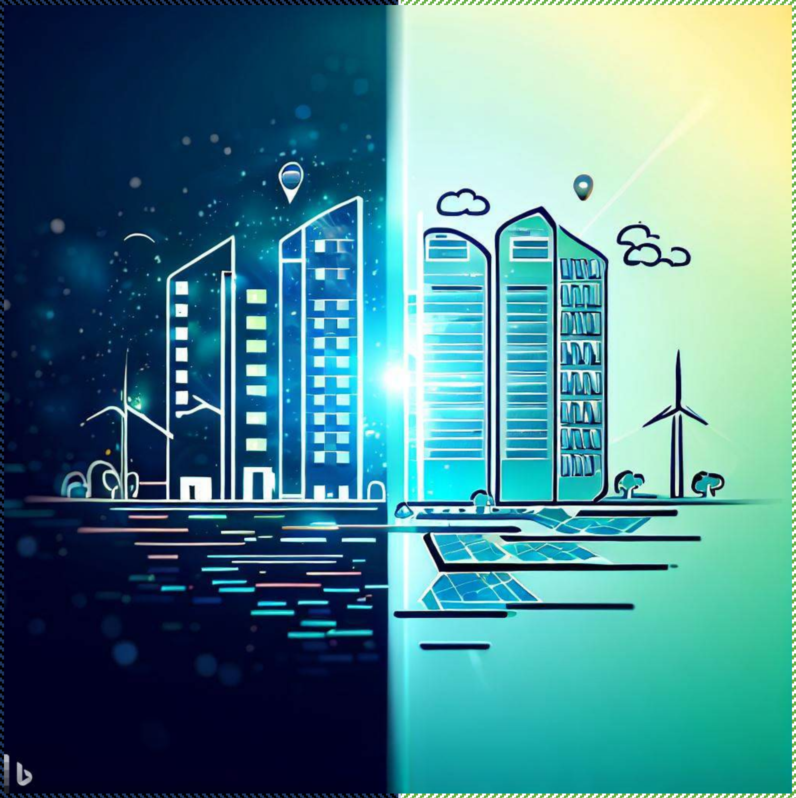

Data-driven green building modeling for energy balancing

PhD Research Portfolio

Promotor:

Prof.dr.ir. Peter van Oosterom

Daily Supervisor:

Dr. Azarakhsh Rafiee, Dr. ing Thaleia Konstantinou

Jun 2023 | Amin Jalilzadeh

A.jalilzadeh@tudelft.nl

Department of Architectural Engineering +Technology

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Summary

Our research aims to leverage Digital Twins (DTs) in creating sustainable urban environments and Positive Energy Districts (PEDs), enhancing energy efficiency, integrating renewable energy sources (RESs), and managing energy in buildings and districts for a more sustainable and low-carbon future by addressing the following objectives:

- Establishing a (Spatial) Data/Information Infrastructure that gathers/manages/disseminates the essential information to model and manage energy within buildings and districts.
- Developing data-driven models for predicting energy demand in buildings, taking into consideration factors such as building characteristics and weather conditions.
- Expanding the energy demand model from a building level to a district level.
- Determining the optimal action sequence regarding energy efficiency, enhancing energy generation from RESs, and energy storing/sharing between buildings as a response to buildings' energy requirement in a district.
- Undertaking spatial analysis to investigate the potential of districts in integrating RESs.
- Analysing scenarios and applying multi-objective optimization algorithms at the building level to enhance Energy Efficiency (EE) and reduce external energy demand.
- Analysing scenarios and applying multi-objective optimization algorithms at the district level for energy balancing between buildings.
- The project aims to be designed with a strong focus on practical applicability, aiming for solutions that can be readily implemented in the real world to optimize energy management in buildings and districts.
- The horizon for this research is for 2030 and 2050, providing solutions for balancing energy and minimizing burden on the electric grid using the DT.

Keywords: *GIS, Digital Twin, Positive Energy Districts, Energy transition, Data-Driven, Data Infrastructure*

1. Introduction:

Producing and consuming energy from fossil fuels contributes to the emission of CO2 into the atmosphere which has a significant impact on global warming and climate change (Rolnick et al., 2022). A global effort was made by countries to reach an agreement to tackle climate change before it transforms our planet irreversibly (Economidou et al., 2020). These strategies prioritize enhancing Energy Efficiency (EE) in buildings and increasing the generation of Renewable Energy Sources (RESs) as essential measures in climate change mitigation (Harvey, 2009).

Cities are responsible for consuming about two-thirds of energy consumption and emitting more than 70% of GHGs. Also, it is estimated that the building section accounted for more than one-third of the energy consumption (Umbark, Alghoul, & Dekam, 2020). With half the global population already urbanized, and expected to rise to 70% by 2050, we anticipate more buildings, higher energy demand, and increased GHG emissions (Fausing, 2020).

In this context, integrating RESs into the urban grid stands as a key solution. This shift towards hybrid energy systems from single-source systems offers hope. However, Integrating RESs into the electricity grid can disturb stability of the grid since RESs such as wind and solar depend on weather conditions and are not stable in producing energy. Therefore, to facilitate integrating RESs in grid, it is vitally important to create a balance between energy demand and supply (Ekren & Ekren, 2010).

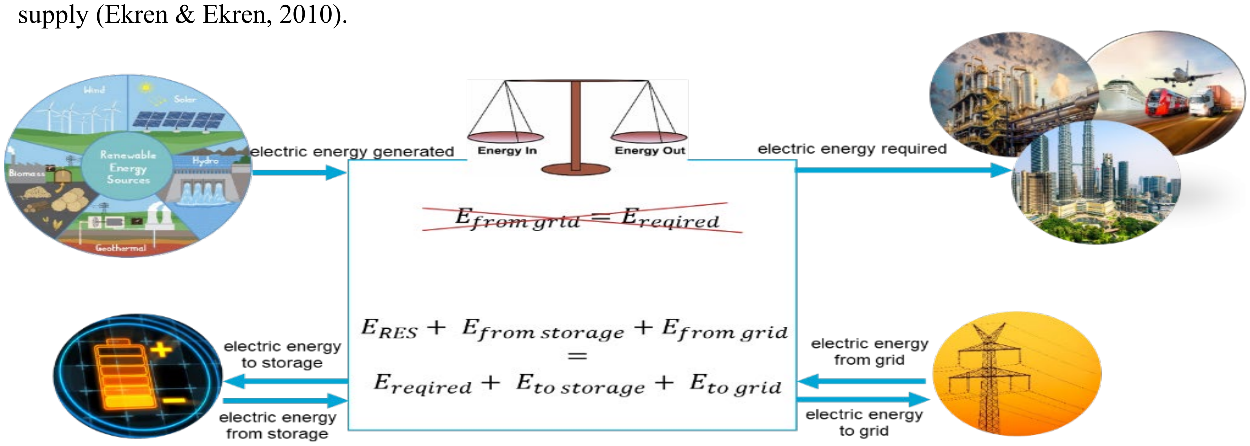


Figure 1. System operation logic. Adopted from (Aruta et al., 2023).

To manage this balance, techniques like Energy Storage Systems (Voorden, Elizondo, Paap, Verboomen, & Sluis, 2007), Demand Response Programs (Chen & Liu, 2017), and advanced grid management systems have been developed (Rathor & Saxena, 2020). As depicted in Fig. 1, as the complexity of maintaining this balance escalates, the need for novel insights and tools to aid decision-makers rise.

Positive Energy Districts (PEDs) have emerged as a response to the growing energy demand of buildings and the complexities of RES integration. PEDs are characterized as energy-efficient and energy-flexible urban zones with an excess of renewable energy production and minimum greenhouse gas emissions (Magrini, Lentini, Cuman, Bodrato, & Marenco, 2020).

Developing PEDs has a group of challenges, such as social, technological, spatial planning, regulations, legal matters, and economic factors (Krangsås et al., 2021). This research will focus more on technical aspects of PEDs. The integration of digital methods can be a solution to the challenges in PEDs (Zhang, Shen, et al., 2021a). Since DT can collect and analyse massive amounts of data (energy usage, occupancies patterns, weather data, etc.), provide real-time monitoring and predictions, and conduct various scenarios to monitor and predict energy production/consumption/distribution, operation optimization, energy security, decision-making for energy management, and balancing the demand and supply. These features make DT a powerful tool for decision-makers seeking managing energy within/between buildings (Rolnick et al., 2022).

The successful management of energy and implementation of PEDs needs massive data. DTs serve data from multiple sources that can create dynamic digital models that can return a virtual mirror of reality at any time. Datasets can be created, collected, processed, managed, stored, and visualized in various ways with different coordinate systems, formats, models, and standards. The prevailing issue in this field stems from the absence of a structured data infrastructure capable of integrating and exchanging a variety of datasets. This problem becomes more pronounced when dealing with energy-related datasets in the built environment, where the absence of standardization and unification impedes efficient data utilization and exchange. this issue underscores the necessity for data infrastructure.

Subsequently, to establish a balance between energy demand and supply, we need to comprehend the demand requirements, identify the necessary measures to meet these demands and strategize to prioritize these measures based on the concept of PED.

Few studies have attempted to develop models for predicting energy demand of buildings based on historical datasets of energy performance (Guo, Zhao, Wang, Shan, & Gong, 2021; Rahman, Srikumar, & Smith, 2018; Yang, Li, & Xun, 2019), weather conditions (Anđelković & Bajatović, 2020; Sendra-Arranz & Gutiérrez, 2020), building interdependency (Hu et al., 2022), occupant behaviour (Fu & Miller, 2022) and electricity price (Guo et al., 2021) using white box, grey box and black box models. The problem that arises from the current research landscape is the inadequacy of extending the energy demand models from individual buildings to encompass entire districts. Given the popularity and proven efficiency of data-driven algorithms, these methodologies can be effectively employed to forecast the energy demand of buildings, with the potential to scale this approach to district-level.

The following challenge that arises in this research involves determining the optimal actions regarding meeting energy demand based on the concept of PEDs, with a focus on increasing EE of buildings, enhancing energy generation from RESs, and energy storing/sharing between buildings.

Improving the EE of buildings is a substantial aspect to reduce energy demand of buildings. This research aims to identify intervention scenarios and algorithms to prioritize them to be applied to optimize energy performance at both building and district levels. Few researchers developed strategies to increase EE of buildings. For example, Dirutigliano, Delmastro, and Torabi Moghadam (2018) used Preference Ranking Organization Method for Enrichment Evaluation method to provide a guideline for ranking different alternatives of building retrofitting. Sanhudo et al. (2018) tried to understand the potential of BIM technology energy retrofitting. In other research, a set of passive design measures that can be effective in achieving high building energy performance were found and simulated by Pajek and Košir (2021). Pinzon Amorocho and Hartmann (2022) presented a Multi-criteria decision-making framework covering environmental, economic, and social aspects and requirements of the decision-making in buildings' renovation. Therefore, optimization algorithms and scenario analysis can be used to investigate intervention scenarios to increase EE of buildings.

Integrating RESs demands an estimation of potential of district to have RESs. Geospatial multi-criteria analysis is used by Elkadeem, Younes, Sharshir, Campana, and Wang (2021) for investigating the potential of integrating solar and wind energies in a grid. Elsner (2019) used spatial analysis for assessing the African offshore wind energy potential. Also, Sahoo, Zuidema, van Stralen, Sijm, and Faaij (2022) developed an analytical approach to include spatial policy considerations in identifying spatial potentials for renewable energy sources of Groningen Province in the northern Netherlands. It can be seen that RESs supply potential are strongly relied on spatial aspects (Ramachandra & Shruthi, 2007; Sahoo et al., 2022), therefore, spatial analysis and Geospatial Information System (GIS) can be used to map and investigate the renewable energy potential.

The PED concept includes provisions on the possibility of sharing and saving energy between buildings within a district (Salom et al., 2021; Tuerk et al., 2021). Thus, the possibility of sharing and storing energy need to be considered when it comes to finding solutions to create a balance between demand and supply.

Optimization algorithms have high potential to be used for enhancing energy efficiency and effectively managing energy sharing between buildings (Beccali, Cellura, Brano, & Marvuglia, 2004; Samadi, Mohsenian-Rad, Schober, & Wong, 2012). Utilizing DT, these algorithms can determine the most energy-efficient strategies for achieving balance in energy demand and supply at a district level (Tao et al., 2018). These optimization techniques ccan play a critical role in decision-making processes, allowing for the evaluation of various energy strategies based on a set of predefined performance indicators, such as total energy consumption, the proportion of energy from renewable sources, peak demand, and overall emissions (Iqbal, Azam, Naeem, Khwaja, & Anpalagan, 2014).

This research is part of the 'DATALESS' project, responsible for the WorkPackage3 (WP3), focusing on Green Building modeling and DTs. Overall, this research aims to develop a digital twin model which is capable to predict energy demand of various types of buildings within a district. With the predictive model in place, the research aims to further explore optimization, Scenario and Spatial analysis strategies to enhance energy efficiency, analyse the potential of renewable energy sources, and energy sharing between buildings to respond energy requirements. These strategies will be tested and fine-tuned to achieve the ultimate goal of creating Positive Energy Districts.

2. Background Studies:

This section focuses on the role of PEDs, Digital Twin, and optimization algorithms for energy balancing. We delve into the intricacies of these areas, examining the establishment and challenges of PEDs, the promising potential of DTs, and the importance of optimization algorithms.

Supplementary information is provided in the appendix, enriching our understanding of energy trends and policies, renewable energy usage, and building characteristics in the Netherlands. Additionally, it further explores the roles and challenges of PEDs and provides more insights into DT. Both the main and appendix sections together form a comprehensive picture of our research themes.

2.1. Role of PEDs and ZEBs in the Dutch energy landscape

The concept of PEDs and ZEBs has emerged as a viable solution to the ever-growing energy use and greenhouse gas emission linked with buildings' sector. PED can be defined as a district with an annual net import of zero energy and zero net CO2 emissions, which produce a surplus of renewable energy to integrate it into an urban energy system" (Magrini et al., 2020).

2.1.1. Aspects of establishing PEDs

In this research three main aspects of developing PEDs will be considered: Energy efficiency measures, Renewable energy production, and Energy sharing/storing.

Energy efficiency measures: the energy-efficiency measures can be classified into two groups including i) minimization of building loads by measures such energy efficient design of building envelope, solar shading, energy-conscious behaviors of occupants, double glazed windows or window-to-wall ratio, and ii) supporting the use of energy-conserving systems and appliances within the building by using energy-efficient equipment such lighting, or refrigerator (Omrany et al., 2022; Wu & Skye, 2021). Our focus will be more on the first group.

Renewable energy production: Producing energy from RESs is a key pillar of PEDs and climate agreements. Solar and wind energy has getting popularity among all other sources. Also, it should be considered that to not just rely on just one source of RESs. However, the share of energy generation from RESs is still slow and there is a lot of potential that needs to be discovered (Dahal, Juhola, & Niemelä, 2018; Omrany et al., 2022).

Energy sharing/storing: As energy infrastructure becomes complex and decentralised, and renewable energy use expands, buildings need to evolve as active participants in the wider district-level energy system. Exploiting peer-to-peer energy exchange and effective storage in microgrid-connected buildings can optimise on-site generation and lower costs, providing a more efficient alternative to exporting electricity to the grid (Vand, Ruusu, Hasan, & Manrique Delgado, 2021).

2.1.2. Challenges of PED

PEDs are still in their infancy, with a multi-faceted challenges which span across a wide array of disciplines that need to be addressed. There are both technical and non-technical challenges to creating an overarching vision and framework for PEDs (Omrany et al., 2022). Krangsås et al. (2021) categorized the challenges of implementing PEDs into seven groups including Governance, Incentives, Social, Process, Market, Technology, and Context. This research aims to deal mainly with the following challenges:

Data Management and Security: PEDs rely on substantial data for energy management, including usage patterns, grid status, and renewable energy production. Ensuring the secure and efficient management of this data is a significant challenge (Tsoumanis, Tsarchopoulos, & Ioannidis).
Scalability and Replicability: Each district has its own unique characteristics, including building types, energy usage patterns, and available RESs. Developing solutions that can be scaled and replicated in different contexts is a significant challenge.
Technical Challenges: managing hybrid energy systems with multiple energy source, especially RESs, requires sophisticated technologies and systems. Creating balance between demand and supply, grid stability, energy storage, and interconnection of various energy systems can be challenging (Ekren & Ekren, 2010).
Lack of information/data on PED projects: Since most PED projects are currently in the design or execution phase, makes it difficult to access the most recent details or data of these projects (Zhang, Penaka, et al., 2021).

2.2. Digital Twin

The concept of DT was developed by Grieves and Vickers (2017) for the first time in 2002, and in 2010 listed as a key technology by Nasa. Then, its usage widely expanded into other domains. DTs as a computational model attracted ever-growing attention in energy management in building environments in recent years (Rolnick et al., 2022).

DT is a synergistic method that combines novel modelling and analysing techniques, leveraging massive amounts of data along with AI. This tactic brings together the capabilities of a virtual model with functions like data management, analysis, simulation, scenario analysis, visual representation, and information sharing (Shen, Saini, & Zhang, 2021).

Integrating DT can be a solution to the challenges in PEDs since it is capable of analysing and managing massive amounts of data, providing predictions, and conducting various scenarios which facilitate energy management in a PED. Also, if the decisions and changes that we want to implement in buildings and districts are modeled, analysed and tested before they are implemented, We can make more adaptable, efficient, and robust decisions with greater effectiveness (Zhang, Shen, et al., 2021a).

Zhang, Shen, et al. (2021b) classified DT into three tires: (1) an enhanced version of BIM model only, (2) semantic platforms for data flow, and (3) big data analysis and feedback operation. Furthermore, Agostinelli, Cumo, Guidi, and Tomazzoli (2021) showed that DTs have a high potential to achieve an intelligent optimization and automation system for energy management for both one and a cluster of buildings. In another article, a review of DTs application domains in smart energy grid is conducted by Cioara et al. (2021). They categorized the most relevant applications into four groups: 1) Asset Model (DTs for energy performance assessment and management), 2) Fault Model (DTs for diagnosis of faults), 3) Operational Model (DTs for optimal energy distribution and EE), 4) Business Model.

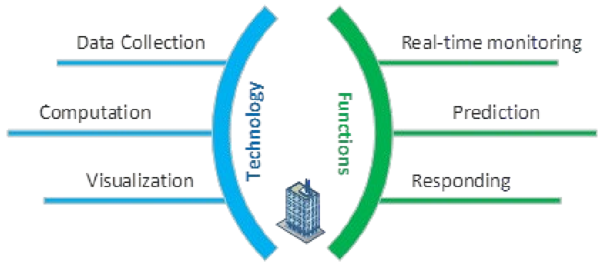


Figure 2. The main parts of a DT.

in Fig. 2 the main parts that a DT should have are shown based on the theoretical definitions that defined for DT (Tao & Qi, 2019).

2.3. The Crucial Role of Data in Energy Management

When it comes to integrating DT for energy management, data is an invaluable resource. in this project, data serves as the backbone for decision-making, planning, predicting and analyzing energy usage patterns, and optimizing energy systems. In the domain of energy management, data can be multifaceted. Essential data types include energy related data (both real-time and historical), meteorological information, building characteristics data, socioeconomic information, occupant related data, building types, indoor environmental data, etc. Each type of data serves specific purposes. For instance, energy consumption data is pivotal in understanding and predicting energy demand patterns, whereas meteorological data is key to both estimating renewable energy potential and predicting energy demand.

2.4. Application of Optimization Algorithms for balancing

Managing the balance between energy demand and supply is a complex task that requires sophisticated solutions. Optimization algorithms, owing to their ability to handle multiple variables and constraints, are increasingly being employed in this domain (Mariano-Hernández, Hernández-Callejo, Zorita-Lamadrid, Duque-Pérez, & García, 2021). These algorithms aid decision-makers in understanding the trade-offs between various energy management strategies, thereby facilitating the identification of optimal solutions that efficiently manage the energy balance.

Optimization algorithms are mathematical tools designed to find the most efficient solution to a complex problem given certain constraints. They help balance the way we generate, distribute, and use energy, and find the best solutions while working within certain limits. This research aim to define the optimization problem for managing energy. Our horizon is for 2030, and solutions are based on the climate agreements and PEDs concepts.

The primary objective is to achieve a PED. The aim is to minimize burden on the grid by getting independent from national electricity grid. Also, while in the PEDs the aim is to maximize the energy surplus in the district, but also need to be considered that selling back to the energy can also cause burden on the grid, and these factors need to be considered in modelling.

Being independent of the grid means that the energy demand of buildings in the district (electrical vehicles are also part of it based on the climate agreements) ned to be covered through the optimal combination of renewable energy generation, energy storage/sharing among buildings, increase energy efficiency of buildings, and other actions.

2.4.1. Solution Methods:

Optimization algorithms, which aim to find the best solutions to complex problems, can be classified into several categories. The most suitable type for a given problem depends on the nature of the problem and the desired outcomes (Fister, Fister Jr, Yang, & Brest, 2013).

1. **Deterministic Methods:** These methods are ideal for problems with a small number of decision variables and objectives. However, they may not be suitable for energy management since it has many problems, uncertainties, and complexities (Bazaraa, Jarvis, & Sherali, 2011).

2. **Stochastic Methods:** These methods introduce randomness, which is useful for handling uncertainties in problem parameters. They may not guarantee the exact optimal solution but often find good solutions when faced with complex and uncertain problems (Rubinstein & Kroese, 2016).

3. **Heuristic Methods and Meta-heuristics:** Heuristic methods, like Genetic Algorithms and Particle Swarm Optimization, are capable of providing near-optimal solutions for large-scale and complex problems. Meta-heuristics, a subset of heuristic methods, guide the search process to explore the search space efficiently and include methods such as Simulated Annealing, Tabu Search, and Ant Colony Optimization (Blum & Roli, 2003; Coello, Lamont, & Van Veldhuizen, 2007).

4. **Machine Learning Methods:** Machine learning methods like Reinforcement Learning can be used for dynamic learning and adjustment of energy management strategies, optimizing multiple objectives over many iterations (Sutton & Barto, 2018).

In practice, a combination of these methods can be utilized, leveraging their respective strengths. For example, meta-heuristics can be used to find a good set of initial solutions, which can then be fine-tuned using deterministic methods for better accuracy. Machine learning methods can be integrated to continuously learn and adapt the model based on the outcomes of the optimization (Mallipeddi, Suganthan, Pan, & Tasgetiren, 2011).

When it comes to choosing an appropriate optimization method, several factors must be taken into account. These include the problem's complexity, the number of decision variables and objectives, the level of uncertainty in the model's parameters, and the available computational resources. Additionally, the presence of multiple conflicting objectives - typical in a district-level energy management problem - demands the need for multi-objective optimization algorithms (Zhou et al., 2011).

3. Problem Statement:

The global mission of carbon-free electricity systems and built environment by 2050 requires integration of RESs and increase of EE of buildings. The integration of RESs is crucial for achieving energy sustainability. However, this process presents several challenges, especially in terms of creating fluctuation and burden on the electricity grid and managing energy within and between buildings (Sandhu & Thakur, 2014). It necessitates a comprehensive understanding of energy demand and supply patterns at both building and district levels, and the ability to balance these elements effectively.

Concepts such as PEDs and Zero Energy Buildings are promising in this regard. They emphasize EE, renewable energy production, and flexibility in energy management. DT is considered as an effective platform and solution for developing PEDs.

DT technology can create a virtual model of the physical system, providing real-time insights and predictive and scenario analytics to optimize system performance. However, leveraging DT technology to achieving these concepts remains unclear.

Therefore, there is a need to explore how DT technology can be effectively utilized to support the concept of PEDs, facilitate the integration of RESs in a decentralized manner, and minimize the burden on the grid.

In the pursuit of developing an effective DT for managing energy within and between buildings, several challenges emerge. For example, collecting and integrating diverse data sources due to variations in data quality, scale, and format, and developing robust predictive models that accurately forecast energy demand and supply based on a wide array of dynamic inputs, such as weather and building occupancy. This complexity extends to the creation of optimization algorithms that ensure a balance between energy demand and supply.

The problem statement, thus, revolves around utilizing DT technology to devise PEDs that can forecast the energy requirements of a district. The primary response to these demands is an integrated strategy that incorporates RESs supply, enhanced energy efficiency in buildings, and energy sharing/storing between buildings.

4. Research Proposal:

4.1. Research Objectives

The crux of this study is to design an effective model for managing and balancing energy within and between buildings through the integration of DT technology and PEDs. The balance we aim to create is to predict and satisfy energy demand at the building level with RES supply at the district level, facilitated by DT models. Therefore, addressing the problem statement, the main objective of the research is to create a DT model for managing RES and predicting energy demand patterns that would be applicable at the building and district level. The objective can be further divided into the following sub-objectives:

1. **PED and ZEB Concepts**: To explore and comprehend the principles of developing PEDs.
2. **Digital Twin Concepts:** To understand the concepts, principles, and technologies of developing DT and its capabilities for providing operational feedback and facilitating decision-making.
3. **Data Infrastructure**: To develop a data infrastructure that captures, processes, and analyzes diverse datasets required for effective energy management in a district.
4. **Energy Prediction**: To utilize AI algorithms to predict energy demand of buildings and districts.
5. **Energy Optimization at Building Level**: To employ DT technology for simulating energy consumption scenarios and analysing different scenarios for implementing intervention scenarios to increase EE of buildings.
6. **Energy Sharing/storing**: To examine the potential for energy storing/sharing between buildings at the district level using DT technology.
7. **Renewable Energy Integration**: To investigate potential of integrating RESs by leveraging the spatial analysis.
8. **Respond to energy requirements**: develop strategies to respond to the energy demand of district
9. **Energy Optimization Algorithms:** Develop and apply advanced optimization algorithms for efficient, sustainable energy management across district.
10. **Framework Development**: To create a framework that employs DT technology for the realization of PEDs.

4.2. Hypothesis

The successful development and implementation of a DT model, capable of integrating key information, precise prediction of energy demand, spatial analysis, and multi-objective optimization algorithms at both building and district levels, can effectively balance energy demand and supply in real-time and long-term scales. This approach can subsequently facilitate enhancing energy efficiency, increase energy generation from renewable energy sources, and facilitate energy sharing between buildings, thereby fostering the transformation towards PEDs.

4.3. Research Questions

4.3.1. Main Research Question.

How can digital twin be designed to facilitate the integration of renewable energy sources in a decentralized manner (with minimum burden on the electricity grid) by managing energy within and between buildings (to develop positive energy districts)?

Sub-Research Question 1. **How can a comprehensive understanding of Positive Energy Districts be established, and in what ways can digital twin technology be utilized to support and enhance the realization of this concept?**

Motivation (M): We aim to establish a concrete understanding of PEDs, ZEBs, and DT technology, and explore how DT can support and enhance these concepts.

Challenges (C): Unifying disparate principles and processes of PEDs, ZEBs, and DT technology could pose a challenge due to their complex and multifaceted nature. Bridging the gap between theories and their practical applications may prove to be a challenging task.

Approach (A): Our approach is based on conducting a detailed examination of relevant literature and an analysis of related case studies. Based on this, we will design a system architecture and energy model for developing a DT in a PED, As part of our methodology, we plan to use the Geodan model as a blueprint, customizing and enhancing it based on our findings and the specific requirements of PEDs and ZEBs.

Expected Outcomes (E): The expected outcome is a well-designed system architecture and energy model that successfully integrates DT technology into the operation and development of PEDs. This architecture would serve as a practical guide for leveraging DT technology in the pursuit of PEDs and efficient management of energy in the context of PEDs.

Risk (R): As both PED and DT are nascent and continually evolving fields, keeping up-to-date with their rapidly changing landscapes is a challenge. Also, our focus is primarily on the development of a technical model, which means I should try to avoid investigating excessive time on just theoretical aspects. Also, getting access to data from related case studies is challenging.

Sub-Research Question 2. How can we design and implement a (spatial) data/information infrastructure for efficient handling of complex datasets in Digital Twin technology for energy management in PEDs?

(M): The aim here is to construct a versatile data infrastructure capable of managing substantial amounts of data for energy management in buildings. It is a critical step towards the realization of the DT model, and effective energy management in PEDs relies on the efficient processing of large datasets. This system should be designed to facilitate real-time analytics, interoperability, data security, and continuous learning.

(C): Challenges arise from managing vast data volumes, ensuring real-time analytics, data security, interoperability, and synchronization. Additionally, the need for standardizing datasets, identifying and investigating necessary datasets for project inclusion, staying updated with evolving data management practices, and maintaining infrastructure flexibility to adapt to new data types and energy management needs also pose substantial difficulties.

(A): We will conduct a detailed analysis of energy management data requirements, followed by the development of a comprehensive data/information model that addresses data integration, synchronization, management, standardization, and governance. The methodology will entail a collaborative effort with Geodan, leveraging their established model as a basis, to ensure the developed model is both grounded in practicality and aligned with advanced data infrastructure practices.

(E): The expectation is to create a data infrastructure and data/information model, tailored to the requirements of energy management in buildings and compatible with the current GEODAN model. This framework will address data collection, storage, processing, and security needs and will help streamline the operation of a digital twin model for efficient energy management. This data infrastructure will serve as a foundation for my next steps and even can be used as a reference point for future studies in this domain.

(R): Risks include the difficulty of acquiring diverse (standardized) datasets from various sources, the rapidly changing landscape of data management technologies and practices. Ensuring the proposed framework's flexibility and adaptability to changes is a challenge that we need to keep in mind. Crucially, the implementation of data security measures and ethical issues may be risky when it comes to handling large amounts of data that includes sensitive information.

Sub-Research Question 3. How can data-driven approaches and spatial analysis be employed to effectively predict and investigate energy supply and demand in PEDs?

This research question investigates the application of data-driven algorithms for energy demand prediction and spatial analysis for evaluating RES potential within PEDs.

> **Sub Research Question 3.1: How Can data-driven algorithms be used for predicting energy demand of different types of buildings and expanding it to a district?**

(M): Our motivation lies in the necessity of understanding energy demand at both the building and district levels to facilitate efficient energy management. Utilizing AI algorithms could help us make more precise demand predictions.

(C): The challenge lies in using AI algorithms that can accurately predict energy demand across different building types and extending this model to encompass a district level. The complexity of these predictions is driven by the quality, availability, and suitability of the input data, alongside the diverse nature of buildings and their energy consumption patterns in a district, and also the required complexity level of AI algorithm(s).

(A): The chosen method involves the use of data-driven algorithms designed to predict energy demand, following a distinct sequence of steps. Our approach also focuses on scalability and applicability across different building types and districts. Additionally, we aim to include both short-term and long-term prediction capabilities in our model.

(E): The expected outcome of this investigation is a data-driven AI algorithm capable of accurately predicting energy demand for various building types and expanding this model to the district level.

(R): Our research heavily relies on the accessibility of diverse building datasets to apply data-driven algorithms effectively. While we have already gained access to some datasets, our work necessitates more. In the scenario where we cannot acquire sufficient data, we may resort to using white or gray box methods for certain types of buildings. Additionally, there is a risk that the algorithms we develop may not be universally applicable or scalable across different contexts or various types of buildings and districts.

Sub_Research Question 3.2: **How can spatial analysis be utilized to assess and predict the potential of Renewable Energy Sources within a district?**

(M): having understanding of potential of districts for integrating RESs is of importance to develop solutions to fulfill energy demand. We aim to leverage spatial analysis to assess the potential of different RESs within a district, fostering a future where dependence on fossil fuels is significantly reduced.

(C): Navigating the multi-faceted dimensions of spatial analysis, considering various factors such as environmental conditions, available space, and costs, poses a challenge. The accuracy and reliability of these predictions can be affected by the availability and quality of historical data and weather conditions.

(A): We plan to apply spatial analysis to evaluate the potential for energy generation from various RESs in a district. This involves taking into account considerations like available space, environmental influences, and costs. The research is planned in line with future forecasts for 2030 and 2050.

(E): The anticipated outcome is a spatial analysis that estimates the renewable energy potential of a district. This will include projections of energy generation from different RESs. The model can help guide energy management strategies for a district, moving towards a less fossil fuel-reliant future.

(R): The inherent uncertainties in spatial analysis, coupled with variability in environmental factors and potential constraints in accessing comprehensive and timely spatial data, may pose a risk to the accuracy of our potential assessments for our targeting RESs.

Sub-Research Question 4. **How can digital twin technology be utilized/designed at the building level to help enhance energy efficiency and decrease the overall energy demand in a district?**

(M): the aim is to identify and rank energy efficiency measures across various building types, to reduce the overall energy demand within a district, and leverage digital twin technology with it.

(C): Designing and implementing digital twin technology at a building level involves a myriad of complexities, especially when it comes to simulating, predicting and prioritizing energy efficiency measures. Additionally, expanding these findings from a building level to an entire district also presents complexities due to variations in building types and energy usage patterns.

(A): the approach involves evaluating, simulating and priorotizing the impact of different energy efficiency measures using algorithm including multiple criteria decision analysis, multi objective optimization algorithms and scenario analyses.

(E): The expected result encompasses energy efficiency measures tailored to various building types, along with their potential to decrease both building and district-wide energy demand.

(R): The identification, prioritization, and implementation of energy efficiency measures pose complexity and variability risks, as solutions may differ significantly from one building to another and across districts. Specific building types, like historical buildings, might offer limited flexibility for implementing certain energy efficiency measures.

Sub-Research Question 5. How can digital twin be used/designed to create balance in/between buildings by integrating RESs in the grid locally, with minimum disturbance in the national grid?

(M): The aim is to explore the potential of DT technology comprising multi-objective optimization algorithms, in facilitating a balanced energy system at the district level. This approach holds promise for developing more resilient and sustainable energy systems, driving a shift toward locally managed RESs.

(C): The primary challenges in achieving this objective lie in the complex nature of integrating DT technology, formulating a comprehensive multi-objective optimization algorithm, and dynamically managing the energy within the district. The optimization must account for several variables and constraints, such as the variability of renewable energy generation, energy demand-supply balance, efficient energy storage and sharing, and minimizing disturbance to the national grid. Moreover, incorporating the feedback into DT's to refine their predictive and operational capabilities further adds complexity.

(A): approach involves utilizing optimization algorithms in conjunction with DT to balance energy demand and supply at the district level. multi-objective optimization algorithms will be applied to address the aforementioned challenges. The algorithm will aim to optimize several objectives, including maximizing energy generation from RESs, enhancing energy efficiency, facilitating energy sharing and storage, but the main and important objective is minimizing disturbing on the electric grid.

(E): the project aims to produce a practical tool that stakeholders can use for effective energy management at the district level. The optimized Digital Twin model can act as a decision-support tool, providing insights on how to balance energy supply and demand, increase use of renewable energy sources, and lead to establish PEDs

(R): Implementing a fully functional Digital Twin for an entire district's energy management is an ambitious and risky endeavor. Formulating the district energy management plan that encapsulates all necessary aspects of energy demand, supply, storage, and sharing is a complex and challenging task. In addition to the complexity of problem, computational time can be another challenge.

5. Research Design:

5.1. Approach and Methodology

The research will be divided into several interconnected stages, each designed to address a particular aspect of the main research question. These stages will guide the structure of the proposed research:

- **Literature Review:** The research begins with an in-depth literature review. This stage will cover the concepts of (Nearly) Zero/Positive Energy Districts/Buildings, and DT technology. It will also explore current applications of DT for energy management of buildings, and how DT’s application can be expanded to develop PEDs.
- **Development of Data Infrastructure:** The next stage will focus on the development of a data infrastructure essential for creating a DT model. This will involve identifying key data requirements, examining potential data sources, and outlining an efficient data management, security, synchronization, and continuous learning.
- **Implementing AI Algorithms for Energy Demand Prediction:** Utilizing advanced data-driven algorithms, we will predict energy demand patterns at the building and district levels. This prediction model will incorporate a diverse range of buildings types.
- **Renewable Energy Supply Analysis:** Spatial analysis will be used to assess and predict the potential for energy generation from various renewable energy sources within a district.
- **Energy Efficiency of Buildings:** We aim to identify, simulate, and prioritize energy efficiency measures of different building types. The ultimate goal is to discover the potential of buildings and district to reduce energy demand
- **Multi-Objective Optimization:** This phase will delve into the design and application of optimization algorithms tailored for efficient energy management across districts. these algorithms will seek to minimize burden on the

grid and minimize energy consumption, maximize use of renewable energy, promote energy sharing and storage, and limit grid imports.

- **Other Measures - Energy Sharing & Storage:** In order to create a more sustainable and balanced energy system, measures such as energy sharing and storage within the district will be explored and incorporated into the model.
- **Multi-Objective Optimization:** Optimization algorithms will be developed and applied, aiming to balance a multitude of objectives. These include maximizing energy generation from RESs, enhancing energy efficiency, facilitating energy sharing and storage, and minimizing disturbances to the national grid.
- **Digital Twin Finalization:** The final step involves the actualization of the Digital Twin model that encapsulates all the previous steps. The DT model will provide a comprehensive view of the energy landscape, serving as a decision-support tool for stakeholders. It will ensure a balance between energy demand and supply, thereby fostering the establishment of Positive Energy Districts.

5.2. DATALESs Project

The DATALESs project, designed to tackle energy sector challenges, emphasizes the importance of optimizing local energy systems and green buildings to meet the emissions reduction targets set for 2030.

The quest for a carbon-neutral energy system involves more integration of unpredictable renewable resources, adding complexities and control challenges. Lowering energy consumption in buildings and enhancing green buildings are integral parts of this project's sustainability strategy. With an increase in distributed RESs, the project calls for advanced flexibility analysis and innovative business models, especially for LESs. The DATALESs project seeks to digitally enhance the energy system in the Netherlands and China, fostering both nations to meet their Climate Agreement's greenhouse gas emissions reduction targets by 2033.

The DATALESs project brings together a consortium of four academic institutions and four industry partners. TU Delft's main contribution to this project is the development of AI and mathematical-based models for LESs control and operation (WP1) and green building modelling and digital twins (WP3). The structure of this project is shown in Fig. 3. Our group is responsible for WP3. Detailed description of WP3 and its tasks are provided in Fig. 5.

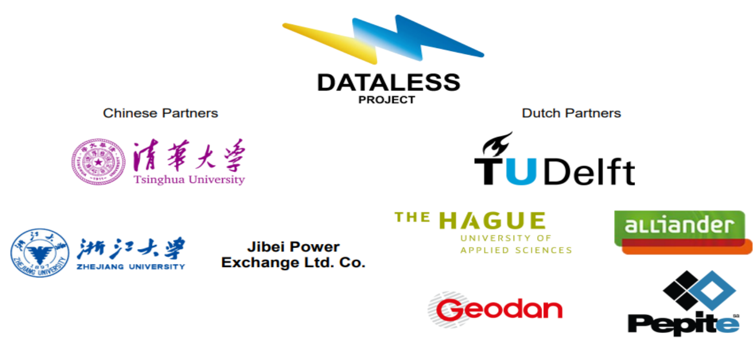


Figure 3. DATALESs partners.

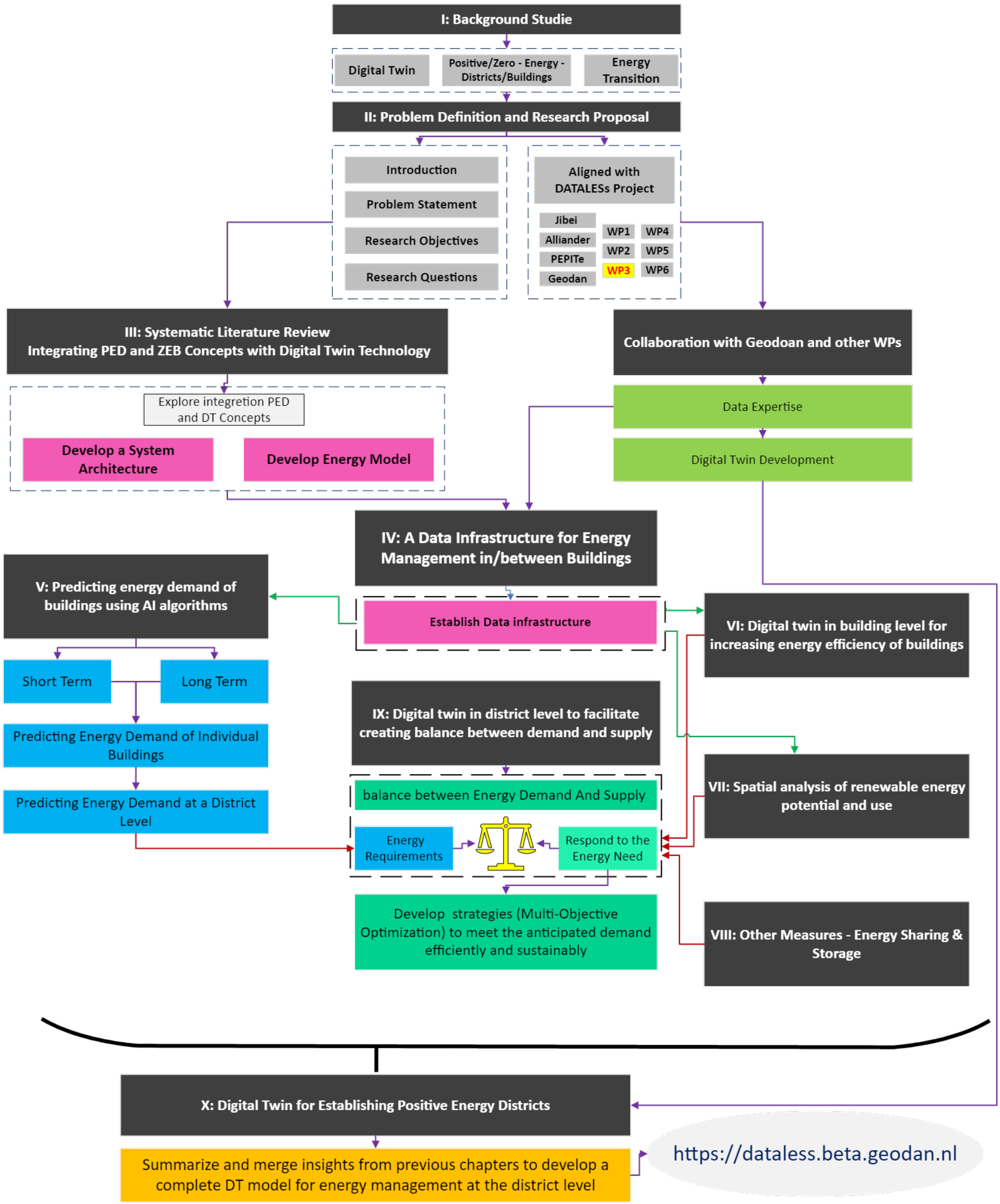


Figure 4. Concept Methodology of the research. The figure illustrates the interrelation between different sections of the study.

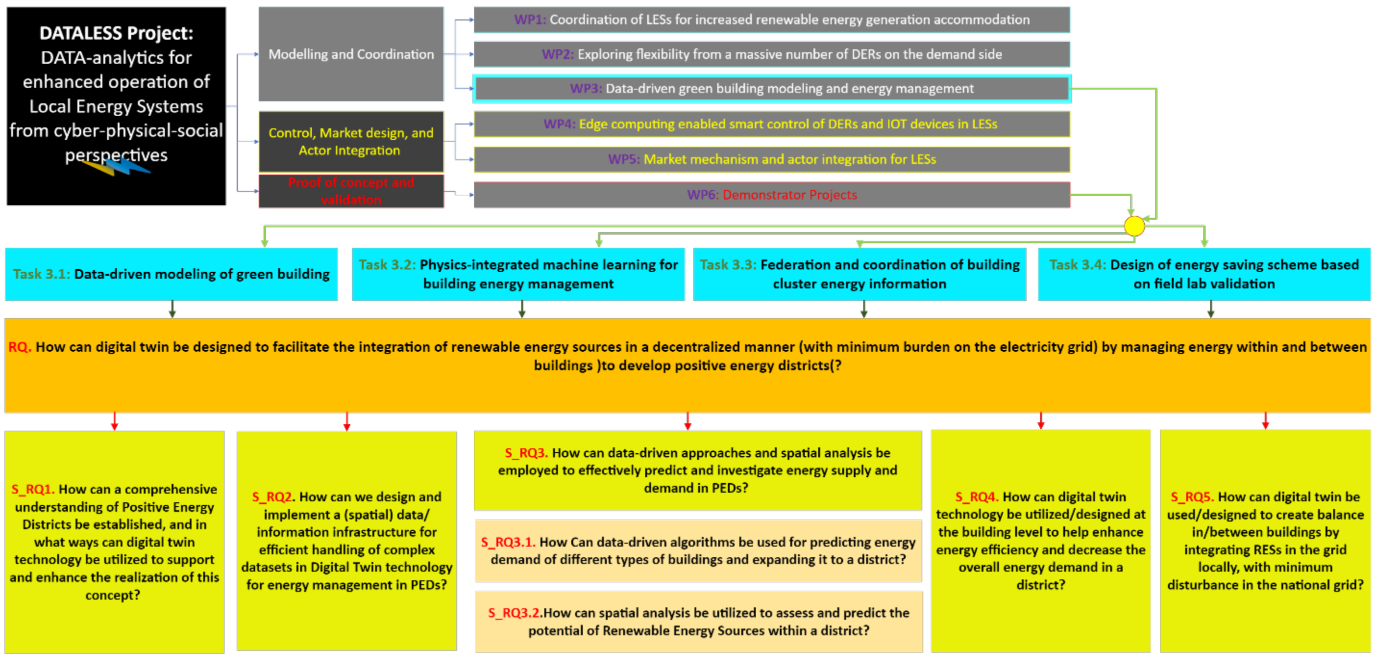


Figure 5. the schema of Dataless project and tasks of WP 3.

5.3. Collaboration with Geodan: Digital Twin Model Version 1.0

In collaboration with Geodan, we successfully developed and launched the first version (1.0) of our Digital Twin model. This model, currently accessible at dataless.beta.geodan.nl, lays the groundwork for the project's ultimate vision. The screenshot in this figure provides a glimpse into the initial version of our model (Fig. 6).

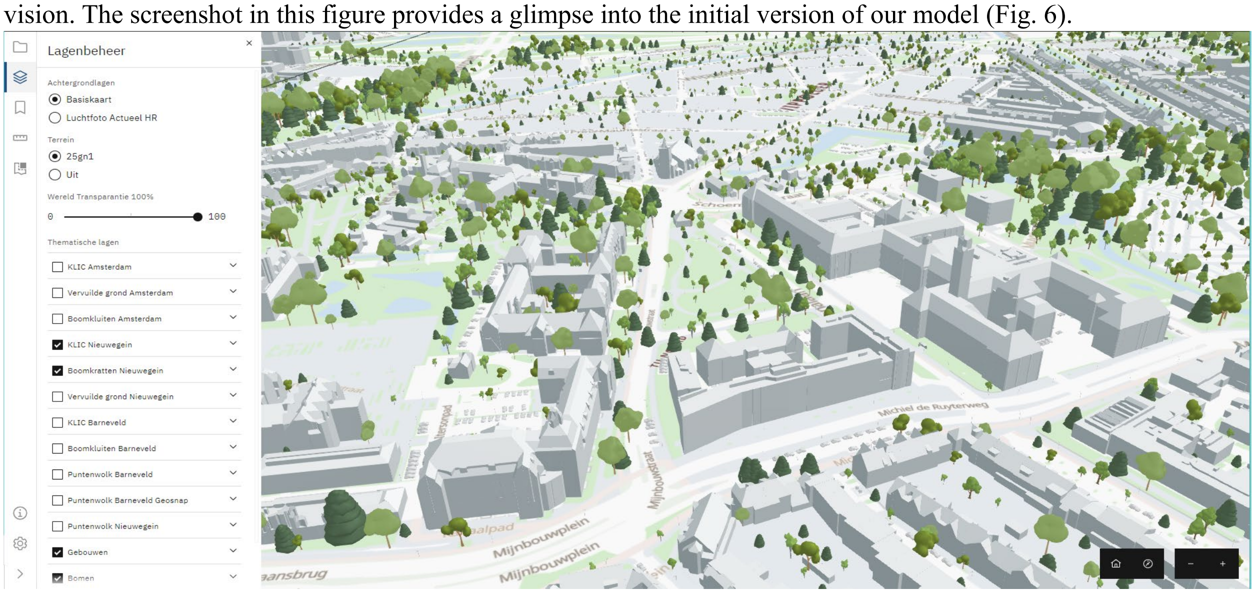
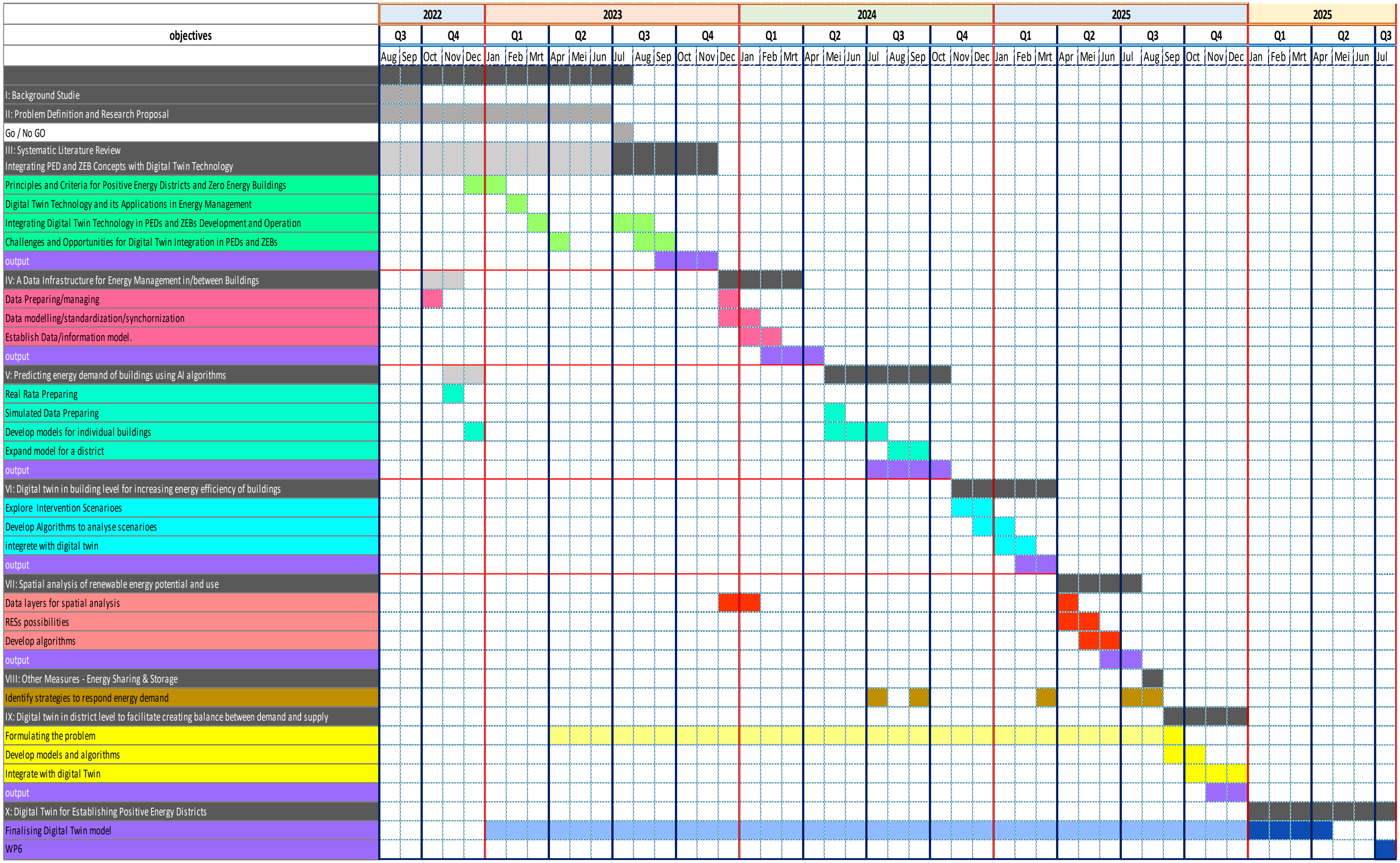


Figure 6. initial version of DT model for this project available from dataless.beta.geodan.nl

Our collaboration with Geodan led to the successful development and launch of our Digital Twin model's initial version (1.0), available at dataless.beta.geodan.nl, marking a significant project milestone. This first iteration, designed using publicly accessible datasets for data privacy and usage rights adherence. The model, as depicted in Figure 6, will evolve to incorporate advanced features such as plugins for data analysis, predicting energy demand, scenario analysis, and more. Our work with Geodan also extends to workshops where we align objectives, share knowledge, identify model gaps, and strategize enhancements to meet scientific standards and the Dataless Project's objectives. Furthermore, Geodan's hardware, software, and workspace support, as well as programming methodology workshops, have been instrumental in understanding the model's underlying architecture and functionality.

5.4. Timeline

Table 1. Research timeline



5.5. Research Relevance:

Expanded Scientific Relevance: The scientific relevance of this research lies in its cross-disciplinary nature, combining concepts from GIS, Architecture, computer science, AI, and electric engineering to address energy management in buildings and districts. The utilization of DT technology in managing energy demand and supply, and enhancing the EE of buildings is an emerging research domain, and this study contributes valuable insights in this field. Furthermore, the exploration and integration of various AI algorithms and spatial analysis in predicting energy demand and supply in building and district level provide novel scientific insights. This research also elucidates the technical complexities involved in creating a data infrastructure for energy management within and between buildings, enriching the existing body of knowledge on the subject.

Expanded Practical Relevance: The research outcomes of integrating DT technology can improvise energy management approaches in buildings and districts, providing optimization of energy use and effective incorporation of renewable resources. These outcomes could advance the development of DT tools, driving cost savings, efficient energy use, and heightened sustainability in the built environment. Furthermore, the synergy between DTs and PEDs could catalyze the creation of sustainable and energy-efficient districts.

5.6. Reflection:

- Merging DT technology with Positive Energy Districts and Zero Energy Buildings demands broad knowledge across multiple disciplines. While this may require expanding my understanding in areas like electricity and architecture, the collaborative nature of the DATALESS project ensures access to required expertise. The Discipline-related courses that I planned to take are in line with these challenges.
- Creating a Digital Twin presents technical challenges like complex data management and advanced modeling techniques. Yet, our partnership with Geodan, with its expertise in digital twin technologies, provides a firm foundation to address these challenges, facilitating an efficient path towards our research goals.
- The integration of diverse data could pose a challenge, but the thrill of working with big data to solve real-world problems is exciting. To handle data effectively, best practices in data handling and robust data analysis tools will be utilized.
- Predicting energy demand across various building types using AI algorithms could be complicated, especially due to the difficulty in accessing real data. However, through a strategic combination of real and simulated data, clustered modeling, and building-specific models, these challenges will be overcome, thus improving prediction accuracy.
- Collaboration with different work packages and partners is essential, albeit challenging. However, I plan to turn this challenge into an opportunity for networking and synergistic cooperation, reinforced by joint academic publications.
- The project's scale may pose time management challenges, requiring balance between detailed research and strict timelines. A comprehensive schedule, effective resource allocation, constant progress tracking, and regular reports to my supervisors will help manage this issue.
- While I anticipate challenges, each presents an opportunity for growth and innovation. With strategic planning, dedication, and resilience, I'm confident these challenges can be effectively addressed.

5.7. Supervision

The progress of this research project has been steadily guided by my supervisory team through structured and frequent meetings. The system we've established entails monthly discussions with my promotor and bi-weekly meetings with daily supervisors. If I ever need extra help, they are always ready to have a meeting right away. Moreover, their exceptional support extended beyond the boundaries of the project, providing me assistance during personal hurdles in the early stages. This support is something I profoundly appreciate. Also, on a monthly basis, I prepare a report that outlines my achievements, any obstacles I encountered, and my plans for the upcoming month. Furthermore, after my go/no go evaluation, I aim to make regular weekly visits to The Geodan.

5.8. Doctoral Education Programme

Table 2. Doctoral Education Programme

Courses	Credit			
	finished	in progress	will take	
Research competences and skills 1	**3.5**	**0**	**11.5**	
R1. RESEARCH MANAGEMENT				
How to select/make a questionnaire and conduct an interview	**2**			**I**
Research Data management 101			**2**	**II**
Research Design			**3**	**II**
R2. ACADEMIC THINKING				
Using creativity to maximize productivity and innovation in your PhD	**1.5**			**I**
Analysis of Interviews and other Unstructured Data			**2**	**III**
R3. ACADEMIC ATTITUDE				
Engineering Ethics			**3**	**IV**
R4. RESEARCH DATA MANAGEMENT				
Research Data management			**1.5**	**II**
Transferable competences and skills 2	**13.5**	**0**	**15.5**	
T1. EFFECTIVE COMMUNICATION				
Designing Scientific Posters and lay-out for Theses with Adobe InDesign	**2**			**I**
Popular Scientific Writing	**2**			**I**
Scientific text processing with Latex			**1.5**	**III**
Presenting scientific research	**3**			**I**
Dutch for foreigners			**3**	**II**
English pronunciation			**2**	**II**
Public speaking training	**2**			**I**
Voice Training			**1**	**III**
Online Scientific Impact			**1**	**III**
Sharing your Research and Work as Simple as a TEDx Talk			**1**	**II**
Academic English 1			**3**	**II**
Academic English 2			**3**	**III**
T2. WORKING WITH OTHERS				
Conversation Skills	**2**			
T3. TEACHING, SUPERVISING, AND COACHING				
T4. AUTONOMY AND SELF-MANAGEMENT				
PhD Solutions: solving your biggest PhD challenges .5	**0.5**			**I**
PhD Startup Module A 1.5	**1.5**			**I**
PhD Startup Module B Scientific Integrity .5	**0.5**			**I**
Discipline-related skills	**XX**	**XX**	**XX**	
Geo Data Base Management Systems	**XX**	**Participated as lab assistant**		**I**
Energy Supply Systems for Buildings		**XX**	**EDX**	**II**
Zero Energy Design: An Approach to Make Your Building Sustainable		**XX**	**EDX**	**I**
Buildings as Sustainable Energy Systems			**XX**	**III**
Need to take a course regarding electricity and grid management from EWI			**XX**	**II,III**
Need to take a course regarding the concept of optimization algorithms				

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APPENDIX

Contents

Figures

Background Studies:

1.1 Energy Trends and Policies in the Netherlands

The 2017 Coalition Agreement in the Netherlands prioritized greenhouse gas (GHG) emissions reduction as the core of their climate and energy policy. The agreement established legally binding targets to reduce GHG emissions by 49% by 2030 and by 95% by 2050 (compared to 1990 levels) ("Coalition Agreement 'Confidence in the Future',").

In the Netherlands, GHG emissions were around 160 Mt CO2-eq in 1990. The Climate Act mandates that these emissions must be reduced to below 113 Mt CO2-eq by 2030 and under 11 Mt CO2-eq by 2050 ("Netherlands: CO2 Country Profile,"). [Netherlands: CO2 Country Profile - Our World in Data]. In Fig. 1, the Netherlands' annual CO2 emissions is represented.

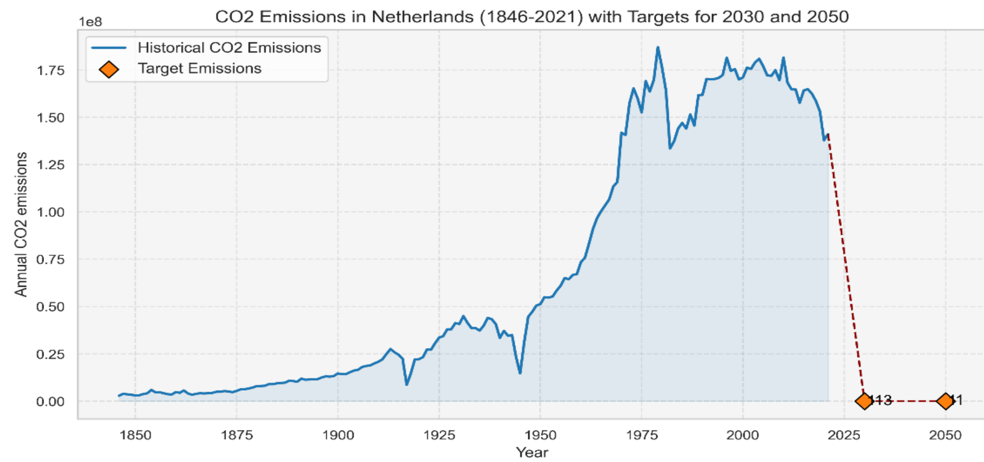

Figure 1. Annual CO2 emissions in Netherlands between 1846-2021 with the targets for 2030 and 2050

The Climate Act mandates the government to create a Climate Plan every five years, outlining a ten-year climate policy. The first Climate Plan, adopted in April 2020, covers the 2021-30 period. The 2021-30 Climate Plan incorporates policy measures designed to meet the Climate Act's targets, the 2017 Coalition Agreement, and relevant EU directives. The Climate Plan primarily builds upon the 2019 Climate Agreement, which was developed through extensive negotiations involving over 100 stakeholders. The Climate Agreement focuses on five sectors: electricity, industry, the built environment, mobility, and agriculture and the natural environment. Our focus is on investigating RESs and built environment. in Fig.2, we can see the Climate Agreement's 2050 goals and 2030 targets ("National Climate Agreement - The Netherlands,").

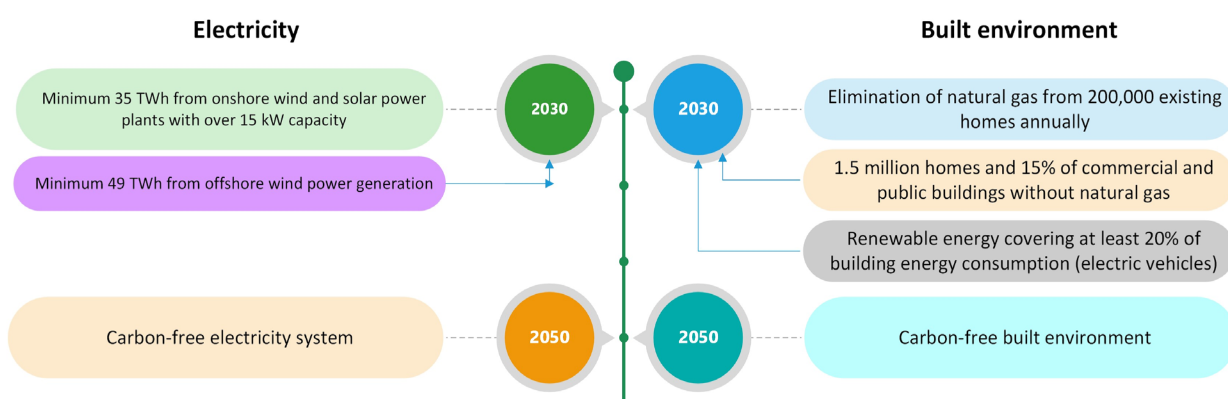

Figure 2. Climate Agreement Goals and Targets for electricity and built environment Sectors

1.2 Renewable Energy in the Netherlands

After examining the international agreements targeting the use of RESs, we have analyzed data to assess the progress of the Netherlands in this area (Fig. 3).

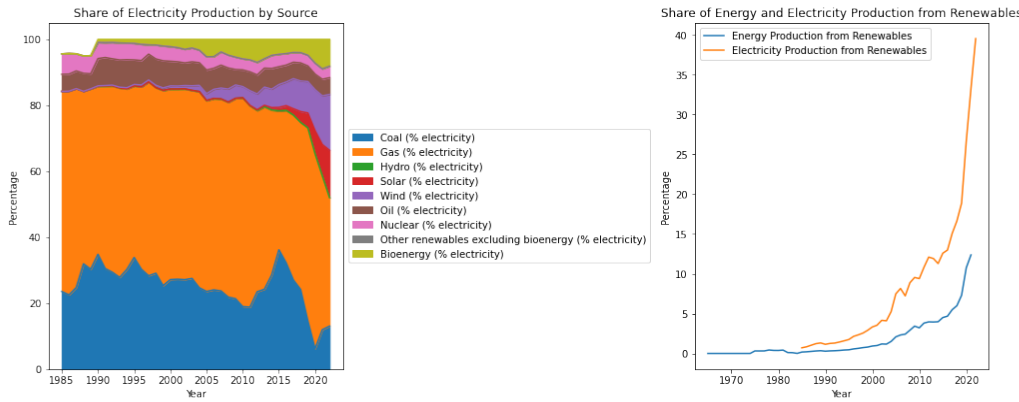

Figure 3. share of energy generation from different sources in Netherlands

The data demonstrates a steady increase in the percentage of energy derived from renewables, with 12.37% of the country's equivalent primary energy coming from these sources in 2021. Additionally, the share of electricity production from renewables has seen substantial growth, reaching 33.28% in 2021.

The promising future of wind and solar power in the Netherlands is evident from the country's consistent growth in renewable energy usage. Additionally, the recent headlines emphasize the Netherlands' commitment to renewable energy and regional collaboration. The €28 billion investment for the 2030 climate targets, the joint efforts of nine North Sea countries to develop 300 GW offshore wind by 2050, and the 1.8 GW cross-border interconnector project between the UK and Netherlands demonstrate the nation's dedication to a sustainable future 1 2 3.

Considering the significant developments and commitments to RESs in the Netherlands and surrounding regions, it is crucial to include RES in my research. incorporating RES in the project will enable us to anticipate future energy supply, facilitate informed decision-making, and contribute to the development of effective strategies to meet the growing need for clean, sustainable energy in the Netherlands.

Predicting the supply from RESs and evaluating the potential of districts and buildings to accommodate RES is a critical element of our research. Such predictions not only provide a solid foundation for understanding the dynamics of energy production and consumption but also guide the optimal integration of RES within the built environment.

With the increasing volatility of weather patterns due to climate change, understanding and predicting RES supply becomes even more crucial for ensuring energy security and resilience.

Moreover, assessing the potential of districts and buildings for harnessing RES offers a blueprint for transitioning towards sustainable and decentralized energy systems.

1.3 Buildings in Netherlands

The escalating energy demand in the building sector, which accounted for 29% of global final energy use in 2020, underscores the pressing need for energy-efficient building designs and operations. As projections suggest increase in building energy consumption, it is important to focus on the building sector in driving sustainable energy transitions (Omrany et al., 2022).

To gain insights into the current challenges and potential opportunities for energy efficiency (EE) in the Dutch built environment, we make a look at status of age and usage of buildings in the Netherlands (Fig. 4 and Fig. 5). Data relating to the age and usage of buildings are extracted from ("Dataset: Basisregistratie Adressen en Gebouwen (BAG),").

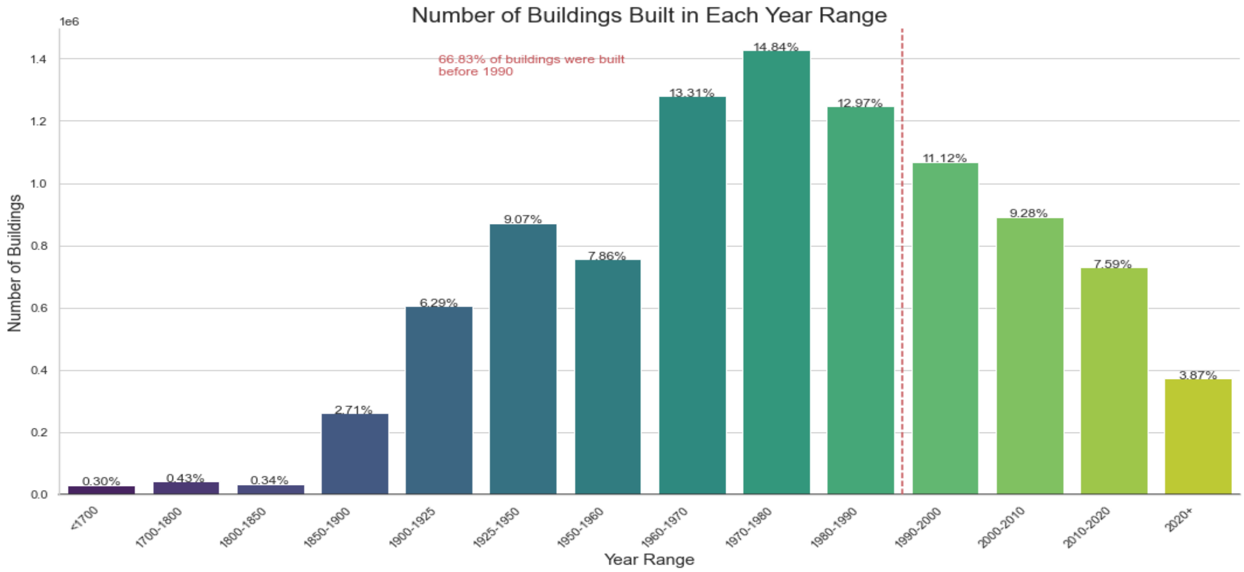

Figure 4. shows the number of built in different year ranges.

While the new buildings are designed to be more efficient, the challenge, however, is not limited to new buildings. In fact, the building stock is inexorably aging, composed of 67% buildings built before 1990 (Fig. 5), with a renewal rate around 1.2% (according to the EU Building Stock Observatory) (Magrini et al., 2020).

Also in Fig. 5, we can see frequency of buildings based on their statuses in the Netherlands. It can be seen that the percentage of residential buildings is extensively high.

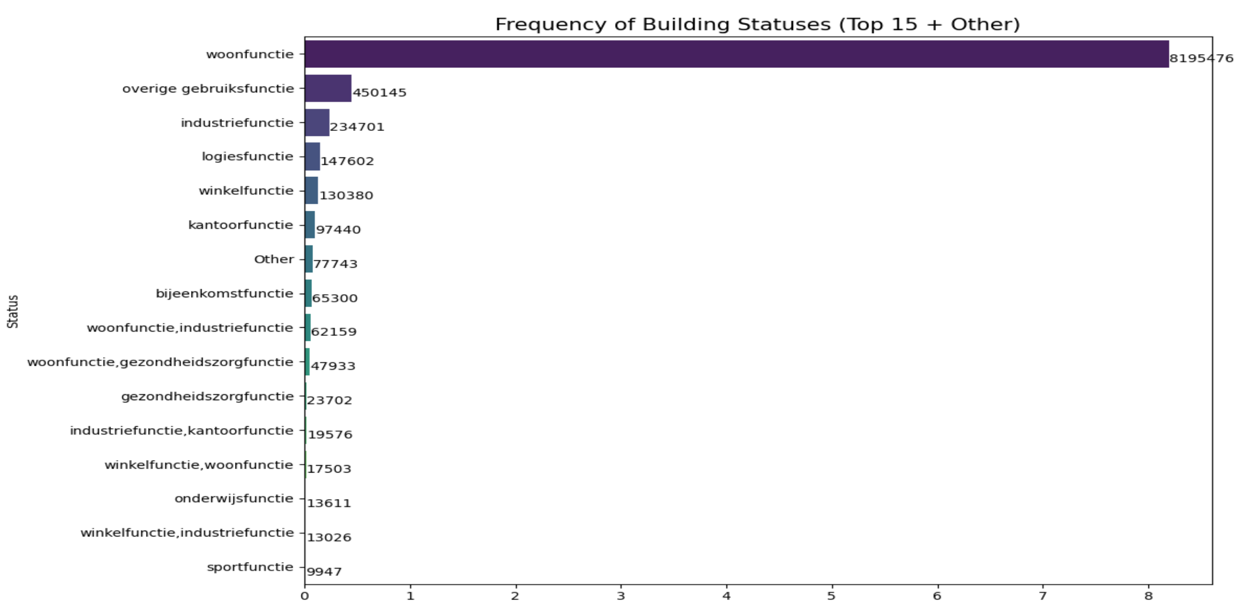

Figure 5. Top 15 statuses of buildings in the Netherlands

The Netherlands is aimed to adapt its buildings by exploiting the digital technology concepts and new protocols such as Nearly Zero Energy Building (NZEB) and PED objective to stimulate the sustainable energy transition of the built environment. Moving to high-performance green buildings needs a structured, integrated and innovative approach embedded in the city's overall vision, requires a departure from perceived notions of building design and operation, and necessitates the inclusion of more sophisticated methods and tools in the design and implementation phases (Simhachalam et al., 2021).

1.4 Role of PEDs and ZEBs in the Dutch energy landscape

The concept of PEDs and ZEBs are emerged as a viable solution to the ever-growing energy use and greenhouse gas emission linked with buildings' sector. PED can be defined as a district with an annual net import of zero energy and zero net CO2 emissions, which produce a surplus of renewable energy to integrate it into an urban energy system" (Magrini et al., 2020). PEDs are further steps of zero and positive energy buildings. These buildings has a very high energy performance, and the low energy required by this buildings are significantly covered by RESs (Magrini et al., 2020).

a PED is an innovative concept to promote the sustainable development of urban energy systems on a district scale with significant impact on the development of our future cities, which are committed to a sustainable and low-carbon pathway.(Neumann, Hainoun, Stollnberger, Etminan, & Schaffler, 2021)

The key importance of PED's concept lies in reducing dependency on fossil fuels by improving EE of building and promoting integrating RES usage (Omrany et al., 2022). In 2017, the EU launched the "Positive Energy Districts and Neighbourhoods for Sustainable Urban Development " programme as part of the SET Plan Action 3.2 "Smart Cities and Communities" (Magrini et al., 2020).

The goal of the SET Plan Action is to establish 100 PEDs by 2025, with the assistance of 20 Member States (Magrini et al., 2020).

In the report, we can see the list of PED projects in EU. This version of booklet includes 61 cases in 19 different EU countries. The highest number of projects are located in Norway (9), Italy (8), Finland (7), Sweden (6), and The Netherlands (6). In table 1 we can see the list of PED projects in Netherlands.

Table 1. List of PED projects in Netherlands

City	Project name	Link
Alkmaar	PoCiTYF	
Amsterdam	ATELIER	https://smartcity-atelier.eu/
Groningen	MAKING City	http://makingcity.eu/
Hoogeveen	Hydrogen district Hoogeveen	https://www.en-tran-ce.org/
Arnhem	Community-focused Energy Transition	https://www.han.nl/onderzoek/zwaartepunten/see/
Amsterdam, Noordoostpolder, Appingedam, Wageningen, Pekela, Tilburg, Loppersum, Zoetermeer, Brunssum, Middelburg, Tytsjerksteradiel, Delfzijl, Katwijk, Den Haag, Purmerend, Hengelo, Utrecht, Sittard-Geleen, Groningen, Assen, Sliedrecht, Rotterdam, Oldambt, Drimmelen, Eindhoven, Nijmegen, Vlieland, Rotterdam	Program Natural-Gas Free Neighbourhoods	http://www.aardgasvrijewijken.nl

1.5 Challenges of PED

Other Challenges: In addition to technical and data management challenges, PEDs also may face other challenges such as economic, social and regulatory challenges. Regulatory challenges are due to energy regulations are often not designed for decentralized systems. Economically, the cost of installing RESs, increasing building EE, and deploying smart grid technologies can be challenging. Furthermore, Achieving a PED requires buy-in from a wide range of stakeholders (Uspenskaia, Specht, Kondziella, & Bruckner, 2021).

The focus of this research will be more on technology aspects of PEDs, however, the providing solutions may cover other challenges including Social and Governance aspects. DT is identified as a solution to tackle PEDs challenges. The illustration 8 indicates briefly the challenges for PEDs and DTs

1.6 Digital Twin

Fig. 6 shows some big moments in the evolution of DT (development in the USA and how its application expanded to energy management in the world and Netherlands).

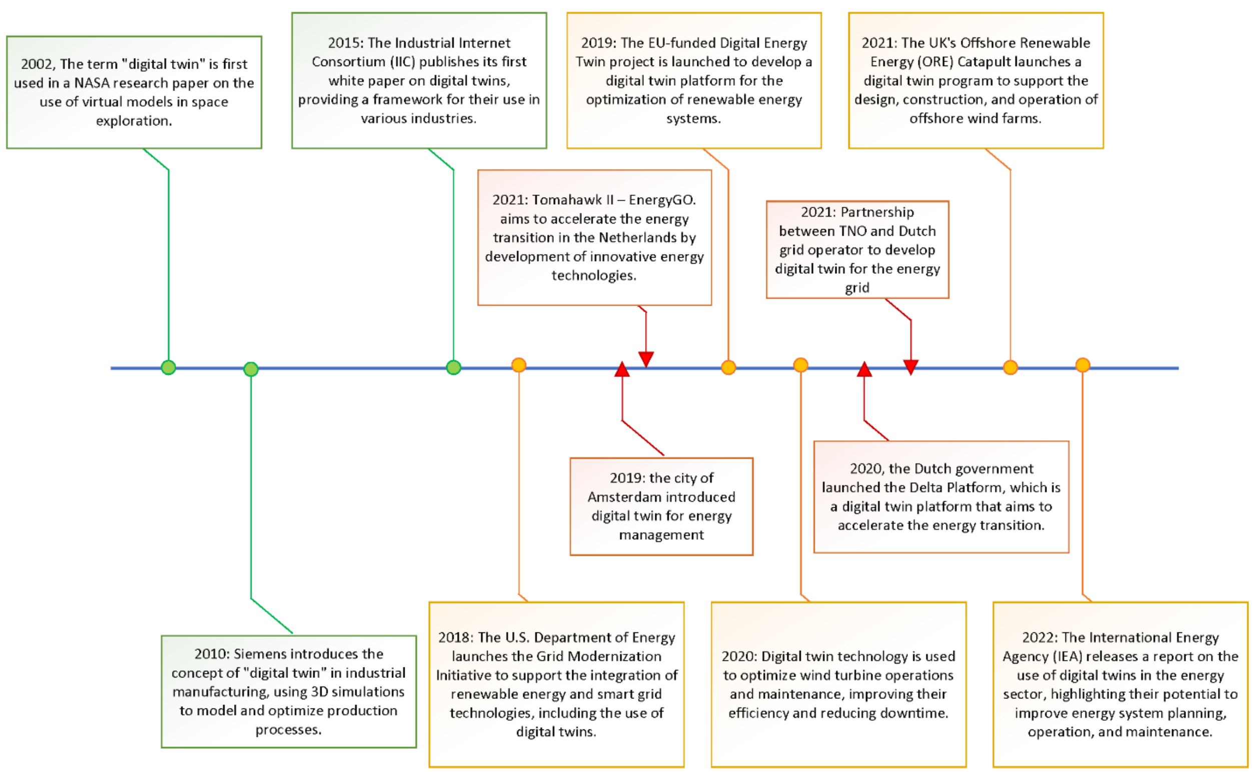

Figure 6. Milestones of DT technology development.

in Fig. 7 the main parts that a DT should have are shown based on the theoretical definitions that defined for DT (Tao & Qi, 2019). We adopted the DT for energy management, and it can be classified into two Main parts and sub-parts:

1) Technology

1.1. Data Collection: DTs are powered by combining data/models from different knowledge domains such as Internet of Things (IoT), GIS, Building Information Model (BIM) and Remote Sensing (RS).
1.2. Computation: the datasets will be pre-processed and exploited by artificial intelligence (AI) algorithms and other data analysis techniques to obtain information from a database.
1.3. Visualization: Web based technologies will be used for 3D visualizing the findings

2) functions

2.1. Real-time monitoring: integrating real-time data from sensors and other sources, can provide a comprehensive understanding of buildings' energy performance.
2.2. Prediction: having a prediction of energy demand and supply is an important tool to create a balance between energy demand and supply.
2.3. Responding: Beyond the capabilities of predicting energy dynamics, the DT model is conceived as a proactive system intended to maintain a harmonious balance within the Energy Demand and Supply. In its responsive role, the DT will be programmed to provide operational feedback that encompass optimization, scenario and spatial analysis strategies to enhance energy efficiency, analyse the potential of renewable energy sources, and energy sharing between buildings
2.4. Optimization: Involves creating and applying algorithms to balance energy demand and supply efficiently, accounting for short-term operations and long-term planning.

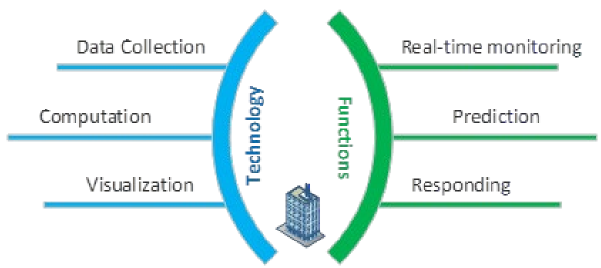

Figure 7. The main parts of a DT.

Figure 8. Challenges of PEDs and DTs

1.7 Boundary Conditions

To streamline the scope of this research and control variability, the following boundary conditions are specified:

Location: The study is limited to buildings typical of urban areas in the Netherlands.

Climate: The research will focus on strategies tailored to the temperate maritime climate of the Netherlands, considering its effect on energy consumption and potential for RES.

Building Types: The diversity in buildings will be limited to their functionality, occupancy, construction that influence energy consumption and production potential.

Energy Systems: The study will focus solely on local decentralized energy systems, involving RES integration and energy management via DTs. However, this research will not encompass the broader national grid and its operations.

Horizon: Our horizon for this research is 2030 and 2050.

DT Development: Given the numerous factors that affect the development and deployment of DTs, such as data acquisition methods, model complexity, and computational resources, this study will firmly adhere to established standards and practices. We will collaborate closely with Geodan, a leading company in this field, utilizing their existing software and DT frameworks. This collaboration allows us to keep the research process consistent and manageable, while also helping us identify potential gaps in current practices. Our goal is to use web technology and adapt their technology, striving to improve and fill any identified gaps. In doing so, we hope to optimize and enhance the application of DTs in the context of energy management within and between buildings.

2. Research Design:

2.1 Research Questions

More details on sub research questions 1, 2, 3 are added.

> Sub Research Question 1. **How can a comprehensive understanding of Positive Energy Districts be established, and in what ways can digital twin technology be utilized to support and enhance the realization of this concept?**

The aspects and topics that will be investigated in this literature review is shown in Fig. 9. Also one of the outputs of this step will be developing a system architecture for the digital twin based on the concepts of PEDs. However, the model will be based on the current model of Geodan (Fig. 10).

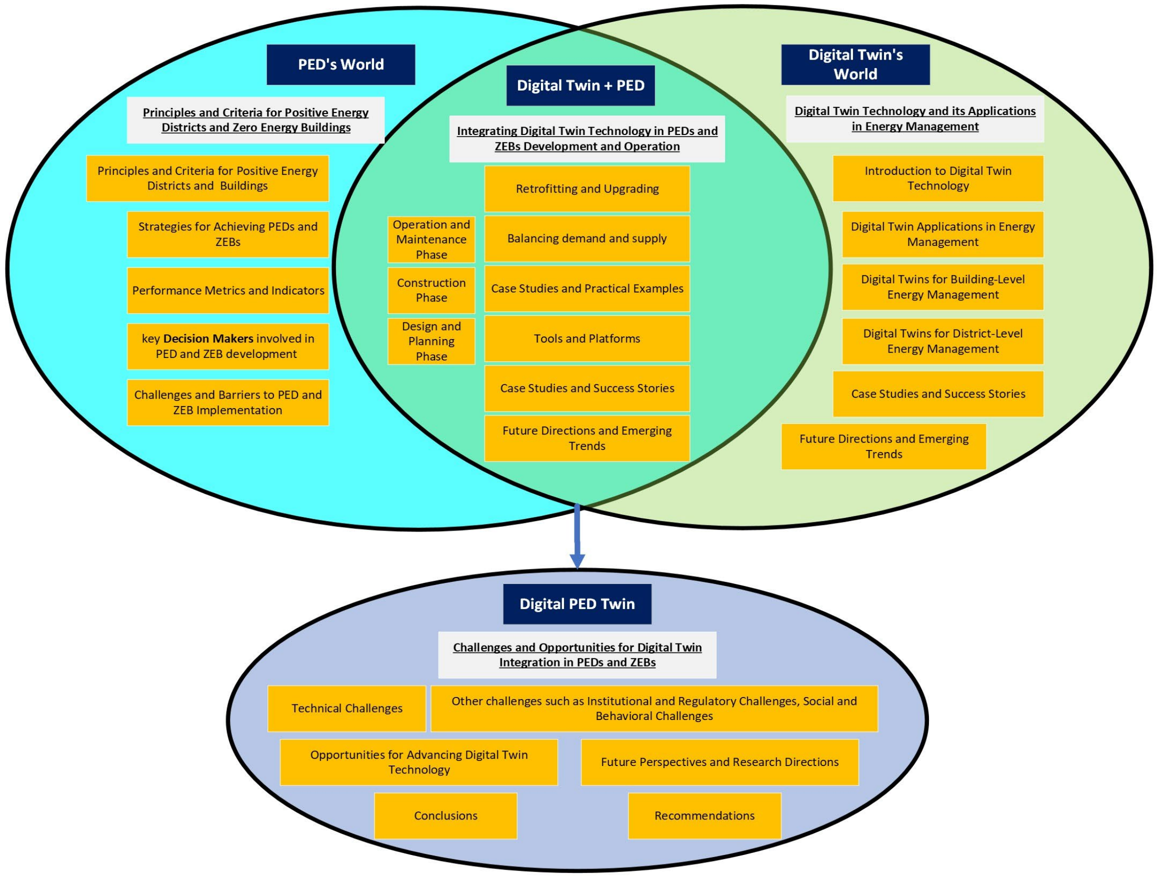

Figure 9. The design for literature review

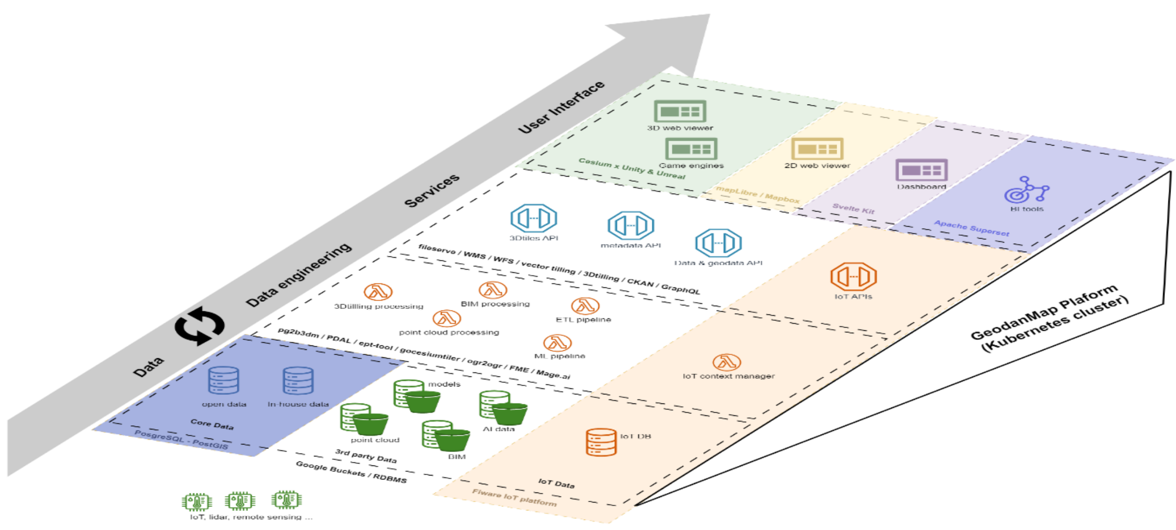

Figure 10. system architecture from GEODAN

Sub Research Question 2. **How can we design and implement a (spatial) data/information infrastructure for efficient handling of complex datasets in Digital Twin technology for energy management in PEDs?**

DT technology offers a powerful approach for optimizing PEDs, by treating them as intricate multi-physics systems, enabling real-time simulations and data-driven enhancement of performance (Shen et al., 2021). However, developing an effective digital twin system for PEDs entails various challenges that need to be carefully addressed.

One of the most significant challenges of developing a DT is handling and analysis of large-scale data sets. Digital twin models for PEDs must integrate an extensive range of data from various sources, including information about weather conditions, building materials, indoor air quality, inhabitant behavior, energy demand, and RES supply data, etc. (Khajavi, Motlagh, Jaribion, Werner, & Holmström, 2019) (Omrany et al., 2022) . Moreover, guaranteeing data security presents significant challenges in the deployment of digital twin technology (Aloraini & Hammoudeh, 2017).

Overall, Overcoming the challenges of handling extensive data, providing real-time analytics, ensuring interoperability, securing data, data synchronization and promoting continuous learning can pave the way for maximizing digital twins' benefits, such as boosting system resilience, enhancing resource efficiency, and fostering better stakeholder collaboration (Aloraini & Hammoudeh, 2017). (Omrany et al., 2022).

Solution to the afore-mentioned challenges lies in the development of a data infrastructure. This infrastructure can provide the necessary framework for efficient data collection, storage, processing, and security measures.

Aim: The aim of this chapter is to elucidate the necessary components and data infrastructure required for developing a DT model to effectively manage energy within and between buildings.

Outline:

- Overview of data requirements for energy management in buildings.
    - Frequency of datasets used in energy management.
    - Analyze the importance of involving these datasets in data-driven models (datasets we must/should/not necessary/ good to have)
    - Availability and source of potential datasets (open-sources/available but need to be processed/need to be collected (field-work, interview, etc.)/ not free/other sources)
- Establish data/information model:
- Data integration: integrating data from different sources and formats.
- Data synchronization: updating the DT with real-time data from buildings and energy system for accurate monitoring and analysing.
- Data management: organizing, storing, and governing of data.
- Data standardization: It will be tried to understand:
    - The standardization models that are developed in the field of energy management of buildings.
    - How we can implement these standards in this research
    - What aspects are missing and need to define new standards
- Data governance policies: Implement data security measures to protect sensitive information.
- Provide data access

Tools and Methods:

- Steps toward developing Data Infrastructure Is visualized in Fig. 11.
- MongoDB, Postgres, POSTGIS, … for data management
- TimescaleDB → PostgreSQL++ for time series
- Improve and adopt the current system architecture of GEODAN
- Develop energy model inspired by ESDL [Home (esdl.nl)](esdl.nl), and adopt to our project

Outcome:

- Data Infra is Identified as an essential components required to develop a DT model for energy management.
- Energy Model
- The data infrastructure will be developed in line with the current model of Geodan which can be seen in figure 12. This is just a simple version of the data infrastructure of Geodan. Wi will try to improve that and make it in line with DATALESS project.

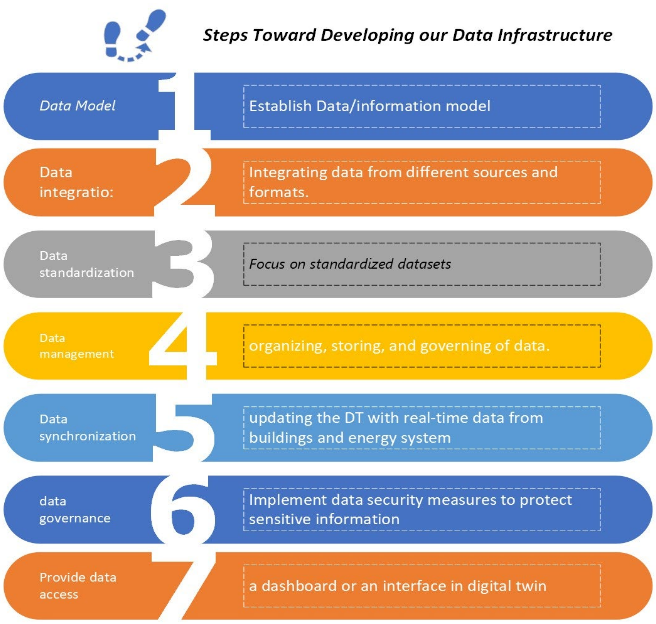

Figure 11. steps toward developing our data infrastructure

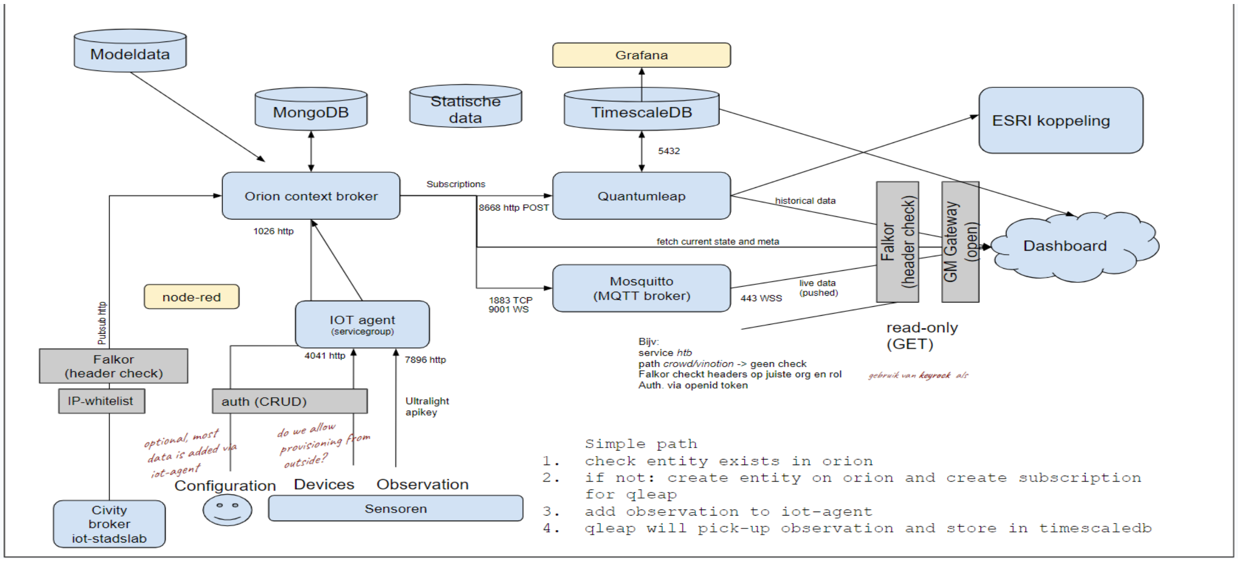

Figure 12. current sketch of data infrastructure from Geodan

Sub Research Question 3.1: How Can data-driven algorithms be used for predicting energy demand of different types of buildings and expanding it to a district?

Energy prediction models are important tools for analyzing energy usage in building sector and developing various strategies to create a balance between demand and supply including (Sun et al., 2020; Yang et al., 2022):

- Quantify energy saving potential of buildings.
- Designing and choosing proper energy intervention models to increase energy efficiency of buildings.
- Optimize energy distribution planning.
- Identify measures to respond the demand

Aim: The aim of this chapter is to delve into the use of AI algorithms for predicting energy demand in buildings (having prediction of the demand of buildings and district is an essential operational feedback that a DT should provide to balance energy in/between buildings).

Outcome:

- Having a prediction of energy demand for different types of buildings
- Expanding the energy demand model from a building level to a district level.

Methods:

To develop a data-driven algorithm for predicting energy demand, the following steps need to be followed.

1) data collection,

Predicting energy consumption of buildings remains challenging task since a variety of factors have effect on the consumption such as weather conditions, building characters, occupant behavior energy consumption data, and other contextual data such as the location and the time of day(Amasyali & El-Gohary, 2018). It is important to ensure the quality and completeness of the collected data, as inaccurate or incomplete data can affect the accuracy. Although Data-driven model requires high-quality data sets, these models are adaptable and can be optimized and updated with new data (Yu, Chang, & Dong, 2022). In chapter 2, this requirements will be covered.

2) data preprocessing,

Data preprocessing is an essential step for data-driven approaches to deal with invalid incomplete, incorrect, inaccurate, irrelevant or noisy inconsistent data that can cause error during analysis. Data preprocessing includes Data integration, Data transformation, Data reduction, Data merging, Data cleaning, Data conversion, Data Normalization: (Dong, Liu, Liu, Li, & Li, 2021) (Olu-Ajayi, Alaka, Sulaimon, Sunmola, & Ajayi, 2022) (Amasyali & El-Gohary, 2018).

3) Feature engineering,

A data-driven model forecasts energy demand based on a set of features. Feature Selection is essential for optimum model performance since all features are not impactful, or some irrelevant features can have significant impact when are used with other features (Dong et al., 2021; Olu-Ajayi et al., 2022). Feature Selection can decrease computation-time of model without sacrificing accuracy of model, and it is considered as the final step of data preparing which try to solve data irrelevance, redundancy, and mismatch (Wang, Xia, Yuan, Srinivasan, & Song, 2022). Based on (Sun, Haghighat, & Fung, 2020), the common feature selection methods in this context are as follow: Variable ranking, Filter and wrapper methods, Embedded method, Principal component analysis (PCA), Autoencoder

4) model selection and training,

There are various AI algorithms that are used for predicting energy demand. it is still a complex task to conclude which algorithm is better than the other, and to have a comparison of algorithms. Therefore, they need to be implemented and analyzed on the same datasets (Olu-Ajayi et al., 2022). In table 1, the more common algorithms in energy demand prediction are shown. The purpose of prediction, building type, input parameters can vary in various studies.

AI algorithms that have been used repetitively in previous several researche includes Linear regression (LR), Multiple Linear Regression (MLR), Time series analysis, Support Vector Machine (SVM), Support Vector Regression (SVR), decision tree, Regression tree (RT), random forests (RF), extreme gradient boosting (XGBoost), Artificial neural network (ANN), K-Nearest Neighbour (kNN), Deep learning and Ensemble methods. Depending on different model integration strategies, ensemble learning can be divided into three categories: bagging, boosting and stacking.

In a review by (Dong et al., 2021), found that ANN and SVR are effective methods that widely used for energy Demand prediction. Additionally, in other review by (Sun et al., 2020), ANN, SVR and LR are found as most popular models, while there is less concentration on time series analysis and RT.

5) model validation and evaluation

Data-driven models need to be tested to evaluate their performance in predicting energy demand. There are various standard evaluation measures that can be used to compare the actual and predicted values (Amasyali & El-Gohary, 2018). Based on (Sun et al., 2020) the commonly-used evaluation measures of energy consumption prediction models are, Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Bias Error (MBE), Normalized MBE (NMBE), Mean Squared Error (MSE), Root Mean Square Error (RMSE), Coefficient of Variation of the Root Mean Square Error (CV(RMSE)) and R Square (R2). (Olu-Ajayi et al., 2022) identified Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and R-Squared (R2) as the most often used evaluation measures. In other research, mean absolute error (MAE), coefficient of variation (CV), mean bias error (MBE), mean absolute percentage error (MAPE), mean squared error (MSE), R-squared (R2), and error rate (δ)and root mean square error (RMSE) introduced as relevant evaluation measures, and CV, MAPE, and RMSE as the most commonly used method. CV is one of the evaluation measures that recommended by ASHRAE for evaluating energy consumption prediction models (Amasyali & El-Gohary, 2018). Additionally, the time needed for training is another index that are used to compare AI algorithms.

Table 2. common algorithms in energy demand prediction

Linear regression (LR) Multiple Linear Regression (MLR)	It is one of the traditional statistical approaches that fit a linear equation to find association among variables (Olu-Ajayi et al., 2022) (Sun et al., 2020)	LR is easy to use and understand. Generally it cannot find nonlinear relationships between inputs and outputs, but extended LR can solve nonlinear problems
Time series analysis	Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) are the most commonly used models for time series analysis (Sun et al., 2020)	the effect of historical data can be considered in this model
Support Vector Machine (SVM)	A machine learning method that developed by Vapnik three decades ago (Olu-Ajayi et al., 2022; Yu et al., 2022).	It can be used for both nonlinear and linear classifications, and it is one of the top accurate models among data mining algorithms (Amasyali & El-Gohary, 2018).
Support Vector Regression (SVR)	SVR is a regression application of SVM	The prediction performance of SVR is not sensitive to the noisy data, and the dimension of feature space doesn't determine the SVR's computational complexity (Sun et al., 2020). Selecting a proper Kernel function is one of the challenges of SVR ince it needs a kernel function for nonlinier regression problems (Sun et al., 2020)
decision tree	It uses tree-like flowchart to partition data into groups (Olu-Ajayi et al., 2022).	Decision tree is a supervised machine learning algorithm that can be used for both classification and regression problems. (Amasyali & El-Gohary, 2018) The classification and regression trees, chi-squared automatic interaction detector, random forest , and boosting trees (BT) are decision tree methods that widely used in energy demand prediction.
Regression tree (RT)	RT is a type of decision tree with continuous target variables (Sun et al., 2020)	RT is used for regression problems and predict a continuous numerical value.
random forests (RF)	RF is an ensemble technique (Olu-Ajayi et al., 2022) that is based on decision tree models	The predicted value of RF is the average results of several decision tree models, and it can reduces overfitting (Yu et al., 2022)
extreme gradient boosting (XGBoost)	(Olu-Ajayi et al., 2022) XGBoost is is a decision-tree-based ensemble algorithm that by combining weak and simple models which form a stronger model.	It uses a gradient boosting framework, and unlike the RF model , is a sequential model that each subsequent tree is dependent on the outcome of the last. (Olu-Ajayi et al., 2022) [53] (Yu et al., 2022)
Artificial neural network (ANN)	ANN is a nonlinear algorithm that has a structure similar to biological neural networks.	(Olu-Ajayi et al., 2022) "Artificial Neural Networks are the most broadly utilized for predicting building energy consumption ANN is widely used for forecasting energy demand of buildings and can deal with nonlinear problems easily. (Olu-Ajayi et al., 2022)
K-Nearest Neighbour (kNN)		KNN is a non-parametric ML method that uses proximity to make a prediction or classification of an individual data (Olu-Ajayi et al., 2022)
Deep learning	(Olu-Ajayi et al., 2022) Deep learning unlike ANN has more layers of neural network and can be more accurate.	deep neural networks (DNN), convolutional neural networks (CNN) and recurrent neural networks (RNN) are deep larning models that can be used in the area of energy demand prediction of buildings
Ensemble methods	(Sun et al., 2020) (Dong et al., 2021) Ensemble learning is an advanced data-driven method that combines two or more models to have a better prediction performance.	based on the combination strategies, ensemble learning can be categorized into three groups: bagging (parallel homogeneous), boosting (sequential homogeneous) and stacking models (heterogeneous).
Depending on different model integration strategies, ensemble learning can be divided into three categories: bagging, boosting and stacking.	(Sun et al., 2020) bagging, boosting and stacking models (also called parallel homogeneous, sequential homogeneous and heterogeneous ensemble methods).	Bagging concentrates on getting an ensemble model with less variance than its components, while boosting will mainly get a strong model with less bias than the underlying model. The advantage of the stacking strategy is that it can significantly improve the overall predicted effect of the model, rather than focusing on the variance or bias."

Sub Research Question 5.

Objective. We aim to maximize energy efficiency, RES integration, and energy storage/sharing, and minimize the reliance on the national grid. The energy surplus needs to be maximized without causing burden on the grid. Mathematically, the multi-objective function could be formulated as follows:

Minimize:

burden on the electricity grid:

$$\sum\sum[\delta * |G_i(t)| - \alpha * RES_k(t) - \beta * E\_ee_i(t) - \gamma * E\_store_j(t) - \omega * E\_buildings_m(t) + D_i(t)$$

Balance:

$$\sum\sum D_i(t) - [\alpha * RES_k(t) + \beta * E_{ee_i}(t) + \gamma * E\_store_j(t) + \omega * E_{buildings_m}(t) + \delta * G_i(t)]$$

Variables

The components of the objective function are:

The constants α, β, γ, ω, and δ are the weights assigned to each objective, which represent their relative importance. The weights can be adjusted to reflect the priorities or preferences of the decision-makers.

$G_i(t)$: energy from grid

$RES_k(t)$: Energy supply from RES K

$E\_ee_i(t)$: The amount of energy demand can be reduced through energy efficiency measures in building i at time t

$E\_store_j(t)$: Energy available from storage k

$E\_buildings_m(t)$: Energy available for sharing from other buildings

$D_i(t)$: The energy demand of building i at time t.

Constraints:

Energy balance:	$D_i(t) <= RES_k(t) + E\_store_j(t) + E\_buildings_m(t) + E\_ee_i(t) + G_i(t)$
Energy generation:	$0 <= RES_k(t) <= RES_{max}$
Energy storage:	$0 <= E\_store_j(t) <= E\_store_{max}$
Energy sharing:	$0 <= E\_buildings_m(t) <= E\_buildings_{max}$
Energy efficiency:	$E\_ee_{min} <= E\_ee_i(t) <= E\_ee_{max}$
Grid interaction:	$G_{min} <= G_i(t) <= G_{max}$

Incorporating multi-objective optimization models into the DT platform, algorithms will be designed to generate optimized energy management solutions. Using real-time and historical data, the DT evolves to make informed decisions for long-term planning. It also provides visual feedback on district-wide energy performance, highlighting areas for improvement. As the DT learns and adapts from decision outcomes, it guides strategic investments towards energy self-sufficiency, making it a critical tool for sustainable energy management.

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Architecting a Digital Twin for Positive Energy Districts: A Dutch Case Study on Decentralized Renewable Energy Management

Amin Jalilzadeh[1], Azarakhsh Rafiee[1], Peter Van Oosterom[1] and Thaleia Konstantinou[1]

[1] Affiliation1: Architecture Department, TU Delft, Delft, Netherlands

Correspondence: Amin Jalilzadeh (A.Jalilzadeh@tudelft.nl)

Abstract. As the world rapidly transitions towards renewable energy sources, the concept of Positive Energy Districts (PEDs) has emerged as a promising framework to foster energy transition. This research proposal explores the integration of digital twin technology into PEDs to manage energy more efficiently within and between buildings, and minimize the burden on the electricity grid. An exploration of how digital twin can be designed and developed to enhance the practical realization of this concept will be established. The architecture includes predictive energy demand features, multi-objective decision-making models, and addresses potential challenges. The results of this research could serve as a practical guide for leveraging digital twin technology in the development and operation of PEDs, and the establishment of sustainable urban environments.

Keywords. GIS, Digital Twin, Positive Energy Districts, Energy transition, Data-Driven, Data Infrastructure

1. Introduction

Cities are responsible for consuming about two-thirds of energy consumption and emitting more than 70% of GHGs. Also, it is estimated that the building section accounted for more than one-third of the energy consumption (Umbark, Alghoul, & Dekam, 2020). With half the global population already urbanized, and expected to rise to 70% by 2050, we anticipate more buildings, higher energy demand, and increased GHG emissions (Fausing, 2020).

A global effort was made by countries to reach an agreement to tackle climate change before it transforms our planet irreversibly (Economidou et al., 2020). These strategies prioritize enhancing Energy Efficiency (EE) in buildings and increasing the generation of Renewable Energy Sources (RESs) as essential measures in climate change mitigation (Harvey, 2009).

However, Integrating RESs into the electricity grid can disturb stability of the grid since RESs such as wind and solar depend on weather conditions and are not stable in producing energy. Therefore, to facilitate integrating RESs in grid, without disturbing grid, it is vitally important to create a balance between energy demand and supply (Ekren & Ekren, 2010).

Positive Energy Districts (PEDs) have emerged as a response to the growing energy demand of buildings and the complexities of RES integration. PEDs are characterized as energy-efficient and energy-flexible urban zones with an excess of renewable energy production and minimum greenhouse gas emissions (Magrini, Lentini, Cuman, Bodrato, & Marenco, 2020).

Developing PEDs has a group of challenges, such as social, technological, spatial planning, regulations, legal matters, and economic factors (Krangsås et al., 2021). The integration of digital methods can be a solution to the technical challenges in PEDs (Zhang et al., 2021a). Since DT has capability to collect and analyse massive amounts of data, provide real-time monitoring and predictions, and conduct various scenarios to monitor and predict energy production/consumption/distribution, operation optimization, decision-making for energy management, and balancing the demand and supply. These features make DT a powerful tool for decision-makers seeking managing energy within/between buildings (Rolnick et al., 2022).

Our objective, therefore, is to design and understand how we can integrate the PED concept with digital twin technology, providing the necessary operations to establish a PED (Zhang et al., 2021a). Our horizon is for 2030 and 2050. To achieve this, several operational requirements are identified, such as the prediction of energy demand at both the building and district levels and identifying ways to meet this demand.

Meeting the energy demand is a multifaceted task that involves increasing the energy efficiency of buildings to decrease the demand, harnessing more energy from RESs, obtaining energy from other positive energy buildings, and implementing energy storage and battery solutions. All these measures are geared towards reducing the burden on the grid and moving towards grid independence (Guo, Zhao, Wang, Shan, & Gong, 2021; Rahman, Srikumar, & Smith, 2018; Salom et al., 2021; Tuerk et al., 2021; T. Yang, Li, & Xun, 2019).

To manage these tasks effectively, multi-objective decision-making models will be employed. These will evaluate various energy strategies based on a set of predefined performance indicators, such as total energy consumption, the proportion of energy from renewable sources, peak demand, and overall emissions (Iqbal, Azam, Naeem, Khwaja, & Anpalagan, 2014). The ultimate goal is the creation of PEDs that can sustainably manage their energy demand and contribute to a more resilient urban energy system.

The paper is organized as follows: Section 1 introduces the concept of PEDs and Digital Twins. Section 2 presents the energy trends and status of buildings in the Netherlands. Section 3 delves into Digital Twins for energy management, particularly for establishing PEDs. Section 4 explores optimization algorithms for balancing energy. Section 5 outlines the expected results of the project, and Section 6 discusses the findings and challenges.

2. Energy trends in Netherlands

The 2017 Coalition Agreement in the Netherlands prioritized greenhouse gas (GHG) emissions reduction as the core of their climate and energy policy. The agreement established legally binding targets to reduce GHG emissions by 49% by 2030 and by 95% by 2050 (compared to 1990 levels) ("Coalition Agreement 'Confidence in the Future',")

The Climate Agreement focuses on five sectors: electricity, industry, the built environment, mobility, and agriculture and the natural environment. Our focus is on investigating RESs and built environment. in Fig.1, we can see the Climate Agreement's 2050 goals and 2030 targets ("National Climate Agreement - The Netherlands,")..

2.1. Renewable status Energy in the Netherlands

After examining the international agreements targeting the use of RESs, we have analyzed data to assess the progress of the Netherlands in this area (Fig. 2). The data demonstrates a steady increase in the percentage of energy derived from renewables.

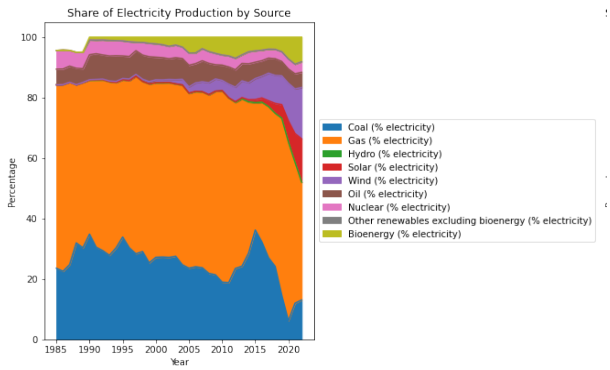

Figure 2. share of energy generation from different sources in Netherlands

2.2. Buildings status in Netherlands

The escalating energy demand in the building sector, which accounted for 29% of global final energy use in 2020, underscores the pressing need for energy-efficient

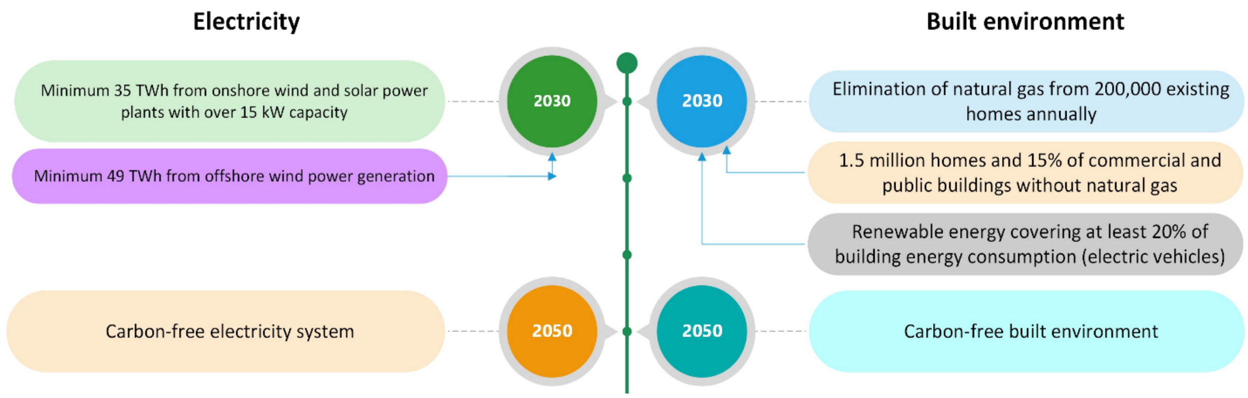

Figure 1. Climate Agreement Goals and Targets for electricity and built environment Sectors

building designs and operations. As projections suggest increase in building energy consumption, it is important to focus on the building sector in driving sustainable energy transitions (Omrany et al., 2022).

To gain insights into the current challenges and potential opportunities for EE in the Dutch built environment, we make a look at status of age and usage of buildings in the Netherlands (Fig.3). Data are extracted from ("Dataset: Basisregistratie Adressen en Gebouwen (BAG),").

While the new buildings are designed to be more efficient, the challenge, however, is not limited to new buildings. In fact, the building stock is inexorably aging, composed of 67% buildings built before 1990 (Fig. 5), with a renewal rate around 1.2% (according to the EU Building Stock Observatory) (Magrini et al., 2020).

2.3. Role of PEDs in the Dutch energy landscape

The concept of PEDs and ZEBs has emerged as a viable solution to the ever-growing energy use and greenhouse gas emission linked with buildings' sector. PED can be defined as a district with an annual net import of zero energy and zero net CO2 emissions, which produce a surplus of renewable energy to integrate it into an urban energy system" (Magrini et al., 2020). In this research three main aspects of developing PEDs will be considered: Energy efficiency measures, Renewable energy production, and Energy sharing/storing.

In 2017, the EU launched the "Positive Energy Districts and Neighbourhoods for Sustainable Urban Development " programme as part of the SET Plan Action 3.2 "Smart Cities and Communities" (Magrini et al., 2020).

The goal of the SET Plan Action is to establish 100 PEDs by 2025, with the assistance of 20 Member States (Magrini et al., 2020).

In the report, we can see the list of PED projects in EU. This version of booklet includes 61 cases in 19 different EU countries. The highest number of projects are located in Norway (9), Italy (8), Finland (7), Sweden (6), and The Netherlands (6). In table 1 we can see the list of PED projects in Netherlands.

Table 1. List of PED projects in Netherlands

City	Project name	Link
Alkmaar	PoCiTYF	
Amsterdam	ATELIER	https://smartcity-atelier.eu/
Groningen	MAKING City	http://makingcity.eu/
Hoogeveen	Hydrogen district Hoogeveen	https://www.en-tran-ce.org/
Arnhem	Community-focused Energy Transition	https://www.han.nl/onderzoek/zwaartepunten/see/
	Program Natural-Gas Free Neighbourhoods	http://www.aardgasvrijewijken.nl
Amsterdam, Noordoostpolder, Appingedam, Wageningen, Pekela, Tilburg, Loppersum, Zoetermeer, Brunssum, Middelburg, Tytsjerksteradiel, Delfzijl, Katwijk, Den Haag, Purmerend, Hengelo, Utrecht, Sittard-Geleen, Groningen, Assen, Sliedrecht, Rotterdam, Oldambt, Drimmelen, Eindhoven, Nijmegen, Vlieland, Rotterdam		

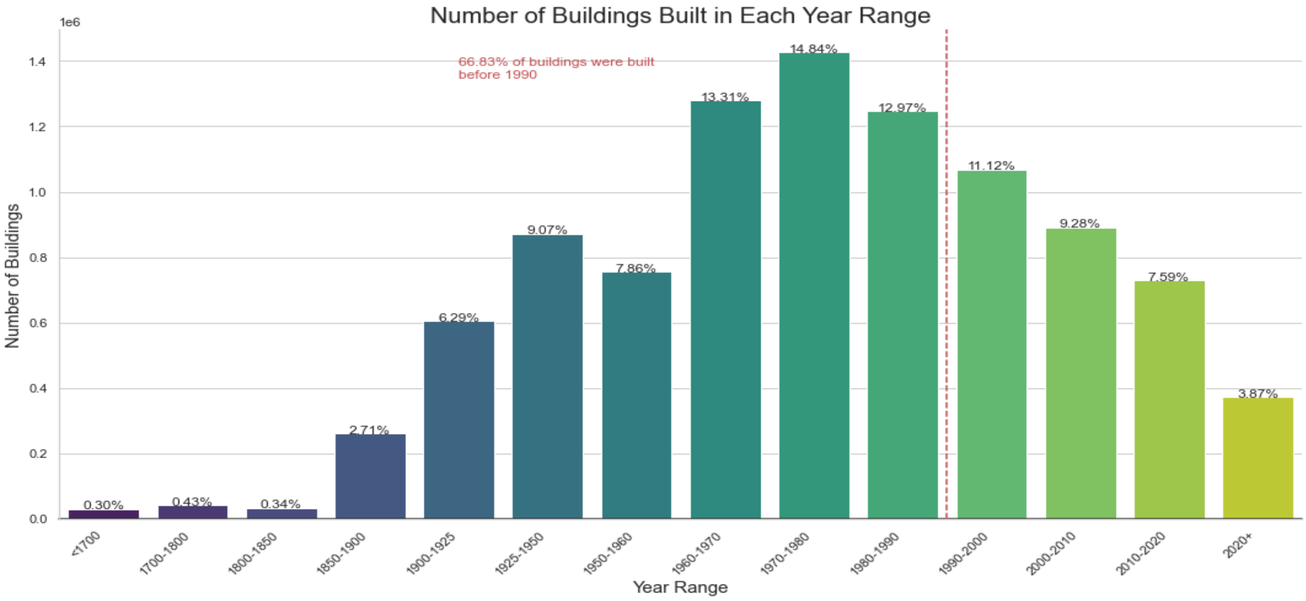

Figure 3. shows the number of built in different year ranges.

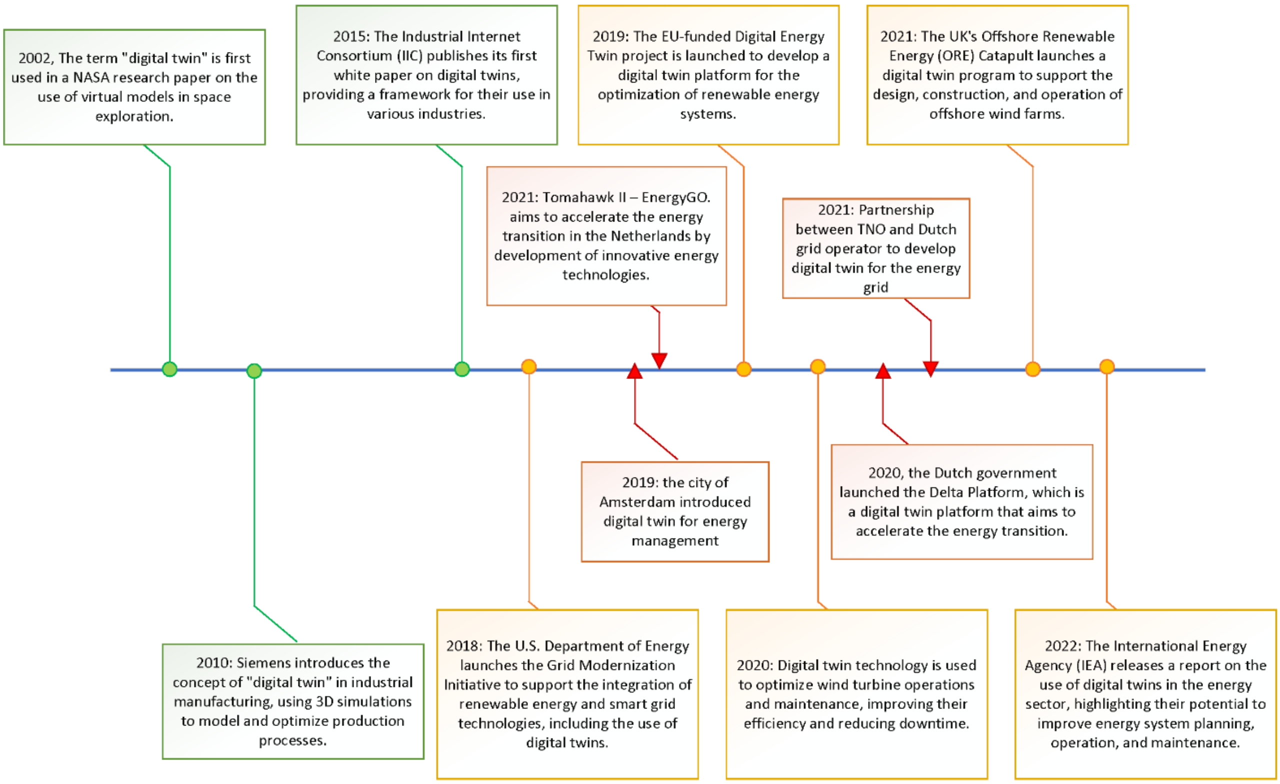

Figure 4. Milestones of DT technology development.

3. Digital Twin for energy management

DTs as a computational model attracted ever-growing attention in energy management in building environments in recent years (Rolnick et al., 2022). Fig. 4 shows some big moments in the evolution of DT (development in the USA and how its application expanded to energy management in the world and Netherlands.

Zhang et al. (2021b) classified DT into three tires: (1) an enhanced version of BIM model only, (2) semantic platforms for data flow, and (3) big data analysis and feedback operation. Furthermore, Agostinelli, Cumo, Guidi, and Tomazzoli (2021) showed that DTs have a high potential to achieve an intelligent optimization and automation system for energy management for both one and a cluster of buildings. In another article, a review of DTs application domains in smart energy grid is conducted by Cioara et al. (2021). They categorized the most relevant applications into four groups: 1) Asset Model (DTs for energy performance assessment and management), 2) Fault Model (DTs for diagnosis of faults), 3) Operational Model (DTs for optimal energy distribution and energy efficiency), 4) Business Model.

3.1. Architecting a Digital Twin for establishing PEDs

based on the theoretical definitions that defined for DT by Tao and Qi (2019), a digital twin has two aspects, technology of development and functions that can provide feedback for the aim that it is developed. in Fig. 5 the main parts that a DT should have are shown.

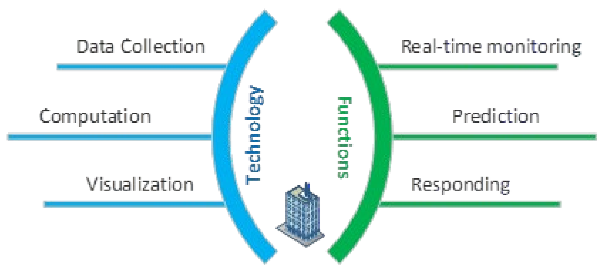

Figure 5. The main parts of a DT.

3.1.1. Technology

DT technology offers a powerful approach for optimizing PEDs, by treating them as intricate multi-physics systems, enabling real-time simulations and data-driven enhancement of performance (Shen, Saini, & Zhang, 2021). However, developing an effective digital twin system for PEDs entails various challenges that need to be carefully addressed.

One of the most significant challenges of developing a DT is handling and analysis of large-scale data sets. Digital twin models for PEDs must integrate an extensive range of data from various sources, including information about weather conditions, building materials, indoor air quality, inhabitant behavior, energy demand, and RES supply data, etc. (Khajavi, Motlagh, Jaribion, Werner, &

Holmström, 2019) (Omrany et al., 2022) . Moreover, guaranteeing data security presents significant challenges in the deployment of digital twin technology (Aloraini & Hammoudeh, 2017).

Overall, Overcoming the challenges of handling extensive data, providing real-time analytics, ensuring interoperability, securing data, data synchronization and promoting continuous learning can pave the way for maximizing digital twins' benefits, such as boosting system resilience, enhancing resource efficiency, and fostering better stakeholder collaboration (Aloraini & Hammoudeh, 2017). (Omrany et al., 2022).

Solution to the afore-mentioned challenges lies in the development of a data infrastructure. This infrastructure can provide the necessary framework for efficient data collection, storage, processing, and security measures.

Steps toward developing Data Infrastructure can be defined as follow:

1. Overview of data requirements for energy management in buildings.

1.1. Frequency of datasets used in energy management.

1.2. Analyze the importance of involving these datasets in data-driven models (datasets we must/should/not necessary/ good to have)

1.3. Availability and source of potential datasets (open-sources/available but need to be processed/need to be collected (field-work, interview, etc.)/ not free/other sources)

2. Establish data/information model:
3. Data integration: integrating data from different sources and formats.
4. Data synchronization: updating the DT with real-time data from buildings and energy system for accurate monitoring and analysing.
5. Data management: organizing, storing, and governing of data.
6. Data standardization: It will be tried to understand:

6.1. The standardization models that are developed in the field of energy management of buildings.

6.2. How we can implement these standards in this research

6.3. What aspects are missing and need to define new standards

7. Data governance policies: Implement data security measures to protect sensitive information.
8. Provide data access

3.1.2. Functions

the functions that we need to define for the DT need to be based on the concept of PED and the horizon for 2030. We aim to reduce the pressure on the power grid. To do this, we need to balance energy supply and demand while relying less on the grid. To achieve this balance, we first need to predict how much energy we'll need, and then figure out ways to meet this need without using too much energy from the grid.

3.1.2.1. Predicting Energy Demand

Energy prediction models are important tools for analyzing energy usage in building sector and developing various strategies to fulfil this demand (Sun, Haghighat, & Fung, 2020; X. e. Yang et al., 2022):

• Quantify energy saving potential of buildings.

• Designing and choosing proper energy intervention models to increase energy efficiency of buildings.

• Fault diagnosis of buildings.

• Optimize energy distribution planning.

Our motivation lies in the necessity of understanding energy demand at both the building and district levels to facilitate efficient energy management. Utilizing AI algorithms can help to make more precise demand predictions. Data-driven approaches received significant attention in building energy prediction (Sun et al., 2020). To have a prediction of demand of a district the plan is to develop models to predict energy demand of most frequent types of buildings, then expand it to the district.

Based on Amasyali and El-Gohary (2018), the steps of developing a data-driven model for energy demand prediction are 1) Data collection; 2) Data preprocessing; to deal with invalid incomplete, incorrect, inaccurate, irrelevant or noisy inconsistent data that can cause error during analysis (Olu-Ajayi, Alaka, Sulaimon, Sunmola, & Ajayi, 2022), 3) Feature Selection: to decrease computation-time of model without sacrificing accuracy of model, and to solve data irrelevance, redundancy, and mismatch (Wang, Xia, Yuan, Srinivasan, & Song, 2022), 4) model selection and training; AI algorithms need to be implemented and analyzed on the same datasets to conclude which algorithm is better than the other (Olu-Ajayi et al., 2022). Sun et al. (2020) found that Artificial Neural Networks, Support Vector Regression are popular models, 5) model validation and evaluation; Data-driven models need to be tested to evaluate their performance in predicting energy demand. Additionally, the time needed for training is another index that is used to compare AI algorithms.

3.1.2.2. Predicting Energy supply

The horizon of this research is for 2030 and 2050 when it is supposed that there will be no place for fossil fuels and energy requirements are covered by RESs. Having understanding of potential of districts for integrating RESs is of importance to develop solutions to fulfil energy demand. Integrating RESs demands an estimation of potential of district to have RESs. Geospatial multi-criteria analysis is used by Elkadeem, Younes, Sharshir, Campana, and Wang (2021) for investigating the potential of integrating solar and wind energies in a grid. Elsner (2019) used spatial analysis for assessing the African offshore wind energy potential. Also, Sahoo, Zuidema, van Stralen, Sijm, and Faaij (2022) developed an analytical approach to include spatial policy considerations in identifying spatial potentials for renewable energy sources of Groningen Province in the northern Netherlands. It can be seen that RESs supply potential are strongly relied on spatial aspects (Ramachandra & Shruthi, 2007; Sahoo et al., 2022), therefore, spatial analysis and Geospatial Information System (GIS) can be used to map and investigate the renewable energy potential.

3.1.2.3. Energy sharing/storing

As energy infrastructure becomes complex and decentralised, and renewable energy use expands, buildings need to evolve as active participants in the wider district-level energy system. Exploiting peer-to-peer energy exchange and effective storage in microgrid-connected buildings can optimise on-site generation and lower costs, providing a more efficient alternative to exporting electricity to the grid (Vand, Ruusu, Hasan, & Manrique Delgado, 2021). Semeraro et al. (2023) classified Energy Storing Systems into five main groups: mechanical energy storage, electrochemical energy storage, thermal energy storage, chemical energy storage, and electromagnetic energy storage. However there still some challenges including high price of these systems that prevent Storing Systems to be used widely (Y. Yang, Bremner, Menictas, & Kay, 2018).

4. Application of Optimization Algorithms

Managing the balance between energy demand and supply is a complex task that requires sophisticated solutions. Optimization algorithms, owing to their ability to handle multiple variables and constraints, are increasingly being employed in this domain (Mariano-Hernández, Hernández-Callejo, Zorita-Lamadrid, Duque-Pérez, & García, 2021). These algorithms aid decision-makers in understanding the trade-offs between various energy management strategies, thereby facilitating the identification of optimal solutions that efficiently manage the energy balance.

Optimization algorithms are mathematical tools designed to find the most efficient solution to a complex problem given certain constraints. They help balance the way we generate, distribute, and use energy, and find the best solutions while working within certain limits. This research aim to define the optimization problem for managing energy. Our horizon is for 2030, and solutions are based on the climate agreements and PEDs concepts.

The primary objective is to achieve a PED. The aim is to minimize burden on the grid by getting independent from national electricity grid. Also, while in the PEDs the aim is to maximize the energy surplus in the district, but also need to be considered that selling back to the energy can also cause burden on the grid, and these factors need to be considered in modelling.

Being independent of the grid means that the energy demand of buildings in the district (electrical vehicles are also part of it based on the climate agreements) ned to be covered through the optimal combination of renewable energy generation, energy storage/sharing among buildings, increase energy efficiency of buildings, and other actions.

Objective. We aim to maximize energy efficiency, RES integration, and energy storage/sharing, and minimize the reliance on the national grid. The energy surplus needs to be maximized without causing burden on the grid. Mathematically, the multi-objective function could be formulated as follows:

Minimize:

burden on the electricity grid:

$$\sum\sum[\delta * |G_i(t)| - \alpha * RES_k(t) - \beta * E\_ee_i(t) - \gamma * E\_store_j(t) - \omega * E\_buildings_m(t) + D_i(t)$$

Balance:

$$\sum\sum D_i(t) - [\alpha * RES_k(t) + \beta * E_{ee_i}(t) + \gamma * E\_store_j(t) + \omega * E_{buildings_m}(t) + \delta * G_i(t)]$$

Variables

The components of the objective function are:

The constants α, β, γ, ω, and δ are the weights assigned to each objective, which represent their relative importance. The weights can be adjusted to reflect the priorities or preferences of the decision-makers.

$G_i(t)$: energy from grid

$RES_k(t)$: Energy supply from RES K

$E\_ee_i(t)$: The amount of energy demand that can be reduced through energy efficiency measures in building i at time t.

$E\_store_j(t)$: Energy available from storage k

$E\_buildings_m(t)$: Energy available for sharing from other buildings

$D_i(t)$: The energy demand of building i at time t.

Constraints:

Energy balance:

$D_i(t) <= RES_k(t) + E\_store_j(t) + E\_buildings_m(t) + E\_ee_i(t) + G_i(t)$

Energy generation:

$0 <= RES_k(t) <= RES_{max}$

Energy storage:

$0 <= E\_store_j(t) <= E\_store_{max}$

Energy sharing:

$0 <= E\_buildings_m(t) <= E\_buildings_{max}$

Energy efficiency:

$E\_ee_{min} <= E\_ee_i(t) <= E\_ee_{max}$

Grid interaction:

$G_{min} <= G_i(t) <= G_{max}$

Incorporating multi-objective optimization models into the DT platform, algorithms will be designed to generate optimized energy management solutions. Using real-time and historical data, the DT evolves to make informed decisions for long-term planning. It also provides visual feedback on district-wide energy performance, highlighting areas for improvement. As the DT learns and adapts from decision outcomes, it guides strategic investments towards energy self-sufficiency, making it a critical tool for sustainable energy management.

5. Deliverable Results

In this section, we unveil the preliminary design of our Digital Twin, a web-based system devised with a vision of creating PEDs. As illustrated in Fig. 6, the initial version of our DT, which is accessible at dataless.beta.geodan.nl, was developed in a collaborative with Geodan.

This first iteration, designed using publicly accessible datasets for data privacy and usage rights adherence. The model, as depicted in Figure 6, will evolve to incorporate advanced features such as plugins for data analysis, predicting energy demand, scenario analysis, and more.

6. Discussion and Conclusion

Buildings are one of the main users of energy, and RESs has the potential to provide the energy need of building sector. However, integrating RESs into energy system can disturb the balance of the power grid. DTs have emerged as a high-potential technique for supporting decision-making, enhancing performance and operation, and lowering operation costs in many fields including energy management of buildings.

This article tried to architect and design a digital twin to establish PEDs, and in this section we discuss challenges and risks associated with this aim.

One of the first obstacles we encounter is the task of reconciling the disparate principles and processes of PEDs and DT technology. The complexity and multifaceted nature of these concepts, combined with the ever-evolving landscapes of PED and DT fields, pose a significant challenge. Furthermore, accessing relevant case study data is also a noted challenge.

Moving into the domain of data management, challenges are multifold. Managing vast data volumes, ensuring real-time analytics, data security, interoperability, and synchronization, all become aspects of concern. The need to standardize datasets, identify and investigate the

Figure 6. initial version of DT model for this project available from dataless.beta.geodan.nl.

necessary datasets for project inclusion, stay updated with evolving data management practices, and maintain infrastructure flexibility to adapt to new data types and energy management needs, are substantial difficulties. Furthermore, issues of data security and ethical considerations become critical when handling large amounts of sensitive data.

With respect to the methodology employed, DT heavily relies on the accessibility of diverse building datasets to apply data-driven algorithms effectively. Risks arise when we are unable to acquire sufficient data, forcing us to resort to using white or gray box methods for certain types of buildings. Furthermore, there is the risk that the algorithms we develop may not be universally applicable or scalable across different contexts or various types of buildings and districts.

In the realm of spatial analysis, inherent uncertainties, coupled with variability in environmental factors and potential constraints in accessing comprehensive and timely spatial data, may pose a risk to the accuracy of our assessments.

When expanding from a building level to an entire district, challenges multiply. Designing and implementing DT technology at this scale brings with it complexities when it comes to simulating, predicting, and prioritizing energy efficiency measures. There are also risks associated with the variability in solutions for different building types and across districts, especially for buildings like historical ones, where flexibility for implementing certain energy efficiency measures might be limited.

Lastly, the ambitious goal of integrating DT technology for district-wide energy management brings with it a host of challenges and risks. These range from the complexity of integrating DT technology, formulating a comprehensive multi-objective optimization algorithm, and dynamically managing the energy within the district. There are numerous variables and constraints to account for, such as the variability of renewable energy generation, energy demand-supply balance, efficient energy storage and sharing, and minimizing disturbance to the national grid. Further complexities arise when trying to incorporate the feedback into DT's to refine their predictive and operational capabilities. Implementing a fully functional Digital Twin for an entire district's energy management is ambitious, and managing the computational time for this complex task is a significant challenge.

In conclusion, the pathway to designing a Digital Twin aimed at establishing Positive Energy Districts presents both substantial challenges and risks. However, it is through understanding and navigating these complexities that we can truly make strides towards a more sustainable future. We aim to meet these challenges head-on, learning and adapting as we progress in our research..

Acknowledgement

This research received funding from the Dutch Research Council (NWO) and National Natural Science Foundation of China (NSFC) in the framework of the Cooperation China-The Netherlands programme. We would also like to express our gratitude to the team members of the DATALESs project for their valuable assistance throughout the project. We are also thankful for Geodan's expertise and guidance in developing the digital twin.

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