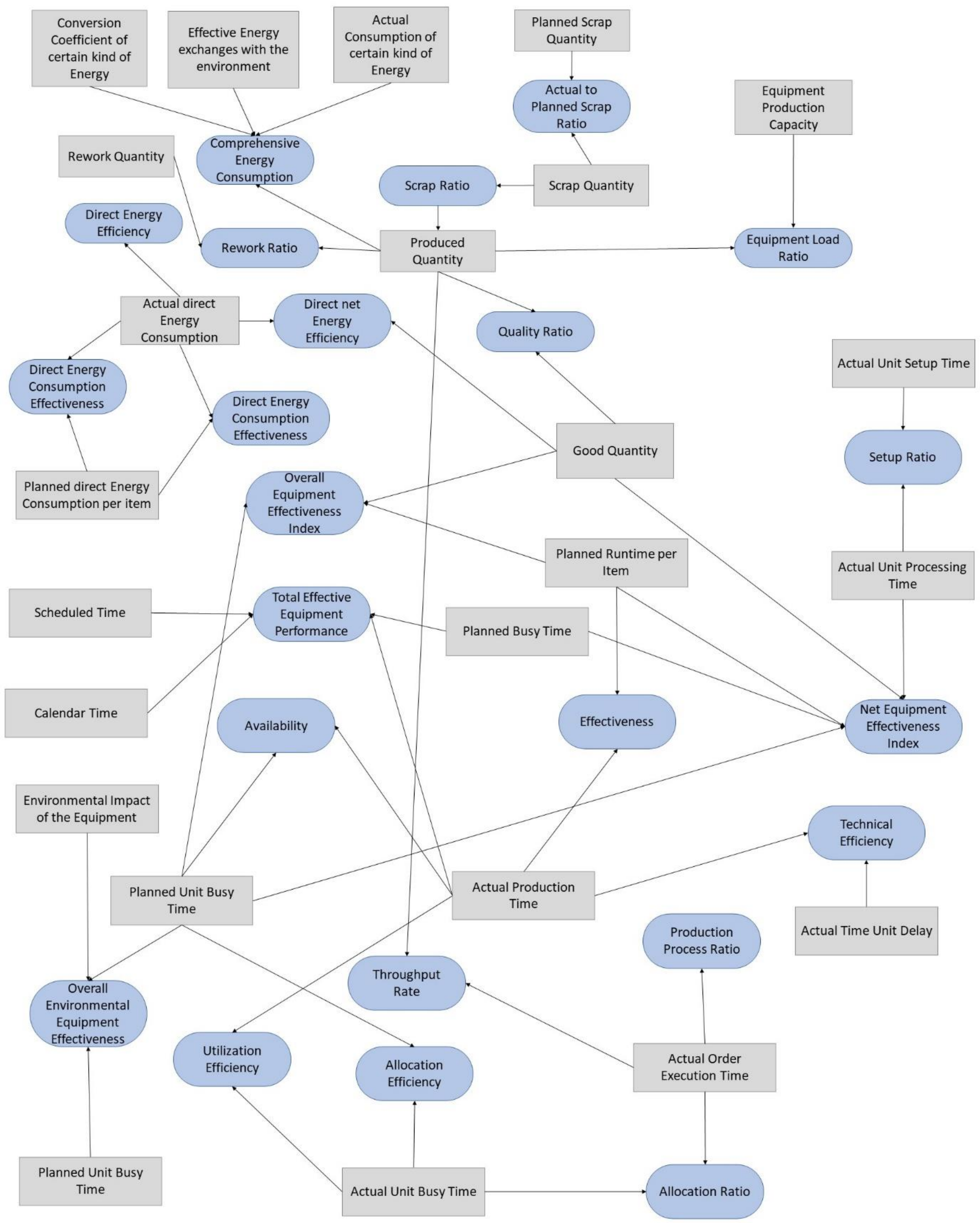
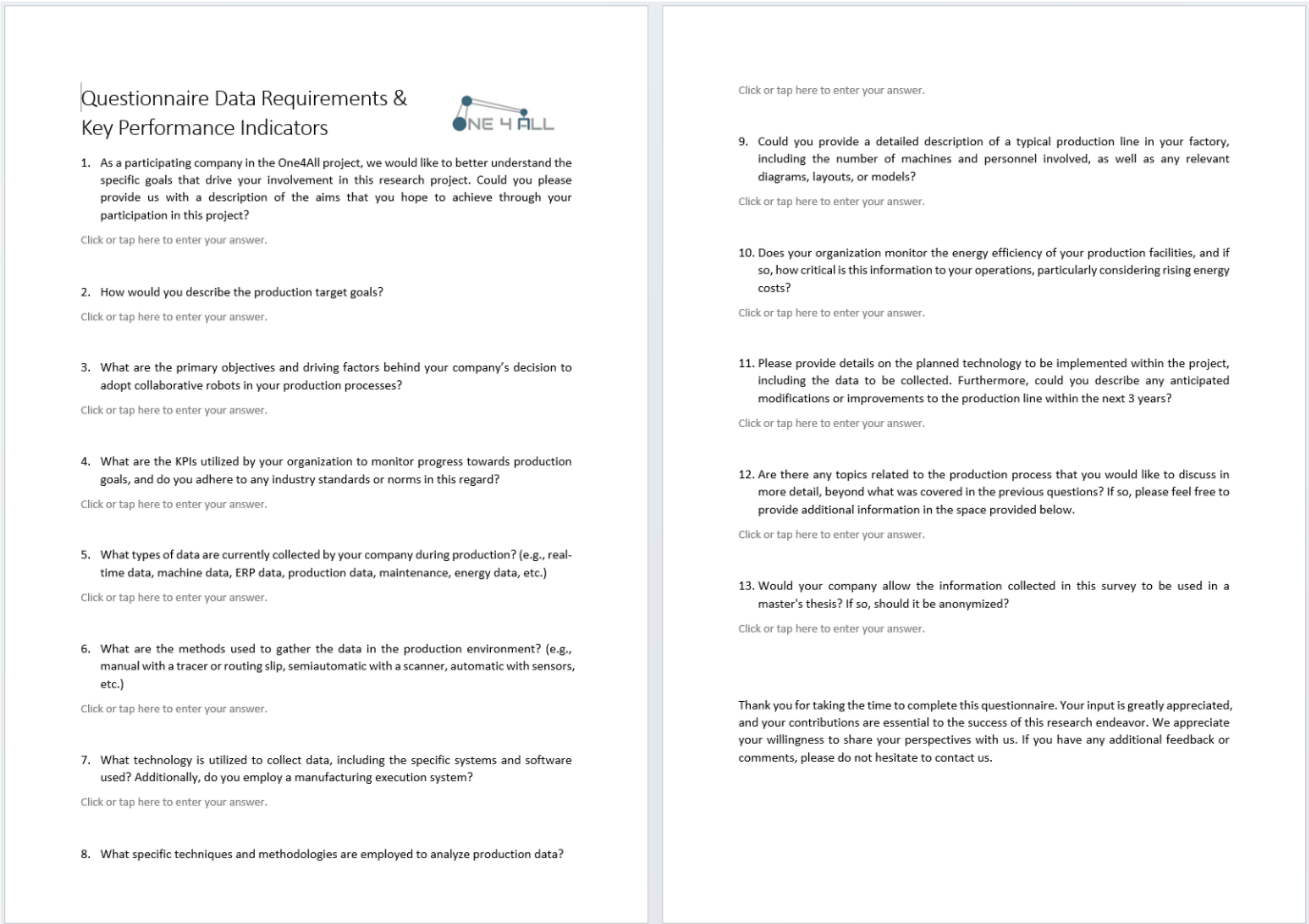


Figure 1: Data Requirements Plot: KPIs (blue ovals) and their corresponding data points (grey boxes)

Literature Review

In the first step a thorough literature review was conducted with the aim of identifying performance metrics in manufacturing systems in relation to the typical goals and, thus, foster the understanding of the demonstrators needs. In this comprehensive analysis, 2227 papers were inspected resulting in 72 relevant KPIs which are utilizing around 100 data points and can be grouped in four main categories of performance metrics. The first category is Work and Production Effectiveness such as Overall Equipment Effectiveness or Overall Throughput Effectiveness. The second category is Sustainable Development such as Direct Energy Consumption Effectiveness or Scrap Ratio. The third category is Digital Transformation such as Data-Driven Decision-Making or Return on Digital



Questionnaire Data Requirements & Key Performance Indicators

1. As a participating company in the One4All project, we would like to better understand the specific goals that drive your involvement in this research project. Could you please provide us with a description of the aims that you hope to achieve through your participation in this project?

Click or tap here to enter your answer.

2. How would you describe the production target goals?

Click or tap here to enter your answer.

3. What are the primary objectives and driving factors behind your company's decision to adopt collaborative robots in your production processes?

Click or tap here to enter your answer.

4. What are the KPIs utilized by your organization to monitor progress towards production goals, and do you adhere to any industry standards or norms in this regard?

Click or tap here to enter your answer.

5. What types of data are currently collected by your company during production? (e.g., real-time data, machine data, ERP data, production data, maintenance, energy data, etc.)

Click or tap here to enter your answer.

6. What are the methods used to gather the data in the production environment? (e.g., manual with a tracer or routing slip, semiautomatic with a scanner, automatic with sensors, etc.)

Click or tap here to enter your answer.

7. What technology is utilized to collect data, including the specific systems and software used? Additionally, do you employ a manufacturing execution system?

Click or tap here to enter your answer.

8. What specific techniques and methodologies are employed to analyze production data?

Click or tap here to enter your answer.

9. Could you provide a detailed description of a typical production line in your factory, including the number of machines and personnel involved, as well as any relevant diagrams, layouts, or models?

Click or tap here to enter your answer.

10. Does your organization monitor the energy efficiency of your production facilities, and if so, how critical is this information to your operations, particularly considering rising energy costs?

Click or tap here to enter your answer.

11. Please provide details on the planned technology to be implemented within the project, including the data to be collected. Furthermore, could you describe any anticipated modifications or improvements to the production line within the next 3 years?

Click or tap here to enter your answer.

12. Are there any topics related to the production process that you would like to discuss in more detail, beyond what was covered in the previous questions? If so, please feel free to provide additional information in the space provided below.

Click or tap here to enter your answer.

13. Would your company allow the information collected in this survey to be used in a master's thesis? If so, should it be anonymized?

Click or tap here to enter your answer.

Thank you for taking the time to complete this questionnaire. Your input is greatly appreciated, and your contributions are essential to the success of this research endeavor. We appreciate your willingness to share your perspectives with us. If you have any additional feedback or comments, please do not hesitate to contact us.

Figure 2: Questionnaire

Investments. The last category is Occupational Health and Safety such as Lost Time Injury Frequency Rate or Average Accident-Free Days. With these KPIs (blue ovals) and their corresponding data points (grey boxes) in place we could create plots such as the one shown in Figure 1. These plots help us to understand the structure of the data requirements, in particular, their interconnections and dependencies. For example, we can analyse which data points and KPIs are depending on other KPIs, how the data points are used within the KPIs and which data point mix enables the largest and least overlapping KPI mix. As a result, we can derive first-level data processing definitions, and define a list of needed data points, which provides guidance to INO and AUTO when installing sensors as well as aiding with the selection process of a resilient, independent, and effective KPI mix.

Meetings with Partners

Throughout T2.1 we had several important meetings with partners. The first one was held with INO, MOL and ORI and aimed to foster their understanding of our WP and methodology. In this meeting we showed them the results of the literature review and discussed how we are going to use them as a foundation for the upcoming steps. In a second step they each provided us feedback on the discussed pointes and examples of which KPIs would fit best for their needs. Based on this meeting we created a questionnaire (shown in Figure 2, described in the section below) and conducted one meeting with each of the demonstrators ORI and MOL. In these meetings, we discussed the questionnaire as well as the impact on our plans and assumptions.

With the start of T2.2, which is led by INO, we had several discussions with all participating partners to ensure the products' quality and alignment with customers' demands. Furthermore, this helped refocus the tasks to ensure optimal cooperation and task alignment given the progress made.

Towards the end of T2.1, the use cases description for MOL and ORI were finalized. For both ORI and MOL, two use cases were identified. For MOL, the objective of the first use case is to identify and discard the defective olives through an AI-based vision system while the second one is concerned with end-of-line product palletization. For ORI, in the first use case a cobot moves MP and FP boxes from a pallet to the production buffer and vice versa. The second use case focuses on the end-of-line product palletization while also incorporating quality control checks.

The last two meetings were held towards the end of T2.1 and mainly focused on the feedback of ORI and MOL on our work. In particular, we focused on their input regarding our simulation models to refine them further. In line with our inductive approach, we were able to capture and model the manufacturing line in greater detail. Thus, the current models form a solid basis for the upcoming T2.3 Data-driven digital twins module development, validation, and tune-up and T2.4 Smart distributed decision support system module development, validation, and tune-up.

Questionnaire

To better understand the manufacturing lines and goals of ORI and MOL, we created the questionnaire shown in Figure 2. This, in conjunction with associated meetings, gave us a lot of insight into their production and enabled us to create initial simulation models. Figure 3 shows the simulation created for MOL and Figure 4 for ORI. These initial models will be further refined with the proceeding of the tasks in WP2 according to the inductive approach used and play a vital role in the creation of the DT and the DSS. The models form the foundation for deriving the data requirements for the DTs and DSS in T2.3 and T2.4 since neither ORI nor MOL currently have enough high-quality data available nor the procedures or technologies to automate the data collection. This challenge will be overcome with the implementation of the IOP and the new sensors.

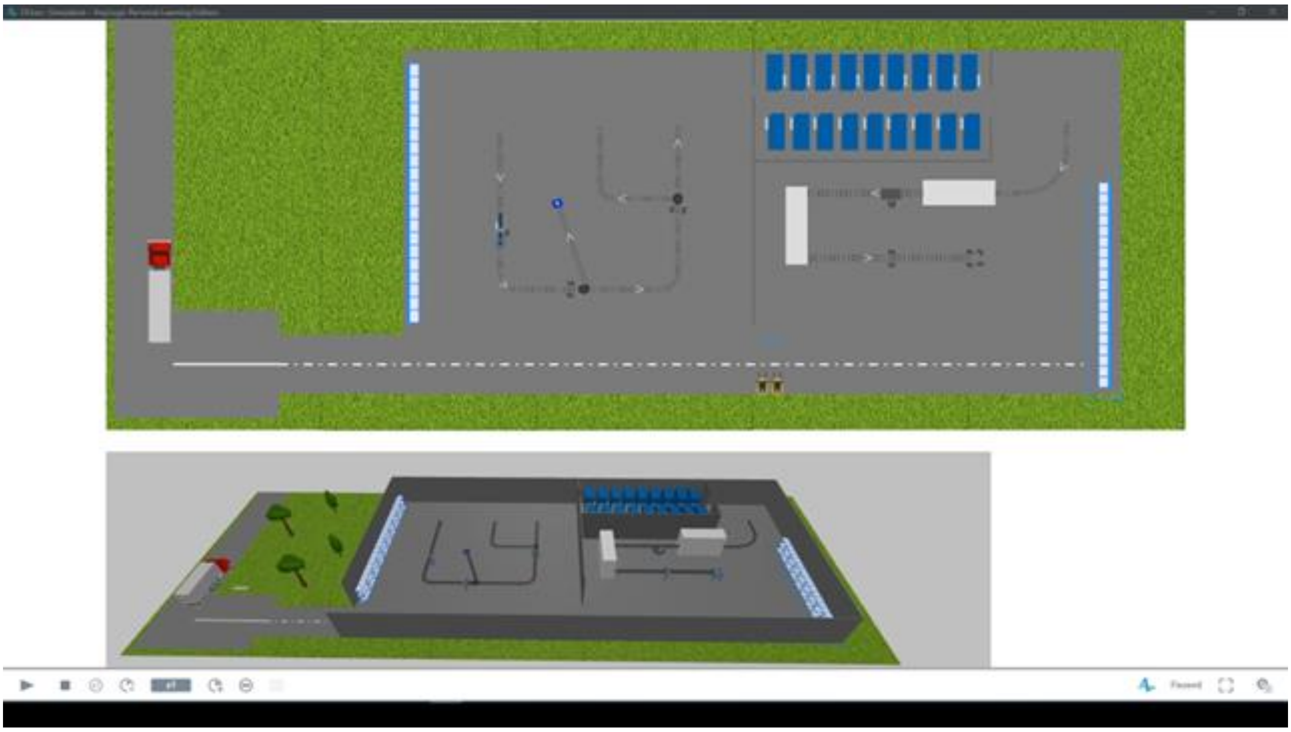


Figure 3: MOL initial AnyLogic Simulation Model

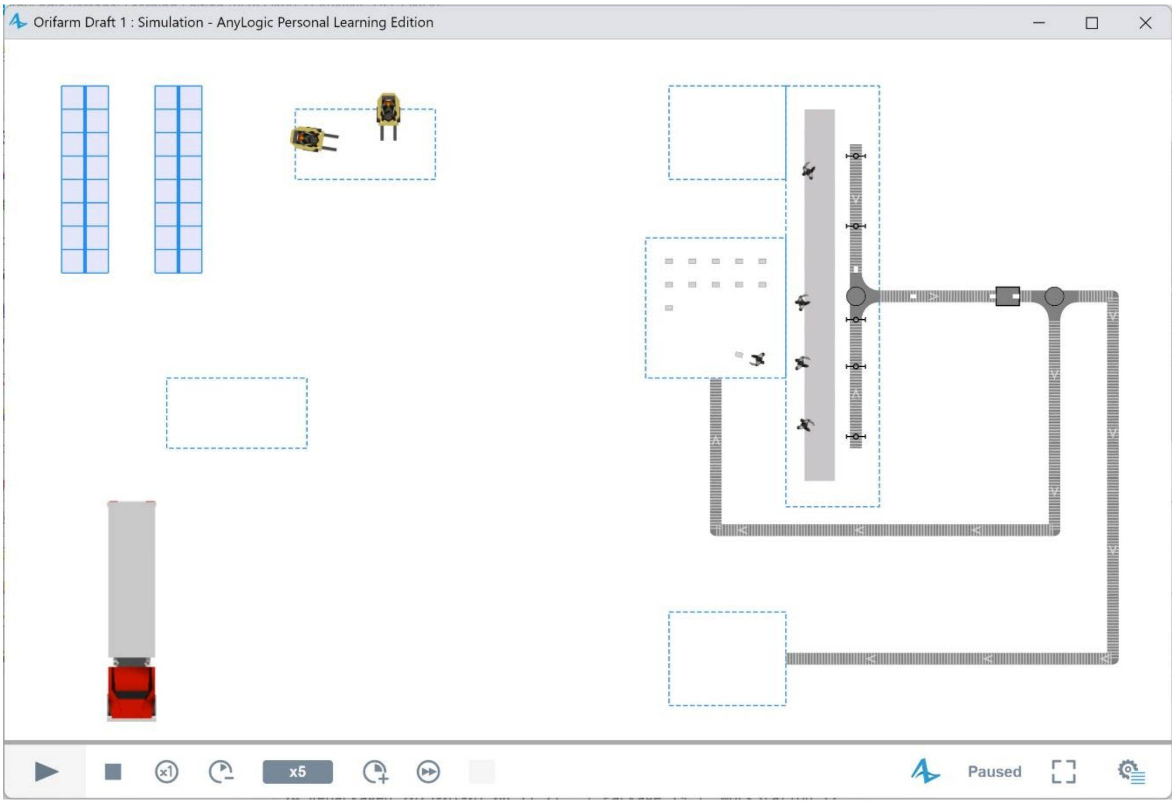


Figure 4: ORI initial AnyLogic Simulation Model

2. Methodology

In WP2 we use an inductive Approach. This entails drawing overarching principles or conclusions by extrapolating from specific observations or instances, thus allowing for the development of a comprehensive and flexible framework that accommodates a wide range of scenarios. For example, we modelled initial versions of both manufacturing pipelines as simulations and are going to refine them iteratively through the development of the DT and DSS in close cooperation with the respective partners. This approach allows us to incrementally grasp and encompass the intricacies of these distinct manufacturing lines. It also enables us to model minute details since individual steps may be relatively small in comparison to the overall complexity of the system. Consequently, we can construct the complexity of the manufacturing lines one step at a time, focusing on specific processes, behaviours, or machines during each step.

WP2 is divided into four phases and an omnipresent phase as seen in Figure 5. The five main phases are not strictly sequential, since they greatly influence each other, or one is derived from the other. Thus, if bigger changes occur in one phase, an earlier phase may very likely need to be revised as well. In the first phase, we defined KPIs that are in sync with the production and environmental goals, as well as capturing the worker's health and well-being sufficiently. Using these we defined the data requirements. This, in particular, entails exploring available data sources and matching them to the KPIs as well as researching and defining appropriate data validation methods and pipelines. “Standard types of validation are related to size (e.g., size of dataset, number of features), data values (e.g. unique values, range values, outliners), quality of data (missing values, value accuracy, value reliability, time-related value, missformats), cross-artifact data validation (missing features, skew). Different types are applied for different artefacts”[1]. In the second phase, we focus on ensuring the products quality and that the customers demand is met. Shortly after, the third phase starts with the model extraction, e.g., of the machines and the human workers within the manufacturing line. Depending on the data sources and model complexity, a variety of methods, such as process mining, data analytics, and machine learning will be employed. For example, psychological stress detection via pupil diameter analysis [16], [17], emotional stress detection via heart rate variability [18], stress detection using accelerometer [19] or Process Mining for reliability modelling [2], [3]. The models themselves also very much depend on their use case, possible representations may be Knowledge Graphs, fuzzy Fault Trees, Artificial Neural Network or stochastic Petri Nets [3]. Additionally, we focus on automating the model validation as part of the digital twin loop. Methods like T-test, F-test, Kolmogorov-Smirnov test and Anderson-Darling test could be used as suggested by [4]–[10]. Therefore, a process needs to be defined and implemented that ensures the quality and correctness of the updated models. While and after implementing the aforementioned points the resulting framework should not only be robust to changes, but also capable of automatically updating the internal models of the DTs to incorporate these changes in the manufacturing processes. In the last phase, we will focus on investigating and implementing decision support and optimization. This aspect, for example, could entail automation of experimenting and optimization [11].

The previously mentioned omnipresent phase analyses data and information security. This entails in particular concerns in relation to data privacy. Throughout the project, it needs to be ensured that the personal and manufacturing data provided, is used with the utmost care and that the architecture of the DT is robust enough to enable data anonymization where necessary and prevent data leaks.

One possibility to achieve this is the use of privacy-preserving data mining techniques [12]. A more in-depth analysis of data privacy can be found in D7.7 chapter 2.1.2.

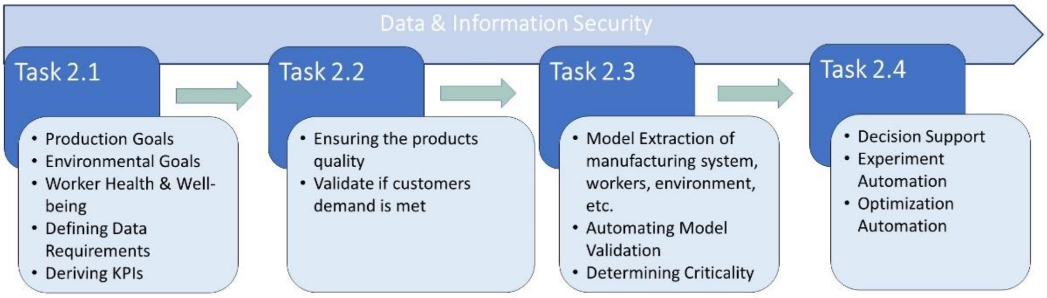


Figure 5: WP2 Phases

3. Data Requirements and Specifications for DTs and DSSs

Table 1 lists the grouped data requirements for enabling the development of DTs and corresponding DSSs. The data points are categorized by the use case. If a data point is used by more than one main goal another suitable group is created to reduce repetitions. The data requirements themselves are derived from the goals and objectives the DT and the DSS are aimed to fulfil. These goals are mainly energy efficiency, worker well-being and system reliability. After evaluating the technical data requirements and before the data is being used, an examination of ethical and data protection consequences is conducted. The data requirements listed are assumed to be as perfect scenario based on the state of the art and advances beyond it. However, it is recognised that, due to lack of data monitoring or ethics & privacy issues some might not be achieved.

Energy Efficiency

The rapid expansion of the global economy and the surging world population have led to an unprecedented increase in energy demand, raising concerns about energy supply limitations, dwindling resources, and severe environmental consequences [13]. Despite more than three decades of political efforts and extensive awareness about the causes and direct implications of climate change, global carbon dioxide emissions persistently surge, now standing at a staggering 60% higher than the 1990 levels [14]. Of particular concern is the industrial manufacturing sector, which not only accounts for over 30% of total primary energy consumption [15] but also contributes approximately 36% of total greenhouse gas emissions [16]. Predictions suggest that by 2040, demand for natural gas will have increased by over 50%, with liquefied natural gas (LNG) trade providing some flexibility to mitigate supply disruptions [17]. In response to these mounting challenges, several nations have set ambitious "net zero" carbon emission targets [18], [19], prompting strict regulations for manufacturing systems to reduce their carbon footprint [20]. The implementation of low carbon audits along with high consumption demand has led to an increase in production costs and thus has a direct impact on the competitiveness of companies in global markets [21]. Achieving "net zero" carbon emission targets necessitates the development of more sophisticated energy-saving technologies and the establishment of a low-carbon energy ecosystem within the industrial manufacturing sector [22], [23]. In this context, the application of the digital twin concept to enhance energy efficiency emerges as a promising research frontier, capitalizing on the advancements in Industry 4.0 technologies [24]. A key driver behind the efficiency of digital twins within the ambit of Smart Manufacturing is the infusion of data-driven methodologies. The concept of a data-driven digital twin is driven by the exponential growth of data in smart factories [25]. Data-driven digital twins capitalize on the wealth of real-time and historical data harvested from sensors, IoT devices, and interconnected systems [26]. Utilizing this data effectively allows for the creation of accurate models representing manufacturing systems [25]. Therefore, the data points listed in Table 1 aim in the first step to foster the understanding of energy consumption and in the second step enabling the prediction of saving possibilities.

Worker Well-being

Worker well-being in general is a complex and multidimensional task that involves assessing various aspects of a person's work life. In fact, many aspects in the private lives can have a tremendous impact on the worker well-being at work, which complicates the matter even more. Nonetheless, it is possible to measure worker well-being meaningfully and purposefully plus the upsides of workers who feel well are significant and worth the business investment. Positive effects can be but are not limited to increased productivity, decreased absenteeism, better job performance, and decreased voluntary turnover [27]. Different methods of evaluating worker well-being have been proposed and implemented, in this project we intend to use the following methods:

1. Psychological Stress detection via pupil diameter analysis [28], [29]
2. Emotional Stress detection via heart rate variability [30]
3. Stress detection using accelerometer [31]

A key benefit of all these methods is that they are non-intrusive into the work environment which means the adjustment period is significantly shortened plus there is no additional stress put onto the workers themselves. Furthermore, by combining the three methods measurement errors or effects of data noise can be minimized increasing the overall predictive capabilities. To further increase it, a number of adjacent factors are considered which can have a direct or indirect effect on the workers well-being. The first factor is the general environment the workers are in. To derive concrete implications on the well-being the following environmental variable are tracked and measured: temperature, humidity, noise and illumination level [32]. The second factor which is considered aims to measure the fatigue level of a worker throughout their shift. To do so three KPIs are inspected: Production Quantity, Throughput Rate and Quality Ratio. The general assumption being that these drop with an increased fatigue level. The third factor tries to incapsulate the individual worker. In particular their physical attributes such as hight and weight and their consumption of alcohol and tobacco. These variables would benefit the results accuracy since they can have a direct and significant impact on heart rate [33] and pupil diameter [34] as well as noise and illumination sensitivity. Nevertheless, due to ethics, privacy and/or legal restrictions it might be difficult to achieve this data. The last factor we want to consider are the product characteristics the worker is working on or with. More specifically the weight of the product (or the parts of the product the worker has to move) its dimensions and if it can be toxic or contain toxic materials. These measurements together with the work schedule of the worker and the current event log of their processes allow us to derive a qualitative judgment about the workers well-being. To do so, we contrast the measured stress levels combined with the four adjacent factors for the given event log against a task or process specific mean stress. This mean stress level is calculated by taking the mean stress level of records of workers with similar event logs. Similar meaning the physical and mental stress levels are comparable. If significant deviations are spotted, the DSS will send out a warning and suggest one or more recommended courses of action.

Reliability

Understanding the reliability of a system is essential for making informed decisions regarding maintenance schedules, safety measures, performance expectations, and overall system design. This knowledge ultimately contributes to the system's efficiency, safety, and long-term success, while also enabling organizations to minimize downtime, reduce operational costs, maintain customer satisfaction, meet regulatory requirements, and achieve their goals and objectives effectively and with confidence. We want to utilize two methods to model the reliability of the manufacturing lines of MOL and ORI. The first method uses event logs in combination with state logs to generate stochastic Petri Nets, as demonstrated by Jonas Friederich and Sanja Lazarova-Molnar [3]. The second method uses fuzzy fault trees to model the reliability of the system [35] given the System Failure Data and Operating Conditions.

Data Requirements for DT and DSS

Use Case	Name	Description	Format/Frequency
Energy Efficency	Energy Consumption Data Whole System	Records of electricity, gas, fuel oil, or other energy sources used over time for whole system.	Time Series, value each hour
	Energy Consumption Data Each Process	Records of electricity, gas, fuel oil, or other energy sources	Time Series, value each minute

		used over time for each Process	
	Energy Consumption Data Each Equipment	Records of electricity, gas, fuel oil, or other energy sources used over time for each Equipment.	Time Series, value each minute
	List of Electrical Equipment	The information includes device name, model, and usage.	List
	Renewable Energy Production Data	Energy generated by renewable sources (solar panels, wind turbines, etc.)	Time Series, value each minute
	Renewable Energy Consumption Data	Renewable energy used/Total energy used for the whole system, process, and single equipment.	Time Series, value each minute
	Energy Tariffs	Information about energy pricing structures, peak and off-peak rates, and demand charges + changes during time.	List
	Grid Connection Information	Information about the existing power grid and its capacity to integrate renewable energy. Voltage levels and connection points for feeding renewable energy into the grid.	List
	Energy Storage Systems	Information about energy storage systems (batteries, capacitors, etc.) if applicable.	List
	Emission Data	CO_2, CH_4, N_2O Emissions (Greenhouse)	Time Series, value each minute
Well-being	Heart Rate	Fitness tracker like Fitbit	Time Series, value each minute
	Movement/Steps	Accelerator	Time Series, value each second
	Work Schedule	At what times does the worker work and when are the breaks.	Ideally past 4 weeks plus current plus planned
	Event Log	Beginning of processing / End of processing for each operator/machine	Time Series, depending on machine and/or process
	Pupil Tracker	Eye-Tracker	Time Series, value each second
	Anonymized Personal Data: Alcohol, tobacco, height, weight	Questionnaire	At the start of work contract, updated every 6 months
	Production Goals	KPIs used to set the target production levels/efficiency	List, updates with timestamp
Reliability	Event Data	Beginning of processing / End of processing for each operator/machine	Time Series, depending on

			process and/or machine
	System Failure Data	Data of past system failures and categorisation of failure types	Time Series, as they occur
	Maintenance records	Scheduled or reactive and associated repair logs	Time Series, as they occur
	Operating Conditions	Pressure, vibrations etc.	Time Series, depending on machine
	State Logs	The state of the machine. OPC-UA, Modbus	Time Series, as they occur
Production and Performance	Production Quantity	Products produced in last hour	Time Series, as data is available
	Throughput Rate	Actual Oder Execution Time + Produced Quantity (ORI: Labour efficiency Production) for each hour	Time Series, as data is available
	Quality Ratio	Produced Quantity + Good Quantity (ORI: Right First Time Production) for each hour	Time Series, as data is available
	Workload	The workload each machine and worker is expected to deliver.	List, updates with timestamp
	Operating Schedules	When different processes and equipment are active. For the current day, ideally also historical and future data.	Ideally past 4 weeks plus current plus planned
Product	Weight	The weight of the product (and its part if the worker has to lift them). Potentially from ERP or MES	List, updates with timestamp.
	Dimensions	Relevant dimensions of the Product. Potentially from ERP or MES	List, updates with timestamp.
	Toxic Material	Can the worker or environment get in contact with toxic materials (e.g., gases or alloys). Potentially from ERP or MES	List, updates with timestamp.
Environment	Temperature	Thermostat at workstations	Time Series, value each minute
	Humidity	Hygrometer	Time Series, value each minute
	Noise Level	Decibel Meter	Time Series, value each second
	Illuminance level	Luxmeter	Time Series, value each minute
	Weather Data	API	Time Series, value each day
	Building Information	Building structure, insulation, and HVAC systems data.	List, updates with timestamp

BIM - Space Use	Information about the building's layout, including walls, windows, doors, and spatial divisions. This geometry data is used to calculate the building's surface area, volume, and distribution of spaces, which are key factors in energy analysis. And insulation levels, window types, and shading devices.	List, updates with timestamp
BIM - Materials and Thermal Properties	Materials and Thermal Properties: about the materials used in construction, including their thermal properties such as insulation values, heat capacity, and conductivity.	List, updates with timestamp
BIM - HVAC Systems:	Heating, ventilation, and air conditioning (HVAC) systems. This includes the location of HVAC equipment, ductwork, air terminals, and specifications about system performance, which impact energy consumption for climate control	List, updates with timestamp

Table 1: Data Requirements for DT and DSS

4. Architecture

This chapter introduces a DT architecture for manufacturing systems with cobots, explaining the components, functionalities, and interconnections of each system component.

The proposed architecture's three main layers plus the physical twin are illustrated in Figure 6:

1. Physical Twin
2. Communication and Data Extraction Layer
3. Virtual Manufacturing System Layer
4. User Interaction Layer

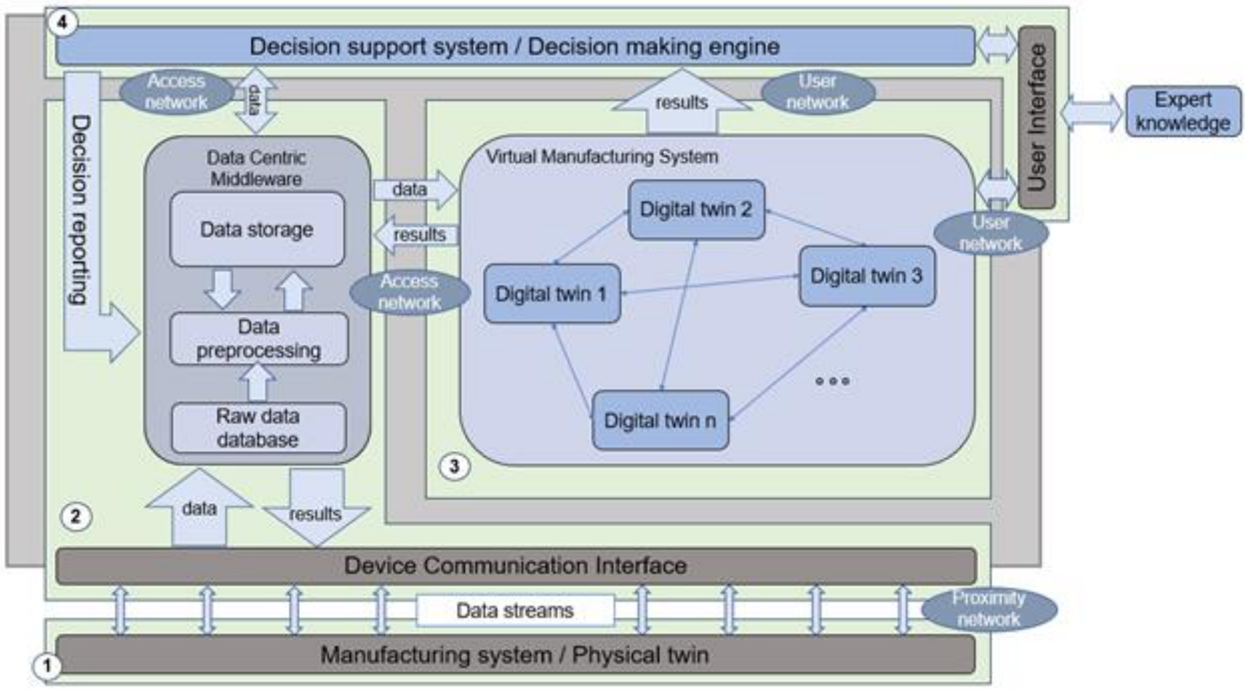


Figure 6: Layer and network view of the architecture

To ensure practical applicability, this architecture adheres to the requirements of ISO 23247 "Automation systems and integration - Digital twin framework for manufacturing". Experts highlighted the importance of two features proposed in the ISO 23247 standardization in a survey: plug-and-play and peer interference. In the presented architecture, plug and play functionality is achieved through the **Device Communication Interface** by enabling a dynamic connection to the physical manufacturing system, which is explained in more detail in the section on the communication and data extraction layer. According to ISO 23247, the peer interface "[...] provides interfaces to other digital twins in conjunction with the interoperability support [...]" [36]. This functionality is realized by the co-simulation interface of each of the digital twin models in our architecture, which allows them to interact with each other. The co-simulation interface is explained in more detail below. In addition, the surveyed experts claimed that data storage and digital twin visioning functionalities are crucial and must be incorporated into any digital twin architecture for manufacturing systems, even if they are not specified in ISO 23247. These two aspects are also considered in this architecture. Figure 7 displays the architecture of a digital twin for a manufacturing system with collaborative robots. The subsequent section describes each layer with its components, structures, and functionalities. Lastly, the information exchange between the layers and the network connections of the architecture are explained.

Physical manufacturing system layer

The **Physical Manufacturing System Layer** (PMSL) represents the actual manufacturing system that should be monitored and analysed with the DT. One of the initial steps in developing a DT is to acquire precise and dependable data of the manufacturing system. That data can be obtained in the manufacturing system through sensors or from the controller and enterprise manufacturing systems such as ERP, MES, WMS or Production Planning System (PPS). Chapter three discusses the data specifications and requirements in detail. The data acquired is seamlessly transferred from this layer to the Communication and Data Extraction Layer without processing or storage [37].

Communication and data extraction layer

The **Communication and Data Extraction Layer** (CDEL) consists of two main elements: The **Device Communication Interface** (DCI) and the **Data-Centric Middleware** (DCM). Together, they operate as an IoT gateway [38] and "[...]act as a bridge between the physical and cyber layer by receiving all the data packets from the physical systems, processing them and converting them into a machine-readable form[...]" [39] and transmitting them to the data storage. "The IoT gateway is a middle-ware between devices and cloud and facilitates computations and communication" [40].

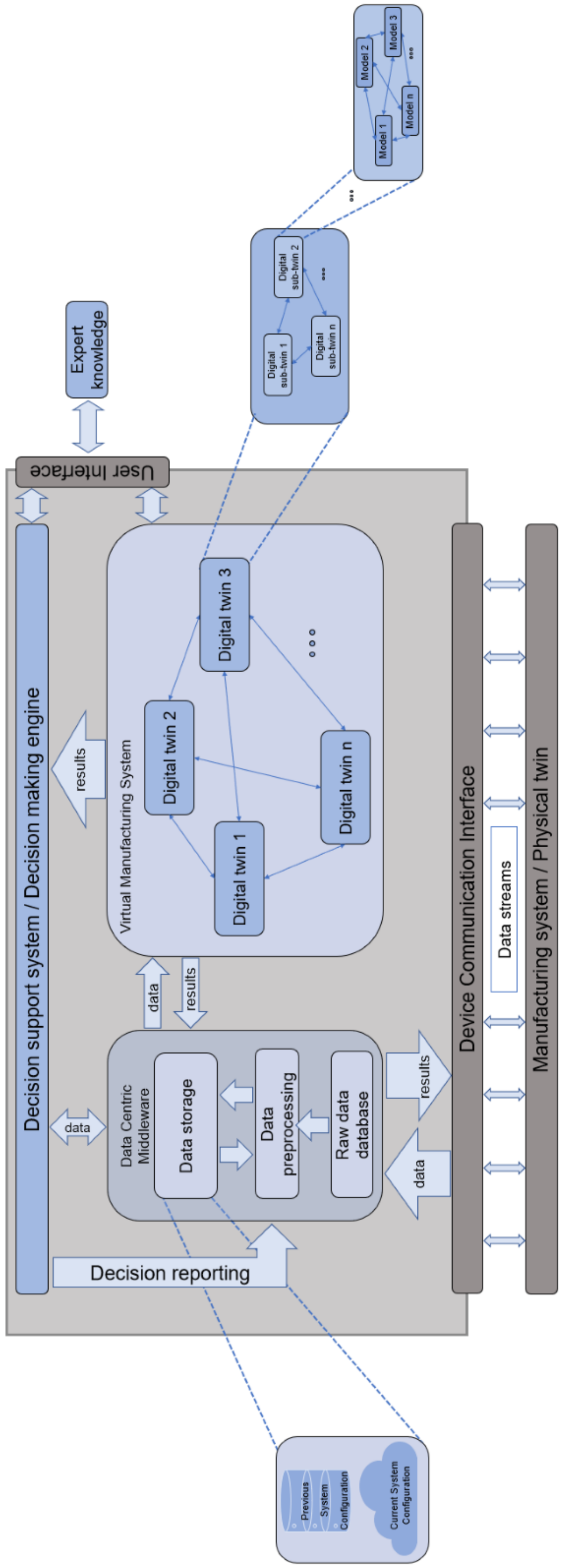


Figure 7: General architecture

The data streams from the physical twin enter the **Device Communication Interface**, which is the only point of contact between the virtual and physical components acting as a standardized service interfaces [41]. Thus, only the DCI needs to be configured and customized during implementation, enabling plug and play of the DT. The DCI enables seamless connection between virtual and physical manufacturing system, achieving real-time synchronization and updating with the huge amount of data [42]. The multimodal data collected from the manufacturing system with cobots is uploaded to the raw database via the DCI through a request-response mechanism, while the results of the analysis, simulation and decision support system are transmitted to the manufacturing system after being converted into control commands[43].

Currently, three key components for digital twin data storage have been identified: raw data storage, real-time data pre-processing, and data storage of processed data[44]. These three steps together constitute the data-centric middleware in our architecture. Before performing data preprocessing, the data is stored in the raw database. This database is hosted in the cloud, facilitating the real-time collection and unification of data from various machines and cobots of the manufacturing system[45]. Data extraction represents the first step of data preprocessing. A scanning algorithm runs on the incoming data during which the communication protocols are identified before the data packets are decoded based on the identified protocols and the corresponding extraction software. To achieve real-time processing of incoming data Apache Kafka is used. Apache Kafka is a software for processing data streams. It is designed especially for storing and processing data streams, and for loading and exporting data to external systems. The central architecture of Kafka is based on a distributed transaction log. In Big Data scenarios, where large volumes of logs are generated continuously, managing, sending and storing these logs can be challenging. Apache Kafka offers a solution for effectively handling and analysing extensive volumes of log files. It is especially suitable for scenarios where there is a need for promptly processing and analysing massive amounts of data [46].

After completing the data extraction, the data from different machines and systems is presented in a machine-readable unified data format such as JSON or CSV files [39]. After conversion, the data is cleaned and filtered before being uploaded to the data storage in the cloud, which makes the data universally accessible [47]. The data storage is the single point of truth, meaning it is the central, single reference point where all data and information for the DT models of a manufacturing system can be found.

The data storage is divided into two stages. On the one side, there is a cloud storage where the current system configuration is stored. This data storage holds the recent data collected from the manufacturing system, the current the DT models, optimization algorithms, methods for modelling and prediction, the results of the latest simulations and information about the current production line, including process information, equipment information, layout information or machine runtime condition[48]. “As the amount of cloud storage is limited and expensive, only the most recent and latest data is stored in the cloud for immediate retrieval” [39]. Subsequently, the data is transferred to offline storage, where all the previous system configurations, old versions of the DT models, previous collected data and results are permanently stored to preserve historical knowledge.

The purpose of applying data-centric middleware is to create a unified platform for exchanging information among the different systems. As aforementioned, as with all incoming data, the outgoing results of analysis, simulation, and decision making, as well as the data identified as necessary, must be transformed into the appropriate control commands or information before being transmitted via the DCI to the physical manufacturing system layer. In this way, the data- centric software fulfils the role of the controlling entity required by ISO 23247.

Virtual manufacturing system layer

The **Virtual Manufacturing System Layer** (VMSL) executes the DTs and is composed of different DT models that are interconnected and synchronized to allow data exchange[39]. As a result, the VMSL should be capable of establishing real synergy among these simulation models and thereby opening new opportunities to address complex scenarios [41].

A DT of a manufacturing system can consist of other digital sub-twins representing, for example, a sub process of the manufacturing system. Each of which can comprise other digital sub-twins, such as a cobot used in that sub process. Multiple sub-DT layers are possible. The simulation-based digital twin models can be realized for example by using Petri Nets, discrete event simulation, Markov reward models, or agent-based modelling, that represent the corresponding subject. “The set of functionalities provided by a parent DT should at least contain the individual functionalities of its children DTs. Nevertheless, higher level functionalities can be added to higher hierarchical levels” [49]. For a simple DT model of a manufacturing system, the representing DT could consist of only one layer with the specific simulation models. Beyond that, each digital twin model is assigned a predetermined function that constitutes a specific goal or object within the manufacturing system [39]. Following this approach, the maximum flexibility and scalability of the DT is realized, as the DT of the manufacturing system with cobots can be tailored to the respective goals or objects of the company that are being targeted for analysis. Another advantage of this hierarchical layered approach is that instead of optimizing or deriving the entire DT of the manufacturing system with cobots from scratch, only a subset of the DT can be considered, saving time and resources [39].

An initial digital twin of the manufacturing system of MOL would be that the first layer consists of the manufacturing system, the manufacturing environment, and the product. The manufacturing system model comprises multiple interconnected digital twins of machines, cobots, process and logistics units, as well as a layout model that simulates system reliability and throughput. The olive processing system's reliability is modelled using a Petri Net, discrete event simulation, reliability block diagram, and a fault tree. Figure 8 provides an illustration of this exemplary structure for olive processing.

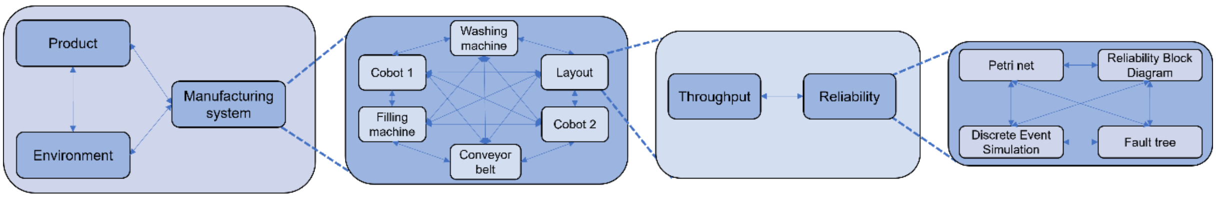


Figure 8: Exemplary design of the different levels of the virtual manufacturing system

One single digital twin model has a two-part structure. The first part is the current model, which performs real-time simulation and monitors the physical manufacturing system. The second part is the iterative optimization process that automatically aims to improve the current model.

The current model must perform two primary tasks. First, it must monitor and analyse the current state of the system, cobot, or machine in real time, depending on the object represented in the model. Functions such as traceability, condition monitoring and current state gathering, are utilized to monitor and analyse the system's current state. Secondly, the model must perform simulation that includes at the machine or process level functionalities such as machine and process KPI estimation as well as damage, wear, or failure estimation. The simulation of the entire manufacturing system with cobots includes performing functionalities such as design validation, production and maintenance planning/scheduling or bottleneck identification [50].

The DT model's second task is to optimize the simulation model itself. To do so, the simulation model is constructed in an iterative manner [51]. After performing the input analysis, the simulation model is developed, before the developed model is verified and validated. During the input analysis, the incoming data undergoes processing and analysis. With data mining, features such as mean, standard deviation, or stochastic distribution are automatically extracted and parameters are estimated, which are then used for constructing the DT models [45]. The next step is to perform output analysis and evaluate the newly created model. If the newly created model outperforms the current simulation model, the latter will be stored in the offline storage to keep track of the model versions, and the new simulation model will be used for monitoring and simulation [51].

We propose a **co-simulation interface** to realize the interconnection of all digital twin models[36]. The co-simulation interface provides four main functionalities: First, the interface supports the exchange of simulation models and data between each other. Second, it enables real-time simulation interworking of different simulation models. By executing different simulation models together, more complex scenarios and synergies among the models can be realized to better replicate the real manufacturing system [41]. The third function is time synchronization among simulators, which is necessary for accurate simulation results. Lastly, the co-simulation interface allows to control the execution of the simulation. A common approach for implementing the co-simulation interface in practice is the Functional Mockup Interface [36]. The Functional Mockup Interface (FMI) is a standardized system that enables the exchange and co-simulation of dynamic models, primarily designed to facilitate the sharing of simulation models across different tools between suppliers and OEMs. The FMI is the result of a collaborative effort between simulation tool vendors, companies, and research institutes to address aspects of model exchange and co-simulation [52].

An **Application Programming Interface** (API) is employed to connect the DT model to the data storage. The API allows the DT model to receive continuously the latest data of the manufacturing system from the cloud and transmit the simulation results back to the data storage[49]. Through the API, the current simulation model, required information, or optimization algorithms can be also accessed. Moreover, the API allows for external applications to excess the system. For example to query the current state of the DT models or to trigger a simulation start [49]. The layout and structure of a DT model is illustrated in *Figure 9*.

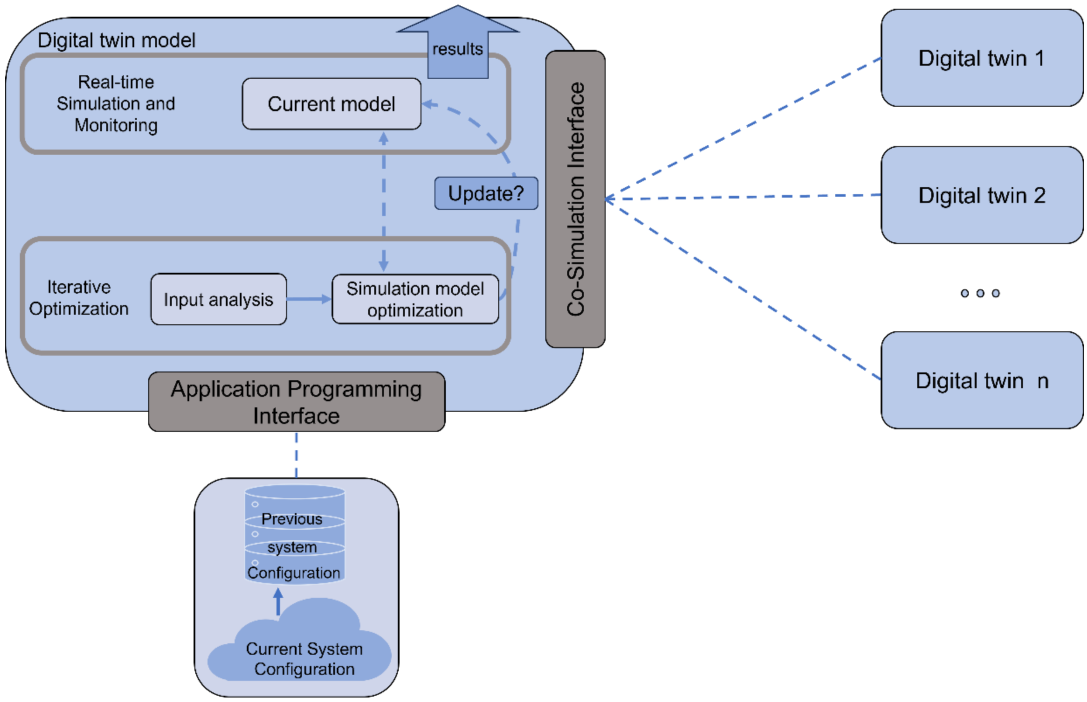


Figure 9: Layout and structure of a digital twin model

User interaction layer

The **User Interaction Layer** is comprised of the **Decision Support System** (DSS) and **User Interface** (UI). A user interface enables an operator to monitor, control, and interact with the DTs and is in line with ISO 23247[44]. The UI allows domain experts to add their expert/domain knowledge into the DT without the need for computer science or programming knowledge. This expert/domain knowledge is often hard or nearly unobtainable to extract from the collected data, and thus the simulation models can be improved drastically.

The DSS performs complex determinations based on the collected data and the results of the simulation and analyses this information. This involves, for example, optimizing the manufacturing system, including functionalities such as system improvement and system optimization[50]. For the system optimization, a method is the simulation-based optimization of manufacturing systems, which enhances the decision-making capabilities of simulation. This approach allows to identify the best solution or a solution close to the best solution for the target object or goal to be optimized. To achieve real-time response of the simulation, methods like symbiotic simulation and online simulations as well as linking the optimization and the decision-making engine to the DT model can be used[50], [53]. The DSS communicates the decision to the DCM, which converts it into control signals and sends those commands to the actuators in the physical manufacturing system[49].

Finally, we will briefly discuss the network connections between the layers shown in Figure 6. The network connections are based on ISO 23247 – Part 4[44]. The PMSL and the CDEL are connected through the proximity network. This network sends the control commands to the PMSL and receives the data from the industrial sensors and the enterprise manufacturing systems. The Industrial Ethernet, such as Profinet, EtherCAT or Modbus, or wireless or proprietary network with a special configuration can be chosen for the proximity network[54]. The access network can be either a wireless communication network using WLAN and mobile (cellular) network, or a wired network such as local area network. The access network is used to facilitate communication between CDEL and the VMSL along with the User Interaction Layer. The VMSL and the User Interaction Layer communicate through the user network, which can be either public Internet or private intranet.

5. Conclusion – Next Steps

As T2.1 concludes with this deliverable, the next steps are to kick of T2.3 and T2.4 which have the goal to develop the DT and the DSS respectively.

T2.3 Data-driven digital twins module development, validation and tune-up [M10-M48]

Expected results:

1. Implementation of a data-driven DTs module;
2. On-the-fly validation methods built in the DT module;
3. Adapt the module to the end-users and integration with the DSS and in the IOP;
4. Demonstration and tune-up.

Activities:

i) Design and customise event detection, and process mining methodology to extract simulation models from ongoing data collection are created based on the DT.
ii) Implementation of the methodology in the DT module (ready to be tested).
iii) Development on-the-fly validation methods that provide quantitative validation of the extracted models using the data generated from the manufacturing plants. Test and validate the DT module in the SDU's Industry 4.0 Lab.
iv) Prepare a final version ready to be integrated in the IOP and deployed for demonstration activities (T5.2).
v) Tune up the DTs based on the demonstration activities results.

T2.4 Smart distributed decision support system module development, validation and tune-up [M10-M48]

Expected results:

1. Development of a DSS;
2. Test and validate;
3. Adapt to use-cases scenarios;
4. Integration with the IOP;
5. Demonstration in a real environment and tune-up based on the results.

Activities:

Based on the KPIs from T2.1, the DSS module will provide recommendations to improve and calibrate manufacturing systems ' behaviours in the demo sites. The DTs created in T2.3 will be used to simulate various 'what-if scenarios' and to optimise configurations on the predefined KPIs. Furthermore, these approaches will also be integrated on the self-learning DSS to prove the whole system's functionality and adaptation (modularity) ability. By M30 there will be presented a final version ready to be integrated with the IOP. Further on, it will be under maintenance and tuned up based on the demonstration results (WP5).

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