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Digital twin for energy management of demand-side flexibility

Seminar I

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Abstract

Energy systems in Europe and around the world are undergoing a transformation toward renewable and decentralised power generation. With increasing generation from renewable energy sources such as wind power and photovoltaics, there is a significant rise in generation variability. Furthermore, replacing fossil-based power plants with cleaner alternatives, which cannot be controlled in the same way, reduces the ability to control power generation. Therefore, the solution for maintaining the balance of the power system on a large scale must rely on demand-side flexibility. The digital twin is a fundamental component of modern and intelligent applications that enables the creation of a virtual representation of physical objects, phenomena, processes, or systems using data from sensors, simulations, and other sources. The twin supports applications with simulated or predicted behavior of the real physical world, such as energy consumption and generation, heat demand and occupancy of objects, available flexibility, or physical process realization under diverse conditions. The outputs of digital twins are vital for optimizing energy management and providing intelligent support to energy consumers. The main objective of the seminar is to explore the use of digital twin services for future energy management applications. The seminar provides a literature review on the concept of the digital twin, its general use, architecture and application with special attention to energy sector. Real-world household and industrial energy management of demand-side flexibility use cases have been collected, studied, and analyzed from the digital twin perspective. These use cases will illustrate and frame the scope of work on the energy-oriented digital twin and point to potential research gaps in the field. In addition, the seminar provides an overview of different modelling approaches, including machine learning, deep learning, physics-based models, and hybrid models, that can be used to create digital twins for energy systems.

Keywords: household energy management, digital twin, machine learning, deep learning

Contents

Chapter 1

Introduction

1.1 Background and significance of the study

The increasing generation from renewable energy sources (RES), such as wind power and photovoltaics (PV), leads to a significant increase in the variability of power generation. Additionally, as we replace fossil-based power plants with cleaner solutions that cannot be controlled in the same manner, demand-side flexibility (DSF) has to become the answer for power system balance at large scale. Fortunately, the electrification of transportation and heating systems, and their sector integration with the power grid, provides great potential for demand-side flexibility management (DSFM). Buildings, as the single largest energy consumer in Europe, offer a great source for DSF as they possess a large thermal mass that can be used as an energy storage, and their HVAC (Heating, Ventilation, and Air Conditioning) systems are a great source for demand-side flexibility. The transportation sector, which consumes roughly 30%[1] of the final energy in the EU, is also a good asset for demand response (DR) as electric vehicles (EVs) can be scheduled to meet the desired load profile. ICT solutions, including advances in Artificial Intelligence (AI) technologies such as deep learning (DL), provide the basis for the development of intelligent DSFM systems based on autonomous agents that adapt to consumers and control their flexible assets to maximize benefits. The emerging energy standards provide the basis for replicable uptake of DSFM solutions. However, the major barrier preventing DSFM business at a large scale is the lack of a cost-efficient software framework that provides offers modular components for the automation and control of flexible assets, allowing for easy integration and deployment. There are two main needs this software framework should address:

- Need 1 – Interoperable, secure, and cost-efficient data exchange
- Need 2 - Automated modelling and control of flexible asse

1.2 Objectives of the Seminar I research

The focus of the Seminar I is related to the Need 2. Traditionally, DR has been used for shifting/shaping peak loads to avoid bottlenecks in distribution networks, as well as, to make it easier to balance loads at the transmission system level. However, when we replace controllable power plants with RES, DSF needs to become the main balancing method. This changes the requirements for DSFM as the assets providing DSF are required to be as deterministic (i.e., their baseline, flexibility, and response to controls are predictable in

[1] https://www.odyssee-mure.eu/publications/efficiency-by-sector/overview/final-energy-consumption-by-sector.html

all conditions) as the power plants currently used for balancing. To this end, there is a need to provide innovative solutions that make it cost-efficient to build accurate and robust models of heterogeneous flexible assets in different sectors. The objective of this seminar is to explore the use of digital twin services for future energy management applications. We provide a literature review on the concept of the digital twin, its general use, and application, with a focus on machine learning and deep learning methods and algorithms used to implement the concept. We also examine the architectures and standards used to integrate the digital twin with other elements of energy management applications. Furthermore, we will collect, study, and analyze real-world household and industrial energy management of demand-side flexibility use cases from the digital twin perspective. Through these use cases, we will illustrate and frame the scope of work on the energy-oriented digital twin and point to potential research gaps in the field.

Chapter 2

Digital twin technology and its concept

2.1 What is a Digital Twin?

Despite the multiple definitions of the Digital Twin across academic and industrial literature [Yu et al., 2022], the general definition of the Digital Twin can be summarized as: *"A Digital Twin is a dynamic and self-evolving digital/virtual model or simulation of a real-life subject or object (part, machine, process, human, etc.) representing the exact state of its physical twin at any given point of time via exchanging the real-time data as well as keeping the historical data. It is not just the Digital Twin which mimics its physical twin but any changes in the Digital Twin are mimicked by the physical twin too."*[Singh et al., 2021]

2.2 Brief History of Digital Twin

The twin concept has been known since at least the 1960s. For the first time, NASA's Apollo program utilized twins. NASA constructed two identical spacecraft; the spacecraft that remained on Earth was referred to as the twin. The twin can be described as a prototype that simulates behavior in real time by replicating actual operation conditions. Before the mission began, the twin served as a training tool and during the mission, the objective was to replicate as closely as possible the flight conditions of the spacecraft's twin. The twin was then used to simulate various circumstances on earth in order to assist astronauts in making critical decisions. In the approach utilized by the Apollo program of NASA, the twin was implemented in hardware and not in digital form [Enders and Hoßbach, 2019]. Michael Grieves then introduced his concept of "virtual, digital equivalent to a physical product" or "Mirrored Spaces Model" in 2003 at the University of Michigan's Executive Course on Product Lifecycle Management[1] [Grieves, 2016]. The name 'Digital Twin' (DT) first appears in NASA's draft version of the technological roadmap in 2010. NASA was the first association to forge the definition of DT; it was described as "an integrated multi-physics, multi-scale, probabilistic simulation of a vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its flying twin" [Singh et al., 2021]. Since the emergence of the Industry of the Future or

[1] Product Lifecycle Management (PLM) is an integrated, information driven approach to all aspects of a product's life from its design inception, through its manufacture, deployment, services and maintenance, and eventually retirement . Essentially it refers to the handling of a good as it moves through the typical stages of its product life and PLM systems help organizations to cope with the increasing complexity and engineering challenges of developing new products.

Smart Factory around 2014, the availability of different technologies such as IioT, AI, and Cloud computing has made it possible to create real-time virtual representations for all industrial areas. This has expanded the usage of DT from just simulation to optimization, prediction, and decision support. Michael Grieves (2014) has proposed DT as a dynamic virtual model for all industrial activities. Additionally, the DT has been listed by Gartner as one of the top 10 key technologies for the next decade since 2017.

2.3 Digital Twin Architecture

The use of Digital Twin technology differs across different domains based on their unique information nature and requirements. A general DT architecture is composed of the following three elements (see Figure 2.1):

- Physical-world entity or process;
- the digital twin (virtual representation) in software form; and
- data that connects the first two elements together through communication services.

These elements incorporate various components, such as sensors for data collection, edge processing, data security, the digital twin itself, data processing enabled by AI, ML, big data, and communication interfaces. User-friendly data visualization is also an essential part of the DT architecture [Botín-Sanabria et al., 2022].

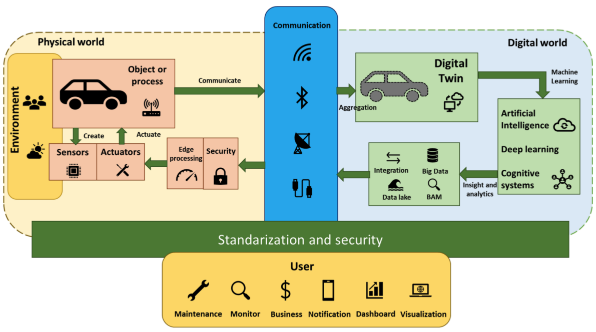

Figure 2.1: Elements of the Digital Twin - *"The physical world is composed of the physical object or process, sensors, actuators and processing capabilities. The digital world is composed of the digital twin itself, machine learning and data processing capabilities and databases. Both are connected in the communication element where several protocols and interfaces are available such as WiFi, Bluetooth and wire connections. For the user, this architecture allows constant monitoring and visualization."*, [Botín-Sanabria et al., 2022]

2.3.1 Types of Digital Twin

There are three types of digital twins:

- *Digital twin instance (DTI)*: This type of digital twin represents its physical counterpart throughout its entire lifecycle, continuously monitoring the state of the physical twin and adapting to any changes or evolution. DTIs are used to validate the expected behavior and performance of a product or object, but don't necessarily intervene or make any changes to the physical twin.

- *Digital twin prototype (DTP)*: DTPs are used in manufacturing and production processes and gather valuable information and characteristics about the physical twin, including computer aided designs (CADs) and drawings. They are able to simulate manufacturing scenarios, perform validation testing and quality control, and reduce production costs and operational time by identifying flaws or possible risks before production.
- *Performance digital twin (PDT)*: PDTs monitor, aggregate, and analyze data from products in real and unpredictable conditions. They are able to process the information being monitored from the physical counterpart and generate actionable data that can be used for design optimization, maintenance and improving its performance[2]

2.3.2 Integration Levels

The proposed integration levels are arranged in ascending order, with digital models being the least integrated and digital twins being the most integrated [Botín-Sanabria et al., 2022].

- *Digital model*: In its basic concept, the digital model does not integrate any automatic information flow from the physical world to the virtual world, which means that the virtual and physical world are not automatically connected, so any change must be reflected through manual modification.
- *Digital shadow*: The digital shadow integrates unidirectional automatic information flow from the physical world to the virtual world. This is best represented by a system with sensors that measure information from the physical model and transfer signals to the virtual model.
- *Digital twin*: A fully integrated twin where the virtual and physical world interact bidirectionally. This means that information flows automatically to and from each world. In this case, information flowing from the virtual world will be useful to perform changes in the physical model or to instruct actuators to perform an operation. Similarly, data from the physical twin may influence the virtual twin automatically in such a way that the digital twin accurately represents the current state and the evolution of its physical counterpart.

2.4 Digital Twin Literature Review

The Digital Twin concept has become increasingly popular in both research and practice, leading to a significant growth in scientific publications and practical applications within the past years. Scientists have made significant contributions to Digital Twin research, developing conceptual approaches such as implementation frameworks and investigating use cases. However, there is a lack of cumulative research in the current Digital Twin literature, with a heavy emphasis on the manufacturing and aircraft industries in existing literature reviews [Enders and Hoßbach, 2019].
Using the latest research, we will briefly discuss Digital Twin applications and introduce a classification scheme to help understand and describe the development and application of Digital Twin.
The paper [Newrzella et al., 2021], describes several models that have been developed to classify existing applications of the Digital Twin concept. These models are useful

[2]While both DTIs and PDTs monitor the behavior of physical twins, the key difference is that a DTI is a passive observer while a PDT actively intervenes to optimize the performance of the physical twin.

for developers to learn from similar applications and develop new applications at lower risk. The purpose of a model is also defined by the authors and achieved by grouping Digital Twin applications into different categories, often referred to as dimensions. Here we will introduce the classification model described by Enders and Hoßbach, 2019. In order to categorize Digital Twin applications across industries, the same study analyzed and conceptualized 87 application based papers and identified six common dimensions. We will describe each dimension (category):

industrial sector - describes the type of outcome produced by a Digital Twin. The subcategories are: *manufacturing, aerospace, energy, automotive, marine, petroleum, agricultural, healthcare, public sector, and mining.*

purpose - describes the type Digital Twin application. There are three subcategories: *Simulation, Monitoring and Control*

physical reference object - physical counterpart of a Digital Twin. The following four subcategories of physical objects have been identified: *manufacturing asset, product, human and infrastructure*

completeness - number of features that DT includes, for example geometry, temperature, humidity, or power consumption. Two subcategories: *applications with one to three features and applications with four or more features.*

creation time - describes whether a Digital Twin is created before or after its physical counterpart. Two subcategories: *Digital Twin prototype - created before the physical counterpart, and Digital Twin instance - bound to a physical object.*

connection - describes the forms of the connection between the physical object and DT. There are three subcategories: *no connection, one-directional, and bi-directional.*

Table 2.2 presents a summary of the six dimensions that have been identified in the described classification system along with their corresponding characteristics.

Dimension	Characteristics (Number of occurrences in parenthesis)									
Industrial Sector	Manufacturing (54)	Aerospace (5)	Energy (4)	Automotive (3)	Marine (3)	Petroleum (2)	Agricultural (2)	Healthcare (2)	Public Sector (1)	Mining (1)
Purpose	Simulation (47)		Monitoring (32)			Control (23)				
Physical Reference Object	Manufacturing Asset (45)		Product (27)		Human (2)		Infrastructure (2)			
Completeness	1-3 Features (57)			>4 Features (30)						
Creation Time	Before Physical Twin creation (11)			After Physical Twin creation (76)						
Connection	No Connection (23)		One-directional (39)			Bi-directional (25)				

Figure 2.2: Dimensions of Digital Twin applications by the classification model described by Enders and Hoßbach, 2019.

2.5 Digital Twin for Energy sector

In this section we will provide a brief explanation of Digital Twin applications and use cases within the energy sector, as our research is focused on this domain. In this context, a recent study [Watkins and McKendry, 2015] aimed to identify and evaluate the use cases of Digital Twins in the energy sector. The study conducted a thorough literature review to establish a framework of criteria and examples of existing Digital Twin applications in the energy sector. This review provides insights into the distribution of publications on

Digital Twin technology in the energy sector. The Figure 2.4 illustrates the distribution of publications across different research areas. Through this review, the authors were also able to identify three main areas of Digital Twin applications in the energy sector: *Energy Production, Energy Consumption, Energy Storage.* Each can be further divided into subcategories (see Figure 2.3). Here we describe the categories of our interest:

Energy production - Digital twin technology is seen as a necessary future step for optimal design and operation of large generators in fossil fuel power systems, renewable power systems, and nuclear power systems. There have been studies on digital twins for renewable power systems, but fewer studies on digital twins for nuclear power systems.

Energy consumption in industry - Digital twin technology has been successfully applied in various industries to monitor, analyze, and optimize energy consumption, achieve production and energy control optimization, increase safety and energy-saving operations, and improve system sustainability.

Energy consumption in transportation - Digital twin technology is used in various industries, including transportation, to model and simulate integrated systems and optimize energy consumption. It has been used in the automotive, railway, and aviation sectors to improve performance, test different energy management strategies, and simulate real-world scenarios.

Energy consumption for buildings - Digital twin technology has been used to simulate the energy performance of different types of buildings such as residential, commercial, industrial, etc. and predict their energy consumption patterns. The technology has been applied to model building systems such as HVAC as well as to simulate building envelope components in order optimize the energy consumption.

Energy storage - Digital twin technology has been used to improve the management of energy ecosystems, enhance computational power and data storage capability, and predict performance in the energy storage industry. Studies have developed digital twins for different types of batteries, thermal energy storage systems, membrane fuel cells, hydro and wind power plants, and smart substations.

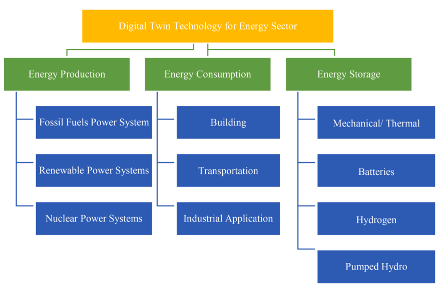

Figure 2.3: Digital Twin Technology for Energy Sector Applications [Watkins and McKendry, 2015].

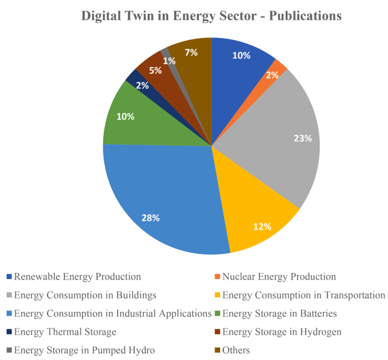

Figure 2.4: Publications of Digital Twin in the Energy Sector [Watkins and McKendry, 2015].

Chapter 3

Energy Management Challenges and Use Cases

3.1 Overview of Challenges to be Addressed

In our research, we have identified a set of challenges that are critical in managing energy systems. We will briefly explain the challenges below, as well as elaborate on the role of digital twin technology in addressing these challenges.

- *Helping consumers and prosumers manage their energy systems in challenging demand side flexibility environment*

  The first challenge is about managing energy demand in a flexible way. Demand side flexibility (DFS) refers to the ability to adjust energy consumption patterns in response to changes in energy supply or price. In this challenge, the focus is on helping consumers and prosumers (those who both consume and produce energy) to manage their energy systems in a way that is both efficient and cost-effective. So, particularly the problem we aim to solve is the issue of balancing energy supply and demand in real-time. For example, in a scenario where there is excess energy supply, the proposed system (i.e. implemented solution) can help consumers and prosumers adjust their energy consumption patterns to take advantage of the surplus energy, or to store the energy for later use. On the other hand, in a scenario where there is a shortage of energy, the proposed system can help consumers and prosumers reduce their energy consumption by adjusting their energy consumption patterns, or by using energy storage systems.

- *Developing energy management solutions for plug-and-play use in managing demand side flexibility*

  The second challenge focuses on developing energy management solutions that can be used to manage demand side flexibility in a plug-and-play manner. One of the main problems that is to be addressed is the lack of scalability and interoperability of existing solutions. For example, a solution that works well for a household may not be suitable for an industrial facility due to different installation types and energy consumption patterns. Therefore, the goal here is to develop a flexible solution that can be adapted to different types of installations while still being user-friendly and easy to implement. By doing so, it can help reduce the complexity of managing demand side flexibility and facilitate the integration of renewable energy sources.

- *Contribution to general network balancing, stability and power quality*

The third challenge is about how energy management solutions can contribute to general network balancing, stability, and power quality. Energy systems are complex, and changes in one part of the system can have a ripple effect on other parts. One of the problems is the issue of network congestion. For example, during periods of high demand, the energy grid may become congested, leading to power outages or voltage fluctuations. The objective of this challenge is to develop solutions that can help to balance energy supply and demand, reduce the risk of network congestion, and improve power quality.

It is worth noting that these challenges are part of the Horizon Projects, which aim to address the issues related to demand side flexibility and network balancing through the implementation and development of the digital twin technology. The projects are:

- iFlex (iFlex, 2023)
- Resonance (Resonance, 2023)

Digital twin technology can play a critical role in addressing the outlined challenges. By creating a virtual model of the energy system, digital twin can provide real-time insights into energy production, consumption, and storage. Furthermore, digital twin model can be used to simulate different scenarios and test the effectiveness of different energy management strategies. In addition, digital twin technology can enable the integration of renewable energy sources, such as solar or wind power, by providing insights into their production and output.
By modeling the energy system as a whole, digital twin is able to:

- Provide insights that can be used to optimize energy consumption and reduce waste, leading to significant cost savings and improved energy efficiency.
- Identify potential problems before they occur and ensure that the energy system remains stable and reliable.
- Help identify potential areas of congestion or imbalance and optimize energy distribution to ensure a stable and reliable energy supply.

3.2 Use Cases

In this section we will provide an overview of the various Use Cases for the Digital Twin, which are all highly relevant to our research. While each Use Case requires a unique approach, the ultimate goal is to develop a general solution that can address and solve all of them. The use cases below are typical for a household with the devices such as: HVAC systems, white goods, solar panels, etc.:

- *Self-optimisation*: This refers to the ability of the digital twin to optimize the consumption of energy produced by the prosumer's own energy production systems, such as solar panels or wind turbines. The digital twin can analyze the energy production and consumption data in real-time to determine the optimal time to use energy from the local production and minimize the need for energy from the grid.
- *Balance consumption with storage*: The digital twin can manage energy storage systems, such as the physical house of the household to balance consumption with production. By analyzing real-time energy data, the digital twin can determine the optimal time to store energy for later use or to draw energy from storage to reduce energy consumption during peak times. This use case can help reduce costs, improve efficiency, and lower carbon footprint.

- *Manage tariff changes - implicit demand response*: The digital twin enables simulation of the real household which can be used to optimise the consumption according to the tariff changes with an aim to minimise consumption costs and help the consumer to interact disregard with its energy devices and system.
- *Participate in DR programs - explicit demand response*: The digital twin can also participate in demand response (DR) programs. DR programs are designed to incentives consumers to reduce energy consumption during peak periods. By participating in DR programs, the digital twin can help balance the grid and reduce the need for expensive peaker plants.
- *Use network battery for DSFM*: The digital twin can use network batteries to help manage demand side flexibility. By analyzing energy production and consumption data in real-time, the digital twin can determine when to draw energy from the network battery to reduce consumption during peak times, or to feed energy back into the grid during periods of high demand.
- *Use households' flexibility to balance network requirements*: The digital twin can use the flexibility of households to balance network requirements. For example, by analyzing energy consumption data in real-time, the digital twin can determine which households have the capacity to reduce energy consumption during peak times and adjust energy consumption patterns accordingly. This use case can help reduce the need for expensive infrastructure upgrades and ensure a stable supply of energy.

Chapter 4

Digital Twin Applications in Energy Management

4.1 Analyzing the Use Case of Balance Consumption with Storage

In the context of balancing energy consumption with storage, the digital twin can play a critical role in managing energy storage systems such as heat storage or batteries. The digital twin will be developed in such a way that can analyze real-time energy data from various sources, such as power grid, HVAC systems, storage boilers, white goods, generation/PV model, to provide an accurate predictions of future energy consumption patterns and determine the optimal time to store energy for later use or to draw energy from storage to reduce energy consumption during peak times. The challenge here is to maintain a balance between energy supply and demand, especially during peak hours when energy consumption is high. In this context we will provide three scenarios that illustrate problematic scenarios and how digital twin addresses them:

- *First problem*: household that is equipped with solar photovoltaic (PV) that produces most of its electricity needs throughout the day. However, during a cloudy day or a sudden drop in PV generation due to weather conditions, the household's energy demand exceeds its power generation capacity. In this case, the household can rely on the electrical grid to supply the additional electricity needed to meet its energy demand. However, sudden increases in demand for electricity from households can cause instability of the grid if the grid is not equipped to handle the surge in demand. In addition, relying solely on the electrical grid for backup power can be costly, especially during peak demand periods when electricity prices are high.

- *Second problem*: building equipped with a large rooftop solar photovoltaic (PV) system that is generating more electricity than the building is currently consuming. The excess electricity is fed back into the electrical grid through a net metering agreement with the local utility company, which allows the building owner to receive credits for the excess electricity produced. However, on a particularly sunny day, the PV system is generating more electricity than the building can consume, and the excess electricity being fed into the grid causes an imbalance in the electrical grid. This is because the electrical grid was not designed to handle large amounts of intermittent and variable generation from renewable sources, and sudden fluctuations in generation can cause frequency and voltage fluctuations, leading to instability and potential outages. To prevent this imbalance, the utility company may need to curtail the excess electricity being fed back into the grid by reducing the amount of electricity the building owner can export, or by implementing other measures such as demand response or energy storage. However, this can lead to a loss of potential revenue for the building owner and limit the use of renewable energy sources.

- *Third problem*: household, but now with installed heat pump that is connected to the electrical grid. During a cold winter day, the heat pump is working at full capacity to keep the house warm. Suddenly, the power generation from the wind turbines, which is the primary source of electricity in the area, drops due to a wind speed decrease. This leads to an imbalance in the power grid as the electricity demand from the households is still high. Without a solution to balance the power grid, the grid operator may have to resort to load shedding or rolling blackouts to prevent a blackout or damage to the grid.

- *Solution*: All three scenarios can be avoided with demand-side flexibility and with the use of digital twin technology. In the first example an energy management system, can automatically adjust the household's energy consumption by reducing energy usage during periods of high demand or by using stored energy from batteries during peak demand periods. This helps to reduce the need for backup power from the grid and ensures a stable energy supply for the household. The role of the digital twin is to learn or predict and optimize the balance between the electricity demand and supply. The same goes for the second and third example, by implementing a digital twin, the energy management system of the household can predict and optimize the use of the heat pump based on the current grid conditions. For instance, if the digital twin predicts a grid imbalance due to the drop in wind turbine generation, it can adjust the heat pump settings to reduce electricity consumption for a certain period. This can help to stabilize the power grid, prevent outages and reduce electricity costs for the household.

4.2 Energy Management for Carbon Footprint Reduction

Another critical challenge in managing energy storage systems is to decrease energy consumption during peak hours when the CO_2 emission is high. Electricity generation is a significant contributor to greenhouse gas emissions, and it is essential to reduce energy consumption during peak hours when electricity is generated from high-carbon sources. By analyzing real-time energy data, the digital twin can determine when energy consumption should be reduced to lower CO_2 emissions. For example, if a high-carbon source is used during peak hours to generate electricity, the digital twin can recommend reducing energy consumption during these times, resulting in lower CO_2 emissions. Therefore, the digital twin can help reduce the carbon footprint and improve the overall environmental impact of energy consumption. This is shown in Figure 4.1. Essentially, what we are trying to achieve is to minimize the integral:

$$\int CO_2 \cdot E \, dt$$

where CO_2 is the intensity of the Carbon emission, E is the electricity demand.

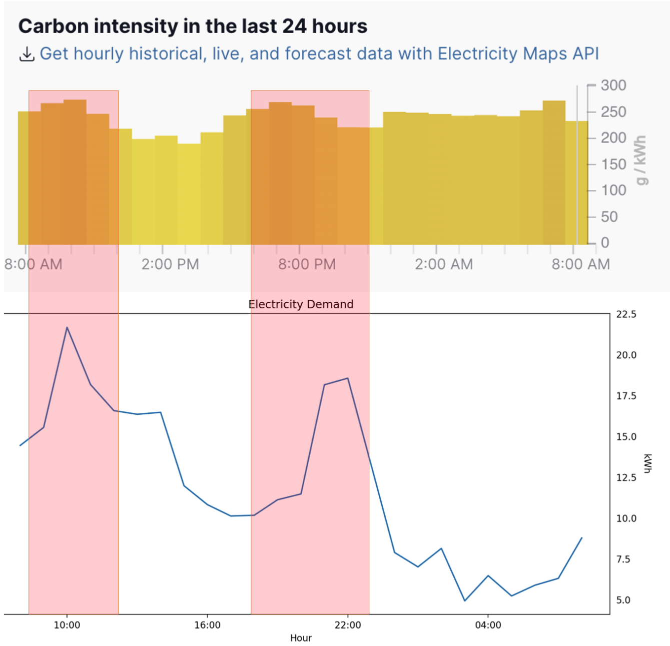

Figure 4.1: Carbon intensity for Slovenia in 24 hours and electricity demand of one Slovenian TP. We observe the alignment of the peaks for carbon emission and electricity demand. Digital Twin learns the distribution i.e. peaks of carbon emission and provides a energy consumption pattern that minimizes the carbon emission, which means it suggests moving the consumption peaks outside the range of high CO_2 emission. The CO_2 emission data is taken from the Electricy-Maps, 2023.

By analyzing the Use Cases we come to general conclusions for the Digital Twin role:

- Digital twin can model various factors that affect energy consumption, such as occupancy patterns and weather conditions, to predict future energy demand accurately. This can help energy managers to plan and optimize energy consumption more efficiently.
- The digital twin can be designed to be scalable, so that it can be used to model energy systems for individual houses, buildings, or even entire neighborhoods. The energy data can be integrated into the digital twin in real-time, so that it can be used to optimize energy consumption patterns on an ongoing basis.
- Overall, the digital twin can help to balance consumption with production, reduce energy costs, improve efficiency, and lower carbon footprint.

Chapter 5

Digital Twin Modelling

5.1 Conceptual Placement of Digital Twin

It is important to clarify the conceptual placement of the Digital Twin in the framework of the energy management solution being proposed. Although we referred to the Digital Twin as the element responsible for optimization in our explanation of the Use Cases, this is not the case. The Digital Twin is responsible for providing predictions of energy consumption, but it is not involved in the optimization process itself. Rather, a separate, unique optimization element is responsible for optimizing i.e. determining the best possible solution for energy consumption.
Roughly speaking the framework of the energy management solution consists of three main elements:

- *User*: in the context of the solution's framework refers to a household that has various devices and resources, each with its own adjustable parameters. These resources could include appliances, heating and cooling systems, lighting, and more. The household also has physical properties and its own preferences, which play a role in determining how the resources are used.

- *Digital Twin*: a digital model of the user that takes into account all of these aspects, including the devices and resources, physical properties, and preferences. Using this model, the digital twin can provide predictions and simulations about how the resources will behave in the future, based on changes to the resource's adjustable parameters and external conditions, such as the weather.

- *Optimization element*: an element that is responsible for taking the predictions and simulations provided by the digital twin and creating an optimization plan for the energy consumption pattern. This optimization plan is prepared according to the space of resource adjustable parameters, external conditions, and optimization criteria.

In summary, the Digital Twin and optimization element have unique roles in the proposed energy management solution. The Digital Twin provides predictions and simulations, while the optimization element performs the actual optimization of the energy consumption pattern. It is important to differentiate between these components to avoid any confusion regarding their roles and responsibilities in the solution.

Now, based on the provided types of Digital Twin (see Section 2.2) and Digital Twin classification (see Section 2.3 and Section 2.4) we conclude that we will be developing a DTI (Digital Twin Instance) for applications in Energy consumption for buildings sector.

As for classifying our Digital Twin model we have the following: *industrial sector: energ; purpose: simulation; physical reference object:infrastructure; completeness: undefined; creation timee: Digital Twin instance (DTI); connection: one-directional.*

5.2 Approaches and methods for modelling Digital Twin

The digital twin is a complex system comprised of multiple components and resources that vary depending on the specific scenario or system being modeled. For instance, when building a digital twin of a household, it is required to create models for each resource that is relevant to the system. Such systems can be:

- HVAC systems
- solar panels (load of production)
- EV charging
- non-flexible baseline load
- white goods

Figure 5.1: Machine Learning Libraries, [fireblazeaischool, 2023]

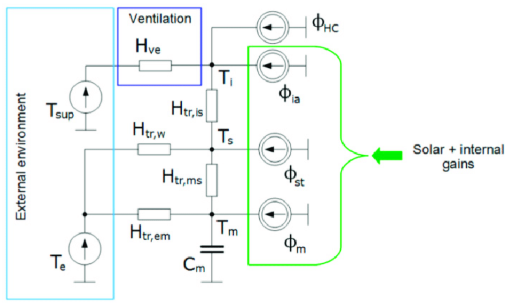

Figure 5.2: The 5R1C thermal network model of a building zone from EN ISO 13790, [Michalak, 2022].

In addition to modeling individual resources, it is important to create models for indoor temperature and occupancy. The indoor temperature model will help in predicting the behavior of the heating and cooling systems and optimizing their usage, while the occupancy model will predict the number of people in the house, which is important for controlling the energy consumption of various appliances and systems.
Each of these components requires a specific approach or method to ensure an accurate representation of its behavior in the digital twin. Therefore, it is crucial to understand the various approaches and methods available for modeling the different components in a digital twin. There are three main approaches to modelling the components or eventually the digital twin:

- *Machine learning/Deep learning models*: This approach involves utilizing machine learning libraries and frameworks, such as scikit-learn, TensorFlow, or PyTorch, to learn patterns and make predictions from data (Figure 5.1). These models can be used for most of the resources and work well when we have a good amount of data. However, when we start to control more complicated systems like the HVAC system, it becomes difficult to collect data from all possible situations. In this case, it makes sense to bring in some physics to support the ML model.

- *Physics-based models*: a type of mathematical model that uses fundamental physical principles and equations to describe the behavior of a system. This approach involves developing a model based on the underlying physical processes governing the system's behavior. For instance, in the context of building energy modeling, an RC (Resistor-Capacitor) model can be used to describe the thermal dynamics of a building (see Figure 5.2). The model considers the thermal mass of the building elements (such as walls, floors, and ceilings) and their thermal resistance (such as insulation), and calculates the rate at which heat flows through the building based on temperature differences. The model also takes into account external factors such as outdoor temperature and solar radiation. These models work quite well in all situations, especially for the HVAC system part. However, it's difficult to fully capture the phenomena being modeled, and high-detail physics models require a lot of work and are difficult to replicate.

- *Hybrid models (ML and physics-based)*: These models combine the strengths of both approaches and result in accurate, robust, and easily replicable models. There are more ways on how to approach to hybrid modelling:

  - ML based models that are modified by physics-inspired RC models.
  - Physics-based models that are modified by ML model.
  - Neural differential equations - enocoding differential equations as layers and training the model end-to-end.

Chapter 6

Conclusions

While the Digital Twin is a powerful tool for predicting energy consumption patterns and optimizing demand-side flexibility, there are several challenges that must be addressed and overcome in the modeling process. One of the primary challenges is determining the most effective approach to modelling the Digital Twin. This could involve machine learning models, physics-based models or most probably hybrid models. Additionally, selecting the appropriate models for each individual resource is a challenge itself for more reasons: different models may be required for different components (HVAC systems, solar panels, EV charging, white goods, etc.) and building a machine learning or deep learning model for complex systems in the early stages is difficult due to the shortage of available data. Another challenge is generalizing the Digital Twin model, and one approach that should be considered is Neural Differential Equations, which allows for fitting the model without measuring the parameters of each facility (household, building, etc.). The results of our research on addressing the challenges in modelling the Digital Twin in the energy sector will have a significant impact on achieving sustainable and efficient energy management practices. By developing effective models for predicting energy consumption patterns and optimizing demand-side flexibility, we can reduce energy waste and increase the efficiency of energy systems. This, in turn, can help reduce greenhouse gas emissions. Furthermore, our findings will serve as the basis for future research and development of Digital Twin Instances for specific applications in the energy sector, leading to more accurate and efficient energy management practices.

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