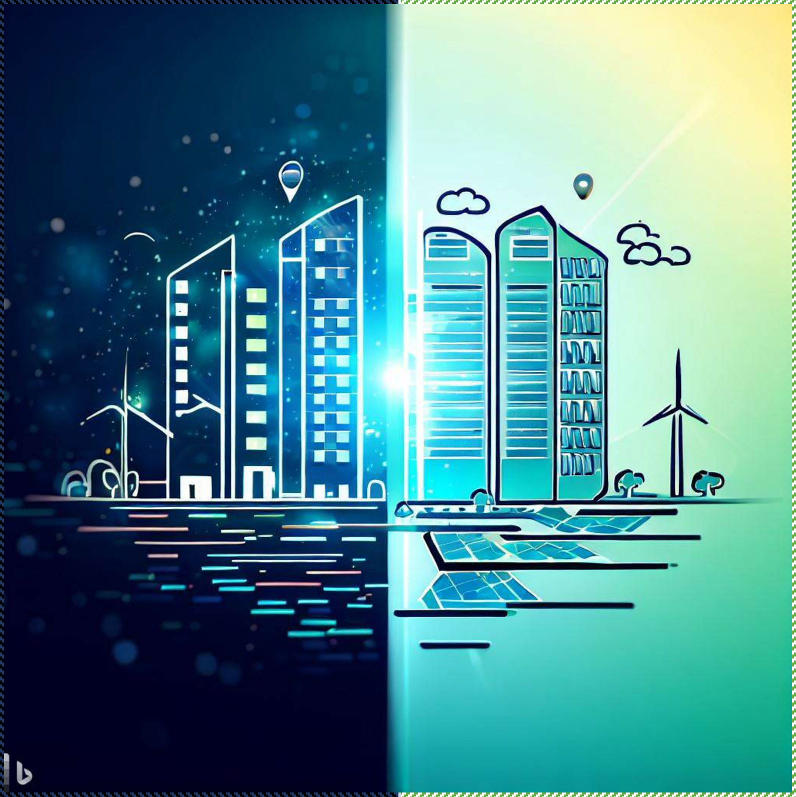

Data-driven green building modeling for energy balancing

PhD Research Portfolio

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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).

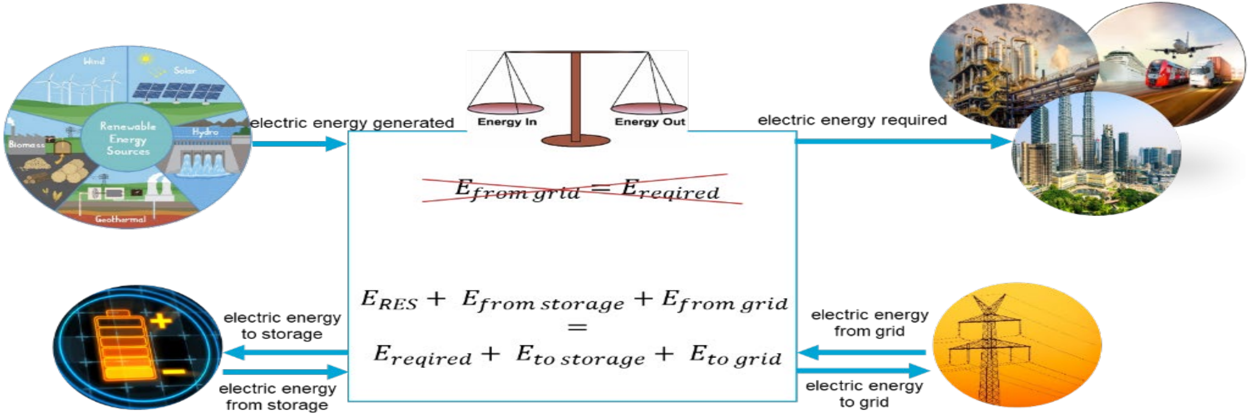


Figure 1. System operation logic. Adopted from (Aruta et al., 2023).

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.

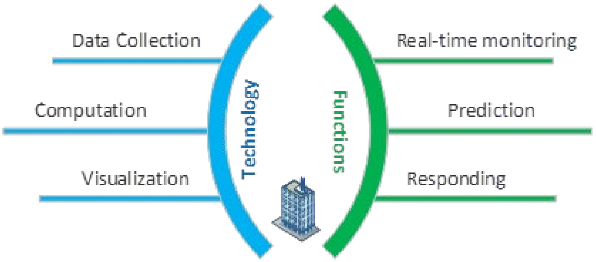


Figure 2. The main parts of a DT.

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 comprehensive data infrastructure smf 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.

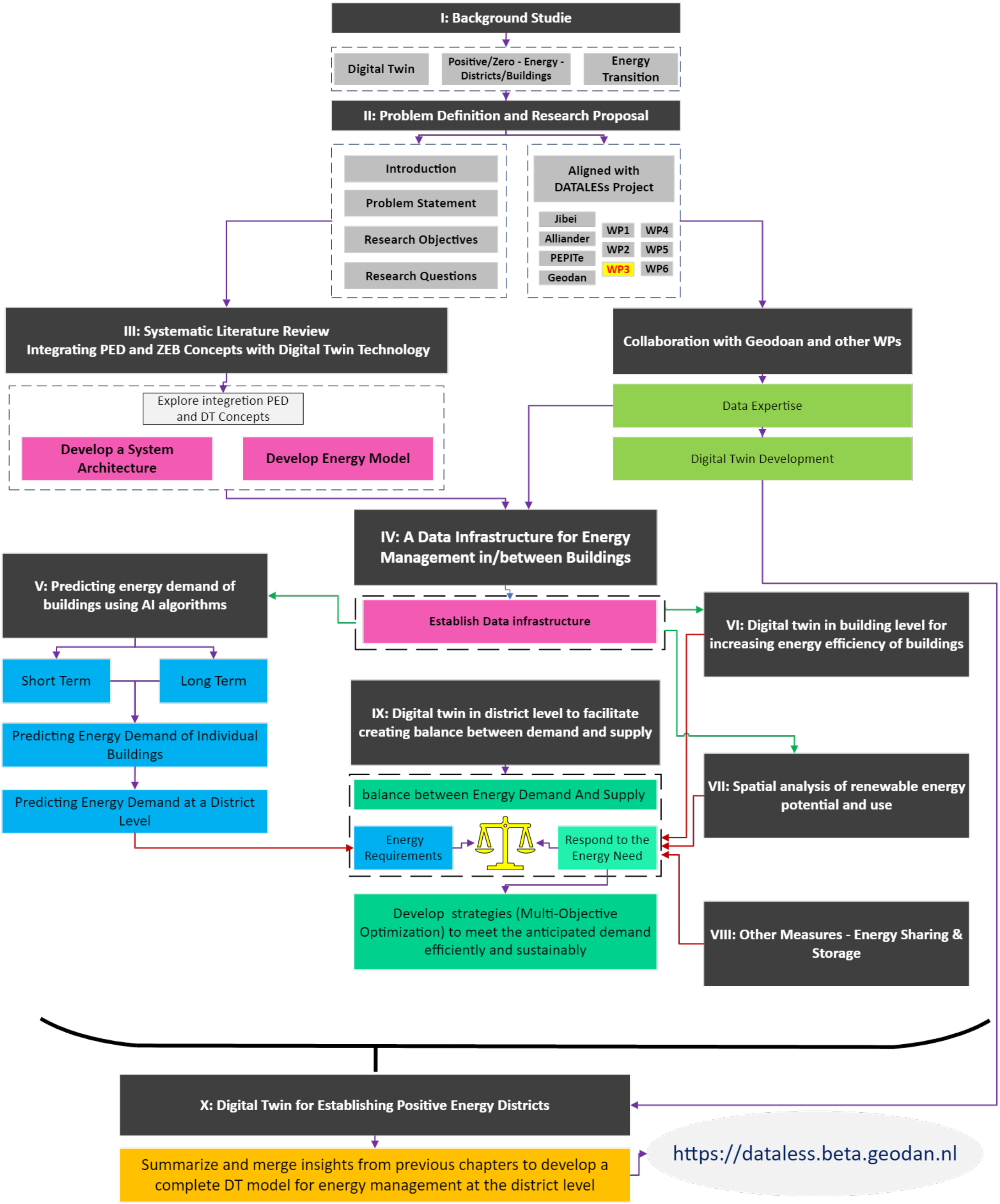
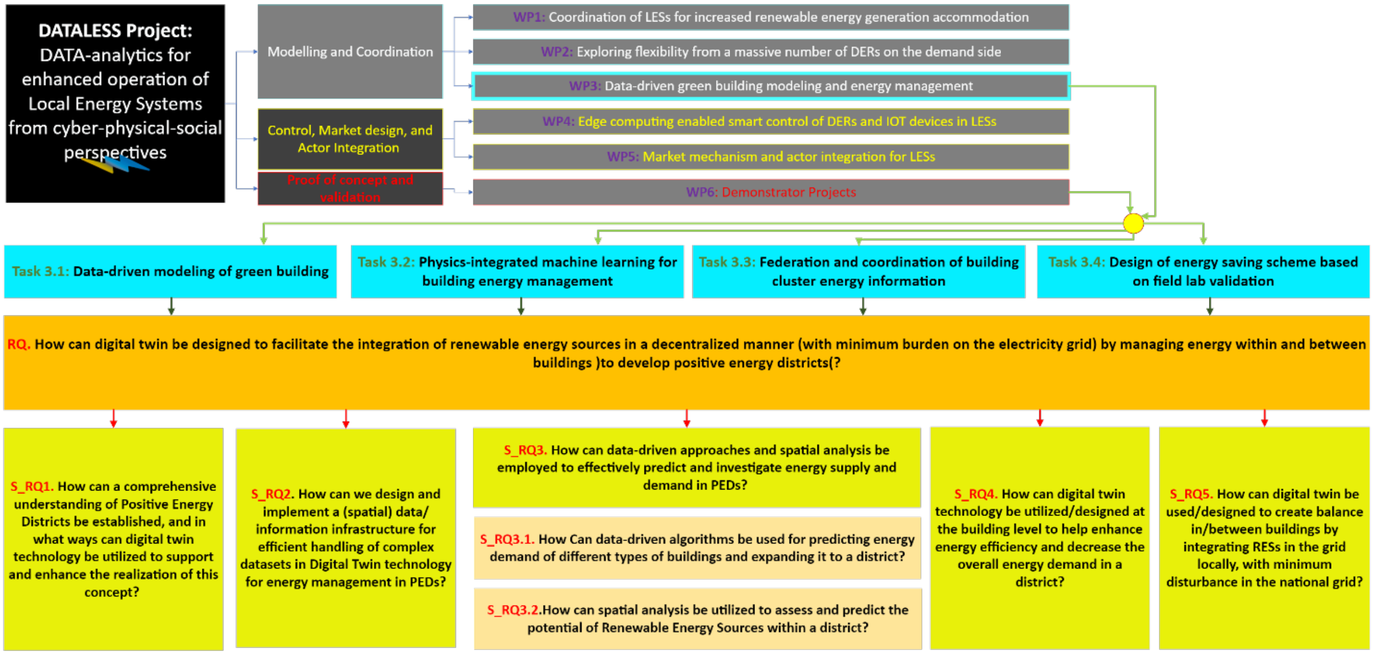


Figure 4. Concept Methodology of the research. The figure illustrates the interrelation between different sections of the study.



RQ. 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(?

S_RQ1. 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?

S_RQ2. 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?

S_RQ3. How can data-driven approaches and spatial analysis be employed to effectively predict and investigate energy supply and demand in PEDs?

S_RQ3.1. How Can data-driven algorithms be used for predicting energy demand of different types of buildings and expanding it to a district?

S_RQ3.2.How can spatial analysis be utilized to assess and predict the potential of Renewable Energy Sources within a district?

S_RQ4. 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?

S_RQ5. 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?

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).


Lagenbeheer

Achtergrondlagen
● Basiskaart
○ Luchtfoto Actueel HR

Terrein
● 25gn1
○ Uit

Wereld Transparantie 100%
0 100

Thematische lagen
☐ KLIC Amsterdam
☐ Vervuilde grond Amsterdam
☐ Boomkluiten Amsterdam
☑ KLIC Nieuwegein
☑ Boomkratten Nieuwegein
☐ Vervuilde grond Nieuwegein
☐ KLIC Barneveld
☐ Boomkluiten Barneveld
☐ Puntenwolk Barneveld
☐ Puntenwolk Barneveld Geosnap
☐ Puntenwolk Nieuwegein
☑ Gebouwen
☑ Bomen

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

	2022					2023												2024												2025												2025						
objectives	Q3		Q4			Q1			Q2			Q3			Q4			Q1			Q2			Q3			Q4			Q1			Q2			Q3			Q4			Q1			Q2			Q3
	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mrt	Apr	Mei	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mrt	Apr	Mei	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mrt	Apr	Mei	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mrt	Apr	Mei	Jun	Jul
	■	■	■	■	■	■	■	■	■	■	■	■																																				
I: Background Studie	■	■																																														
II: Problem Definition and Research Proposal	■	■	■	■	■	■	■	■	■	■	■																																					
Go / No GO												■																																				
III: Systematic Literature Review Integrating PED and ZEB Concepts with Digital Twin Technology	░	░	░	░	░	░	░	░	░	░	░	■	■	■	■	■																																
Principles and Criteria for Positive Energy Districts and Zero Energy Buildings					■	■																																										
Digital Twin Technology and its Applications in Energy Management							■																																									
Integrating Digital Twin Technology in PEDs and ZEBs Development and Operation								■				■	■																																			
Challenges and Opportunities for Digital Twin Integration in PEDs and ZEBs									■				■	■																																		
output														■	■	■																																
IV: A Data Infrastructure for Energy Management in/between Buildings			░	░													■	■	■	■																												
Data Preparing/managing			■														■																															
Data modelling/standardization/synchronization																	■	■																														
Establish Data/information model.																		■	■																													
output																			■	■	■																											
V: Predicting energy demand of buildings using AI algorithms				░	░																	■	■	■	■	■	■																					
Real Rata Preparing				■																																												
Simulated Data Preparing																						■																										
Develop models for individual buildings					■																	■	■	■																								
Expand model for a district																									■	■																						
output																								■	■	■	■																					
VI: Digital twin in building level for increasing energy efficiency of buildings																												■	■	■	■	■																
Explore Intervention Scenarioes																												■	■																			
Develop Algorithms to analyse scenarioes																													■	■																		
integrete with digital twin																														■	■																	
output																															■	■																
VII: Spatial analysis of renewable energy potential and use																																	■	■	■	■												
Data layers for spatial analysis																	■	■															■															
RESs possibilities																																	■	■														
Develop algorithms																																		■	■													
output																																			■	■												
VIII: Other Measures - Energy Sharing & Storage																																					■											
Identify strategies to respond energy demand																								■		■						■				■	■											
IX: Digital twin in district level to facilitate creating balance between demand and supply																																						■	■	■	■							
Formulating the problem									░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	■										
Develop models and algorithms																																						■	■									
Integrate with digital Twin																																							■	■	■							
output																																								■	■							
X: Digital Twin for Establishing Positive Energy Districts																																										■	■	■	■	■	■	■
Finalising Digital Twin model						░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	░	■	■	■	■			
WP6																																																■

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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