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Enhancing the energy efficiency in district heating networks through digital twins

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Abstract

Europe prioritizes energy efficiency for sustainable development and climate action, with buildings consuming 40% of the EU's energy and contributing over 30% of CO_2 emissions. To address this, the EU implements policies targeting energy efficiency across sectors like industry, transportation, and district heating. The Energy Efficiency Directive mandates reductions in energy consumption, promoting measures such as energy audits and performance standards. Initiatives like the European Green Deal and Renovation Wave Strategy underscore the importance of energy efficiency in achieving carbon neutrality. District heating systems play a vital role in this strategy, offering efficient heating solutions for urban areas, and optimizing their operation is a key focus of research. Techniques include mathematical modeling, advanced control strategies, and integration of renewable energy sources. This work focuses on the application of a digital twin to model the district heating network combined with prediction tools to enhance system efficiency. A procedure to integrate physics (white-box) and data-driven (black-box) approaches to foster better-informed decisions in the optimal energy resources management is presented.

Keywords: District heating; digital twin; optimal energy management; grey-box approach

1. Introduction

Europe has long been at the forefront of efforts to improve energy efficiency, recognizing it as a cornerstone of sustainable development and climate action. Energy consumption in European buildings accounts for approximately the 40% of the total energy consumed in the European Union (EU) [1]. Additionally, CO_2 emissions from buildings

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surpass 30% of the total emissions [2]. To overcome these challenges, the EU is working towards improving the energy efficiency of buildings, through a set of ambitious policies and initiatives aimed at enhancing energy efficiency across various sectors [3, 4]. These include not only buildings, but also industry, transportation, and district heating systems. The EU's Energy Efficiency Directive [3, 4] sets binding targets for member states to achieve significant reductions in energy consumption, promoting measures such as energy efficiency improvements, energy audits, and the establishment of energy performance standards. Furthermore, initiatives like the European Green Deal [5] and the Renovation Wave Strategy [6] emphasize the importance of energy efficiency in achieving carbon neutrality and fostering economic growth. Despite progress in recent years, challenges remain, including the need for more stringent regulations, increased investment in energy-efficient technologies, and greater public awareness and engagement. Nonetheless, Europe's commitment to energy efficiency continues to drive innovation and collaboration, positioning the region as a global leader in sustainable energy practices.

Within this energy efficiency strategy, district heating systems play a crucial role in providing efficient and sustainable heating solutions for urban areas, seen as a combination of buildings interacting among them, offering benefits such as reduced energy consumption, lower greenhouse gas emissions, and increased resilience to supply disruptions [7]. With the growing emphasis on energy efficiency and environmental sustainability, optimizing the operation of district heating networks has become a significant focus of research and development efforts [8].

The optimization of district heating network operation involves the utilization of various techniques and methodologies [9] to enhance system performance, minimize energy losses, and improve overall efficiency. These techniques encompass a wide range of approaches, including mathematical modeling, simulation, advanced control strategies, and integration of renewable energy sources [9]. By employing optimization techniques, operators can achieve significant improvements in energy utilization, cost-effectiveness, and environmental impact. A fundamental aspect of district heating network optimization is the development of accurate mathematical models that capture the complex interactions among components such as heat sources, distribution pipelines, and consumer demands [10]. These models serve as the basis for analyzing system behavior, identifying potential bottlenecks, and evaluating the effectiveness of different optimization strategies. Researchers have made significant advancements in this area, incorporating detailed physics-based models, computational algorithms, and optimization algorithms to achieve higher levels of accuracy and predictive capability [8, 9, 10, 11, 12].

In addition to mathematical modeling, optimization techniques for district heating networks often involve the integration of advanced control strategies to dynamically adjust system operation in response to changing conditions. Model predictive control (MPC), for instance, has emerged as a powerful tool for optimizing the operation of district heating systems [11] by considering future system states and constraints to make proactive control decisions. Other approaches such as fuzzy logic control, neural networks, and evolutionary algorithms offer alternative methods for achieving optimal system performance under varying operating conditions [12].

Furthermore, the integration of renewable energy sources such as solar thermal, biomass, and waste heat recovery presents new opportunities for enhancing the sustainability and efficiency of district heating networks. Optimization techniques play a crucial role in maximizing the utilization of renewable energy resources, optimizing their integration into existing infrastructure, and minimizing reliance on conventional fossil fuel-based heating sources [11, 12].

In this manuscript, a comprehensive procedure to make better-informed decisions in terms of district heating optimal management is overviewed. It combines physical characterization of the network together data-driven algorithms, namely grey-box approach, to obtain more accurate results, reducing the computational needs. This combination is presented in the form of a digital twin, enabling the interaction with the users to simulate different conditions; thus, gathering operation recommendations and facilitating decision-making to district heating operators. This approach benefits with respect to the current practices in the way of reducing the computational requirements to run the optimisation algorithms, as well as integrating physics from the network to increase the accuracy of the decisions.

The rest of the work is structured as follows. Section 2 reviews recent works in the same topic, providing insights about the novelty of this research. Section 3 describes the methodology that has been followed to design the digital twin concept, which is explained in Section 4. Preliminary results about the simulation engine and buildings' clustering are described in Section 5. To finalise, a set of conclusions is extracted in Section 6.

Nomenclature

ADE	Application Domain Extension
DH	District Heating
DHIM	District Heating Information Model
EU	European Union
GML	Geography Markup Language
HDD	Heating Degree Days
LoD	Level of Detail
MIQCP	Mixed Integer Quadratically Constrained Program
MPC	Model Predictive Control
PCA	Principal Component Analysis
PSO	Particle Swarm Optimization
PV	Photovoltaics
SCADA	Supervisory Control And Data Acquisition

2. Literature review

A range of optimization tools have been developed for district heating networks, with a focus on minimizing operational costs and maximizing efficiency. An example is Sameti et al. [13], who discuss the use of optimization techniques in district energy systems, highlighting the challenges posed by real-world applications. The authors emphasise the significance of modelling, simulating, and optimising the buildings within a district collectively, taking into account their interactions. Treating them as isolated structures does not align with the goal of enhancing efficiency. Within the research, mathematical approaches and multi-objective optimization techniques are discussed, where, commonly, the objective functions used in the literature are related to carbon emission, production, revenue, operation costs, investment, fuel costs, and renewable exploitation [13]. Moreover, multi-objective optimization problems are reduced to single-objective problems by providing weighted-sum functions, which is still a challenge. Additionally, most models suffer from very long computational time, which limits the capabilities of optimization.

Bella et al. [14] present an optimization-based algorithm for managing district heating networks, which minimizes operational costs and maximizes efficiency. The authors apply a mixed-integer formulation method to properly control the operations of gas boilers and co-generation systems at the central heating station. The modelling approach in this work is focused on machine-learning from temperature dynamics. Its objective function looks for minimizing the network heat losses, and enabling co-generation systems to optimally participate to the day-ahead energy market.

Hering et al. [15] introduce a design optimization model for heating networks with multiple heat pumps, emphasizing the trade-off between economic and ecological considerations. These studies collectively demonstrate the potential of optimization tools in enhancing the operation and energy efficiency of 4th and 5th generation district heating networks. In contrast to other works that are focused on energy flows and result in mixed integer linear programs, the authors present a Mixed Integer Quadratically Constrained Program (MIQCP) with temperature constraints. Its advantage is the removal of the need for simplifications, as happens in the linear programs. The results in economical terms show savings between 120 k€ and 307 k€, while CO_2 emissions avoided between 193 tons and 605 tons [15].

Resimont et al. [16] highlight the limited computational load in the optimization methods intended to draft efficient management strategies using heating consumption profiles. In this line, the authors describe a multi-period mixed integer linear programming model for the optimal outline and sizing of a district heating network. More recent studies have made significant strides in optimizing district heating systems. For instance, Vonzudaité et al. [17] propose a methodology for selecting heat pump systems that minimize costs and CO_2 emissions. The approach uses mixed-integer nonlinear programming and multi-objective optimization for heat production and supply systems over a desired period. Results show that the optimal heating system includes air-to-water heat pumps and electric heaters.

The need to increase the flexibility, energy efficiency, and environmental friendliness is made evident in district heating networks. Boyko et al. [18] propose the concept of ”intellectualization”, which basically consists of intelligent control system to ensure the interaction of various heat sources. The combination of multiple energy vectors is also investigated by Capone et al. [19], who also include the thermal demand response. By using a mixed integer linear programming technique is obtained that, approximately, 3% of the operational costs might be reduced.

2.1. Contributions with respect to the state of the practice

Literature is broad and covering multiple aspects in the context of optimization of district heating networks. Nevertheless, one of the major challenges that is remarked by the authors is the high computational load required to run the algorithms. It should be noted that district heating networks are usually composed by multiple demand nodes (i.e., buildings) with several distribution systems; therefore, its complexity should not be neglected.

In order to overcome the previous challenges, this work proposes a digital twin approach for the optimization of district heating network operation. The main contributions with respect to the literature review are listed below.

- A grey-box approach is used based on the combination of physical characterization of the district with data-driven algorithms. The advantage is the capability of modelling and simulating the district heating features in a very simplified way to enrich the results with forecasting models to run the optimization algorithm.
- Reduction of the computational load by applying a simulation engine to pre-load the heat losses in the distribution network.
- Simplified (lower computational requirements) data-driven models by applying a two-step algorithm [20]: 1) Clustering of the buildings according the thermal demand parameterization; 2) Demand prediction for selected buildings within the cluster.

This work is performed within the scope of the EU project DigiBUILD [21], funded under Horizon Europe programme, whose main aim is the transformation of traditional silo approaches into digital and smart buildings. By making use of high-quality data and next generation digital building services, it looks for better-informed decision-making for performance monitoring & assessment, planning of building infrastructure, policy making and de-risking investments.

3. Methodology

The work has been performed following a four step methodology, such as depicted in Fig. 1.

- The first step has consisted in the characterization of the district heating (DH), compiling the buildings that compose the network, as well as the topology (i.e., distribution network, pipes, forks, etc.), including the thermal properties. This stage helps to understand how the network is configured. For that end, a CityGML (Geography Markup Language) [22] model has been built using the energy extension [23] to integrate the different thermal features for each one of the elements of the network.
- Next, CityGML data is used to feed the simulation engine in charge of determining the thermal and pressure losses that are produced in the distribution network. They are mainly due to thermal insulation of pipes and losses in the valves and heat exchangers.
- Thirdly, a data-driven algorithm is implemented obtaining the building features, such as orientation, shadowing façades, windows thermal characteristics or heated area, among others. The objective of this step is to classify the buildings according to the thermal demand, so that a forecasting algorithm could obtain the predicted demand for selected buildings [20] within the cluster, reducing the computational load for training the full stock of buildings.
- Last step is the optimization itself. Instead of collecting all the datasets from the monitoring systems, this optimization algorithm receives just the total demand of the district heating (i.e., thermal losses plus the demand prediction), as well as minor operation parameters (such as supply and return temperatures and the boilers' power). Three main objectives are followed by the algorithm: 1) Minimize the cost of the energy; 2) Avoid CO_2 emissions (in other words, maximize the renewable energy); 3) Provide optimal management strategies for the boilers, increasing the life cycle (i.e., balancing them).

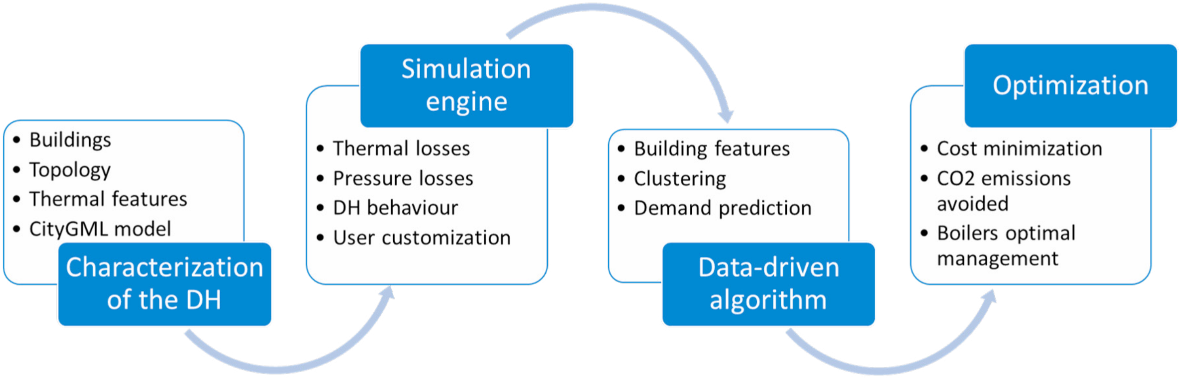

Fig. 1. Methodology for the creation of the digital twin for district heating optimal management

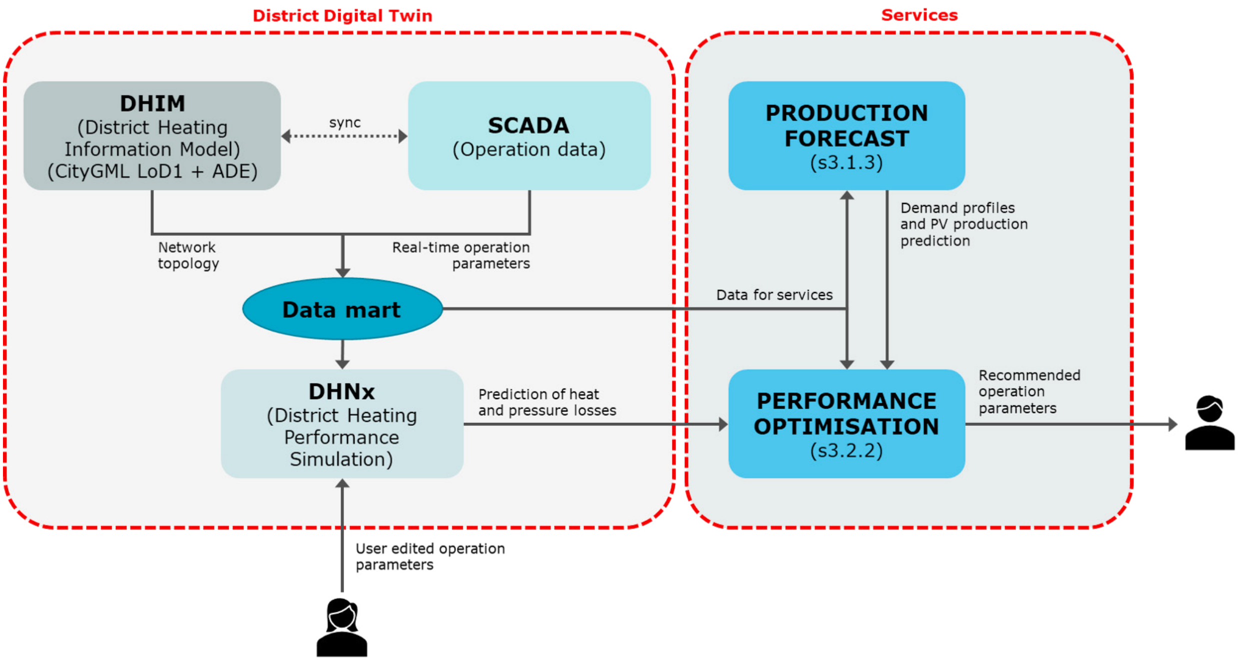

Fig. 2. District heating digital twin conceptualization

4. Digital twin approach for optimal district heating management

The methodology explained before is represented by an entities diagram that illustrates the conceptualization of the proposed solution. Fig. 2 depicts the concept of the digital twin with the different components that are part of. It is observed two differentiated sides. The left side shows the district digital twin, whereas the right side contains the services that the digital twin uses. Next subsections describes each one of the components.

4.1. District digital twin

As marked in Fig. 2, the left side encompasses the digital twin itself. It combines the static and dynamic data of the district heating network to simulate the operation of the network. Similarly, it enables the users' interaction by allowing the insertion of parameters that change the network configuration. To cover all these aspects, a set of modules are integrated as follows:

- SCADA (Supervisory Control And Data Acquisition), which is the monitoring system from the network operator and compiles the operation data (i.e., dynamic data). The information that is obtained from this element contains the real supply and return temperatures of the substations, supply and return temperatures of the boilers, set-points, water flows, valves statuses, etc.
- DHIM (District Heating Information Model), which represents the static data of the district heating. This means the buildings, pipes, substations and boilers' room. Apart from the visual (3D) visualization, it also enriches the model with the thermal properties of the systems (e.g., boilers' power). The way to model the static information has used CityGML LoD1 (Level of Detail 1 that is the well-known blocks model comprising prismatic buildings with flat roofs [22]) with the Energy ADE (Application Domain Extension) [23] to enrich the model with such thermal parameters. Fig. 3 illustrates the district heating model including the buildings and the boilers' room (in grey within Fig. 3) together the piping elements (lines).
- Data mart element is the business oriented object in charge of the combination of the dynamic and static data in order to provide a single dataset to the simulation engine.
- Simulation engine (or District Heating Performance Simulation), implemented by the Python library DHNx [24]. It is a toolbox for optimization and simulation of district heating and cooling systems and tries to answer the questions about how the heat losses depend on the temperatures of inlet and return pipes and ambient temperature; how much energy is necessary for the pumps to overcome the pressure losses; and how these properties behave if the supply temperatures change. The library makes uses of four main components, which are included in Table 1 [24]. In this sense, the physical elements modelled within the CityGML are enriched with the properties according to the attributes column.
- User interaction, which is pivotal in any digital twin concept. Here, the operators of the network are allowed to modify some of the DHNx attributes, such as the delta temperature of the consumers or the supply temperature of the boilers. The re-parametrization allows determining thermal and pressure losses in different working conditions.

Table 1. Thermal network components being used by the simulation engine

Component	Description	Attributes
Consumer	Heat consumer (i.e., buildings)	id, component_type, latitude, longitude, mass_flow, delta_temp_drop, pressure loss inlet & pressure loss return
Producer	Heat producer (i.e., boilers)	id, component_type, latitude, longitude, temp_inlet, pressure loss inlet & pressure loss return
Fork	Node where several pipes meet	id, component_type, latitude, longitude, pressure loss inlet & pressure loss return
Pipe	Pipes representing double pipes (feed and return) that connect nodes	id, component_type, latitude, longitude, from_node, to_node, length, diameter, heat_transfer_coeff & roughness

4.2. Supporting services

District digital twin itself does not provide more functionality beyond the simulation of the network behavior. While the district digital twin represents the white side (i.e., physics) of the grey-box approach, the supporting services are the black part (i.e., data-driven). Two main services are integrated. On the one hand the production and demand forecasting and, on the other hand, the optimisation of the operation set-points.

Starting with the forecasting services, the objective is twofold: 1) determine the thermal demand of the buildings; 2) predict the contribution from PV (Photovoltaics). The first service combines two machine-learning techniques. On one hand, clustering to classify the buildings in multiple sets. On the other hand, regression methods to determine the energy usage in function of the consumer elements (set-points) and weather forecast [20].

Clustering is a static classification of the buildings as consumer elements based on different parameters. The purpose is to groupe the demands under similar constructive features. The applied technique is k-means, where the algorithms looks for the optimal k (number of clusters) in the range 3-6. The Elkan's algorithm has been used with 5000 iterations and silhouette coefficient with euclidean metric for scoring. The clustering parameters are listed below.

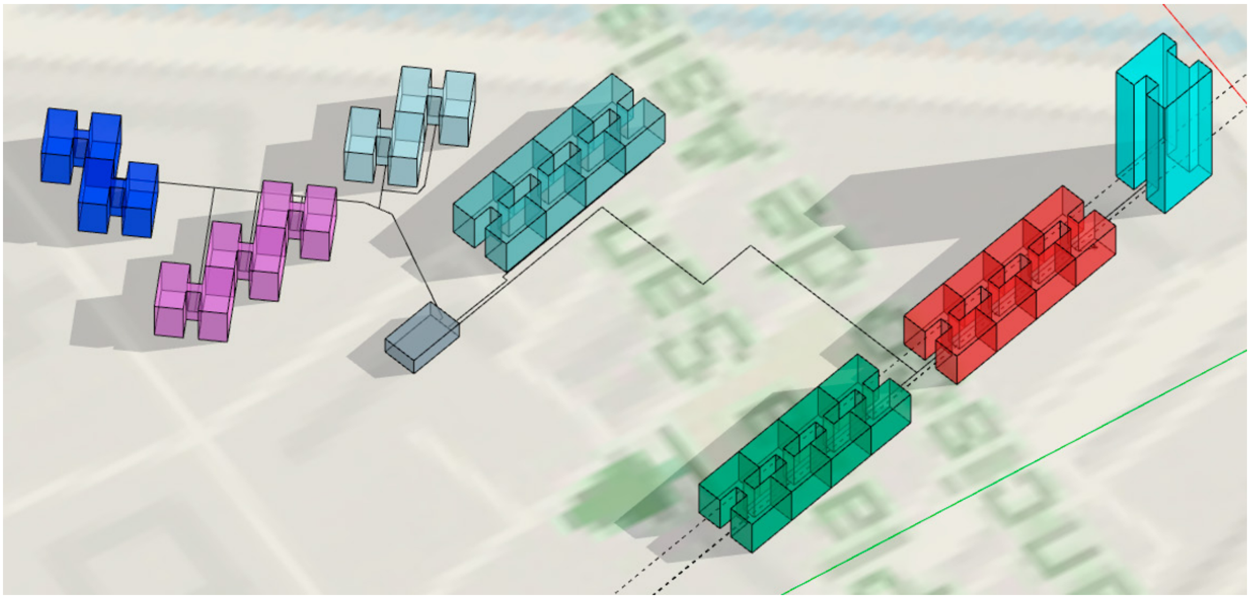

Fig. 3. Digital twin of the district heating network

- Orientation: It establishes the building orientation in order to “quantify” the solar gains. The possible values are 0-North, 0.5-East/West or 1-South. It also includes the intermediate orientations (i.e., NE / NW = 0.25 and SE / SW = 0.75)
- Height of the building in meters. Normalized according to the maximum value.
- Heated area of the building: Three typologies of buildings have been considered according to the dwelling sizes and the area that is used for heating. Normalized according to the maximum value.
- Existence of adjoining block so as to determine the effects of the wind and thermal losses/gains. 0 means non-adjoining block and 1 if this exists.
- Shadowing by other buildings nearby, which limits the solar gains. 0 is shadowed building and 1 solar gains.
- Windows replacement percentage that also affects the tightness. Normalized according to the maximum rate.
- Double windows percentage that also affects the demand. Normalized according to the maximum rate.

The second technique used is linear regression machine-learning, being one of the simplest and most common algorithms to match energy and climate conditions (HDD, Heating Degree Days). One regression is calculated for one sample of the cluster, randomly selected, reducing the time to execute the model, i.e. less computational needs. Finally, the result is extrapolated to the rest of the buildings of the district by applying proportionality (i.e. adjustment of the heated area).

Having the thermal demand of the buildings, the renewable contribution from PV is also calculated by linear regression, but relating produced energy with radiation. The use of PV is important as the electricity being generated is injected in a power-to-heat solution to heat water. This hot water is then contributing to the distribution network.

On the other hand, thanks to the modelling and simulation, thermal and pressure losses are obtained, which deals with the total needs of heating in the network. Total demand is the sum of the buildings demand and the losses. Subtracting the renewable contribution, the result is the energy to be produced by the boilers, which is the input for the optimization service, responsible for determining the optimal parameters, such as supply temperature of the boilers, as well as the load balancing of the boilers in order to comply with cost minimization, renewable contribution maximization and boilers’ performance. To that end, a PSO (Particle Swarm Optimization) algorithm is being developed.

5. Preliminary results

Initial tests have been carried out, where a simplified network has been modelled. As observed in Fig. 3, three main distribution circuits compose the network. From the boilers' room, three branches heat the buildings. Although three boilers are also available, one single generation system has been considered (total power as the sum of the individual boilers' power). With respect to the consumers, one single demand side has been included representing the set of buildings per circuit. For instance, the four buildings connected to the central branch are considered as a single demand load representing the total demand associated to this distribution circuit.

With this configuration, the preliminary results are related to the simulation engine and the clustering tool. Linear regression and optimisation are still under development, without results to be shown, which is the future work. Regarding the simulation engine, Table 2 shows the heat losses and required power for each one of the circuits (i.e., distribution branches) obtained by the simulator. It is observed as the three circuits/branches have similar heat losses, which is logic as the length, diameter and insulation of the pipes is also similar. However, the required power differs, being the circuit 2 the one with the highest power. The reason lies in the buildings connected (even though it is represented by a single consumer).

Table 2. Simulation of the thermal network for testing

Network element	Heat losses (W)	Pump power (kW)
Circuit 1	4968.49 W	3.92 kW
Circuit 2	4974.30 W	6.95 kW
Circuit 3	4963.34 W	2.74 kW

The case of clustering is also tested, obtaining 3 clusters as the optimal number of groups. In contrast to the simulation engine, the clustering has considered the 20 buildings in the network. Fig. 4 depicts the distribution of the two-dimension clustering results by using PCA (Principal Component Analysis) technique. Each cluster is clearly identified, with similar behaviour according to the parametrisation of the district. It is worth to say the cluster 3 is composed by just one single building. This is because one building is completely different to the rest, being a tower with different height and area. In the case of the other clusters, the difference is mainly focused on the orientation of the buildings and windows (double-glazed).

6. Conclusions

The implementation of a district heating energy management system holds immense promise in enhancing the efficiency, sustainability, and resilience of urban energy networks. Through sophisticated monitoring, control, and optimization strategies, such systems can significantly reduce energy waste, lower operational costs, and mitigate environmental impacts. Moreover, by integrating renewable energy sources and advanced technologies, district heating networks can adapt to changing energy landscapes, fostering a transition towards greener, more resilient cities. To confront the challenges of climate change and energy security, the advancement and widespread adoption of district heating energy management systems stand as pivotal steps towards building a more sustainable and prosperous future.

Within this manuscript, a conceptual approach for a district heating digital twin has been described to optimally control the energy resources. A hybrid approach (namely grey-box) is proposed where physical assets are modelled under CityGML, enabling the calculation of the energy losses in the network. Data-driven algorithms complement the physics of the network with the objective of forecasting the energy needs and; thus, being able to obtain recommendations for an optimal use of resources. Under this approach, the main expected benefit is the capability of obtaining the network behaviour in terms of distribution network, which is usually neglected in the current scientific approaches, allowing better-informed decisions with more accurate results.

The aforementioned approach is applied in a real district heating network located in Spain. At the moment, only the simulation engine and clustering technique are implemented. However, it illustrates the capability of the digital twin to determine the distribution needs (thermal losses and power needs) and grouping the buildings with similar energy requirements. The initial results show how the approach is useful to determine the energy needs of the district heating

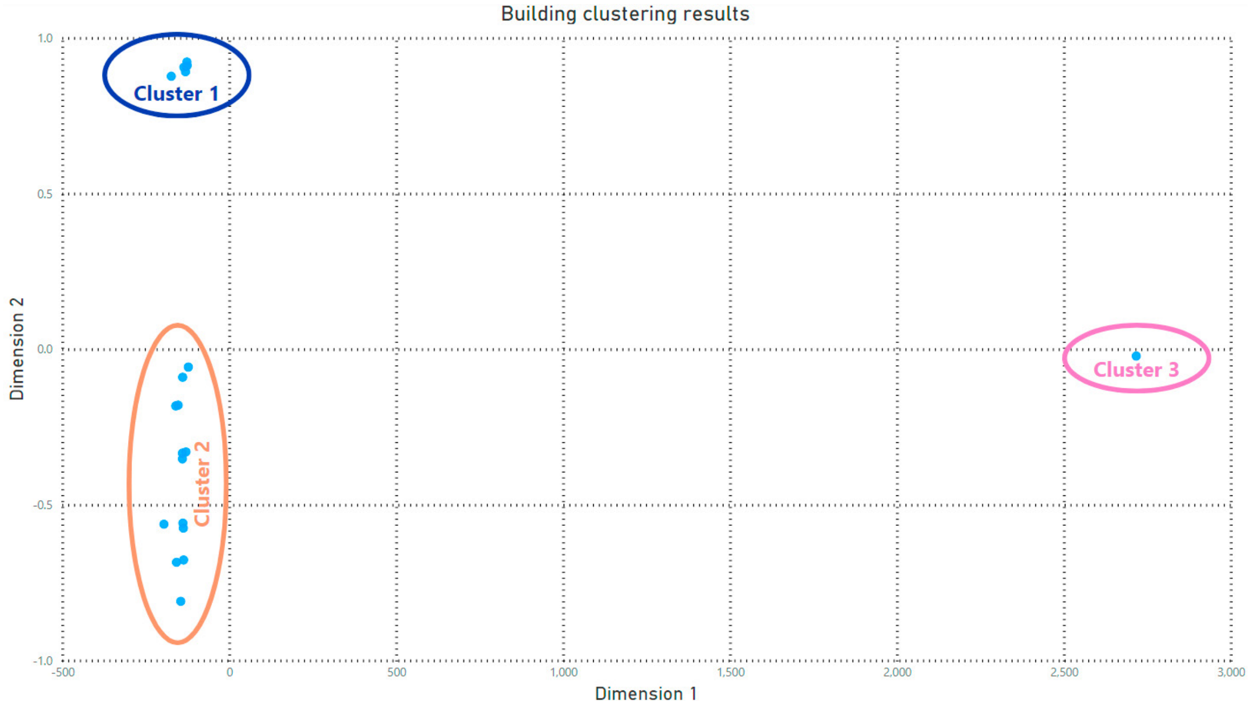

Fig. 4. Buildings' clustering results

network and, then, modelling and simulating the distribution and demand sides. As future work and lines of research, the full implementation of the linear regression for energy forecasting and optimisation algorithm is envisaged in order to determine the optimal operation parameters to deal with minimal costs and reduction of greenhouse gas emissions.

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