DIGITAL PROCESS TWIN

Revision 0.1

SUMMARY

This document provides an overview of the digital twin, including its history and definition. In addition, it introduces a new term in digital twin technology, the digital process twin, and explores its application in the power system based on the aims of the AISOP project.

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Table of Contents

List of Figures

List of Tables

1 Abstract

This report reviews the definition of the "digital twin" within the context of distribution system monitoring, data acquisition, situational awareness and operational planning. The definition of the digital twin is expanded to include the digital representation of the processes that are performed by human experts. This reports is a deliverable, within the scope of the AISOP project.

The deployment of digital technologies along with the custom-designed hardware has exploded in the past two decades in various industries. The applications of artificial intelligence (AI) in language processing, autonomous mobility, cancer diagnosis, etc., thanks to ever-increasing computational power and advanced machine learning (ML) methods (e.g., reinforcement learning, deep learning) demonstrate the vast potential of opportunities in different industries in the future.

As the early adopters of digitalization by deploying the first commercial computers in daily operations, electrical energy industry (the generation, transmission and distribution) has created the largest human-made machine – the interconnected transmission system – thanks to the vast deployment of advanced measurement and protection systems supported by autonomous local control frameworks as well as automated decision-making processes. The electromechanical measurement systems deployed in early 1900s, transformed to digital sensors by 2000s, and SCADA/EMS applications such as grid situational awareness and operational planning became the standard in the control rooms of transmission system operators. In the meantime, the distribution networks, especially the low voltage grids, are designed to serve the demand only, with limited number of deployed sensors, and with relatively less need for SCADA/EMS systems. Today, in the pursuit of an energy transition, unprecedented proliferation of distributed technologies such as solar PV, e-mobility and heat pumps in low voltage grids are foreseen. Such a transition can only be realized if the digitalization in distribution grids significantly increases so that the reliability of the electric power supply is not compromised and network infrastructure is optimally expanded.

AISOP project proposes an **operational planning framework for distribution system operators** to increase grid situational awareness by ingesting, exploiting, and processing heterogeneous data leading to fast and efficient anomaly detection (e.g., grid faults, peculiarities in end-user generation/demand behavior, etc.), identifying the potential risks (e.g., thermal and voltage violations, loss of supply) and steering the end-user generation/demand behavior by data-driven dynamic tariffs to mitigate the identified risks. The overall framework relies on an integrated workflow, which can be performed by human experts, or can be automated partially or fully. This integrated workflow is referred to as the "**digital process twin**" within the scope of this project.

While a digital twin is commonly defined as the virtual representation of equipment, which is already deployed in the field, leveraging real-time measurements from the equipment (e.g., electrical, mechanical, etc.) to monitor the equipment and perform virtual simulations for operational reasons, the "digital process twin" expands this definition to include a "process" as well which can consist of utilization of digital twins of equipments and systems, processing of data by statistical means, and propose actions for operational planning to the reliability and efficiency of the electricity supply and demand. The report provides a review of "digital twin" definitions and requirements, expands the definition to include the "processes" for an active distribution system within the scope of AISOP project.

2 Digital twin

Digital twin (DT) technology has gained significant attention and interest in the recent decade. Figure 1 shows how the power industries adopted the use of digital computers in the early 1960s by installing first-generation computer systems to improve boiler turbine efficiency, process raw data into understandable information, improve unit operation safety by monitoring, and accumulate experience through online digital systems [1]. NASA useddigital technology during its space exploration missions of the 1960s. The notion of DT technology was articulated in 1991 in David Gelernter's book "Mirror Worlds"[2]. Dr. Michael Grieves, then a faculty member at the University of Michigan, is credited with first applying the concept of DT to manufacturing in 2002 and formally introducing the idea of DT software. In 2010, John Vickers of NASA introduced the term "digital twin," which has since become a widely used term in the field of engineering and has gained significant attention in recent years as a key enabler for future space exploration. The concept of Industry 4.0 was introduced by the German federal government as part of its High-Tech Strategy in 2011. The emergence of Industry 4.0 has influenced the creation of a new simulation modeling paradigm embodied by the DT concept [3].

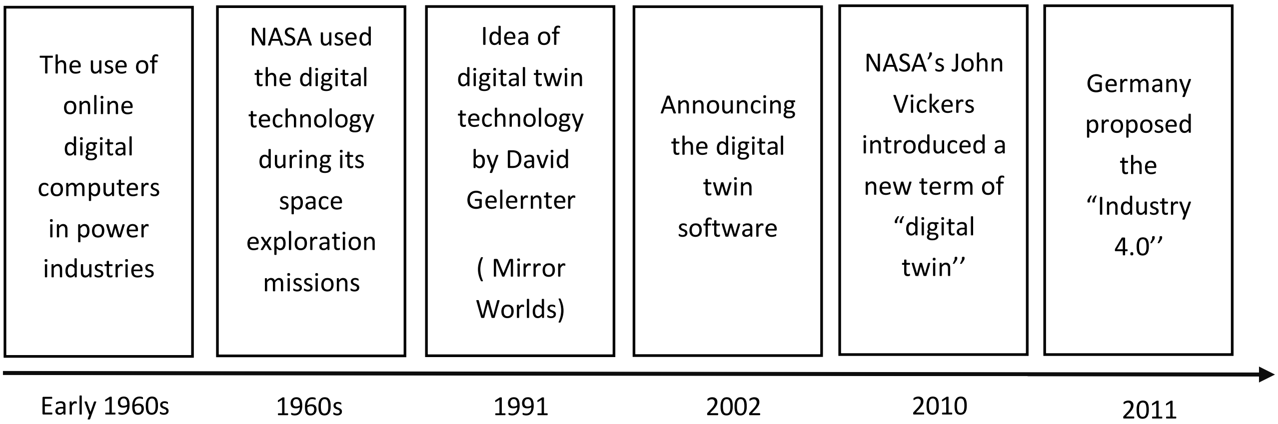

Figure 1: History of DT

The DT is an online or offline-visualization of a case that could be a physical asset, system, or process. As shown in Table 1, there are several definitions of DTs. The table summarizes some of the definitions provided by various authors and articles.

Table 1: Definition of DT

Reference	DT Definition
NASA 2012 [4]	“A digital twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin.’’
Rosen et al. 2015[5]	“The autonomous systems will need access to very realistic models of the current state of the process and their own behavior in interaction with their environment in the real world, typically called the Digital Twin.’’

Bochert et al. 2016 [6]	“The digital twin refers to a comprehensive physical and functional description of a component, product or system, which includes more or less all information which could be useful in all—the current and subsequent—lifecycle phases.’’
Grieves et al. 2017[7]	“The digital twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.’’
Liu et al. 2018[8]	“The digital twin is actually a living model of the physical asset or system, which continually adapts to operational changes based on the collected online data and information, and can forecast the future of the corresponding physical counterpart.’’
Häger et al. 2023 [9]	“The digital twin (DT) is a virtual representation of an existing or constructed real object, process, or system, which is composed of its description of attributes as well as its functional characteristics, and directly or in some cases indirectly coupled with the real object (process or system) through a communication infrastructure.’’

DTs are employed for several aims and use cases in various fields of study, such as healthcare, industry, aviation, and energy [10]. Table 2 highlights different use cases of DT technology, with a particular emphasis on a few specific examples.

Table 2: DT in various fields of studies

Field of study	Example
Power industry	[1] introduced the use of online digital computers and digital modeling and computer solutions in power systems, especially in the US
Smart cities	[11] introduced the DT of the city of Zurich.
Manufacturing	[12] introduced a fault diagnosis method to achieve intelligent manufacturing with the help of DT
Healthcare	[13] used a DT to create virtual reality in the development of a physical robot fish
Energy	[14] introduced a tool for energy analysis to improve energy efficiency

DTs are categorized into several types based on the aims of the area of application[15], as shown in Figure 2. Component Twins of a DT are the smallest example of a functional component. When two or more components work together, they form a so-called asset. An asset comprises of various components that function collectively. The system twins show the formation of a complete system by various assets coming together. The twin process shows how the systems work together to create a complete production facility.

A DT for the object can comprise various types of digital models. [16] , including:

- Numerical model: This model relies on data-driven methods and uses artificial intelligence (AI) algorithms,
- 1-D simulation: A flow diagram is paired with blocks that simulate the system's performance in this model.
- 3-D simulation: This model is used to depict the dynamics and structure of the system.
- In some cases, a DT can be a combination of these models for different parts of the system.

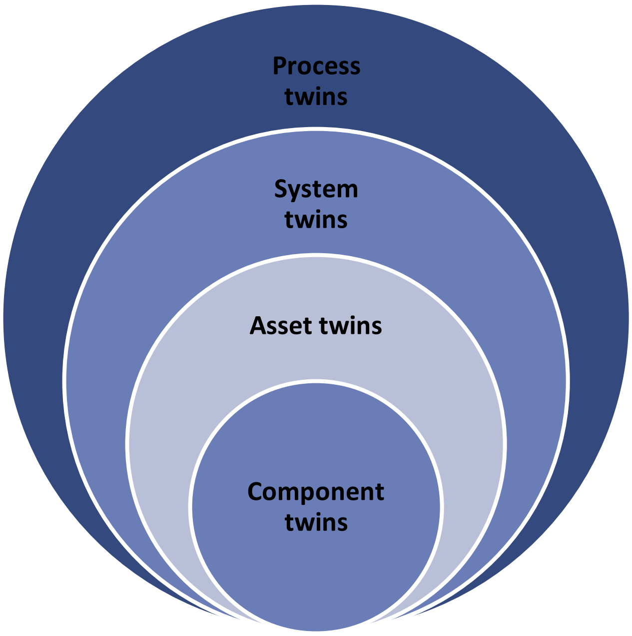

FIGURE 2: DIFFERENT TYPES OF DT BASED ON THE AREA APPLICATIONS

To be able to create DTs, system models are needed. To be able to have system models, the system has to be identified properly. To be able to perform system identification, data-driven methods are relied upon. The evolution of the Internet of Things (IoT) has made such system identification easier since more data about components and systems are available. The evolution of DT technology is parallel to the progression of artificial intelligence (AI) and the IoT. This leads to common challenges in all three areas. The various challenges of DT, AI, and IoT are explained in Table 3 [10].

Table 3: Challenges of DT technology

AI Challenges	
IT Infrastructure	The costs of high-performance graphics processing units (GPUs) capable of performing machine and deep learning algorithms
Data	Ensuring that the AI algorithms are fed with the highest quality data
Privacy and Security	Regulations and measures concerning AI will need to be developed as the technology continues to grow
IoT Challenges	
Data, Privacy, Security	Collecting a substantial amount of data Controlling the flow of data Sorting and organizing data Cyber attack
Infrastructure	Modernization of outdated infrastructure and the integration of new technology
Connectivity	Simultaneously connecting a vast number of sensors Software errors or ongoing deployment issues
DT Challenges	
Data	High-quality data Noise-free data Importance of the quality and number of IoT signals
Infrastructure	A robust infrastructure is essential for the successful implementation of IoT and data analytics

Standard Modeling	Ensuring standard approach, especially for physics-based or designed based Guaranteeing information flow at every stage of DT development and implementation

The connection between the real object and DT can be direct or indirect. In the direct phase, the DT is connected to the real object and updates automatically based on current data. In contrast, indirect DTs are updated manually as new data becomes available.

The lifetime of a DT starts at the design stage before manufacturing. DT can be utilized to identify issues and potential risks during the design process, resulting in an improved design. The DT's time horizon encompasses the design phase, commissioning, operation, and disposal. The DT learns from the past, understands the present, and forecasts the future.

As illustrated in Figure 3, DTs can receive data from the real object (process or system) and other DTs at varying sampling rates. This is because there is no unique sampling time for receiving and transmitting data for DTs. DTs can operate at different speeds. The data received by DTs are diverse and depend on the real system they are connected to. For example, for the power system's DT, the data are measurement data, asset model data, information on devices and cables, etc. These raw data can be consolidated into higher-level models, such as network models.

The data must be accurate and valid. Otherwise, it can lead to wrong decisions. To ensure the quality of the data, it must undergo a data check process, which includes unique identification and validity checks. The better the data quality, the more efficient the system will perform.

DTs can be defined as per the requirement. If needed, the DTs can also get data from the field and give control commands to the field devices. These depend on the desired goals of the system. For example, in a power system's DT, the outputs may include feedback, control commands, operational planning decisions, etc. DTs send the outputs to the real system, SCADA/EMS systems, digital representation of lines and cables, transformers, and monitoring equipment (e.g., transformer oil control, winding temperature, insulation materials) at the required time, taking into account the current system conditions similarly, to inputs, there is no unique sampling time for sending data.

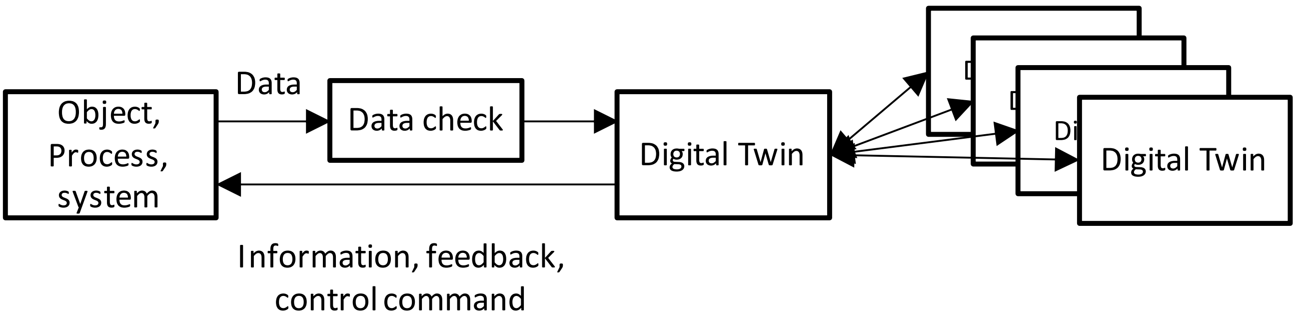

Figure 3: Schematic of DT

Based on the specific objectives of a DT, the following general requirements are needed for the operational phase [17]:

- Duplicate its physical counterpart,
- Unique Identity,
- Data Aggregation and Data Storage,

- Computational Power,
- Interface & Interaction,
- Decision-Making,
- Security and Privacy.

DTs offer a wide range of advantages, depending on when and where they are used. Some of the most common advantages of using DTs include the following:

- Reducing costs at various levels of the system, such as in operations, maintenance, and control,
- Enhancing system monitoring capabilities for improved visibility and control,
- Increasing the reliability and availability of the system by minimizing the risk of errors or failures,
- Improving performance through advanced analytics and data-driven insights.

When multiple DTs are connected and linked with each other, it leads to several mutual benefits, including improving the overall performance and efficiency of the connected systems and providing a more comprehensive view of the entire system.

3 DT in power systems

Expectations to reduce CO_2 emissions are a strong force to change the power system, leading to widespread renewable energy sources, a growing number of electric vehicles, electric heat pumps, storage, and bidirectional power flows in the grid [18]. As a result, the power grid is becoming increasingly non-linear, diverse, and hierarchical, making it challenging to model and analyze [19]. Therefore DTs in the power grid can effectively manage multi-directional and complex energy systems, and data-driven methods are employed to handle this complexity in most parts of the DTs of power networks. The modeling of cyber-physical power systems is one of the most extremely complex models that has been built, and determining the details of the model can be a significant challenge in the manufacturing DTs of power systems [20].

The use of DT in power system monitoring and control represents a practical approach that can push power system control center technology to the next evolutionary stage. A comparison of advances in simulation and control center technology is shown in Table 4 [21].

Table 4: Evolution of control center technology in power system

	Simulation Technology	Control center Technology
1^{st} Generation	Simulation limited to very specific topics	Hard-wired, Fully analog communication
2^{st} Generation	Simulation tools: A simulation is a standard tool for engineering	IP/TCP-based communication
3^{st} Generation	Simulation-based system design	Dynamic assessment tools
4^{st} Generation	Simulations based on interconnected data from various objects managed by DT	Data-driven support systems enabled by DT

One of the impacts of DTs solutions on the business world is in the field of utilities and using it for power grid planning, improving observability across the physical grid, improving grid efficiency, and power grid self-evaluation [22]. Table 5 represents a summary of some studies that have explored the use of DT in the power system. These studies have shown the effectiveness of DTs in improving power system performance, optimizing system control, and facilitating real-time decision-making, which helps in the modernization of the power grid.

“Networked DTs” are a set of digital twins connected through a network. This allows them to work together to simulate and optimize complex systems or processes. For example, the entire European power grid can be considered a network DT, where each DT can represent a subnet, a component such as power plants, substations, and transmission lines, or a process such as monitoring, optimizing, and control. These DTs can exchange data and interact with each other to simulate and optimize the behavior of the entire power grid.

The power network DTs are composed of several DTs, as shown in Figure 4. Each DT covers a specific object (or system or process) and can belong to different manufacturers. The DTs from several manufacturers must be interoperable, allowing for seamless data transfer and ensuring that these systems maintain a single source of truth (SSOT) among them. To achieve this, DTs must have consistent formatting and naming conventions for data. Each DT can consist of multiple objects (or systems or processes) within a subnet, such as DT of transmission lines, DT of secondary control, and DT of transformers.

Table 5: Studies of DT in power system

Reference	Objective	Main conclusions from the paper
Xing He et al. [19]	DTs are explained for real-time power flow analysis.	DT for power systems offers several advantages such as real-time data integration achieved by active integration between digital and physical spaces, big data analytics in high-dimensional space, and self-adaptation enabled by data and feedback accumulation.
Mohammadi Moghadam et al. [23]	DT applications are reviewed in some parts of power, such as wind turbines, solar panels, power electronic converters, and shipboard electrical systems.	DT can be used for diagnostics, fault analysis, and control of some parts of power in real-time. For example fault diagnosis in PV panels and a decrease in the differentiation between physical and software-in-loop controllers in wind turbines.
Baldassarre et al. [24]	A new method for the design of wind turbine blades is introduced, and a DT is developed to match the data obtained from the experimental test.	An affordable digital twin model is designed for wind turbine blades which is useful for reducing uncertainties, predicting structural changes, and assessing remaining life.
Jain et al. [25]	A design method for fault detection is introduced by developing a DT that estimates the measurable characteristic outputs of a PV power conversion unit in real-time.	The DT for fault diagnosis is able to quickly detect and precisely identify various fault types, regardless of the converter topology or type of PV installation.
Brosinsky et al. [26]	Combine machine learning (ML) techniques and DTs to provide new insights into security (dynamic) monitoring and control for electric power systems. It covers the following topics • Combining machine learning and DTs for power system analysis • Dynamic security assessment with DTs • Probability and risk analysis with DT and ML	The combination of ML and DTs has the potential to improve security monitoring and control by providing real-time decision support and accurately predicting overall system response to high-risk scenarios, while also increasing solution speed.

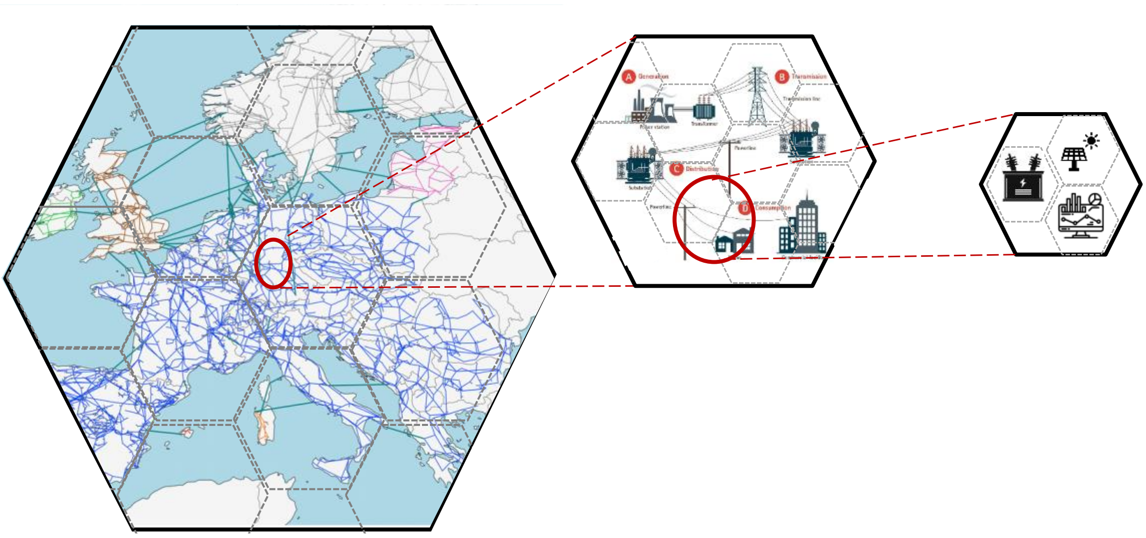

Figure 4: The cellular structure of the networked DR for the power systems

A DT for grid monitoring, operation, optimization, and control is a viable approach. It could pave the way for future developments in grid control center technology and improve system efficiency and reliability. Power system DTs can be used to evaluate and simulate the effects of various scenarios on the network, such as the impact of new generation resources, extreme events, or adding new transmission lines.

Based on the requirements mentioned for implementing DT embedded infrastructure, the following are necessary to effectively implement a DT of power systems.

- Sensors and advanced meters for data acquisition (data on the grid and grids' components information)
- Development of models
- Data validation, processing and analysis, and interpretation,
- Common interfaces and architecture models that ensure SSOT of DT,
- Communication and connectivity to other DTs.

Power systems' DTs are used to achieve the following goals (among others) for the system: [27–30]

- Enhance monitoring capabilities,
- Increase situational awareness,
- Optimize grid performance,
- Improve reliability, efficiency, and resilience,
- Facilitate virtual testing to support operational planning decisions,
- Manage urgent situations,
- Improve maintenance and asset management,
- Re-parametrization and control,
- Reduce the risk of outages,
- Identify and anticipate potential problems,

- Achieve significant time (>90% time) cost savings in the creation and maintenance of the network model, as well as faster fault recovery.

However, implementing and utilizing DTs poses several challenges, such as:

- Data acquisition (Acquiring high-quality data from sensors and meters, especially in some cases, meters are not available in the networks),
- Data storage,
- Ensuring data privacy and security,
- Protecting against cyber attacks (as the digitization of power systems increases the potential attack surface),
- Latency,
- DTs connectivity,
- Integration with existing systems,
- Workforce training to effectively use the new system.

The big challenge for DTs is acquiring high-quality data and implementing an appropriate data architecture that enables effective data management according to specific requirements to achieve desired tasks. One of the implementing challenges is that it requires significant efforts to establish it, particularly regarding quality assurance. Additionally, employees of a company will need to be trained on the new system and must be convinced of its benefits.

4 Digital process twin in power system and AISOP project

Digital process twins (DPT) are a virtual representation of processes that can be used to identify bottlenecks and undesired events, analyze network performance, and optimize operations. DPTs can either replace human tasks (operators) or augment operators in their tasks in various potential areas such as data analysis, bottleneck identification, network performance monitoring, maintenance alerts, optimal network performance, and assisting in making decisions

DPT in power system is a digital representation of tasks performed by network operators, including tasks engineered by operators but performed by software and the secure acquisition and display of network and consumer data. It is integrated with the system and expands on the DT definition to address the specific needs of the Distribution System Operator (DSO). DPT uses data from various sources to model and simulate the behavior of system processes, enabling real-time monitoring and analysis of process performance and identification of optimization opportunities.

DPTs are used to facilitate the sharing and exchange of validated data and functions between processes and other processes or objects. This approach allows for high data consistency and transparency in the interactions between multiple processes and/or entities.

In this project, the real systems are real distribution grids in Germany and Switzerland. The DT outputs are designed to achieve project goals to support operational planning decisions for these grids. The DPT of the AISOP project will be further explained in detail in the following.

Input and output data are defined based on DPT objectives. For example, for the decision-making and control objective of an LV grid, inputs include sensor and meter data (energy consumption, generation, voltage, and current) and the grid model (node locations, equipment, devices, and cables), and restrictions of the grid. Outputs include simulation results for various scenarios (fault conditions, high renewable energy integration, and demand changes), operational planning simulation, feedback, and control commands to improve the grid condition and re-parameterization of the grid data.

In the AISOP project, the inputs data are classified into three groups based on the data sources as it is shown in Figure 5; equipment information (changes to tap changers or transformers for grid control), the grid data (model of the grid, installed PVs, and storages), measurement data (power consumption, power generation, weather data, and tariff data).

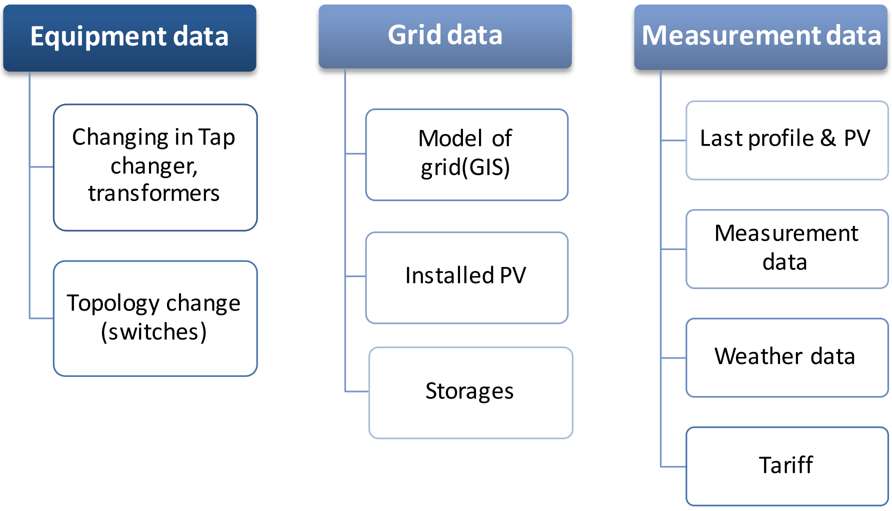

Figure 5: AISOP project classifed data

The AISOP project involves the creation of DT platforms by Logarithmo and ETH Zürch (Resim platform). The DT architecture, as shown in Figure 6, involves data validation steps (This includes ensuring data cleanliness, consistency in format, validity, and security). The DTs in this project have various functionalities, including feedback preparation, and decision-making assistance, all aimed at creating an artificial intelligence-assisted decision support system for electricity distribution system operators. One of the challenges is the interaction between these two platforms to implement an algorithm from one DT platform on another. The two developers have to ensure that the data is compatible between the two platforms. Additionally, the developers must ensure that the algorithms used by each platform are compatible with them.

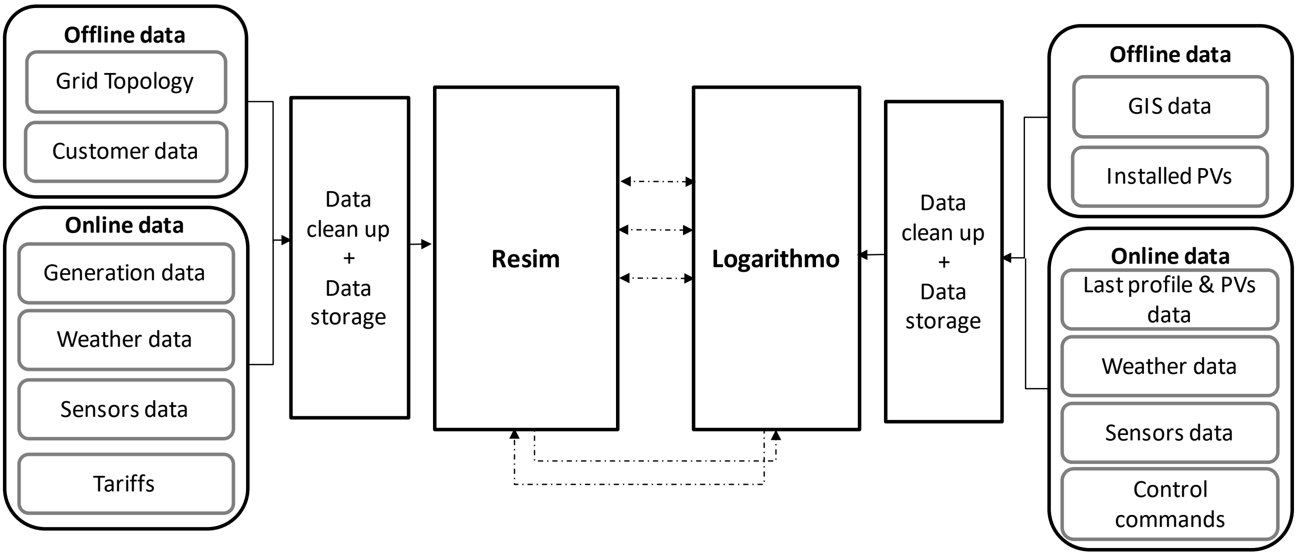

Figure 6: DTS architecture of the AISOP project

The inputs in this project are utilized to achieve its goal, which can be applied in various use cases such as grid planning, operational planning, and asset management. The goal of the project is to enhance system monitoring and situational awareness and aid operational planning by providing early warning systems.

The DPTs can be designed to do specific tasks with a high degree of autonomy, such as data preprocessing and analysis. However, in other tasks, human involvement may be necessary. Combining human knowledge and experience with the results generated by DT can yield the best outcome. For example, in decision-making for operational planning, DT can provide valuable insights and assist in identifying patterns in data that may not be obvious to the operator.

Figure 7 shows the configuration of the AISOP project, explicitly detailing the inputs for each functionality and the potential for human task reduction. As shown, nearly all functionalities can be digitized, and some functionalities have a more prominent role for DT.

In conclusion, DPT is a valuable tool for improving efficiency within the power grid by automating a multitude of human-performed tasks. Considering the potential benefits of the digital process twin in improving power grid efficiency through automation, it would be helpful for power grid operators to consider implementing this technology to streamline their processes and increase overall efficiency.

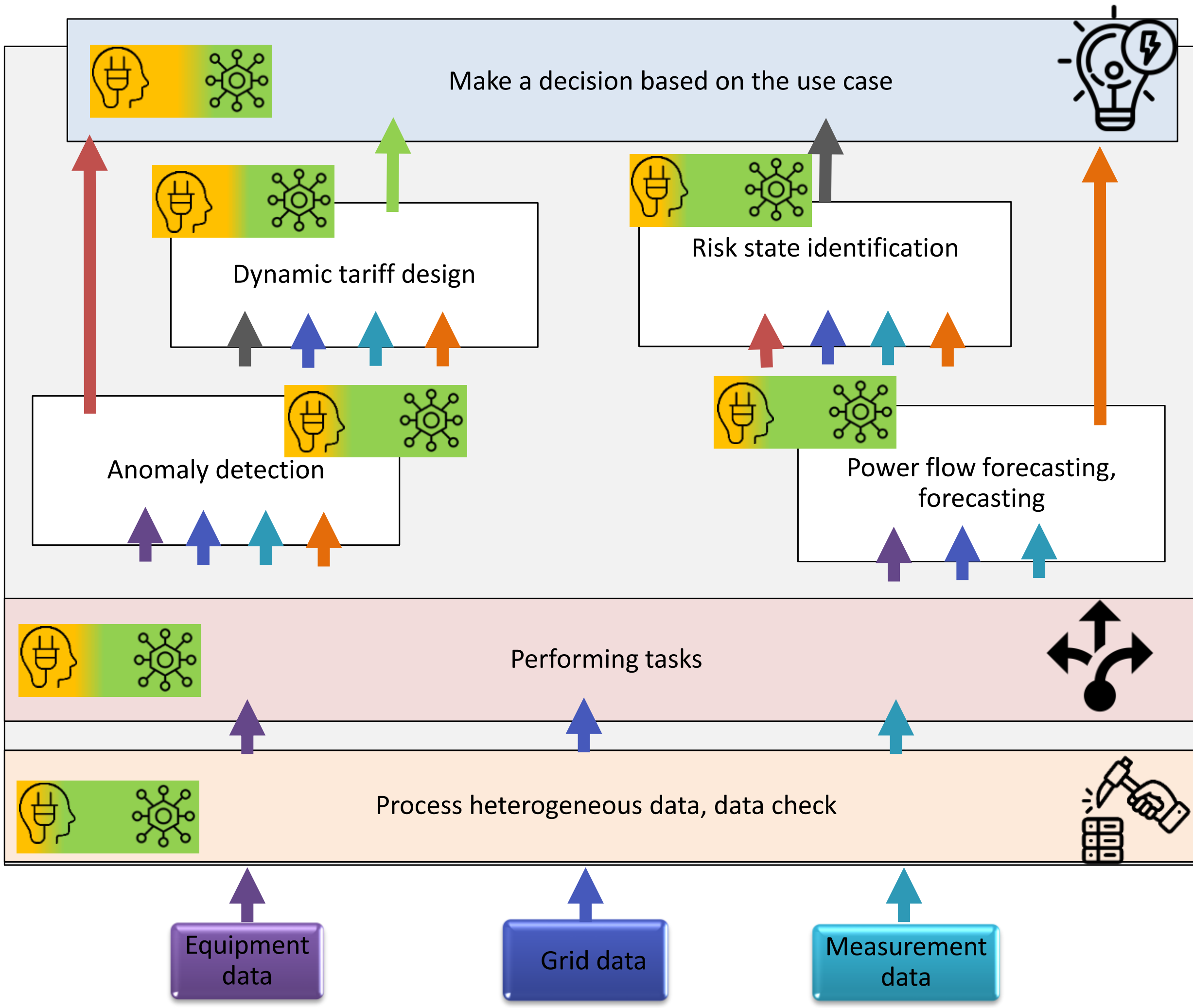

Figure 7: AISOP project configuration and the extent of human and DT roles in each functionality

5 Conclusion

DT technology has rapidly gained popularity across industries as a powerful tool for optimizing processes and improving outcomes. DTs are virtual representations of a physical system, object, or process that can be used to monitor and optimize its performance in real-time. This technology offers numerous benefits, including reduced costs, increased efficiency, and improved product quality.

DPTs are a specific application of DT technology that has emerged as a powerful tool for optimizing processes. In power systems, a DPT is a digital representation of the tasks performed by network operators. This enables real-time monitoring and analysis of process performance, allowing operators to identify potential issues before they occur. With real-time data and advanced analytics, DPTs provide valuable insights into system behavior.

The AISOP project aims to use the potential of DPTs in power systems to monitor power grid performance in real time, identify potential issues, and assist decision-making. Using DPT in power systems is an important step toward achieving a more stable, reliable, and efficient energy system.

It will be expected to see even greater adoption of DPTs, leading to further advancements in the power systems and beyond.

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