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Waste heat recovery from data centers for urban heating via 4th/5th genera- tion networks: a methodology for thermo- economic analysis.

TESI DI LAUREA MAGISTRALE IN
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*The most beautiful ocean is the one we have not yet sailed.
The most beautiful child has not yet grown up.
Our most beautiful days are those we have not yet lived.
And the most beautiful words I wanted to tell you I have not yet spoken.*

— Nazim Hikmet

Abstract

The integration of waste heat from Data Centers into fourth and fifth-generation district heating and cooling networks (4/5GDHC) represents a critical solution for the decarbonization of urban energy systems and the recovery of otherwise dissipated thermal resources. The primary objective of this study is to transform energy waste into a strategic asset for urban decarbonization, adopting the perspective of an Energy Service Company (ESCO) to evaluate its commercial sustainability and economic competitiveness compared to conventional technologies. The methodology utilizes an automated bottom-up approach for infrastructure design and simulation. By integrating Google Maps and Open Meteo APIs, the model reconstructs hourly thermal demands for building case studies with high granularity, based on actual envelope characteristics and local climate data. The network topology is dynamically generated using the Minimum Spanning Tree (MST) algorithm to optimize pipe extension and minimize capital expenditures (CAPEX). The hourly thermo-hydraulic simulation in MatLab R2022b operates through a hybrid logic that alternates between direct heat exchange (4G) and heat pump substations (5G) depending on the Thermal Energy Storage (TES) temperature. The system is optimized via Bayesian optimization to minimize the Levelized Cost of Heat (LCOH) across three different economic scenarios (WCS, BAU, and BCS), calibrating variables such as set-point temperature, storage volume, and Data Center power capacity. The analysis reveals a clear advantage for an ESCO investing in such networks: systems coupled with liquid-cooled DCs achieve an average LCOH of 74.11 €/MWh (BAU scenario), ensuring a 23.6% cost reduction compared to stand-alone solutions. The study highlights how the business case is strengthened by resilience to electricity price volatility. Future developments could extend the model to a total conversion into 5G systems for distributed summer cooling.

Keywords: Data Center, District Heating, 4GHD, 5GHD, LCOH, Waste Heat Recovery.

Abstract in lingua italiana

L'integrazione del calore di scarto dei Data Center nelle reti di teleriscaldamento di quarta e quinta generazione (4/5GDHC) rappresenta una soluzione critica per la decarbonizzazione dei sistemi energetici urbani e il recupero di risorse termiche altrimenti dissipate. L'obiettivo principale di questo studio consiste nel trasformare uno scarto energetico in un asset strategico per la decarbonizzazione urbana, adottando la prospettiva di una Energy Service Company (ESCo) per valutarne la sostenibilità commerciale e la competitività economica rispetto alle tecnologie convenzionali. La metodologia si avvale di un approccio bottom-up automatizzato per la progettazione e la simulazione delle infrastrutture. Tramite l'integrazione delle API di Google Maps e Open Meteo, il modello ricostruisce con elevata granularità i fabbisogni termici orari dei Case study edilizi in base alle reali caratteristiche dell'involucro e ai dati climatici locali. La topologia della rete viene generata dinamicamente tramite l'algoritmo Minimum Spanning Tree (MST) per ottimizzare l'estensione delle tubazioni e minimizzare i costi di capitale (CAPEX). La simulazione termo-idraulica oraria in MatLab R2022b opera mediante una logica ibrida che alterna lo scambio termico diretto (4G) a sottostazioni con pompa di calore (5G) in funzione della temperatura dell'accumulo termico (TES). Il sistema viene ottimizzato tramite ottimizzazione bayesiana per minimizzare il costo livellato del calore (LCOH) in tre diversi scenari economici (WCS, BAU e BCS), calibrando variabili quali la temperatura di set-point, il volume dell'accumulo e la potenza del Data Center. Dall'analisi emerge la chiara convenienza per una ESCo nell'investire in tali reti: i sistemi accoppiati a DC liquid-cooled raggiungono un LCOH medio di 74.11 €/MWh (scenario BAU), garantendo una riduzione dei costi del 23.6% rispetto alle soluzioni stand-alone. Lo studio evidenzia come il business case sia rafforzato dalla resilienza alla volatilità dei prezzi elettrici. Sviluppi futuri potrebbero estendere il modello alla conversione totale in sistemi 5G per il raffrescamento estivo distribuito.

Parole chiave: Data Center, Teleriscaldamento, 4GHD, 5GHD, LCOH, Recupero del calore di scarto.

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1 | Introduction

The current energy transition, aimed at achieving the climate neutrality targets set at the European level, necessitates a profound revision of heat supply and management strategies in urban environments. In this scenario, the Information and Communications Technology (ICT) sector, and specifically Data Center (DC) infrastructures, emerge as key players in a circular energy paradigm shift. Although Data Centers are traditionally regarded as energy-intensive facilities responsible for a growing share of global electricity consumption, they simultaneously represent potential thermal *prosumers* of extraordinary significance. In fact, nearly all the electrical power absorbed by servers is converted into waste heat which, if properly managed, can be fed back into civil heating systems instead of being dissipated into the atmosphere. The integration of such infrastructures with fourth and fifth-generation district heating and cooling networks (4GDH and 5GDHC) constitutes an excellent technological solution to foster the decarbonization of urban centers. 5GDHC networks, operating at ultra-low temperatures close to ambient levels, serve as the ideal vector for thermal recovery from Data Centers, as they drastically reduce exergy destruction and allow heat pumps to operate with high coefficients of performance (COP). This approach not only optimizes the overall efficiency of the energy system but also acts as a catalyst for the electrification of heat, offering a concrete alternative to natural gas combustion. Moving away from fossil fuel boilers in favor of integrated systems powered by electrical sources, preferably renewable, significantly contributes to national energy resilience. In a geopolitical context characterized by marked instability and the need to reduce strategic dependence on hydrocarbon imports from third countries, the valorization of local thermal resources and the push toward a no-gas configuration become not only environmental imperatives but also matters of energy security. This thesis, therefore, aims to demonstrate how the synergy between digital infrastructures and advanced thermal systems can transform an environmental criticality into a strategic asset for the creation of resilient, independent, and sustainable energy communities.

To understand the potential of these infrastructures as thermal hubs, it is first necessary to define their operational nature and the energy challenges they face.

Data Centers (DCs) are computing structures housing a large number of Information and Communications Technology (ICT) devices installed for processing, storing and transmitting information. They support daily activities including online searching, social networking, telecommunication, banking, and shopping. To ensure these services remain uninterrupted, DCs must operate with minimal to zero downtime. Achieving this reliability depends on two critical factors: sufficient power and effective cooling. DCs consume around 2% of today's world power generation and due to their significant demand, this consumption is annually expanding at a rate of 12% [2]. About 40% of energy use goes to cooling [36], mainly consumed by chillers that provide chilled water to remove server heat, along with cooling towers, pumps, and fans. It is therefore vitally important to find energy-saving solutions for DC cooling and, at the same time, try to reuse waste heat that would otherwise be dispersed into the environment, with the aim of minimizing the environmental impact of these structures.

The evaluation of such energy-saving solutions requires standardized metrics to quantify the efficiency of the infrastructure.

The Power Usage Effectiveness (PUE) metric was introduced by The Green Grid consortium as a standardized indicator of energy efficiency in data centers. It is mathematically expressed as:

$$PUE = \frac{\text{Total Facility Energy Consumption}}{\text{IT Equipment Energy Consumption}} \quad (1.1)$$

A theoretical PUE of 1.0 would indicate that all incoming energy is delivered directly to IT equipment, with no overhead for cooling, power distribution, or auxiliary systems. In practice, PUE values are always greater than 1.0, with reported averages between 1.2 and 2.0 depending on infrastructure design, climatic conditions, and applied cooling strategies [39]. PUE is an essential performance metric, as it is often used to evaluate the effectiveness of airflow containment, liquid cooling, and immersion cooling technologies [1, 9, 74]. Reducing cooling costs directly improves PUE, which translates into lower operating costs and a reduced environmental impact. Nevertheless, PUE has limitations. It does not fully reflect IT-side efficiency improvements, such as reduced fan power in liquid- or immersion-cooled systems, nor does it capture the benefits of heat reuse. For these reasons, complementary metrics such as Total Usage Effectiveness (TUE) have been proposed to supplement PUE and provide a more holistic evaluation. Despite these shortcomings, PUE remains the dominant benchmark in both academia and industry.

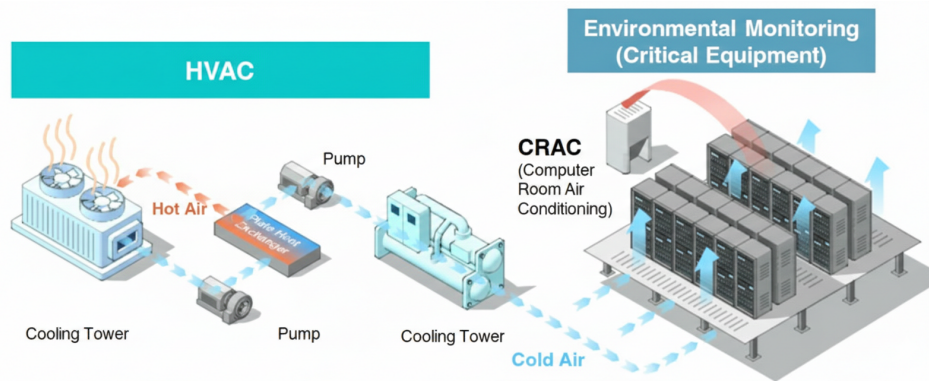


Figure 1.1: Data center cooling system diagram (image credits: 42U.com).

The evolution of cooling strategies, often monitored through PUE, has led to a wide spectrum of technological approaches designed to manage the increasing heat loads of modern facilities.

The sustained growth in computational demand, driven by cloud computing, artificial intelligence, and high-performance computing (HPC), has produced unprecedented heat loads in modern data centers. Traditional cooling methods, primarily based on air distribution, are increasingly unable to meet the thermal and energy-efficiency requirements of next-generation facilities. As a result, a wide spectrum of alternative approaches has been developed, ranging from incremental airflow optimizations to disruptive liquid-based solutions. Conventional room-level air cooling remains the baseline against which newer systems are evaluated. CRAC (Computer Room Air Conditioning) or CRAH (Computer Room Air Handler) units deliver conditioned air through raised floors or overhead ducts, maintaining cold aisles at prescribed setpoints. Servers ingest this air, and heat is subsequently rejected into hot aisles before returning to cooling units [1]. The main advantages of this system are architectural simplicity and decades of operational maturity. However, inefficiencies arise from mixing between cold and hot air streams, non-uniform temperature distribution, and high fan power consumption required to maintain adequate flow rates [62]. Reported PUE values for such facilities typically range from 1.4 to 1.8, with efficiency strongly influenced by climate, containment strategies, and utilization rates [62]. Supply air temperatures are commonly maintained at 20–23 °C, while hot aisle returns range between 35–40 °C [73]. This corresponds to a thermal rise of 10–15 °C, consistent with ASHRAE guidelines. While adequate for racks with power densities up to 10–15 kW, the system becomes energetically prohibitive when applied to racks exceeding 20 kW, as airflow requirements increase non-linearly with load.

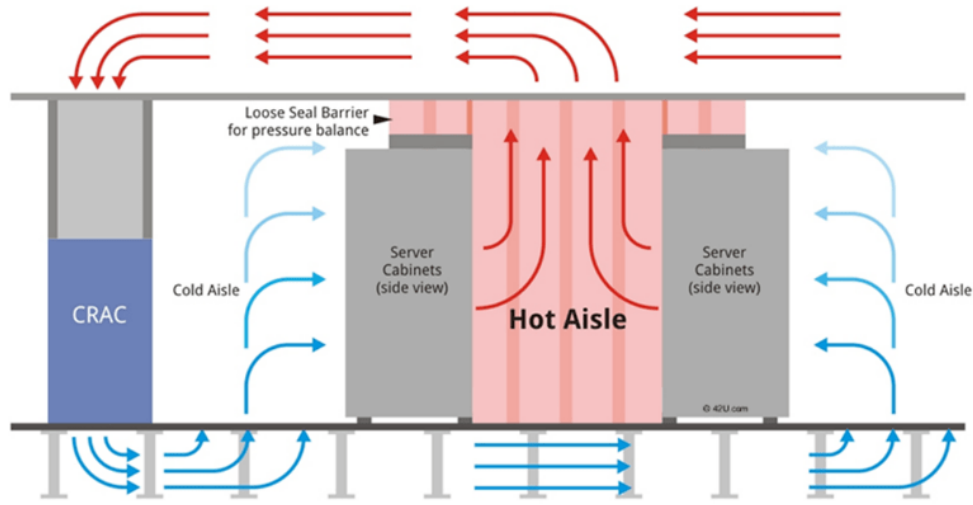


Figure 1.2: Data center air cooling system diagram (image credits: 42U.com).

When air-based systems reach their physical limits, more radical technologies such as immersion cooling become necessary to ensure both density and higher-grade heat recovery.

Immersion cooling is a radical departure from conventional air or hybrid systems. Servers are submerged in dielectric fluids that either absorb heat sensibly (single-phase) or undergo phase change at component surfaces (two-phase) [9]. In single-phase immersion, heated fluid is pumped to a heat exchanger connected to facility water loops. In two-phase systems, boiling at the chip surface ensures nearly isothermal operation, with vapor condensed externally [18]. This approach eliminates server-level fans and drastically reduces facility air-handling requirements. Reported PUE values are among the lowest in literature, typically 1.02-1.05 [74]. Single-phase immersion often employs fluid supply temperatures of 40-45 °C with return above 60 °C, while two-phase systems operate at saturation temperatures of 40-50 °C, depending on the chosen working fluid [18]. Rad et al. reported that immersion systems can reduce total data center energy use by up to 50% compared to air-cooled facilities [37]. The technology also supports ultra-high rack densities, exceeding 200 kW per rack, which are unfeasible with air-based systems. Nevertheless, immersion cooling introduces challenges including dielectric fluid cost, material compatibility, and non-standardized maintenance practices, which currently limit widespread adoption.

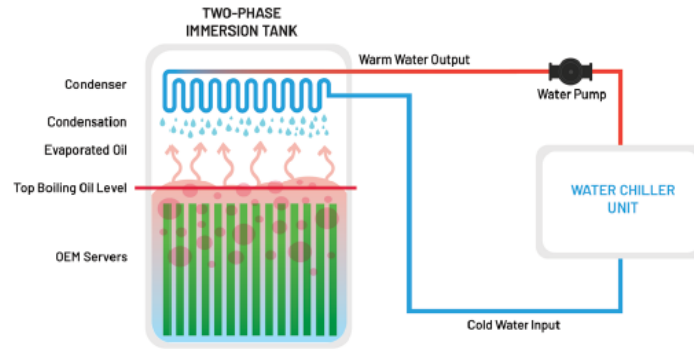


Figure 1.3: Data center immersion cooling system diagram (credits: LiquidStack.com).

The high-quality waste heat produced by these advanced cooling systems finds its most efficient application when integrated into urban district heating systems.

The established DH taxonomy identifies four generations up to 4GDH: high-temperature steam networks (1GDH); centralized high-temperature hot-water systems (2GDH); reduced supply temperatures with better pipe insulation (3GDH); and further temperature reduction with improved integration of renewables and heat recovery, but still with predominantly unidirectional flows and governance centered on central plants (4GDH).

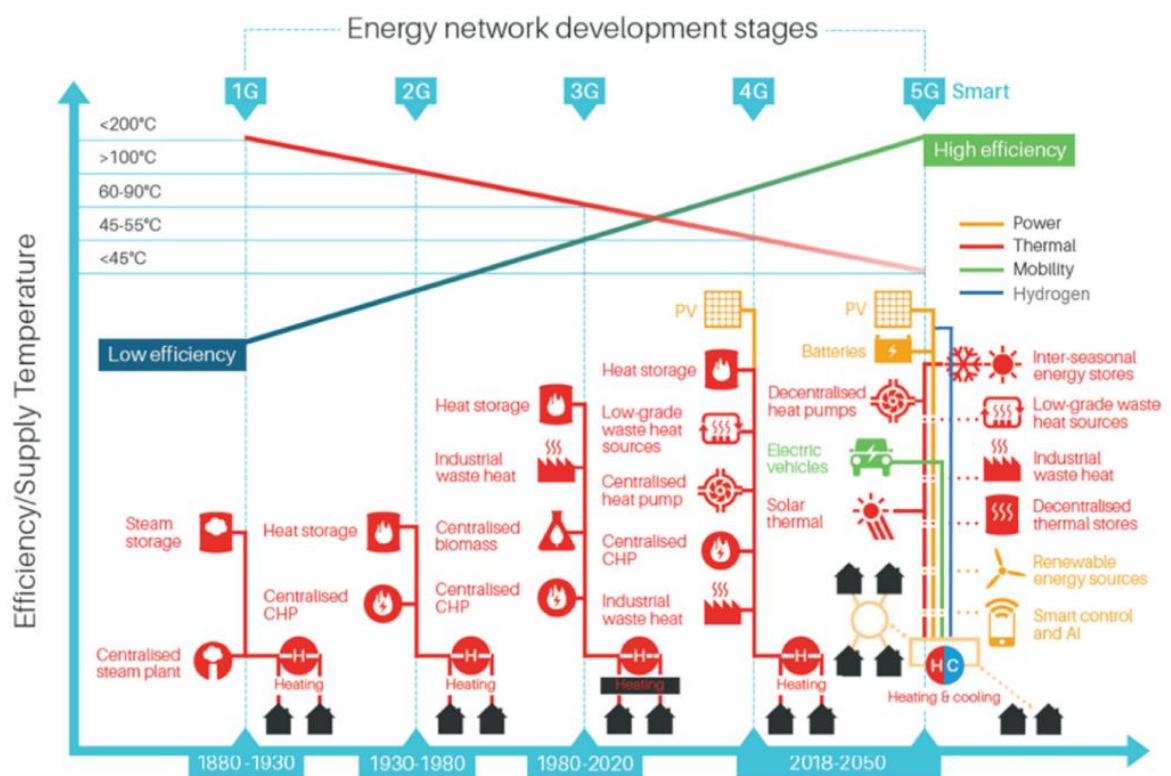


Figure 1.4: Evolution of district heating technology (image credits: Lund et al. [47]).

The implementation of water-to-water (W/W) heat pumps within a 5GDHC architecture, as opposed to conventional air-to-water (A/W) units, offers intrinsic thermodynamic advantages stemming from the superior thermophysical properties of the carrier fluid and the thermal stability of the source. The primary benefit lies in the significant enhancement of the Coefficient of Performance (COP), defined as the ratio between the useful thermal energy delivered and the required work input:

$$COP = \frac{Q_H}{L_{in}} \quad (1.2)$$

In 5GDHC networks, the source temperature at the evaporator remains higher and more consistent than external ambient air during the winter season. This drastically minimizes the thermal lift that the compressor must overcome to reach the delivery temperature required by the end-user. According to the Carnot cycle, the maximum theoretical efficiency improves as the temperature difference between the condenser (T_{cond}) and the evaporator (T_{evap}) decreases:

$$\eta_C = \frac{T_{cond}}{T_{cond} - T_{evap}} \quad (1.3)$$

Utilizing an anergic loop fed by Data Center waste heat ensures an elevated T_{evap} , thereby minimizing the pressure ratio and the resulting electrical power consumption. Beyond energy performance, the liquid nature of the source eliminates operational criticalities typical of A/W units in cold or humid climates, specifically the accumulation of frost on the evaporator fins. The absence of defrosting cycles prevents temporary COP degradation and interruptions in heat supply, while simultaneously ensuring steady-state operating conditions for the refrigerant circuit. This reduces mechanical fatigue and optimizes the infrastructure's lifespan. Furthermore, the higher specific heat capacity of water relative to air enables more efficient heat transfer within more compact heat exchanger geometries, facilitating precise and dynamic regulation of the thermal output.

Fifth-generation systems therefore introduce ambient-temperature networks, bidirectional exchange, and distributed production near the point of use via heat pumps, replacing fixed supply temperatures and single-direction thermal flows. The network operates as an anergic hydraulic loop in which the bulk temperature is not imposed by a central generator but floats within a narrow band set by local exchanges and distributed sources, while useful temperature levels are achieved by local boosters. This arrangement reduces distribution losses, enables simultaneous heat–cold recovery, and increases operational flexibility compared with earlier DHC generations. The literature positions 5GDHC as

a continuation of the low-temperature trajectory initiated with 4GDH, yet distinct for its thermal neutrality at network level, modularity, and the prosumer role of end users [14, 32, 47].

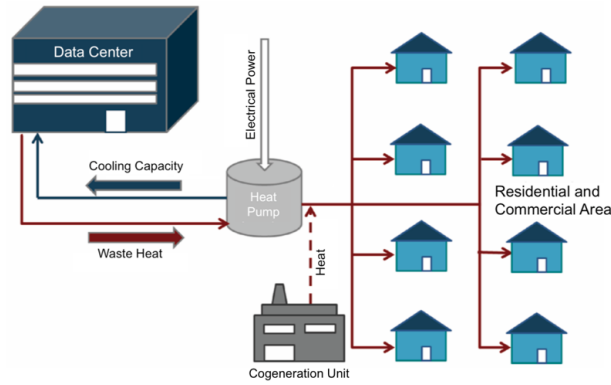


Figure 1.5: Data center district heating scheme (image credits: Danfoss/Mäntsälä Case Study).

In surveyed European cases, a 5GDHC network is configured as a two-pipe ambient loop, hydraulically simple and operated at near-environment temperatures. Thermal energy circulates bidirectionally: users with opposite thermal demands exchange heat through the network, reducing net generation needs. Building substations include heat exchangers and reversible heat pumps that raise or lower temperature levels for space heating, domestic hot water, and cooling. Energy sources include industrial and tertiary waste heat, groundwater or surface water, thermal storage tanks or geo-storage, and, when beneficial, one or more central heat pumps that provide coarse balancing and manage the network's mean temperature. The network temperature can be allowed to float within design limits and is stabilized by the dynamic balance between injections and withdrawals, which minimizes linear losses and preserves the exergy of low-temperature sources [14, 32]. A defining feature is coupling with the power system. Heat pumps, supported by thermal storage, enable temporal load shifting and demand-response services. Urban energy models indicate that a properly designed 5GDHC can provide power-to-heat flexibility with favorable impacts on integrating variable renewables and on the overall operation of the local energy system [24].

Beyond the architectural principles, the viability of 5GDHC is determined by its technical advantages and economic competitiveness compared to traditional systems.

Three macro-configurations emerge from the literature: pure anergic networks, hybrid systems with central nodes, and multi-source integrated layouts. In all variants, the

separation between a neutral-temperature network and temperature lifting at substations allows adaptation to existing terminals or staged retrofit without raising the primary network temperature [14, 32]. Loss reduction is a primary advantage of 5GDHC. Because the temperature gradient to the ground is small, linear heat losses decrease markedly relative to high-supply networks. Local heat pumps improve seasonal efficiency, as COPs benefit from higher source temperatures in heating mode and cooler sinks in cooling mode than centralized solutions. Comparative thermo-economic analyses between 4GDH and 5GDHC show that economic benefits for 5GDHC depend on load structure and availability of low-exergy sources. Where sufficient simultaneity between heat and cold exists, operating costs decrease due to higher efficiency and lower net compression work enabled by local exchanges [14, 15].

Despite the clear thermodynamic benefits, non-technical barriers remain, requiring a comprehensive design approach to ensure the success of future implementations.

Recent reviews list non-technical barriers that affect bankability: business models not yet standardized for networks with thermal *prosumers* and tariff regulations designed for unidirectional flows [32, 47]. Nevertheless, 5GDHC emerges as a thermal infrastructure with high exergy efficiency and strong sector coupling. Technical and economic performance peaks in districts with complementary end-use mixes and recoverable low-temperature sources. The choice between fully distributed production and hybrid layouts should follow from analysis of load profiles, hydraulic distances, and opportunities for power-to-heat coupling. Overall, the analyzed literature converges on 5GDHC as a step beyond 4GDH toward more flexible, resilient, and integrated thermal networks, provided the urban and regulatory context is aligned and design leverages load complementarity and local thermal reservoirs [14, 15, 24, 32, 47].

The proposed system architecture focuses strategically on winter space heating and Domestic Hot Water (DHW) production. This approach is supported by three key assumptions that underpin its technical feasibility, regulatory alignment, and overall efficiency.

1) Optimization of building substation conversion: the transition toward advanced district heating paradigms is technically more straightforward for heating services, particularly in urban contexts characterized by high building density and the prevalence of radiator-based emission systems. In such scenarios, the integration of decentralized Heat Pumps (HPs) allows for interfacing with the network by elevating the thermal carrier temperature to the levels required by existing terminals. This method minimizes the invasive and costly indoor building retrofits that would be necessary for low-temperature heating systems, such as radiant panels or fan-coil units, thereby accelerating the energy renovation process

and reducing Capital Expenditures (CAPEX).

2) Regulatory framework and energy performance constraints: in contrast to space heating, residential summer cooling is not yet subject to stringent national regulations. In the Italian context, Legislative Decree 192/2005 [31] and the subsequent Ministerial Decree 26/06/2015 (the so-called "Minimum Requirements" Decree) [49] impose rigorous criteria on the global energy performance of buildings and the efficiency of thermal vectors specifically for the winter season and DHW production. Consequently, the decarbonization of these thermal loads represents an essential legislative priority for achieving European climate neutrality targets and ensuring regulatory compliance as certified by the Energy Performance Certificate (APE). From the perspective of District Heating (DH) operators, the regulatory pressure is equally significant. Directive (EU) 2023/1791 [27] mandates the progressive transformation of existing networks into "efficient district heating and cooling" systems. In this context, the integration of waste heat recovery becomes a fundamental pillar for the sector's survival, as the directive imposes strict decarbonization milestones that require a transition away from fossil fuels toward renewable sources and industrial heat recovery to maintain the legal and economic viability of DH infrastructure.

3) Maximization of the annual capacity factor through DHW loads: the inclusion of domestic hot water production enables the valorization of Data Center waste heat throughout the entire annual cycle. While the space heating demand is confined to the winter months, DHW demand constitutes a nearly constant base thermal load. Utilizing the heat dissipated by ICT infrastructures as a source for heat pumps dedicated to water heating ensures a high utilization rate of the recovery infrastructure even during the summer season, preventing the inefficient dissipation of thermal energy into the atmosphere.

To effectively manage the complexity arising from the coexistence of these loads and the different thermal levels required, this analysis introduces the technology of hybrid fourth and fifth-generation district heating and cooling (4/5GDHC) networks. This configuration represents a flexible evolution capable of overcoming the rigidity of traditional architectures by operating at an intermediate temperature regime that allows for the coexistence of different interface logics. Within a hybrid network, users with loads compatible with the network operating temperatures can be served through heat exchanger substations, directly utilizing passive heat exchange. Simultaneously, the same infrastructure functions as an anergic loop for users equipped with decentralized heat pumps, which use the network water as a thermal source to lift the fluid potential to the levels necessary for supplying radiators or ensuring thermal disinfection cycles (anti-legionella) for DHW. This operational duality identifies the 4/5GDHC network as an ideal transition tool, capable of integrating buildings with diverse efficiency classes and simultaneously valorizing sources

with different exergy content, such as waste heat derived from air-cooled or immersion-cooled Data Center technologies.

Furthermore, the designed network architecture offers the inherent flexibility for a future conversion into a full 5th Generation District Heating and Cooling (5GDHC) system. This evolution would involve the installation of water-cooled chillers at the building level, utilizing the network as a thermal sink for summer cooling. In this prospective configuration, rather than injecting heat from the Data Center into the loop, the infrastructure would function as a neutral-temperature circuit. The network would then act as a medium for heat dissipation, where the return of the cold water loop effectively absorbs the thermal energy rejected by the building cooling systems, provided that an efficient centralized heat rejection system is implemented to maintain the network within the required operational temperature range.

1.1. Literature Review

The transition towards sustainable urban energy systems has been extensively documented in recent years, necessitating a holistic integration of high-density waste heat recovery and the evolution of thermal infrastructures. This section analyzes the state-of-the-art regarding Data Center (DC) energy management, advanced cooling technologies, and the architectural shift towards 5th Generation District Heating and Cooling (5GDHC) networks, culminating in a rigorous economic assessment of these technologies within the specific constraints of the Italian context.

1.1.1. Data Center Energy Management and Cooling Evolution

A primary focus in Data Center literature is the quantification of energy overhead, where cooling is consistently identified as the dominant factor affecting overall efficiency. Habibi Khalaj and Halgamuge [36] provide an extensive review of thermal management strategies, reporting that cooling systems can account for approximately 40% of the total energy consumption in traditional air-cooled facilities. They highlight that finding energy-saving solutions is vital for minimizing the environmental footprint of the ICT sector. To benchmark these infrastructures, the Power Usage Effectiveness (PUE) metric remains the dominant industry standard. However, Horner and Azevedo [39] critically evaluate its application, arguing that while PUE is effective for monitoring facility-level efficiency, it remains an incomplete metric because it fails to capture hardware productivity or the thermodynamic benefits of waste heat reuse. This gap in standardized metrics is further explored by Zhang et al. [71], who emphasize that PUE must be supplemented by more holistic evaluations that consider the exergy value of the recovered heat rather than just electricity consumption.

The evolution of cooling strategies has moved from incremental airflow optimizations to disruptive liquid-based solutions to manage increasing heat fluxes. Alkrush et al. [1] demonstrate that optimized airflow and innovative rack-level containment can reduce energy consumption by up to 67.2% compared to legacy methods. However, as power densities increase, traditional air-based systems reach their physical limits. Haghshenas et al. [37] quantitatively compare air-cooling and immersion cooling, reporting a total energy reduction of approximately 50% when using immersion systems. Furthermore, Zhou et al. [74] and Chen and Li [18] analyze the development of single-phase and two-phase immersion cooling. Their findings show that these technologies not only support ultra-high rack densities (exceeding 200 kW) but also provide higher-grade waste heat, with return temperatures reaching 50 °C to 60 °C. This specific contribution is crucial for

the present work, as Yuan et al. [70] note that liquid cooling significantly enhances the feasibility of downstream heat integration into thermal grids compared to low-grade air systems.

1.1.2. Evolution of District Heating Paradigms

The integration of high-density thermal sources requires a modern network architecture. Lund et al. [46] established the framework for 4th Generation District Heating (4GDH), defined as a smart thermal grid operating at low temperatures to integrate renewable sources. Unlike previous generations based on steam or superheated water, 4GDH operates with supply temperatures in the range of 50 °C to 70 °C. Technologically, this system relies on three fundamental pillars: low-loss distribution using pre-insulated twin pipes to minimize linear thermal dispersion; multi-source integration capable of accommodating heat from renewable sources; and a centralized logic where, despite the smart grid definition, the topology remains predominantly unidirectional.

The subsequent shift to 5th Generation District Heating and Cooling (5GDHC), also referred to as an *Ambient Loop* or *Anergic Network*, disrupts the centralization paradigm. Comprehensively described by Buffa et al. [14] through an extensive review of 40 European cases, 5GDHC is identified as a decentralized platform where bidirectional energy flows allow users to act as *prosumers*. These systems are founded on decoupling the transport temperature from the utilization temperature. The heat transfer fluid circulates at "neutral" temperatures (15 °C to 25 °C), acting as a thermal source for decentralized Booster Heat Pumps (BHP) installed at each user substation. Yao et al. [69] emphasize that this architecture minimizes thermal distribution losses to negligible levels, often allowing the use of non-insulated polymer pipes. Moreover, Edtmayer et al. [24] investigate the sector-coupling potentials of these networks, evaluating how decentralized heat pumps and thermal storage can provide essential flexibility for power-to-heat applications. However, Angelidis [4] warns that questions remain regarding 5GDHC's hydraulic stability and economic viability compared to simpler 4GDH solutions, particularly in established urban fabrics.

1.1.3. Comparative Economic Assessment

The scientific discourse regarding the decarbonization of urban heating systems has progressively shifted from assessing technical feasibility to evaluating economic sustainability. The current debate is no longer limited to the thermodynamic efficiency of the solutions but focuses on identifying the specific economic break-even point between cen-

tralized infrastructures and decentralized electrification strategies based on Stand-Alone Heat Pumps.

The economic viability of district heating is historically correlated with linear heat density. In the mature markets of Northern Europe, Hansen and Gudmundsson (2018) [35] demonstrated through energy mapping that while DH represents the economic optimum in dense urban cores, the specific costs of the distribution grid rise exponentially in suburban areas, eroding the competitive advantage. This relationship was quantified by Truong and Gustavsson (2019) [60] through a techno-economic analysis applied to new residential developments. By calculating the Levelized Cost Of Heat (LCOH) with a 3% real discount rate, the authors established a cost range for district heating between 63 and 75 €/MWh, compared to a range of 78–95 €/MWh for individual Ground-Source Heat Pumps (GSHP). However, the same study highlights that the improvement of building envelope performance, by reducing absolute heat demand, increases the relative weight of the fixed grid CAPEX, progressively reducing the economic gap with Air-Source Heat Pumps (ASHP), which benefit from significantly lower initial investment costs. The economics of the system change radically when introducing the scale factor. Volkova et al. (2022) [66] analyzed the potential of Large-Scale Heat Pumps integrated into the networks of the Baltic countries. Using an energy system optimization model, the study concludes that these units could achieve an LCOH of 30–50 €/MWh by 2050. The key economic driver identified lies in the ability of centralized utilities to access industrial electricity tariffs and exploit stable, high-capacity heat sources, such as sewage or seawater. Conversely, Resimont et al. [55] and Brumana et al. [13] note that for smaller applications, centralized cogeneration or DH solutions often struggle to justify the installation costs compared to autonomous boilers, with break-even points shifting decades into the future.

The Italian market presents unique challenges due to a milder climate, which reduces the equivalent hours of plant utilization, and electricity prices among the highest in Europe. Recent empirical studies have disaggregated the cost structure of district heating compared to individual solutions in this specific context, highlighting significant infrastructural barriers.

Di Nunzio et al. (2024) [23] provided a detailed decomposition of the LCOH for a geothermal district heating system in a medium-sized city in Northern Italy over a 30-year horizon. The study reveals that the Capital Expenditure (CAPEX) for drilling and network construction accounts for over 60% of the final cost of heat. Sensitivity analysis demonstrates that, in the absence of public incentives covering at least 50% of the initial investment, the LCOH of centralized systems in medium-density areas remains higher than that of individual fossil fuel boilers. This criticality is corroborated and expanded by Villa

et al. (2025) [64], who conducted a Life Cycle Cost (LCC) assessment for a residential Positive Energy District (PED) in Bologna. Comparing the Global Cost normalized per surface area ($\text{€}/\text{m}^2$) over 30 years, the authors report that the 5GDHC network presents a global cost between 501 and 555 $\text{€}/\text{m}^2$, significantly higher than the 459 $\text{€}/\text{m}^2$ calculated for individual air-source heat pumps. The authors explicitly attribute this disadvantage to the high cost of the distribution network and the complexity of prosumer substations, which are not compensated by sufficient operational savings due to the low simultaneity of loads in purely residential districts. Belliardi et al. (2023) [10] confirm this limitation by simulating shallow geothermal 5GDHC networks using the PILEDHC tool, concluding that the high investment costs for geothermal fields and piping can only be recovered in the presence of a balanced mix of tertiary and residential users.

While CAPEX penalizes networks, the comparison of operational costs (OPEX) presents a complex picture linked to efficiency and the cost of electricity. Corradi et al. (2021) [19], analyzing an existing network in Central Italy, found that district heating is economically convenient for the end-user in 84.7% of the analyzed cases. However, this validity primarily subsists in comparison with obsolete gas boilers, while the margin shrinks drastically when the competitor is a modern high-efficiency heat pump. From the perspective of environmental sustainability, Famiglietti et al. (2021) [29] conducted a comparative Life Cycle Assessment (LCA) for a new development in Milan. The results indicate that groundwater heat pumps (GWHP) installed at the single condominium level outperform the environmental performance of a traditional district heating network in 14 out of 16 analyzed impact categories, suggesting that centralization is advantageous only if the network is fully decarbonized.

A crucial technical aspect for the economic sustainability of low-temperature networks is represented by the temperature lift required from the heat pumps. De Pasquale et al. (2017) [22] modeled a system in Milan using the drinking water network (15°C) as a thermal source. The dynamic simulation highlighted that, due to the high ratio between electricity and gas prices in Italy, the system reaches the economic break-even only if it guarantees a Coefficient of Performance (COP) greater than 4.5. This constraint underscores the imperative necessity of utilizing waste heat sources at higher temperatures to reduce the thermal lift and ensure economic sustainability.

Despite the challenges at the single-building level, Bellocchi et al. (2020) [11] offer a fundamental systemic perspective using the EnergyPLAN software. Analyzing a scenario of complete electrification of the Italian heating sector through individual heat pumps, the authors estimate an increase in the annualized costs of the national energy system of 34%, due to the need for massive reinforcements of the electrical grid to manage demand

peaks. This suggests that thermal networks are essential for system balancing, provided their internal efficiency is improved. In this perspective, Capone et al. (2023) [16] demonstrated, through the analysis of the Turin network, that the integration of large heat pumps reduces operational costs only if managed with Demand Response algorithms that exploit the thermal inertia of the network to operate arbitrage on day-ahead electricity prices.

1.1.4. Waste Heat Integration

Parallel to the infrastructural challenges, the integration of waste heat from Data Centers is constrained by transport and technological costs. Wahlroos et al. (2017) [67] indicate that pumping costs grow linearly with distance, risking the nullification of the economic value of the recovered heat if the hydraulics are not optimized. Tofani [59] adds that hydraulic instability from variable DC flows requires complex controls. Furthermore, Amiri et al. (2021) [3] and Wirtz et al. (2020) [68] warn that the thermal upgrade of low-temperature sources, such as air-cooled data centers at 30 °C, requires investments in absorption chillers or heat pumps that extend the return on investment beyond the limits of commercial acceptability. Zhou et al. [73] and Guccione et al. [34] suggest thermal storage (TES) to mitigate this, but at the cost of increased CAPEX.

A synthesis of the analyzed literature reveals a specific techno-economic paradox for the Italian context. At the macroscopic level, Bellocchi et al. (2020) [11] demonstrate the necessity of thermal networks to avoid the collapse of national electric grid costs. However, at the district level, Villa et al. (2025) [64] and Di Nunzio et al. (2024) [23] prove that the high infrastructural CAPEX renders current 5GDHC networks uncompetitive compared to individual solutions. Furthermore, De Pasquale et al. (2017) [22] highlight that the use of low-temperature sources entails unsustainable operational costs due to the resulting low COP.

1.2. Focus and Aim of the Research

The main focus and goal of this thesis is to investigate the technical and economic integration of Data Center (DC) waste heat recovery within advanced thermal infrastructures. By bridging the gap between high-density ICT cooling requirements and urban heating needs, the research can be summarised as follows:

- **Technical feasibility of waste heat recovery:** evaluation of the thermal potential and integration strategies of various DC cooling technologies—ranging from traditional air cooling to advanced immersion systems—into hybrid 4th/5th Generation District Heating (4/5GDH) networks.
- **Identification of design parameters:** definition of characteristic parameters and scaling factors to support the sizing of future district heating networks based on the thermal capacity and cooling technology of newly constructed Data Centers.
- **Thermo-economic assessment:** detailed analysis of the investment and operational costs associated with DC heat recovery, providing a quantitative comparison with stand-alone heat pump systems.
- **Retrofitting and system implementation:** investigation of the feasibility of implementing recovery solutions into existing facilities and infrastructures, identifying technical barriers and the potential for phased expansion within the urban energy system.
- **Environmental impact:** verification of the environmental impact of the proposed configurations, with attention to the quantity of greenhouse gas emissions, in particular specific CO_2 per unit of energy produced.

The methodology developed in this research adopts a bottom-up, automated approach for the design and simulation of hybrid 4th and 5th generation district heating (DH) networks. The procedure begins with the acquisition of building footprints via Google Maps API, which are then processed to estimate thermal demands based on the specific envelope characteristics and real-time climatic data retrieved from the Open Meteo API. The network topology is not pre-defined but is dynamically generated through a Minimum Spanning Tree (MST) algorithm, ensuring the optimization of the total pipe length. The thermal-hydraulic simulation, implemented in MatLab R2022b, evaluates the hourly feasibility of recovering waste heat from Data Center (DC) case studies, adopting a hybrid logic that switches between direct heat exchange (4G) and heat pump temperature lifting (5G) based on seasonal setpoints and source availability.

Due to the high computational complexity inherent in hourly multi-node simulations and the combinatorial nature of MST optimization for large urban case studies, several optimized approximations have been introduced. These include the linearization of certain hydraulic parameters and the use of simplified thermal resistance-capacitance (RC) models for building envelopes, which ensure a robust balance between physical accuracy and calculation time. The complete and detailed explanation of the proposed methodology, including the governing equations and the optimization logic, is described later in Chapter 2.2.

When compared to existing scientific literature, this approach presents several distinctive features. While many studies, such as the analysis of the Espoo Case study [67], utilize a top-down perspective focused on integrating waste heat into existing networks, the current method prioritizes the ex-novo design of low-temperature infrastructures. Unlike simulations performed with standard software like TRNSYS [13], which typically rely on static "building archetypes", this automated workflow captures the geographical and climatic specificity of the urban fabric with higher granularity. Furthermore, while specialized research often focuses exclusively on the thermodynamic optimization of high-temperature heat pumps [34, 38], the model proposed here integrates the hydraulic constraints of the distribution network and the stochastic nature of urban thermal loads [73]. Similarly, in contrast to studies employing Mathematical Optimization for sizing conversion units [68] or fixed ring-topologies [16], the use of MST optimization provides a more rigorous engineering basis for minimizing capital expenditures (CAPEX) without sacrificing the scalability of the model. Ultimately, this integrated approach bridges the gap between high-level urban planning and detailed thermal-hydraulic modeling, offering a scalable tool for the decarbonization of thermal loads in compliance with the latest European energy efficiency mandates [27].

2 | Goals and Methodology

2.1. Research Question

The primary objective of this research consists in defining and validating a comprehensive set of Key Performance Indicators (KPIs) designed to evaluate the technical and economic feasibility of Waste Heat Recovery (WHR) from Data Centers (DCs). This framework aims at transforming thermal waste into a strategic asset for urban decarbonization through the integration of 4th and 5th generation hybrid district heating networks (4GDH and 5GDH).

2.1.1. Technical KPI Framework

From a technical perspective, the study moves beyond isolated energy assessments to establish scalable metrics centered on:

- **Waste Heat Recovery Rate (WHR%):** Quantifying the thermal efficiency of the DC cooling system and its capacity to transfer energy at usable temperature levels, thereby minimizing dissipation losses.

$$WHR\% = \frac{E_{out} - W_{el,ec}}{E_{DC}} \quad (2.1)$$

Where E_{out} is the thermal energy output from the TES, $W_{el,ec}$ is the electrical work of the energy center's heat pump, if any, and E_{DC} is the electrical energy dissipated from the Data Center in the form of heat.

- **Specific Sizing Indicators:** Formulation of parameters that correlate recoverable thermal power and optimal storage volume to heated floor area (m^2). These metrics are intended as predictive design tools: for any potential data center, they allow for determining the building density that the infrastructure can effectively support.

2.1.2. Economic Sustainability and LCOH

In parallel, the investigation seeks to ascertain the economic competitiveness of this integration compared to conventional heating technologies. The analytical core relies on the **Levelized Cost of Heat (LCOH)** applied to the recovered heat. This calculation enables:

- Internalizing Capital Expenditures (CAPEX) regarding heat pumps, heat exchangers, and network infrastructure.
- Evaluating Operational Expenditures (OPEX), predominantly influenced by the electricity consumption required for thermal lifting.
- Providing a benchmark value (€/MWh) to substantiate the investment in hybrid networks compared to the expansion of stand-alone air-to-water heat pump systems.

Ultimately, this research aims to frame the analysis from the perspective of an Energy Service Company (ESCO). Beyond the technical validation, the goal is to determine the commercial viability of such integrated systems by assessing their competitiveness in the current energy market.

The study conducts a comparative cost analysis in the context of electrification of heating and domestic hot water services. Traditional solutions based on stand-alone heat pumps are compared to district heating by evaluating the efficiency gains of WHRs, taking into account operational challenges such as frost formation on evaporators, which significantly penalizes performance in cold climates.

By quantifying these variables, the study intends to define a clear business case for WHR, identifying the economic thresholds under which the recovery of thermal waste from Data Centers becomes a superior commercial alternative to both traditional and emerging electrified heating technologies.

2.2. System method and modeling

The methodological approach developed for this study aims to evaluate the technical and economic feasibility of integrating Data Center (DC) waste heat into urban thermal infrastructures. The entire simulation framework is implemented in the MatLab R2022b environment, which allows for a dynamic, hourly-based analysis of the energy flows between the thermal source, the storage system, and the end users.

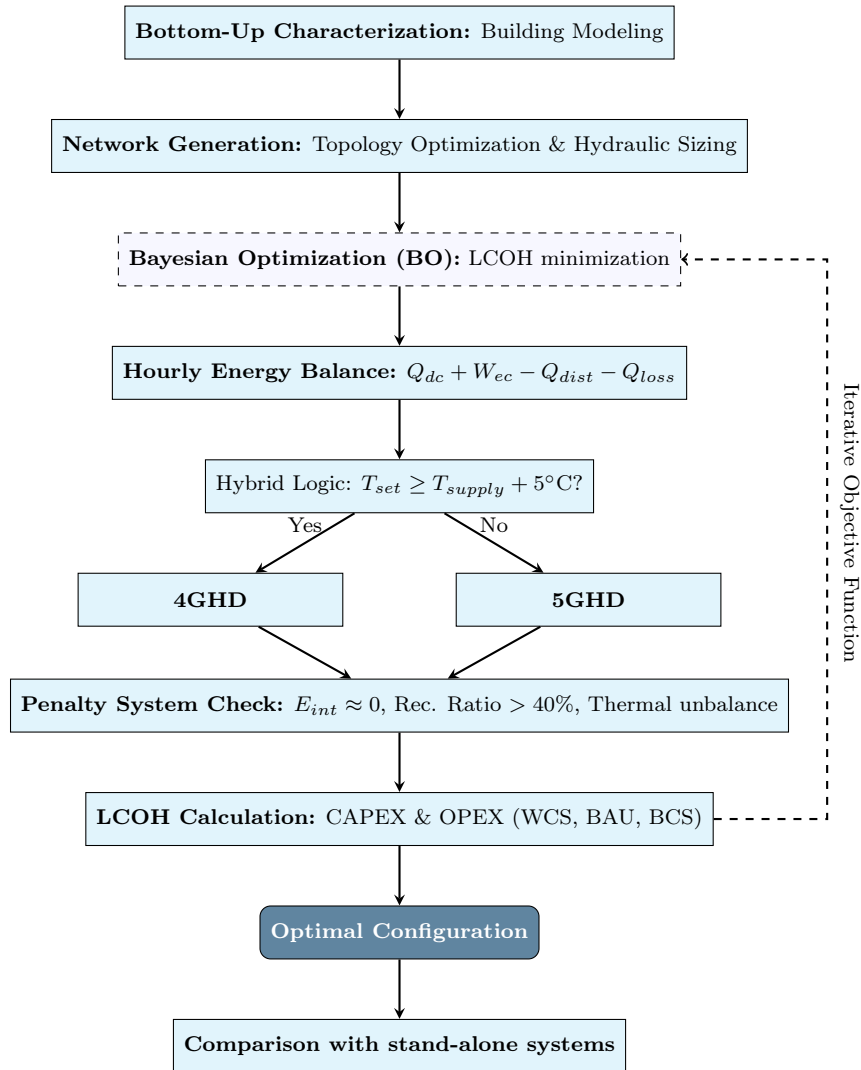


Figure 2.1: Integrated methodological flowchart highlighting the Bayesian optimization loop, the hourly simulation for 4GHD or 5GHD networks, and the penalty-based constraint system for LCOH minimization.

The modeling process begins with a detailed bottom-up characterization of the building case studies. To ensure high geographical and geometric accuracy, the MatLab code is integrated with Google Maps API services, enabling the identification of the footprint area of specific buildings. By defining the number of floors and the intended use, the model reconstructs the heated volumes, the total heat-dissipating surface area, and the glazed surfaces. These geometric data are then cross-referenced with a specifically developed thermophysical database that categorizes buildings based on their construction era. This database provides critical parameters, such as thermal transmittance values (U) for envelopes and the typical operating temperatures of the installed emission systems, based on the technical regulations in force at the time of construction. The energy demand is subsequently calculated through an annual dynamic simulation (8760 hours) that utilizes hourly climatic data (including ambient temperature) retrieved via the Open Meteo API for the specific coordinates of the site.

Central to the system is the concept of the *Energy Center*, which acts as the thermal hub for heat recovery. The Data Center is modeled as a source of constant thermal power, reflecting the typical steady-state operation of IT equipment. To bridge the temporal gap between the continuous heat production of the DC and the fluctuating demand of the buildings, a Thermal Energy Storage (TES) system is integrated. The TES consists of a large, insulated water tank whose thermal behavior is governed by a precise control logic designed to maintain the storage temperature within an optimal range, defined by a set-point ($T_{setpoint}$) and an allowed deviation (ΔT). The energy balance of the TES is calculated at each time step t according to the following expression:

$$Q_{TES,t} = Q_{DC,t} + W_{EC,t} - Q_{dist,t} - Q_{loss,t}$$

In this equation, W_{EC} represents the electrical work of the Energy Center's heat pump (if active), Q_{dist} is the thermal energy withdrawn by the district heating network, and Q_{loss} accounts for the thermal losses to the environment. The control logic ensures that if the temperature exceeds the upper threshold ($T_{setpoint} + \Delta T$), the excess heat is bypassed and dissipated. Conversely, if the temperature falls below the lower threshold ($T_{setpoint} - \Delta T$), an external integration source (condensing boiler) is activated to maintain the service's reliability.

The heat distribution is managed through a hybrid network architecture that combines the principles of fourth and fifth-generation district heating (4GDH and 5GDHC). For each hour of the simulation, the system evaluates the most efficient supply mode based on the temperature available in the TES. If the storage temperature is sufficiently high (at

least 5°C above the user's required supply temperature), the system operates in a 4GDH asset, delivering heat through a simple heat exchanger. If the storage temperature is lower than the required threshold, the system shifts to a 5GDH asset, utilizing decentralized heat pumps in the building substations to lift the thermal potential to the required level. The electrical consumption of these heat pumps is calculated dynamically based on their instantaneous Coefficient of Performance (COP).

The model operates through an iterative hourly energy balance, where the thermal storage temperature (T_{acc}) represents the fundamental state variable for the entire system. For each time interval i , the energy balance within the control volume of the tank (V_{acc}) is defined by the following relation:

$$B(i) = Q_{in}(i) - Q_{out}(i) - Q_{loss,tes}(i) \quad (2.2)$$

In this equation, Q_{in} represents the thermal power injected into the storage, derived from the Data Center waste heat recovery (Q_{DC}) and potentially upgraded by the electrical work of the Energy Center heat pump (W_{ec}). The term Q_{out} aggregates the net thermal demand of the Case study, calculated as the sum of space heating ($Q_{load,net}$) and Domestic Hot Water ($Q_{acs,net}$) actually drawn from the network. The thermal losses of the tank to the ground, $Q_{loss,tes}$, are modeled as follows:

$$Q_{loss,tes}(i) = \frac{T_{acc}(i) - T_{ground}}{R_{th}} \quad (2.3)$$

The storage temperature update for the subsequent hour follows the law of conservation of energy:

$$T_{acc}(i+1) = T_{acc}(i) + \frac{B(i) \cdot 3600}{V_{acc} \cdot \rho \cdot c_p} \quad (2.4)$$

At the building substation level, the model evaluates the activation of decentralized heat pumps by comparing the supply temperature required by the existing terminals with the temperature available in the network. If the network temperature is insufficient, the heat extracted is integrated by electrical work, calculated through a dynamic COP :

$$W_{load/acs}(i, j) = \frac{Q_{load/acs}(i, j)}{COP_{WWB}(T_{acc}(i) - 2, T_{supply, j})} \quad (2.5)$$

The sizing of the district heating network is performed through a deterministic algorithm

that integrates graph theory with technical fluid dynamics. The process begins with the definition of the network topology using the Minimum Spanning Tree (MST) approach, which identifies the connection tree that minimizes the total linear development between the Energy Center and the demand nodes to optimize infrastructure costs. For each identified segment, the volumetric flow rate $\dot{V}$ is calculated based on the cumulative downstream peak thermal load P_{peak} and the design temperature difference ΔT (set at 5 K) according to the energy balance equation:

$$P_{peak} = \rho \cdot c_p \cdot \dot{V} \cdot \Delta T \quad (2.6)$$

The pipe sizing follows an iterative selection process where the smallest commercial internal diameter D is chosen such that the linear pressure drop J remains below the design limit of 20 mm c.w./m. This pressure drop is evaluated via the Darcy-Weisbach equation:

$$J = f \cdot \frac{\rho}{2} \cdot \frac{v^2}{D} \quad (2.7)$$

where the friction factor f is determined using the Haaland formula as a function of pipe roughness and the Reynolds number. Finally, the total pump head Δp_{pump} is calculated by doubling the pressure losses of the hydraulically most critical path to account for both supply and return lines, directly informing the electrical power requirement, which is a fundamental parameter for estimating the system's CAPEX and operational expenses.

$$P_{el} = \frac{\Delta p_{pump} \cdot \dot{V}_{tot}}{\eta_{pump}} \quad (2.8)$$

The evaluation of advanced energy systems, such as the integration of Data Center waste heat into district heating networks, is intrinsically linked to the management of uncertainty, which arises from the stochastic nature of key cost variables, including the high volatility of electricity prices, the fluctuation of maintenance rates, and the empirical margins of error in estimating the initial investment (CAPEX) for bespoke thermal components. To synthesize the system performance, the simulation returns three primary technical indicators: the total annual integration energy required from external sources, the overall recovery percentage—defined as the ratio between the heat utilized by the network and the total heat rejected by the Data Center—and the thermal drift, which monitors the balance between the initial and final states of the storage tank to prevent long-term thermal unbalance. Finally, the model performs an economic assessment to determine the Levelized Cost Of Heat (LCOH), integrating the CAPEX of the network

and equipment with the operational costs (OPEX) related to electricity consumption and maintenance.

$$LCOH = \frac{\sum_{t=1}^n \frac{CAPEX_t + OPEX_t}{(1+r)^t}}{\sum_{t=1}^n \frac{E_t}{(1+r)^t}} \quad (2.9)$$

Given the sensitivity of the LCOH to these fluctuating inputs, adopting a static evaluation framework is often insufficient for long-term strategic planning. Consequently, scenario analysis constitutes an essential methodological pillar for assessing the resilience of complex energy systems operating under conditions of profound economic uncertainty. This approach must not be misconstrued as deterministic forecasting, as it aims to explore a plurality of plausible evolutionary trajectories rather than identifying a single future state. According to the findings of Virdis et al. [65], the construction of such scenarios necessitates the integration of macroeconomic drivers, such as the volatility of fossil fuel prices, and regulatory drivers, primarily concerning the taxation of climate-altering emissions.

In the thermoeconomic field, the application of this methodology allows for the quantification of how shifts in the external environment influence the exergetic cost of final products. As highlighted by Rovira et al. [54], the internal coherence of each scenario is fundamental to ensure that variations in parameters, such as capital expenditures (CAPEX) and operational efficiency, reflect realistic technological outlooks. The integration of these narratives into diagnostic models enables the identification of structural inefficiencies that might emerge under different market pressures, thereby facilitating robust design oriented toward long-term sustainability, as extensively discussed by Usón et al. [61]. Furthermore, the adoption of updated guidelines, such as those proposed by the EBA (European Banking Authority) [25], emphasizes the critical importance of including climate transition risk parameters within the modeling of financial and energy scenarios.

To make operational the scenario analysis within the thermoeconomic assessment, the methodology typically defines three boundary configurations that represent the spectrum of possible futures. The Business as Usual (BAU) scenario serves as the baseline, assuming that current market trends, such as existing electricity price indices and inflation rates, persist without significant structural disruptions.

Conversely, the Worst-Case Scenario (WCS) simulates a high-risk environment characterized by unfavorable conditions, such as a sharp increase in fuel costs, higher interest rates affecting the CAPEX amortization, or the removal of green incentives, in this scenario a 15% cost increase is considered.

On the other end of the spectrum, the Best-Case Scenario (BCS) explores the most optimistic outcome, where technological breakthroughs lead to lower maintenance costs and aggressive regulatory support significantly reduces the Levelized Cost Of Heat, in this scenario a 15% cost decrease is considered.

By comparing these three states, the designer can evaluate the financial robustness of the system and identify the threshold beyond which the investment ceases to be viable.

In order to establish a rigorous comparative benchmark for the proposed district heating network, a stand-alone scenario was defined, based on the complete decentralization of thermal generation through the adoption of individual air-to-water heat pumps (AWHP) for each building. The sizing of the installed capacity (P_{design}) for each unit was determined by assuming a 10% safety factor relative to the simulated hourly peak thermal demand.

The operational performance of these systems was modeled through a dynamic annual simulation consisting of 8,760 time-steps. The model evaluates the instantaneous Coefficient of Performance (COP) as a function of local outdoor temperature (T_{ext}) and the specific supply temperature (T_{supply}) required by the building's emission systems. For Domestic Hot Water (DHW) production, a fixed 65°C setpoint was enforced to ensure sanitary safety and anti-legionella protection. A critical aspect of the stand-alone scenario is the performance degradation caused by defrost cycles, which significantly penalizes the COP in cold climates. When the evaporator surface temperature drops below the dew point of the outdoor air and T_{ext} is near or below freezing, frost accumulation occurs. The energy required to melt this frost layer is accounted for by a correction factor $f_{defrost}$ within the simulation, which reduces the effective COP .

The resulting economic analysis is based on the Levelized Cost Of Heat ($LCOH$). This methodology integrates a sensitivity analysis across three configurations—Business-As-Usual (BAU), Worst-Case (WCS), and Best-Case (BCS)—modulating investment and operational costs through specific scenario multipliers.

2.3. Bayesian optimization

Bayesian Optimization (BO) is an advanced global optimization strategy for "black-box" objective functions $f(x)$ characterized by high evaluation costs and the absence of a known analytical form. In complex engineering contexts, such as the hourly dynamic simulation of a district heating network, conventional optimization methods based on gradients or exhaustive grid searches are often inefficient or inapplicable due to the excessive computational time required for each iteration.

BO overcomes these limitations by adopting a sequential approach rooted in statistical learning. Instead of sampling the domain deterministically or randomly, the algorithm constructs a probabilistic model of the observed data and utilizes this knowledge to intelligently decide where to perform the next evaluation, thereby maximizing the informational efficiency of every simulation.

2.3.1. Theoretical Foundation

The theoretical core of BO lies in the systematic application of **Bayes' Theorem**, which enables the continuous updating of knowledge regarding an objective function as new data points become available [56]. Formally, the theorem is expressed as:

$$P(f|\mathcal{D}_n) = \frac{P(\mathcal{D}_n|f)P(f)}{P(\mathcal{D}_n)} \quad (2.10)$$

In this framework, each term serves a specific operational purpose:

- **Prior** $P(f)$: Represents the initial assumptions about the objective function (e.g., its continuity and smoothness) before any simulations are performed.
- **Likelihood** $P(\mathcal{D}_n|f)$: Describes the probability of observing the set of results $\mathcal{D}_n = \{(x_i, y_i)\}_{i=1}^n$ given a specific configuration of function f .
- **Posterior** $P(f|\mathcal{D}_n)$: Constitutes the updated model of the objective function, integrating initial assumptions with the actual data obtained from simulations [12].
- **Evidence** $P(\mathcal{D}_n)$: A normalization factor ensuring that the posterior distribution is a valid probability distribution.

Bayesian inference thus transforms the optimization problem into a process of uncertainty reduction: each new simulation narrows the space of possible functions, causing the model to "collapse" toward the true form of the objective function in the regions of interest. To make Bayes' Theorem computationally tractable over a function space, BO utilizes a

Surrogate Model, typically based on **Gaussian Processes (GP)** [53]. A GP is an extension of the multivariate normal distribution to an infinite-dimensional function space. It is entirely defined by its mean function $m(x)$ and its covariance function, or **Kernel** $k(x, x')$:

$$f(x) \sim \mathcal{GP}(m(x), k(x, x')) \quad (2.11)$$

The Kernel is the engine of the surrogate model, defining the spatial relationship between points in the domain. Commonly used kernels, such as the Squared Exponential or the Matérn kernel, assume that nearby points in the parameter space should produce similar outcomes. When the model is updated with n observations, the GP provides a normal distribution for every unsampled point x , characterized by a mean $\mu_n(x)$ and a variance $\sigma_n^2(x)$ [57]. In proximity to observed data, the variance tends toward zero, while it increases in unexplored regions. While the surrogate model provides a probabilistic representation, the **Acquisition Function** $\alpha(x)$ acts as the decision criterion. It must resolve the fundamental trade-off between two conflicting dynamics:

1. **Exploitation:** Sampling in regions where the surrogate model predicts optimal values.
2. **Exploration:** Sampling in regions where the uncertainty $\sigma_n(x)$ is high [30].

The most rigorous acquisition functions include:

- **Expected Improvement (EI):** Evaluates the expected value of the improvement over the current best value $f(x^*)$ [42].
- **Upper Confidence Bound (UCB):** Defines a statistical confidence bound of the type $\mu(x) \pm \beta\sigma(x)$. By adjusting β , the operator can decide how aggressively the algorithm should explore [58].

2.3.2. Network optimization

The choice of Bayesian Optimization (BO) for the optimization of the analyzed energy system has proven superior to traditional stochastic and deterministic methods due to its extreme efficiency in handling computationally expensive "black-box" functions. In the literature, the optimization of complex district heating networks has often been entrusted to Genetic Algorithms (GA) or Particle Swarm Optimization (PSO) [57]. However, these approaches require a high number of objective function evaluations, making them impractical for non-linear thermo-hydraulic models that demand significant calculation time for each simulation. Conversely, BO utilizes a probabilistic surrogate model, based on Gaus-

sian Processes, and an acquisition function to balance the exploration of unknown areas and the exploitation of promising ones, drastically reducing the number of iterations required to converge to the optimum. Recent examples confirm its validity: Li et al. (2023) [45] employed BO for the efficiency improvement of HVAC systems, while Khosravi et al. (2020) [44] demonstrated its effectiveness in tuning real heat pumps, highlighting how the "model-free" approach overcomes the limitations of simplified physical models. Compared to techniques such as Mixed-Integer Linear Programming (MILP), which would impose heavy linearizations and degrade physical accuracy, BO allowed for the optimization of critical variables such as T_{set} , ΔT , and V_{acc} while maintaining the thermodynamic fidelity of the model. This choice is also supported by Zhang et al. (2025) [72], who demonstrated that BO is significantly more sample-efficient than genetic algorithms in the capacity planning of hybrid heat systems, confirming it as the most suitable tool to ensure the economic sustainability of the analyzed case studies.

The Bayesian optimization process is implemented to identify the plant configuration that minimizes the Levelized Cost Of Heat (LCOH) for the selected building Case study. The procedure operates through a sequential learning logic that integrates hourly thermodynamic simulations with technical feasibility constraints.

The algorithm simultaneously optimizes four key decision variables within predefined ranges to explore the system's performance:

- T_{set} : the set-point temperature of the thermal energy storage (TES), ranging from 10 to 80 °C.
- ΔT : the maximum allowable temperature deviation for the operational management of the storage (2 to 12 °C).
- V_{acc} : the volume of the water storage tank, scaled according to the total thermal energy demand (E_{fab}) of the Case study.
- P_{DC} : the thermal power dissipated by the Data Center's ICT infrastructure.

The "black-box" objective function is represented by the hourly MatLab energy balance simulation. To guide the search, the expected-improvement-plus acquisition function is employed, which effectively balances the exploration of new configurations with the exploitation of known low-LCOH regions.

Since the optimizer aims to minimize the LCOH, the code incorporates a penalty system to enforce physical and regulatory constraints. If a configuration fails to meet specific technical requirements, the LCOH is artificially forced to an extreme value, effectively discarding the solution. These constraints include:

- **Energy Integration:** Configurations requiring external energy sources to maintain the set-point temperature ($E_{int} > 0$) are penalized to ensure the system relies solely on waste heat recovery.
- **Minimum Recovery Ratio:** A minimum efficiency threshold for heat recovery is imposed (typically 40%); configurations falling below this limit are considered sub-optimal.
- **Thermal Stability (Thermal Drift):** The model verifies that the storage temperature at the end of the annual cycle is consistent with the initial state to prevent long-term thermal unbalance.

The simulation is executed through a parallel processing loop (`parfor`), performing multiple optimization cycles to ensure the statistical robustness of the identified minima. For each cycle, the algorithm monitors the convergence of the LCOH up to 500 evaluations.

The results highlight how the thermal interface varies significantly between air-cooled and liquid-cooled Data Centers. Liquid-cooled systems allow for higher set-point temperatures and more direct heat utilization, whereas air-cooled infrastructures often require an intermediate heat pump upgrade. The final output provides a comprehensive technical-economic mapping, identifying the optimal balance between capital expenditures (CAPEX) and the operational efficiency (OPEX) of the hybrid 4th/5th generation network.

2.4. Calculation hypothesis

To provide a solid foundation for the thermo-economic analysis, a set of calculation hypotheses has been defined based on the most recent regulatory frameworks and technical standards available for the 2024-2025 period. These assumptions encompass energy market prices, specifically tailored to the Italian context, and technical specifications for data center cooling and district heating infrastructures.

The following table summarizes the primary parameters used to drive the optimization model, ensuring that the results remain aligned with current industrial benchmarks and economic trends.

Variable	Description	Value	Technical Notes
$C_{EE,dom}$	Domestic Electricity Cost	0.30 €/kWh	Vulnerability tariff [5]
$C_{EE,ind}$	Industrial Electricity Cost	150 €/MWh	Average PUN + Taxes [33]
C_{gas}	Natural Gas Cost	0.38 €/Smc	Italy business market [6]
C_{sub}	Substation Cost	600 €/kW _t	Residential connection [52]
C_{HP}	Heat Pump Cost	~ 400 €/kW _t	Large-Scale size [20]
C_{hex}	Heat Exchangers Cost	120 €/kW _t	Special applications [50]
C_{TES}	Storage Cost	~ 150 €/m ³	Tank > 5000 m ³ [20]
T_{air}	Air Cooling Temp.	15-20 °C	ASHRAE Class A1 [8]
T_{liq}	Liquid Cooling Temp.	40-45 °C	ASHRAE Class W4 [8]
C_{pump}	Pumps Cost	250 €/kW _e	Variable speed [63]
OM	Operating Costs	3 %	Percentage of CAPEX [20]
FE_{el}	El. Emission Factor	0.257 kgCO ₂ /kWh _{el}	National grid mix [41]
FE_{gas}	Gas Emission Factor	0.202 kgCO ₂ /kWh _{th}	Standard gas combustion [41]
η_{boiler}	Boiler Efficiency	0.95	Condensing boiler [20]
N_{sub}	Substation Lifetime	15 years	Technical standard [43]
N_{net}	Network Lifetime	50 years	Pre-insulated pipes [20]
r	Interest Rate	5 %	Social Discount Rate [26]

Table 2.1: Technical-Economic Assumptions for the Model (Reference 2024-2025)

To accurately model the district heating network's distribution costs, a detailed investment analysis per linear meter was conducted. The following table presents the estimated capital expenditure (CAPEX) for pre-insulated steel pipes across a range of nominal diameters (DN 20 to DN 500). [21] These values, aligned with 2024-2025 market benchmarks, account for the supply of bonded pipe systems, insulation layers, and outer casing, which represent the primary cost drivers in the expansion of thermal energy infrastructure. [51]

Diameter (DN)	20	32	50	80	100	150	200	300	500
Cost [€/m]	60	80	100	120	150	200	240	300	450

Table 2.2: Investment costs for pre-insulated district heating pipes by nominal diameter (Reference 2024-2025)

A further calculation assumption is the assumption of a fully renovated building stock. This calculation condition is based on the need to align the analysis with the strategic objectives of the Energy Performance of Buildings Directive, known as EPBD IV. This regulation requires Member States to define clear pathways to transform existing buildings into zero-emission buildings by 2050, making deep renovation no longer a discretionary option, but an unavoidable technical and regulatory requirement [28]. In addition to legislative obligations, the economic sustainability of this choice is supported by the concept of green premium: buildings with high thermal performance drastically reduce operating costs related to energy consumption and have significantly lower depreciation over time compared to energy-intensive buildings [40]. The reduction in heating requirements, achieved through the efficiency of the building envelope, also allows for the optimal integration of low-temperature systems and renewable sources, ensuring an accelerated return on investment and protecting against energy price volatility [17].

For these reasons, all buildings have been considered renovated in accordance with the legal requirements in reference to the Ministerial Decree D.M. 26/06/2015 for renovations after 2021 in climate zone E [49].

Variable	Description	Value
U_{wall}	Wall thermal transmittance	0,28 W/(m ² K)
U_{roof}	Roof thermal transmittance	0,24 W/(m ² K)
U_{floor}	Floor thermal transmittance	0,29 W/(m ² K)
w_{ratio}	Window-to-wall ratio	0,12
U_{win}	Window thermal transmittance	1,4 W/(m ² K)

Table 2.3: Minimum requirements for the thermophysical properties and characteristics of buildings imposed by the Ministerial Decree of 26/06/2015 for post-2021 renovations in climate zone E.

3 | Case studies

The accurate quantification of building energy demand represents a fundamental prerequisite for the optimal design and integration of hybrid 4/5GDHC networks. In this study, the thermal characterization of the selected case studies was performed through a multi-level simulation approach, aimed at capturing the dynamic interaction between building envelopes and local climatic conditions.

The case study selection was guided by a spatial and functional optimization strategy, with the aim of analyzing different network morphologies. The adoption of specific location criteria was essential to ensure the technical and economic feasibility of the district heating network.

- **Infrastructural Logistics:** preference was given to sites in proximity to greenfield or brownfield areas. These locations are ideal for accommodating the volumetric footprints of the Data Center (DC) and the Thermal Energy Storage (TES) units, significantly reducing the complexity and cost of excavation and civil works.
- **Thermal Load Density:** identifying densely populated residential areas was a priority to ensure high thermo-fluid dynamic efficiency. A high linear heat density (MWh/m) minimizes thermal distribution losses relative to the energy delivered, thereby optimizing the ratio between capital expenditure (CAPEX) and long-term energy performance.
- **Retrofitting feasibility:** buildings of historical importance or subject to strict architectural heritage protection constraints were deliberately excluded. This strategic choice ensures less difficulty in renovation and lower redevelopment costs.

The analysis focuses on heterogeneous building case studies, categorized by construction period, intended use, and thermophysical properties of the envelope. This case study approach allows for the evaluation of diversified thermal load profiles, which are essential for identifying the potential for load complementarity within the district. For each case study, the steady-state and transient thermal demands were modeled to assess the impact of energy retrofit interventions—specifically high-performance insulation and advanced

glazing—on the peak power requirements and the annual energy intensity.

The simulation framework integrates high-resolution climate data with physical modeling of the built environment to determine the supply temperature thresholds compatible with existing emission systems. This step is crucial to define the operational boundary conditions for the decentralized heat pumps or heat exchangers and to evaluate the thermal synchronization between the waste heat availability from Data Centers and the residential heating and Domestic Hot Water (DHW) demand.

The selection process, guided by the aforementioned criteria, led to the identification of several dozen potential sites suitable for evaluation. However, due to the high computational demand of the high-resolution hourly simulations and the complexity of the integrated hydraulic modeling, the analysis was restricted to seven representative case studies. These specific case studies were selected to ensure a diverse range of urban morphologies and building typologies, providing a statistically significant sample of the potential scenarios while remaining compatible with the project's computational time constraints.

The following sections detail the computational results for the primary case studies, providing the technical basis for the subsequent thermo-economic and exergy analysis.

3.1. Building consumption simulation

To ensure the reliability of the numerical models, the building simulations were validated by comparing the obtained results with the reference values provided by the CENED database [7]. This comparison confirmed that the models accurately reflect real-world energy consumption patterns.

All analyzed buildings are located within the municipal territory of Milan, characterized by the following climatic and geographical parameters:

- **Climate Zone:** E
- **Degree Days:** 2404
- **Altitude:** 122 m a.s.l.

Energy simulations were conducted considering standard hourly climatic profiles for the location.

To facilitate reading, only one example Case study will be detailed, and the main characteristic data for the other case studies will be reported. For completeness, the complete

data for the other case studies can be found in Appendix A.1.

3.1.1. Case study MI 003

The complex has 60 786 m² of heated surface area and a total volume of 182 358 m³. The simulation conducted shows that the heat requirement for heating is approximately 3 898 MWh and that for domestic hot water is approximately 1 266 MWh, for a total heat demand of 5 164 MWh. The geographic location of the case study is shown below, detailing the buildings, the network simulated using the tool, and the location of the energy center.



Figure 3.1: Case study MI 003: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

The thermophysical characterization of the complex is based on the integration of geo-

metric parameters, such as heated volumes and envelope surfaces, with dynamic energy requirements. These data, derived from hourly simulations, account for transmission and ventilation losses to define the specific demand for space heating and domestic hot water for each building unit. This detailed registry provides the necessary input for the thermal balance of the storage system and the optimization of the heat recovery process from the data center.

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	3 759	11 278	4 226	241	78	320
2	3 632	10 897	4 145	235	76	311
3	3 884	11 653	4 297	247	81	328
4	3 768	11 303	4 262	243	78	321
5	3 681	11 043	4 222	239	77	316
6	4 084	12 251	4 431	258	85	343
7	3 915	11 744	4 319	249	82	331
8	3 937	11 812	4 326	250	82	332
9	3 750	11 251	4 232	241	78	319
10	3 812	11 436	4 249	244	79	323
11	3 872	11 615	4 334	248	81	329
12	3 995	11 984	4 332	252	83	335
13	4 027	12 080	4 373	254	84	338
14	3 656	10 967	4 193	237	76	313
15	3 324	9 972	4 033	222	69	291
16	3 691	11 072	4 165	238	77	314
Total	60 786	182 358	68 140	3 898	1 266	5 164

Table 3.1: Detailed thermophysical characteristics of the MI 003 case study for each building and heat requirement for heating, hot water and total and total demand.

The following table summarizes the technical performance and infrastructural parameters of the MI 003 case study. It integrates absolute consumption data with normalized indicators, such as the specific peak power and linear network density, which are essential for the sizing of the district heating system. These values define the thermal load density and the pumping requirements necessary to ensure efficient energy distribution.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	5 164
Specific Heating Demand per Floor Area	[kWh/m ² y]	64.13
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	84.95
Specific Demand per Volume	[kWh/m ³ y]	28.32
Peak Power	[kW]	2 523
Specific Peak Power per Floor Area	[W/m ²]	41.51
DH Network Length	[m]	~ 694
Specific Network Length (Linear Density)	[m/MWh]	0.13
Pumping Electric Power	[kW]	~ 14

Table 3.2: Characteristic data of the MI 003 case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

3.1.2. Case studies summarized

The results presented in this section reflect the methodological approach described in Chapter 2.4, in which the building stock was modeled using standardized thermophysical properties. By assuming consistent building envelope performance and system efficiencies across all units, the analysis isolates the impact of urban density and network geometry. Consequently, observed energy demands increase proportionally to heated volumes, ensuring that performance comparisons between case studies are based on a comparable baseline for the quality of the building fabric.

The first part of this summary analysis focuses on the global thermophysical properties and absolute energy demands of the selected case studies. Aggregating the data for each case study highlights the significant scale of the project: the total heated volume exceeds 1.1 million cubic meters, with a cumulative heating demand of approximately 29.4 GWh/year. This overview highlights the consistent relationship between space heating and domestic hot water (DHW) needs, a direct result of uniform modeling assumptions applied to different urban contexts.

Case study	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
MI 003	60 786	182 358	68 140	3 898	1 266	5 164
MI 004	87 295	261 884	68 579	4 847	1 817	6 665
MI 005	31 075	93 226	27 878	1 758	647	2 405
MI 006	46 024	138 071	35 567	2 498	958	3 456
MI 007	59 734	179 203	46 825	3 296	1 244	4 539
MI 017	40 952	122 856	41 915	2 444	853	3 296
MI 019	64 816	194 447	50 222	3 540	1 349	4 890
Total	390 682	1 172 045	339 126	21 281	8 134	29 415

Table 3.3: Summary of total thermophysical characteristics and annual energy requirements for all analyzed case studies.

To facilitate a technical comparison between areas of different sizes, the following table presents normalized performance indicators and key infrastructural parameters. The stability of the specific demand values confirms the validity of the uniform thermal assumptions, while the variations in peak power and DH network length highlight the influence of the specific urban layout. These indicators are crucial for identifying thermal load den-

sity and evaluating the linear efficiency of the distribution system, which are the primary drivers for the optimization of the district heating network.

Case study	Spec. Heat. Demand [kWh/m ² y]	Spec. Total Demand [kWh/m ² y]	Peak Power [kW]	Spec. Peak Power [W/m ²]	DH Length [m]
MI 003	64.13	84.95	2 523	41.51	~694
MI 004	55.53	76.35	3 157	36.17	~904
MI 005	56.58	77.40	1 145	36.85	~249
MI 006	54.27	75.09	1 627	35.35	~252
MI 007	55.17	75.99	2 146	35.93	~406
MI 017	59.67	80.49	1 600	39.08	~455
MI 019	54.62	75.44	2 306	35.58	~472

Table 3.4: Summary of technical performance and infrastructural indicators for the analyzed case studies.

3.2. Conversion of existing networks

The conversion of a third-generation (3G) network into a hybrid 4/5GDHC architecture is intrinsically linked to the deep energy retrofit of the served building stock. In traditional 3G systems, the use of high supply temperatures, typically in the 90–70°C range, is necessitated by the requirement to compensate for the significant thermal dispersions of inefficient building envelopes. The integration of structural interventions, such as external thermal insulation and the replacement of windows, enables a drastic contraction of the specific thermal demand Q . This reduction in peak thermal load allows for the supply of existing emission terminals at significantly lower temperatures, effectively transforming energy-intensive users into resilient nodes compatible with 4G thermal regimes or suitable for integration via booster heat pumps in a 5G configuration.

From a fluid-dynamic perspective, the variation in energy demand is decisive for the hydraulic balance of the system, as described by the energy balance equation:

$$Q = \dot{m} \cdot c_p \cdot (T_{supply} - T_{return}) = \dot{m} \cdot c_p \cdot \Delta T \quad (3.1)$$

Although the transition to low-temperature regimes generally entails a reduction in the temperature lift ΔT —which, for a constant load, would necessitate an increase in the mass flow rate $\dot{m}$ —the simultaneous decrease in the post-retrofit thermal power Q_{post} allows for the recalculation of the design mass flow rate as follows:

$$\dot{m}_{new} = \frac{Q_{post}}{c_p \cdot \Delta T_{new}} \quad (3.2)$$

If the reduction in energy demand Q_{post} is proportionally greater than the contraction of the thermal jump ΔT_{new} , the resulting mass flow rate will be lower than or equal to the original one. This synergy is fundamental to preventing the hydraulic saturation of existing pipelines and limiting the electrical pumping power P_{pump} , which depends quadratically on the flow rate through the pressure drops Δp :

$$P_{pump} = \frac{\dot{V} \cdot \Delta p}{\eta} \quad (3.3)$$

In this configuration, the engineering challenge shifts toward managing load simultaneity.

3.2.1. Hypothesis of a typical case - MI 001

The complex has 149 013 m² of heated surface area and a total volume of 447 038 m³. The simulation conducted shows that the heat requirement for heating is approximately 8 488 MW h and that for domestic hot water is approximately 3 102 MW h, for a total heat demand of 11 590 MW h. The geographic location of the case study is shown below, detailing the buildings, the network simulated using the tool, and the location of the energy center.

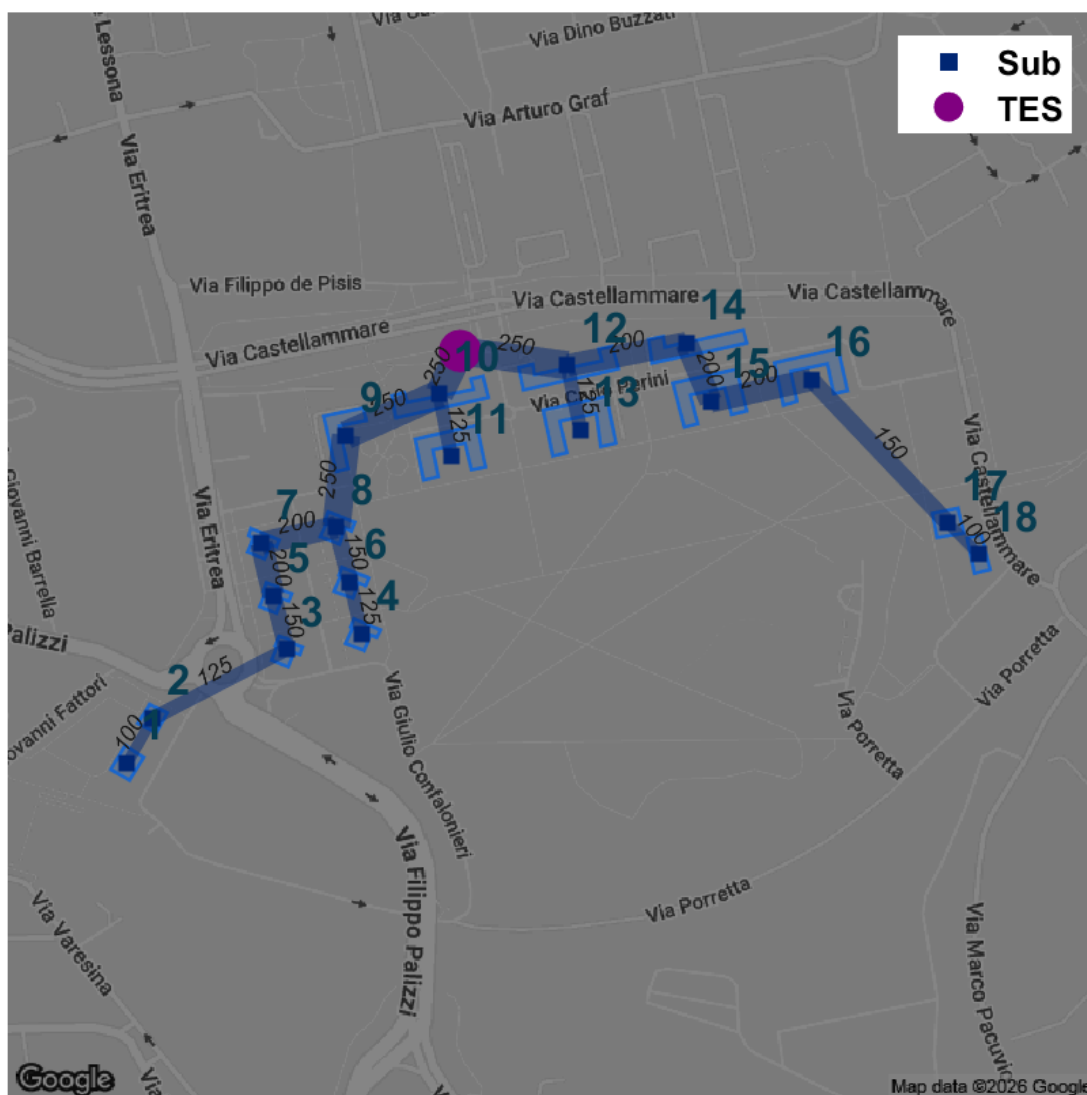


Figure 3.2: Case study MI 001: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

The thermophysical characterization of the complex is based on the integration of geometric parameters, such as heated volumes and envelope surfaces, with dynamic energy requirements. These data, derived from hourly simulations, account for transmission and ventilation losses to define the specific demand for space heating and domestic hot water for each building unit. This detailed registry provides the necessary input for the thermal balance of the storage system and the optimization of the heat recovery process from the data center.

Bldg.	Heat surf. [m²]	Heat vol. [m³]	Disp. surf. [m²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	5 244	15 732	3 965	291	109	401
2	3 971	11 912	3 324	230	83	313
3	7 689	23 067	5 947	438	160	598
4	8 643	25 930	6 444	485	180	665
5	7 683	23 048	6 334	449	160	609
6	8 460	25 380	6 455	479	176	655
7	7 675	23 025	6 242	446	160	606
8	8 891	26 672	6 686	501	185	686
9	3 762	11 287	4 177	236	78	314
10	10 994	32 982	9 184	634	229	863
11	9 157	27 472	7 753	520	191	711
12	11 657	34 972	9 609	668	243	911
13	9 831	29 493	8 470	563	205	767
14	11 269	33 807	8 892	634	235	869
15	9 718	29 153	8 134	549	202	752
16	8 656	25 969	7 826	506	180	687
17	9 401	28 202	6 085	500	196	696
18	6 311	18 934	4 923	358	131	490
Total	149 013	447 038	120 452	8 488	3 102	11 590

Table 3.5: Detailed thermophysical characteristics of the MI 001 case study for each building and heat requirement for heating, hot water and total and total demand.

The following table summarizes the technical performance and infrastructural parameters of the MI 001 case study. It integrates absolute consumption data with normalized in-

dicators, such as the specific peak power and linear network density, which are essential for the sizing of the district heating system. These values define the thermal load density and the pumping requirements necessary to ensure efficient energy distribution.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	11 590
Specific Heating Demand per Floor Area	[kWh/m ² y]	56.96
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	77.78
Specific Demand per Volume	[kWh/m ³ y]	25.93
Peak Power	[kW]	5 494
Specific Peak Power per Floor Area	[W/m ²]	36.87
DH Network Length	[m]	~ 1483
Specific Network Length (Linear Density)	[m/MWh]	0.13
Pumping Electric Power	[kW]	~ 48

Table 3.6: Characteristic data of the MI 001 case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

3.3. Types of plant solutions

Below, the main system configurations adopted for the thermal integration between the Data Center and the urban case study are examined, focusing on the two key components of the infrastructure: the Energy Center and the Substations.

3.3.1. Energy center

The Energy Center serves as a pivotal element in the system's architecture, acting as the central hub for the district heating network. Within this infrastructure, the recovery and management of waste heat from the Data Center (DC) take place, following the integrated operational logic described in Chapter 2.2. It is fundamental to emphasize that the Data Center maintains its own dedicated cooling systems (Chillers or Free-cooling), designed with high redundancy standards to ensure maximum operational reliability for the ICT equipment. The heat extraction by the network occurs through an energy exchange that does not interfere with the DC's internal cooling system, which remains autonomous and prioritized for data safety.

Depending on the thermal gradient required by the network and the exit temperatures from the Data Center, the Energy Center can operate according to two main plant configurations.

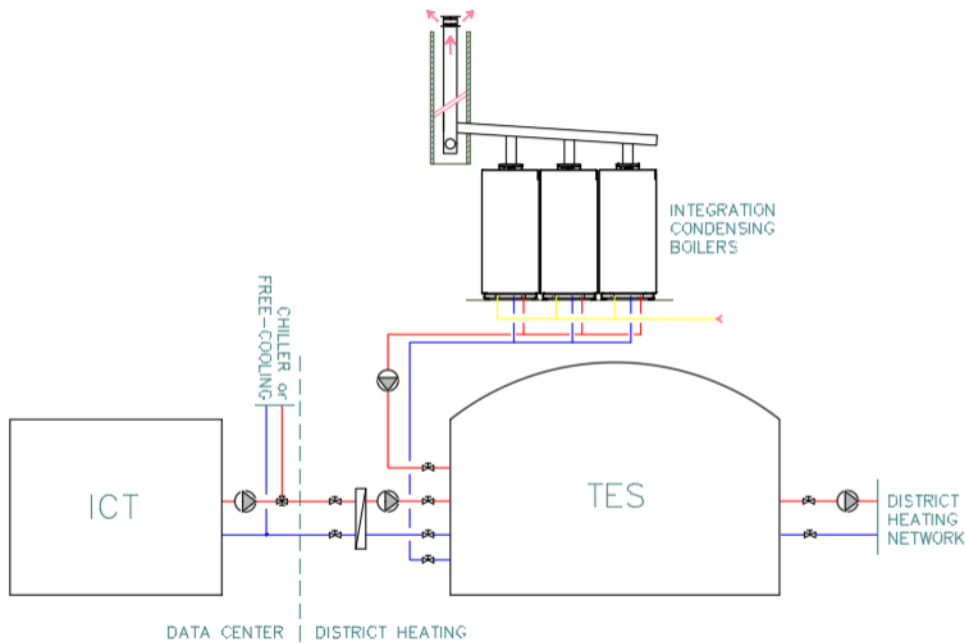


Figure 3.3: Functional diagram of the energy center without a central heat pump.

1) **Direct Exchange:** heat is transferred from the Data Center circuit to the Thermal Energy Storage (TES) via a plate heat exchanger, an ideal solution when the DC temperatures are already compatible with the network set-points.

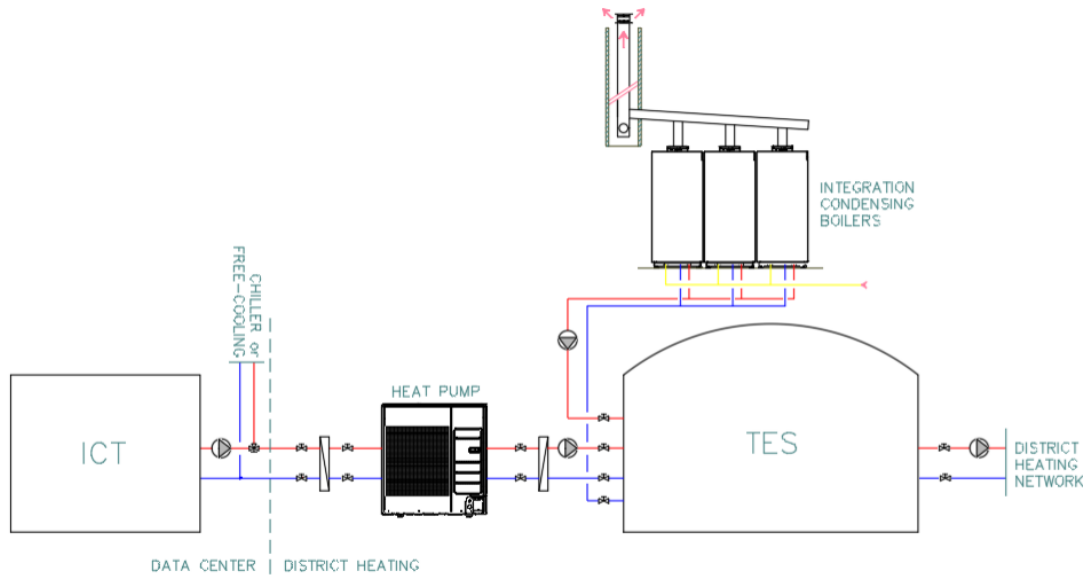


Figure 3.4: Functional diagram of the energy center with a central heat pump.

2) **Heat Pump Integration:** in this configuration, a centralized heat pump intervenes to raise the thermal potential of the recovered heat, ensuring the achievement of the temperatures necessary for district heating even under more challenging operating conditions.

In both cases, the system is supported by integration condensing boilers that intervene exclusively to cover peak demands or manage seasonal thermal deficits.

To address the varying flow temperatures of the network, the study analyzed various system solutions, ranging from fourth-generation (4G) substations, featuring low-temperature distribution and instantaneous domestic hot water (DHW) production, to fifth-generation district heating and cooling (5GDHC) systems. In the latter, the network acts as a thermal bus, often operating at temperatures close to ambient, necessitating the use of decentralized heat pumps (HPs) to boost thermal energy for heating or to dissipate heat during cooling cycles. The following subsections describe the hydraulic and functional architectures of these solutions, highlighting the integration of heat exchangers, heat pumps, and cooling systems.

3.3.2. 4GHD substation

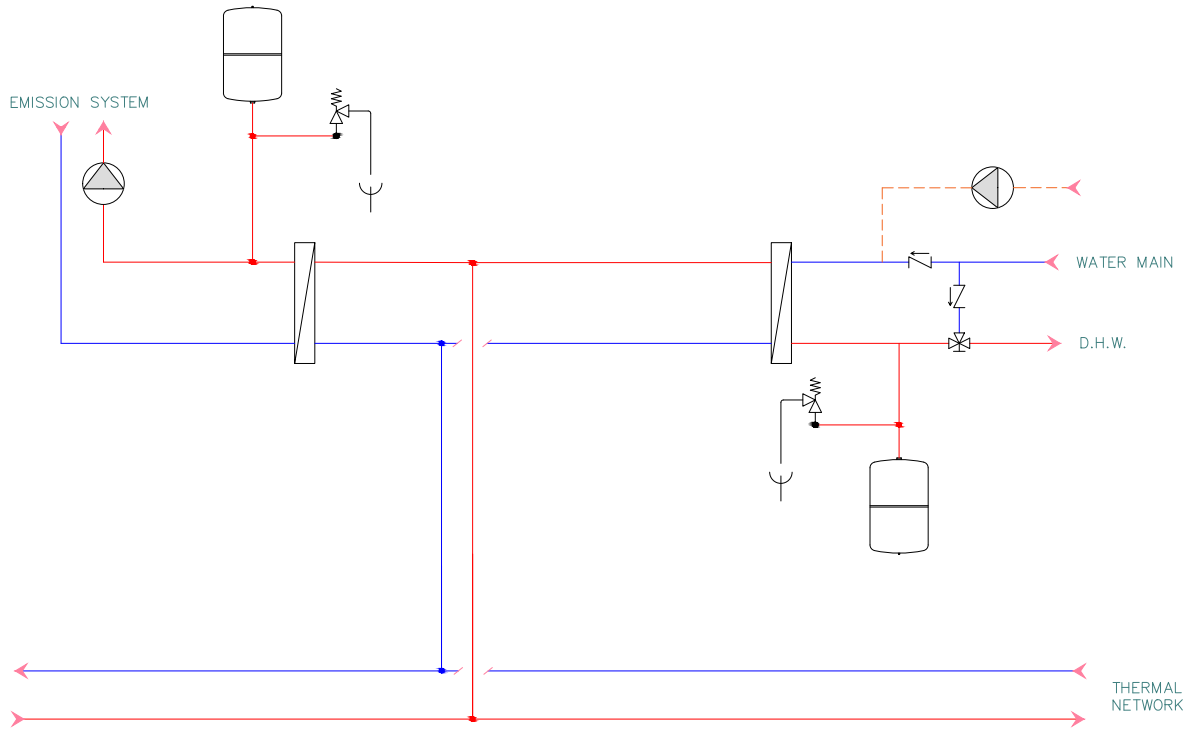


Figure 3.5: Functional diagram of a 4th generation district heating substation.

The hydraulic architecture is based on two Plate Heat Exchangers (PHE) that interface the primary network (DH inlet/outlet) with the building's secondary circuits:

- **Space Heating Circuit:** the heating return fluid is circulated by a pump through the upper PHE. The supply temperature (*heating send*) is controlled via a motorized two-way valve on the primary side, regulated by a climatic control unit (Q.E.) that processes data from an outdoor sensor and a room thermostat.
- **DHW Production:** cold inlet water (CIW) is heated instantaneously in the lower PHE. A flow switch detects demand and modulates the primary regulation valve to ensure the required set-point at the hot water outlet.

3.3.3. 4/5GHD substation

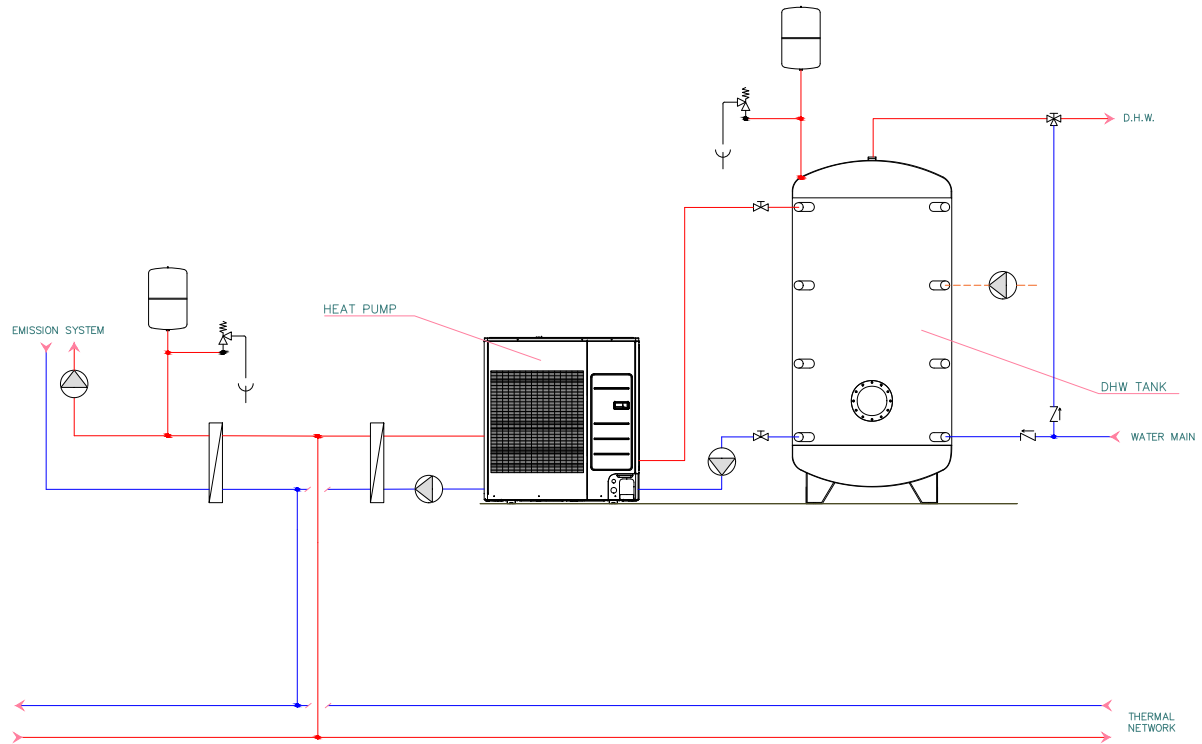


Figure 3.6: Functional diagram of a substation of a 4th/5th generation hybrid district heating system.

The system is based on a hybridization of 4th and 5th generation substations, meaning we find both a direct exchanger and a heat pump to bring the heat to the service temperature:

- **Space Heating Circuit:** the heating circuit is similar to the 4th generation substation.
- **DHW Production:** unlike the instantaneous production found in the 4th generation, this configuration features a heat pump that raises the network temperature for DHW production via stratified storage in a dedicated boiler. Special attention must be paid to the storage temperature, which must not fall below 55-60°C, otherwise there is a risk of legionella formation.

3.3.4. Cooling integration

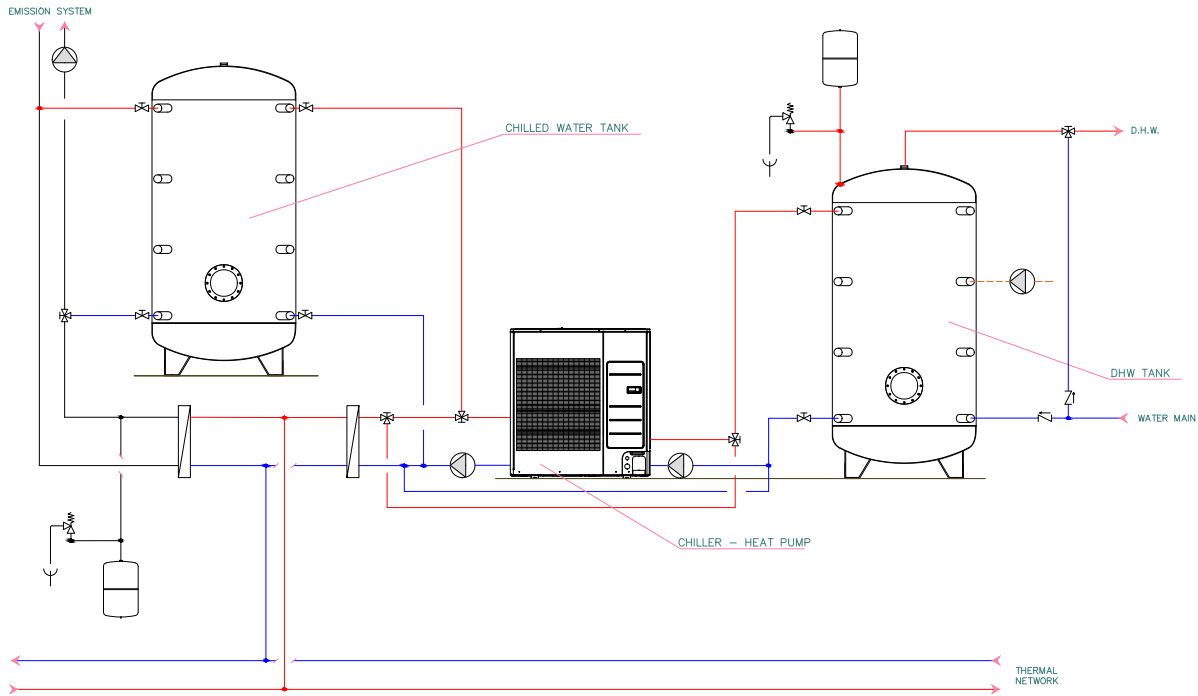


Figure 3.7: Functional diagram of a substation of a 4th/5th generation hybrid district heating system with cooling system integration.

This scheme integrates the production of cooling through the same heat pump that in the previous scheme was used exclusively for domestic hot water:

- **Space Heating Circuit:** the heating circuit also becomes a cooling circuit; by operating a three-way valve, it is possible to divert the flow of the secondary circuit either from the network exchanger (as in the previous cases) or from a buffer tank that is cooled by the heat pump for the DHW.
- **DHW Production:** the production of DHW is similar to the previous system.
- **Cooling Production:** cooling energy can be produced in two ways: either by extracting heat from the cooling circuit, bringing it to a high temperature for DHW production, or by condensing it with the network heat exchanger. During summer operation, the network must therefore be cooled and not heated by the data center's waste heat. The cold tank is used to temporally decouple the demand for DHW

and the need for cooling.

3.3.5. 5GHD substation

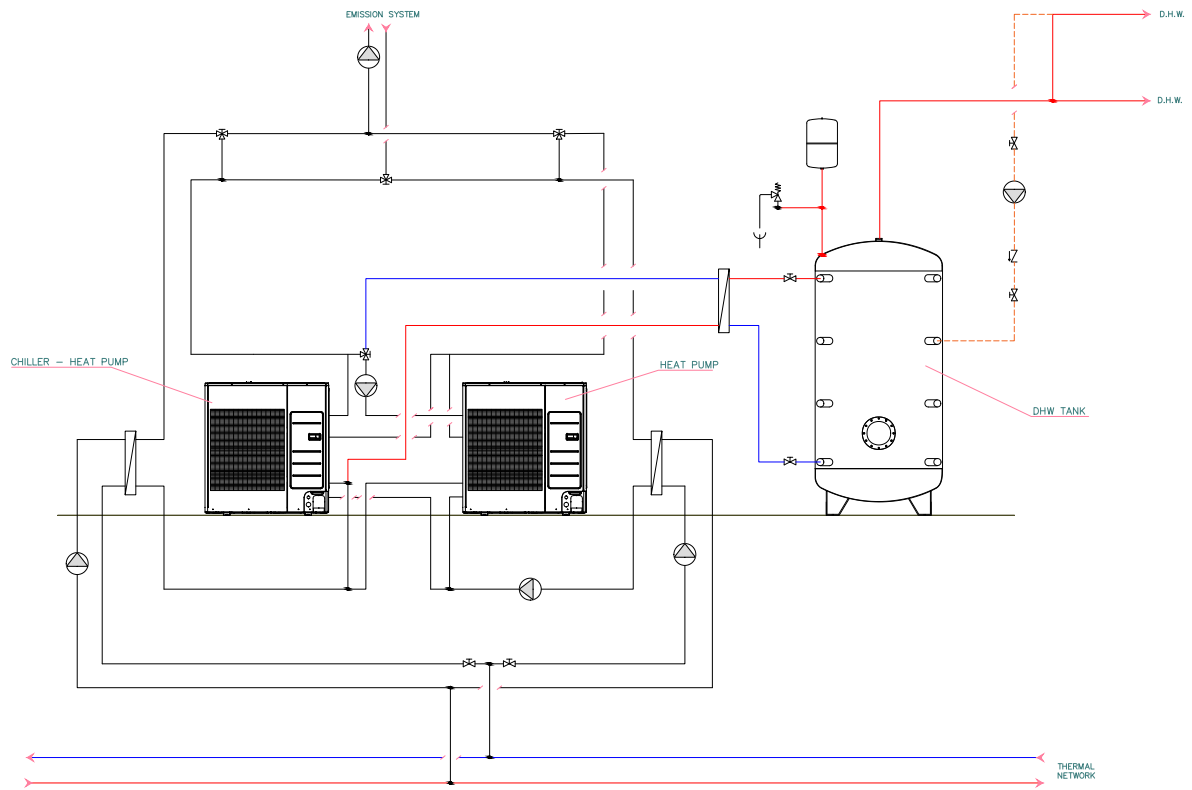


Figure 3.8: Functional diagram of a 5th generation district heating substation.

Finally, the 5th generation substation uses two heat pumps that can simultaneously produce DHW and heat for space heating and cooling and DHW.

4 | Results

The analysis yielded five optimized configurations for each scenario investigated (WCS, BAU, BCS), distinguishing between air-cooled and liquid-cooled data centers. The results for the seven case studies and finally for the existing grid inversion hypothesis are reported below.

4.1. Economic and technical results

The following section will detail only one of the seven cases analyzed, as the results found are very similar. This is primarily due to the fact that all buildings were considered renovated and therefore had virtually identical thermophysical properties. The heat emission terminals, which strongly influence the network temperature (especially for fourth-generation technologies), were also all considered operating at the same temperature of 50°C. For completeness, the average values obtained from the calculations for each scenario and cooling type are reported; the complete tables are available in Appendix A.2.

4.1.1. Case study MI 003

Air cooled Data Center

Analyzing figure 4.1 the system maintains a thermal energy storage (TES) temperature between 55°C and 60°C, but the energy balance varies significantly between summer and winter. During the summer months, a sharp drop in building heating demand leads to underutilization of the heat recovered from the data center; consequently, this excess thermal energy is dispersed into the environment, causing the TES temperature to stabilize at its upper operating limit.

Conversely, the winter season sees a substantial increase in the case study's total heating load, due to both space heating and domestic hot water demand. During these periods, the heat recovered from the data center is not sufficient to meet the load on its own. When the ambient temperature drops below 10°C, integrating a backup system becomes essential, providing peak power outputs of up to 1,500 kW to cover the thermal deficit.

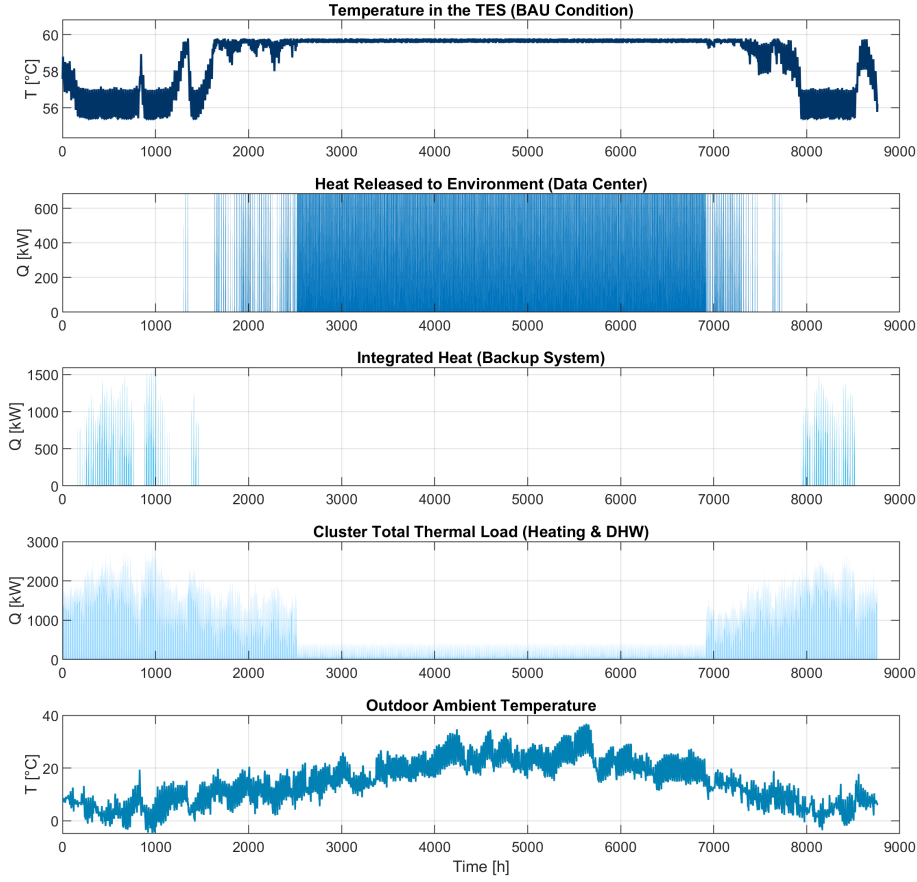


Figure 4.1: Analysis of the annual hourly trend of the network temperature, the heat dissipated by the DC, the heat integrated into the network, the total heat demand of the case study and the external air temperature for case study MI 003 (BAU - air cooled).

The economic analysis focuses on the evaluation of the Levelized Cost Of Heat (LCOH), a key parameter for determining the average cost of thermal energy produced over the entire life cycle of the infrastructure. Under standard operating conditions (BAU), the system has a net LCOH of 76.51 €/MWh. The cost structure reveals a strong dependence on energy prices: the electricity component represents the largest expense, accounting for 54% in the BAU and WCS scenario.

The analysis assumed Incentives/Recovery, understood as a share of financial compensation paid to the grid operator by the Data Center operator (*DC*). This financial transfer mechanism is justified by the waste heat evacuation service provided by the grid itself. Without integration with the district heating infrastructure, the DC would be forced to dissipate this thermal energy into the surrounding environment, incurring an additional energy burden related to the operation of fans or chillers which would lead to significant electricity consumption. In particular, it has been assumed that the *SCOP* for a freecool-

ing system in winter is approximately 6. The energy that the grid draws from the Data Center is therefore valued as a saving on the DC's cooling operating costs, translating into a negative contribution that reduces the gross *LCOH*.

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	86.87	59.53	57.22	2.03	3618	678
R2	87.09	60.16	57.88	2.51	3570	670
R3	86.60	60.48	57.42	2.30	3596	669
R4	86.45	60.84	57.60	2.22	3531	665
R5	87.26	58.86	57.57	2.07	3547	683
Avg	86.50	59.97	57.54	2.23	3572	673

Table 4.1: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 003 - WCS Scenario (Air Cooled).

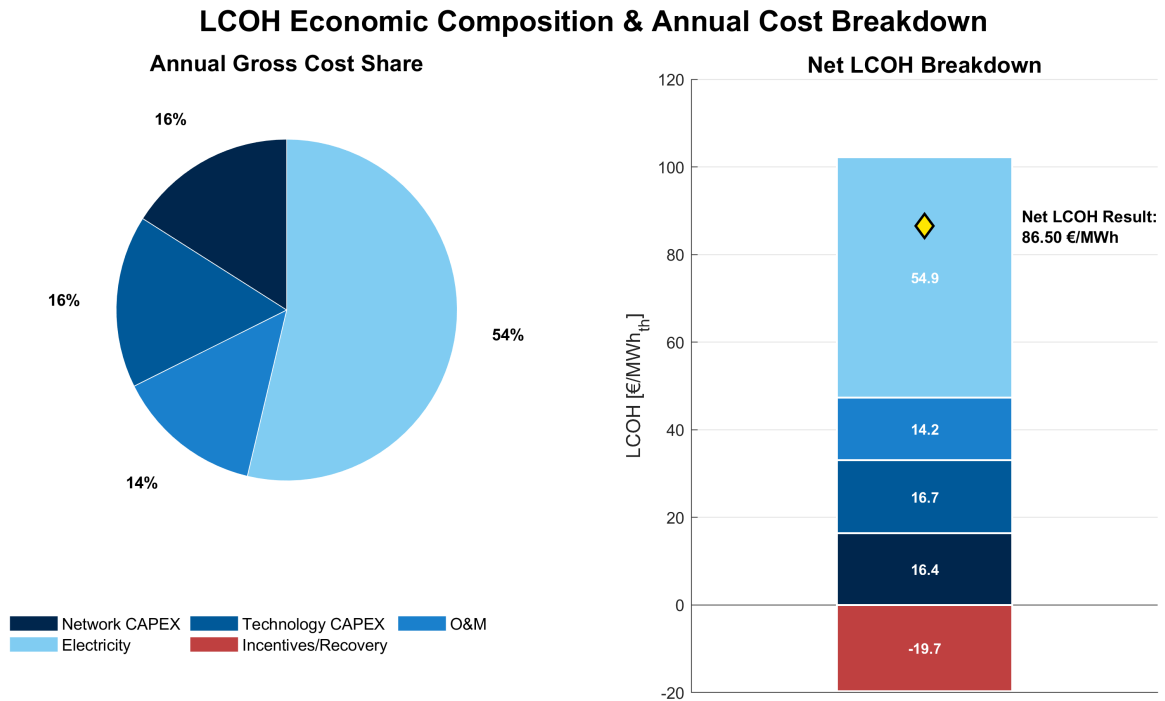


Figure 4.2: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 003 (WCS - air cooled).

In the scenarios analyzed, this share has a significant impact on the sustainability of the air configuration, ranging from -14.50 €/MWh in the *BCS* case up to -19.70 €/MWh in the *WCS* scenario, where the intrinsic inefficiency of the system would otherwise make the cost of thermal energy prohibitive. Overall, the variability between the different optimization scenarios leads the final cost to range from a minimum of 65.30 €/MWh (*BCS*) to a maximum of 86.50 €/MWh (*WCS*).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	76.87	59.44	58.35	2.46	3593	673
R2	76.02	59.21	57.49	2.13	3510	680
R3	75.45	60.83	57.11	2.03	3630	667
R4	76.19	60.04	57.74	2.24	3611	671
R5	78.03	54.41	57.23	2.17	3614	729
Avg	76.17	58.79	57.58	2.21	3592	684

Table 4.2: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 003 - BAU Scenario (Air Cooled).

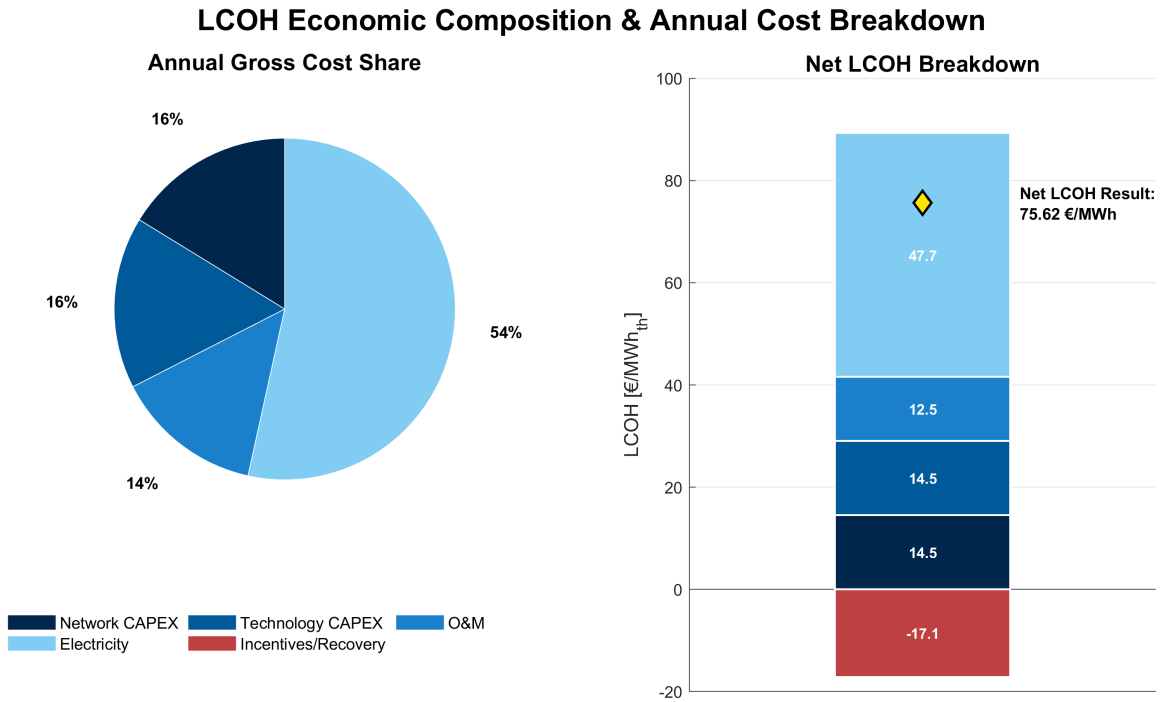


Figure 4.3: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 003 (BAU - air cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	65.21	58.88	57.54	2.00	3549	683
R2	65.52	57.51	57.44	2.15	3510	696
R3	64.13	61.15	57.04	2.08	3509	665
R4	66.75	58.54	58.35	2.34	3934	681
R5	66.29	59.03	59.12	2.50	3529	673
Avg	65.30	59.02	57.90	2.21	3606	680

Table 4.3: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 003 - BCS Scenario (Air Cooled).

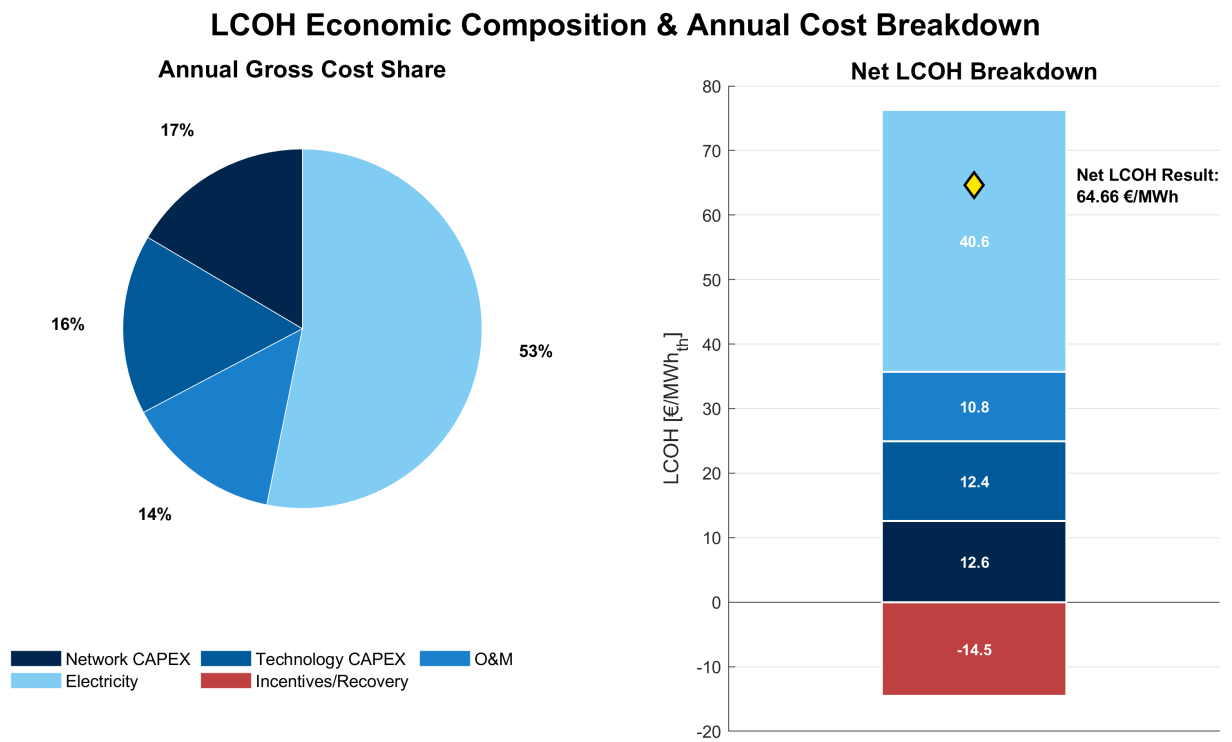


Figure 4.4: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 003 (BCS - air cooled).

From an examination of the results produced by the Bayesian optimization process, it clearly emerges that the most efficient configuration for all the scenarios analyzed (WCS, BAU, and BCS) is a fourth-generation district heating network (4GDH). This architecture is characterized by the absence of heat pumps (HPs) delocalized at user nodes, entrusting the entire thermal gradient elevation to a single centralized system. The systematic preference for this technical solution is primarily due to the economies of scale that govern the heat pump technology market: the specific cost per unit of installed power is significantly lower for large-scale equipment compared to a multitude of small-scale devices distributed across the territory. Therefore, centralizing thermal capacity allows for the optimization of initial investment and operating costs, consolidating the economic advantage necessary to achieve the minimum *LCOH* highlighted in the previous analyses.

The summary results for the three scenarios are reported below.

Scenario	LCOH [€/MWh]	Rec. [%]	T_{set} [°C]	ΔT [°C]	V_{acc} [m³]	P_{DC} [kW]
WCS	86.50	59.97	57.54	2.23	3572	673
BAU	76.17	58.79	57.58	2.21	3592	684
BCS	65.30	59.02	57.90	2.21	3606	680

Table 4.4: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 003 (Air Cooled).

Liquid cooled Data Center

The temperature inside the *TES* is maintained precisely in the range 55 - 60 °C, showing a saturation trend towards the upper limit during the summer due to the drastic reduction in the case study's thermal demand, as in the previous case (graph 4.1). Similarly, the heat recovered from the Data Center is dissipated into the environment for most of the central months of the year. This confirms that the system's limit does not lie in the efficiency of the cooling technology, but rather in the seasonal imbalance between the constant production of waste heat and user demand. The use of the backup system (*Integrated Heat*) follows the same temporal logic, with interventions concentrated exclusively in the winter months to compensate for peak thermal loads of up to 1 500 kW.

Below, the Bayesian optimization results are detailed for the BAU scenario only. The analysis shows that the liquid-cooled data center configuration is slightly more cost-effective than the air-cooled one, demonstrating a reduction in LCOH. This difference is primarily due to a greater heat extraction capacity, which ensures an increase in available thermal resources. This occurs because liquid cooling allows for higher heat source temperatures, improving the heat pump's coefficient of performance (COP) and consequently reducing electricity consumption, which represents more than half of the system's gross costs. From a financial perspective, the "Incentive/Recovery" contribution for the liquid-cooled configuration is not considered. This is because, in addition to being much more limited (since free cooling would have a much higher SCOP than the air-cooled case), it takes into account the greater investment by data center operators in installing the cooling technology. Therefore, it was decided not to provide financial compensation for the heat evacuated via the district heating network. As with the previous case (air-cooled), the optimal configuration is the fourth generation network.

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	73.50	48.72	57.68	2.73	3516	984
R2	73.29	50.66	57.91	2.95	3570	948
R3	73.86	46.61	57.42	2.30	3521	1028
R4	74.46	46.82	59.01	2.27	3518	1018
R5	73.88	48.06	58.15	2.66	3534	996
Avg	73.50	48.17	58.03	2.58	3532	995

Table 4.5: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 003 - BAU Scenario (Liquid Cooled).

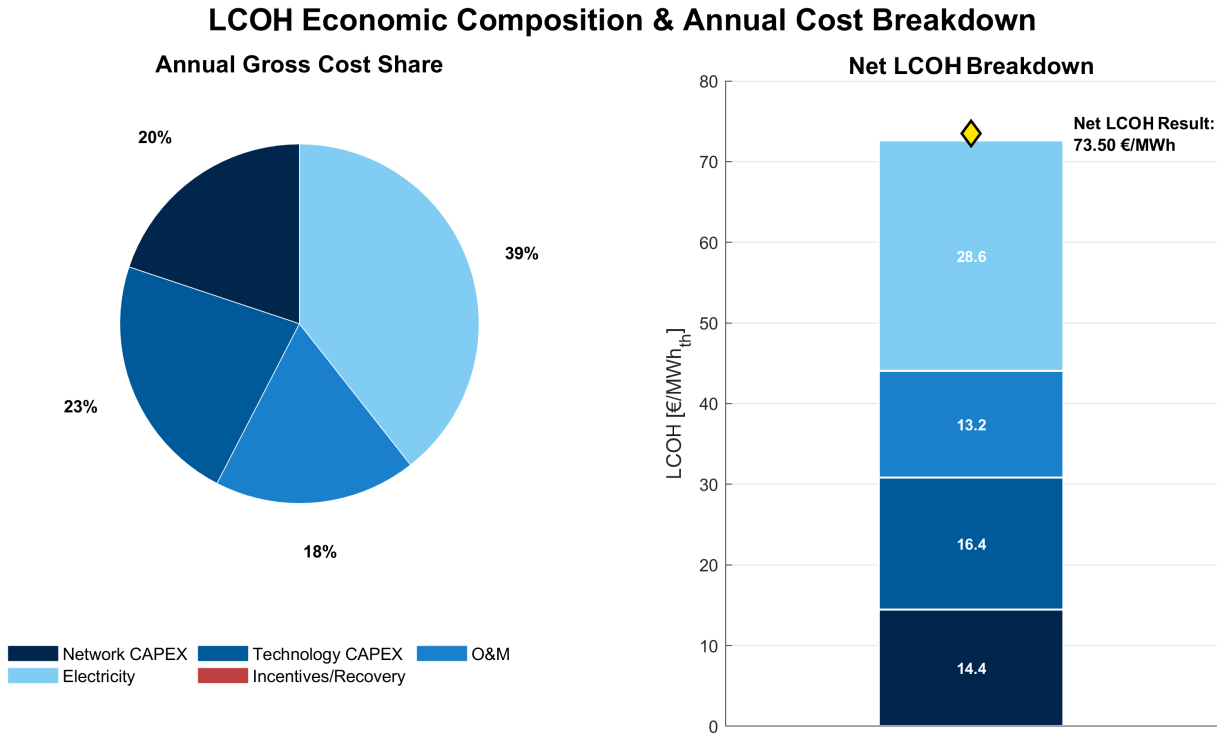


Figure 4.5: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 003 (BAU - liquid cooled).

For completeness, the summary results for the three scenarios are reported, highlighting a slight economic convenience in the liquid-cooled case and optimization results very similar to the air-cooled case.

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	84.20	47.64	58.20	2.38	3517	1005
BAU	73.50	48.17	58.03	2.58	3532	995
BCS	63.23	46.09	57.96	2.23	3525	1037

Table 4.6: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 003 (Liquid Cooled).

The summary results for each case study are shown below, highlighting that the cost differences are practically zero.

4.1.2. Case study MI 004

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	86.41	61.96	57.57	2.20	4420	844
BAU	76.18	59.98	57.43	2.19	4423	871
BCS	65.45	59.58	57.61	2.32	4394	872

Table 4.7: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 004 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	84.41	48.13	57.85	2.19	4389	1287
BAU	74.49	47.57	58.84	2.73	4386	1293
BCS	63.71	46.49	58.19	2.23	4407	1325

Table 4.8: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 004 (Liquid Cooled).

4.1.3. Case study MI 005

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	88.29	61.66	57.56	2.19	1601	306
BAU	77.74	60.34	57.77	2.20	1603	310
BCS	66.90	59.04	57.93	2.29	1601	316

Table 4.9: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 005 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	86.23	49.18	58.39	2.36	1590	454
BAU	75.79	46.52	57.83	2.36	1593	478
BCS	65.10	45.99	58.41	2.41	1593	482

Table 4.10: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 005 (Liquid Cooled).

4.1.4. Case study MI 006

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	85.43	61.45	57.43	2.20	2276	441
BAU	75.18	58.83	57.15	2.09	2283	457
BCS	64.00	60.85	57.77	2.16	2289	443

Table 4.11: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 006 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	83.24	48.79	58.16	2.21	2263	658
BAU	72.81	48.02	58.12	2.25	2271	667
BCS	62.73	45.93	58.43	2.51	2254	693

Table 4.12: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 006 (Liquid Cooled).

4.1.5. Case study MI 007

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	85.17	62.78	57.76	2.36	2998	568
BAU	75.06	60.58	57.74	2.42	2990	585
BCS	64.56	59.19	57.82	2.37	2999	596

Table 4.13: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 007 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	83.05	49.72	58.21	2.16	2986	850
BAU	72.90	47.71	58.00	2.17	2991	882
BCS	62.66	46.60	58.32	2.41	2992	899

Table 4.14: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 007 (Liquid Cooled).

4.1.6. Case study MI 017

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	89.22	58.21	57.54	2.18	2233	441
BAU	77.30	60.05	57.69	2.31	2214	429
BCS	66.78	57.62	57.54	2.06	2223	443

Table 4.15: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 017 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	85.12	50.31	57.72	2.15	2210	612
BAU	75.26	48.35	58.63	2.34	2205	632
BCS	64.94	45.63	58.29	2.27	2220	667

Table 4.16: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 017 (Liquid Cooled).

4.1.7. Case study MI 019

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	85.83	62.36	57.76	2.26	3207	615
BAU	75.34	61.60	57.91	2.23	3216	620
BCS	65.42	57.74	57.71	2.09	3217	655

Table 4.17: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 019 (Air Cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	83.67	49.29	58.22	2.36	3206	921
BAU	73.69	47.02	58.18	2.37	3222	962
BCS	63.39	45.77	58.46	2.47	3225	984

Table 4.18: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 019 (Liquid Cooled).

4.1.8. Typical conversion case - MI 001

Finally, we analyze the typical case of converting a third-generation network to a fourth/fifth-generation network. The main difference is the reduction in CAPEX, as the existing pipes are assumed to be reused. Regarding operation, it does not differ from previous results, and even the optimization results, albeit with lower LCOHs, return optimized parameter sets similar to the cases analyzed above. This is always due to the calculation conditions, in which it was assumed that the buildings have similar thermal properties and heat emission systems at the same temperature.

Air cooled Data Center

Analyzing figure 4.6, we note the similarity with the MI 001 case study configuration.

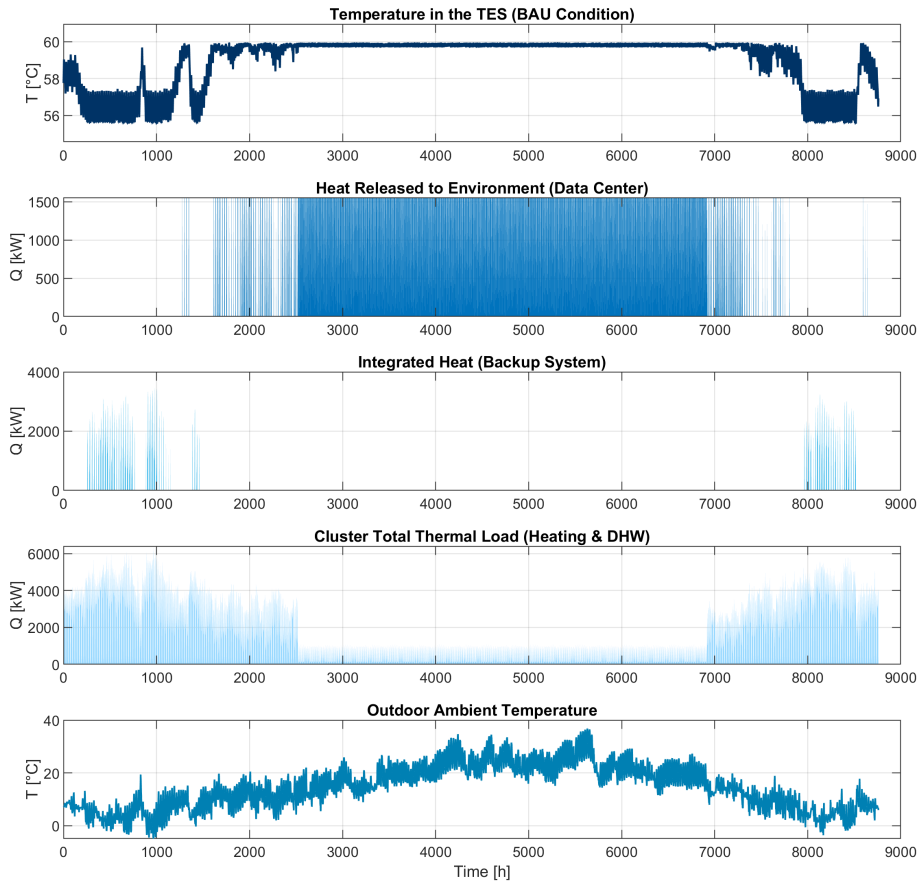


Figure 4.6: Analysis of the annual hourly trend of the network temperature, the heat dissipated by the DC, the heat integrated into the network, the total heat demand of the case study and the external air temperature for case study MI 001 (BAU - air cooled).

The economic analysis of the MI 001 scenario shows a general improvement in financial competitiveness compared to the MI 003 case. Under Business As Usual (BAU) conditions, the net Levelized Cost Of Heat (LCOH) is 70.55 €/MWh, representing a 7.4% reduction from the 76.17 €/MWh calculated for the MI 003 configuration. This decrease is primarily attributed to the exclusion of capital expenditures (CAPEX) related to the supply and installation of network piping, which significantly lowers the initial investment requirements in the MI 001 scenario.

Despite the lower overall cost, the structure remains highly sensitive to energy market fluctuations. The electricity component now accounts for 58% of the gross cost, confirming that operational expenditures are the dominant factor in the economic profile. The sustainability of the system continues to rely on the heat recovery mechanism (Incentives/Recovery), which accounts for the cooling service provided to the Data Center. This contribution reduces the net LCOH by values ranging from -14.4 €/MWh in the Best Case Scenario (BCS) to -19.8 €/MWh in the Worst Case Scenario (WCS). Compared to the 65.30–86.50 €/MWh range of the MI 003 case, the MI 001 scenario demonstrates a more favorable cost interval, varying between 59.97 €/MWh and 78.97 €/MWh.

The following are the calculation results of the bayesian optimization process.

BAU	LCOH [€/MWh]	Rec. [%]	T_{set} [°C]	ΔT [°C]	V_{acc} [m ³]	P_{DC} [kW]
R1	68.62	62.93	57.41	2.14	7915	1452
R2	69.47	59.16	57.25	2.21	7652	1526
R3	71.42	56.89	58.12	2.37	7861	1564
R4	69.61	61.05	58.22	2.63	7641	1478
R5	70.55	58.82	57.40	2.11	7800	1532
Avg	69.79	59.77	57.68	2.29	7774	1510

Table 4.19: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 001 - BAU Scenario (Air Cooled).

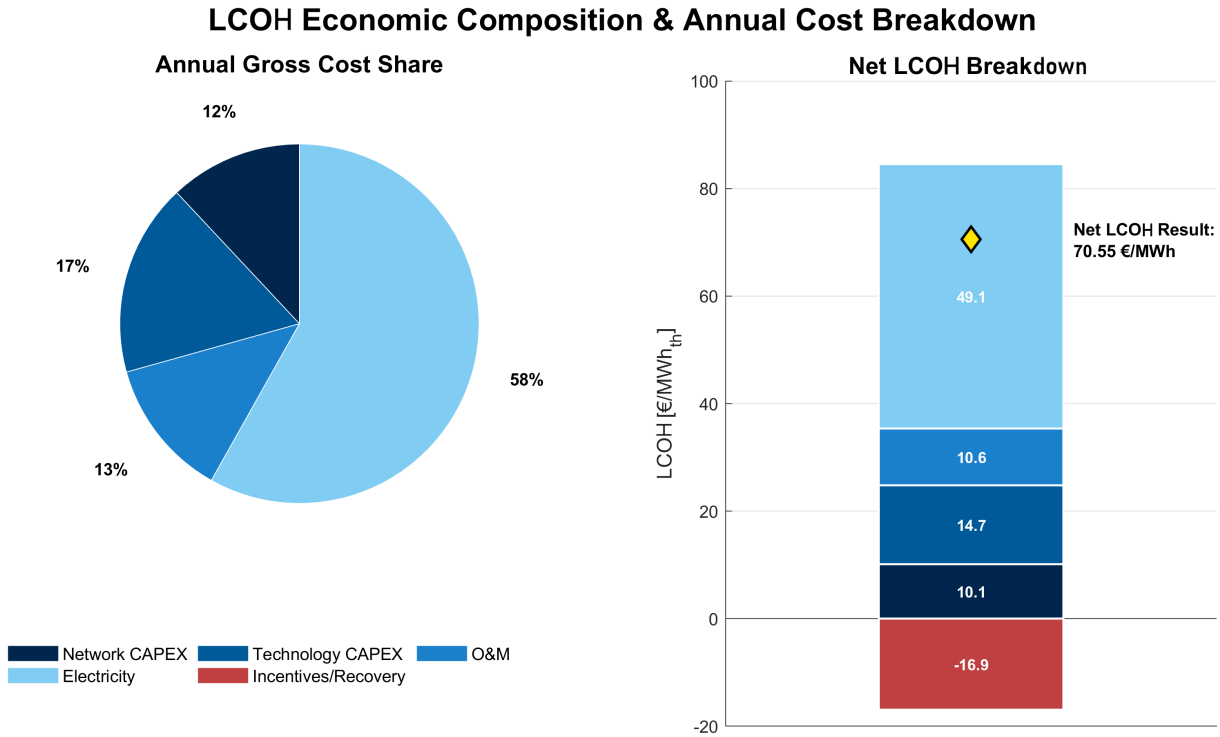


Figure 4.7: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 001 (BAU - air cooled).

The following summarizes the average results found for each scenario. Note that the optimized parameter sets, in this case too, are very similar to each other and are analogous to the previous cases.

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	78.97	62.24	57.30	2.23	7743	1467
BAU	70.55	59.77	57.68	2.29	7774	1510
BCS	59.97	58.14	57.76	2.19	7775	1548

Table 4.20: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 001 (Air Cooled).

Liquid cooled Data Center

The behavior of the network in the liquid-cooled case is completely similar to the air-cooled case, with a set point temperature around 58°C and a maximum deviation of about 2°C. The qualitative trend of the temperatures is entirely attributable to the 4.6 graph, as is the thermal requirement of the case study.

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	66.83	48.76	57.67	2.37	7667	2209
R2	66.90	49.39	58.26	2.32	7658	2179
R3	67.68	46.46	58.07	2.51	7679	2305
R4	67.69	46.45	58.20	2.49	7658	2305
R5	67.20	46.97	57.37	2.42	7652	2288
Avg	66.98	47.61	57.91	2.42	7663	2257

Table 4.21: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for case study MI 001 - BAU Scenario (Liquid Cooled).

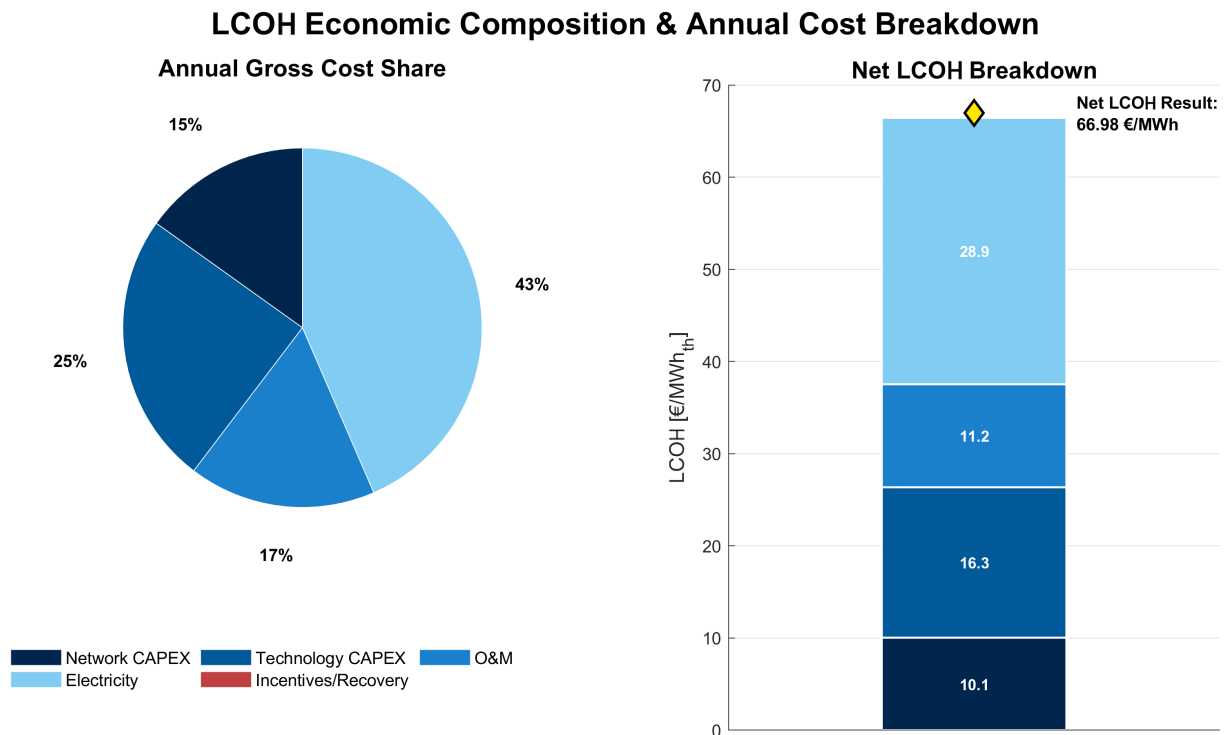


Figure 4.8: Composition of the Levelized Cost Of Heat showing the main cost items for case study MI 001 (BAU - liquid cooled).

Scenario	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
WCS	77.06	48.08	58.05	2.18	7817	2238
BAU	66.98	47.61	57.91	2.42	7663	2257
BCS	57.24	46.92	58.29	2.42	7670	2285

Table 4.22: Optimized average results of LCOH, network set point temperature, maximum delta, TES volume and data center power for case study MI 001Bis (Liquid Cooled).

The analysis highlights how the liquid-cooled configuration of the case study is slightly more cost-effective, but its true strength lies in its superior resilience to energy market fluctuations. This stability stems from a significantly different gross cost structure: while the air-cooled solution is dominated by electricity, the liquid-cooled variant's electricity share drops to 43%. This reduced dependence on electricity, combined with a higher average recovered power of 2,257 kW, makes the system less vulnerable to raw material price increases, ensuring greater long-term cost predictability. Under BAU conditions, the net LCOH of 66.98 €/MWh therefore benefits not only from the absence of network piping costs but also from this thermodynamic optimization, which, by improving the overall coefficient of performance, limits financial exposure to electricity price dynamics compared to the air-cooled configuration.

From the analysis of all the case studies, the best system configuration resulting from the bayesian optimization process is the fourth-generation technology. This, as mentioned in the previous cases, is primarily due to the function that regulates the cost of heat pumps according to economies of scale, and therefore favors a single larger unit over a configuration with many smaller units.

4.2. Comparison of district heating with a stand-alone system

To compare decentralized air-to-water heat pump systems with district heating solutions, the performance and cost-effectiveness of the former were modeled using high-resolution dynamic simulations.

The efficiency of the air-to-water heat pumps was characterized by a dynamic Coefficient of Performance (COP), calculated as a function of the hourly outdoor air temperature (T_{air}) and the required supply water temperature ($T_{water,out}$). The model utilizes a performance map based on R32 monobloc units, processed through a two-dimensional linear interpolation to capture the equipment's behavior across varying climatic conditions. To ensure physical consistency with real-world operations, the theoretical COP is adjusted by an efficiency factor ($\eta \approx 0.9$) and a specific penalty for defrost cycles.

$$COP = f(T_{air}, T_{water,out}) \cdot \eta \cdot f_{defrost} \quad (4.1)$$

where $f_{defrost}$ accounts for a 10% reduction in efficiency when $T_{air} < 5^\circ C$ to simulate the energy intensive frost removal process. The electrical work required to satisfy the thermal load (Q_{load}) is then derived hourly.

$$W_{el} = Q_{load}/COP \quad (4.2)$$

Therefore, the $LCOH$ was calculated considering a useful life of the plant equal to 12 years. The total annual cost for the decentralized configuration includes the annualized Capital Expenditure ($CAPEX$), calculated for each building sub-unit through a power-law scaling to reflect the economies of scale.

$$C_{unit} = 20\,000 \cdot k_{scen} \cdot (P_{peak}/50)^{0.65}. \quad (4.3)$$

The gross investment is further reduced by specific policy incentives (36% - Conto Termico [48]). Operating expenses ($OPEX$) are composed of fixed maintenance costs, estimated at 2.5% of the gross $CAPEX$, and variable costs derived from the annual electricity consumption ($E_{el} \cdot p_{el}$).

$$LCOH = \frac{(CAPEX_{Gross} - Incentive) \cdot CRF + OPEX_{fixed} + OPEX_{variable}}{E_{del}} \quad (4.4)$$

where CRF denotes the Capital Recovery Factor based on the discount rate r and the plant's lifetime N .

The calculation results for the three scenarios analyzed (WCS, BAU, BCS) are reported below.

Case study	LCOH [€/MWh]
MI_001	112.04
MI_003	109.12
MI_004	112.06
MI_005	111.57
MI_006	112.67
MI_007	112.24
MI_017	110.08
MI_019	112.50
Avg	111.53

Table 4.23: LCOH for stand-alone air-to-water systems - scenario WCS

Case study	LCOH [€/MWh]
MI_001	97.43
MI_003	94.89
MI_004	97.45
MI_005	97.02
MI_006	97.98
MI_007	97.60
MI_017	95.72
MI_019	97.83
Avg	96.98

Table 4.24: LCOH for stand-alone air-to-water systems - scenario BAU

Case study	LCOH [€/MWh]
MI_001	82.82
MI_003	80.65
MI_004	82.83
MI_005	82.47
MI_006	83.28
MI_007	82.96
MI_017	81.36
MI_019	83.15
Avg	82.44

Table 4.25: LCOH for stand-alone air-to-water systems - scenario BCS

The cost analysis below shows that electricity costs account for more than 80% of the LCOH breakdown. This data not only highlights clear LCOH volatility as a function of energy prices, but also indicates increased electricity consumption by stand-alone systems, an aspect that should not be underestimated in the context of electrification of urban services.

LCOH Economic Composition & Annual Cost Breakdown

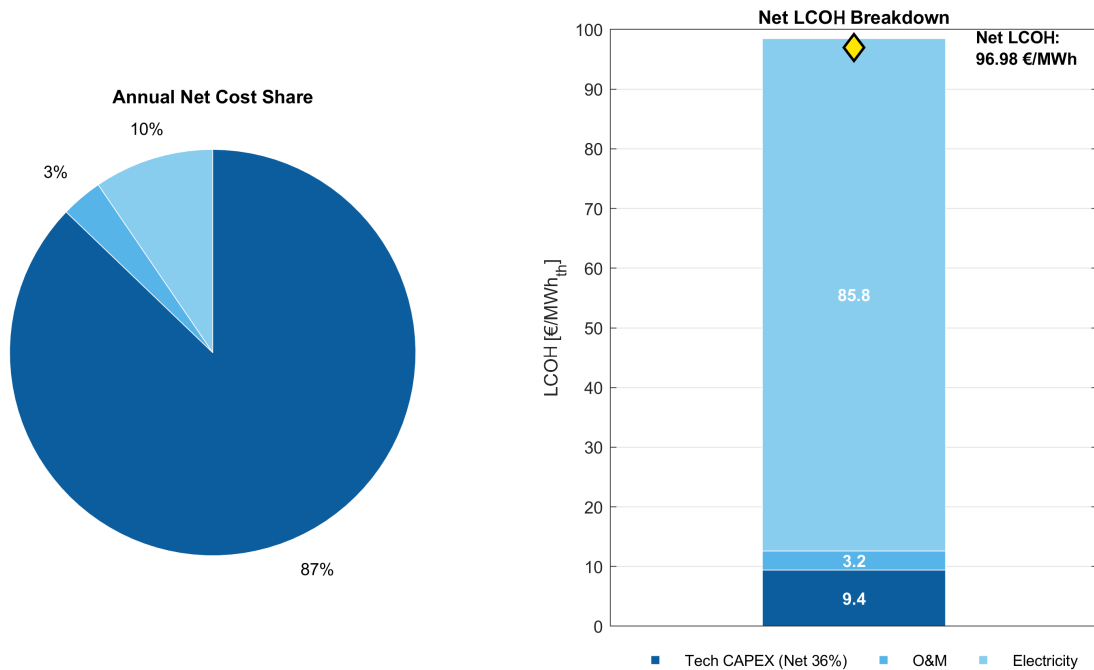


Figure 4.9: Composition of the Levelized Cost Of Heat showing the main cost items for the average of the analyzed case studies in the case of stand-alone heat pump systems (BAU).

4.2.1. Cost comparison

The results of the Levelized Cost Of Heat of autonomous systems are therefore compared with those of average district heating.

Scenario	LCOH [€/MWh]
WCS	111.53
BAU	96.98
BCS	82.44

Table 4.26: Global mean LCOH results for stand-alone air-to-water systems

Scenario	LCOH [€/MWh]
WCS	86.74
BAU	76.19
BCS	65.53

Table 4.27: Global mean LCOH results for district heating combined with air cooled Data Center systems.

Scenario	LCOH [€/MWh]
WCS	84.33
BAU	74.11
BCS	63.72

Table 4.28: Global mean LCOH results for district heating combined with liquid cooled Data Center systems.

The comparative analysis of the Levelized Cost Of Heat (*LCOH*) results demonstrates a clear economic advantage for district heating (DH) solutions over stand-alone air-to-water heat pump (SAHP) systems across all analyzed scenarios. In the Business-As-Usual (BAU) scenario, DH systems coupled with liquid-cooled data centers achieve a thermal energy cost of 74.11 €/MWh, representing a 23.6% reduction compared to the 96.98 €/MWh required by decentralized SAHP units. Beyond the immediate economic benefit, district heating offers significantly higher resilience to the volatility of electricity prices (p_{el}). Stand-alone systems are characterized by a direct and high dependency on the electrical market, as the entire thermal load must be met through the compressor's work, which is strictly governed by the *COP* and local electricity tariffs. District heating

networks integrated with data centers therefore ensure greater long-term price stability for end users.

Below is a graph for a direct comparison between the three different technologies, grouped according to the three economic scenarios investigated.

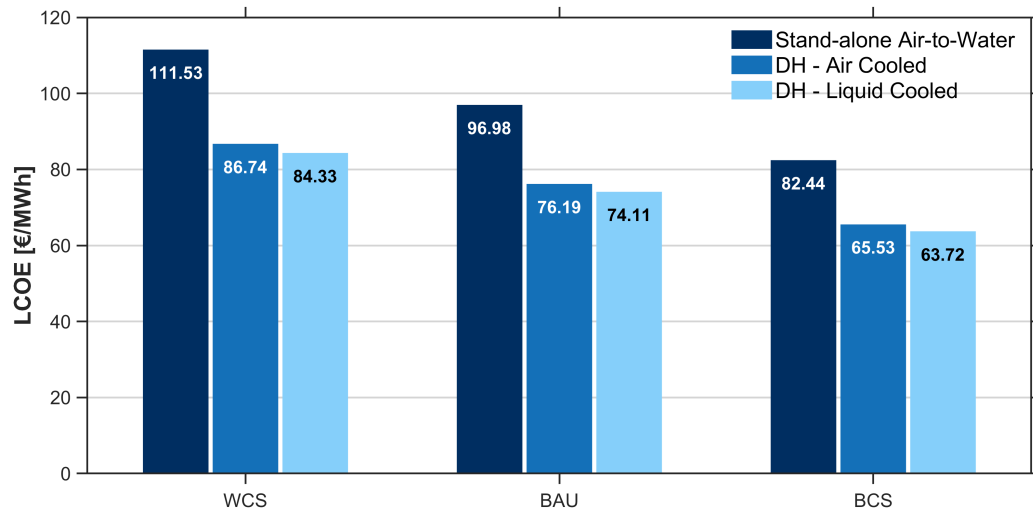


Figure 4.10: Comparison of case study averages of the Levelized Cost Of Heat (LCOH) for different technologies and economic scenarios.

4.2.2. Environmental impact comparison

The environmental impact analysis aims to evaluate the greenhouse gas savings achievable through the thermal recovery of Data Centers, performing a rigorous comparison between the proposed configurations and a technological reference scenario. The analytical process begins with the definition of the emission baseline, which quantifies the CO_2 produced by traditional natural gas thermal generators to provide the energy required by the district.

$$CO_{2,Baseline} = \frac{Q_{th}}{\eta_{th}} \cdot EF_{gas} \quad (4.5)$$

The actual emissions of the project system are then subtracted from this value, where the electricity consumption reflects the operational efficiencies of the heat pumps and pumping systems, directly influenced by the adopted cooling technologies and the identified scaling factors.

$$CO_{2,Produced} = E_{el} \cdot EF_{grid} \quad (4.6)$$

$$CO_{2,Saved} = CO_{2,Baseline} - CO_{2,Produced} \quad (4.7)$$

The final result allows for the validation of the effectiveness of integration into district heating (DH) networks compared to decentralized solutions, demonstrating how COP optimization through Liquid Cooling is the key to maximizing urban decarbonization. The values of EF_{gas} and EF_{grid} are reported in chapter 2.4 in the table 2.1.

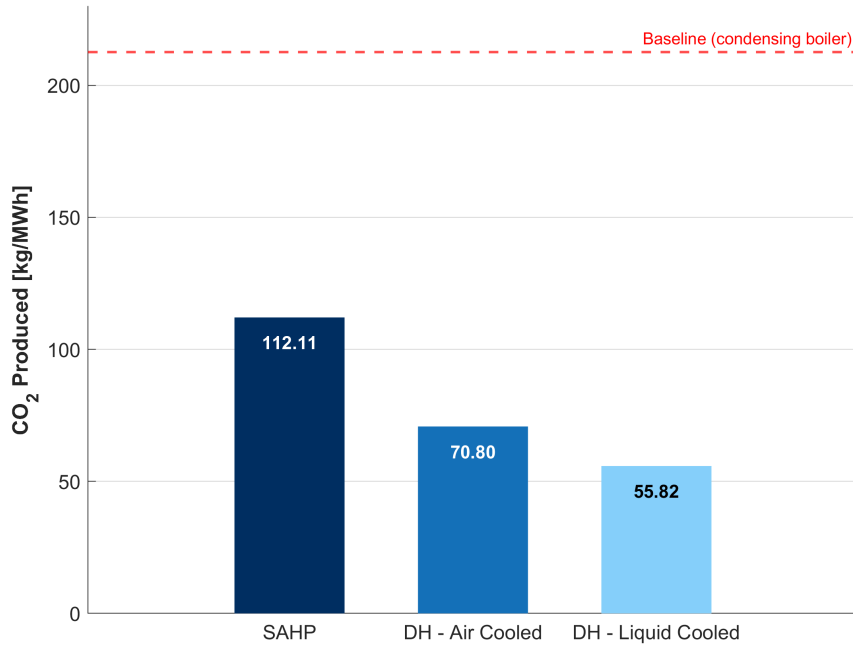


Figure 4.11: Comparison of case study average CO_2 specific emissions for different technologies.

Case study	DC Cooling	CO_2 Produced [kg/MWh]	CO_2 Baseline [kg/MWh]	CO_2 not emitted [kg/MWh]
MI_001	Air	69.70	212.63	142.93
MI_001	Liquid	54.64	212.63	157.99
MI_003	Air	69.29	212.63	143.35
MI_003	Liquid	54.36	212.63	158.27
MI_004	Air	70.90	212.63	141.73
MI_004	Liquid	56.04	212.63	156.60
MI_005	Air	71.56	212.63	141.07
MI_005	Liquid	56.47	212.63	156.17
MI_006	Air	71.09	212.63	141.54
MI_006	Liquid	57.21	212.63	155.42
MI_007	Air	70.90	212.63	141.74
MI_007	Liquid	55.89	212.63	156.74
MI_017	Air	70.99	212.63	141.64
MI_017	Liquid	56.28	212.63	156.35
MI_019	Air	71.08	212.63	141.55
MI_019	Liquid	56.69	212.63	155.95

Table 4.29: Summary of CO_2 specific emissions across all case studies for district heating technology - air cooled and liquid cooled Data Center.

The environmental analysis highlights a significant improvement in performance as the level of technological integration increases. Compared to the condensing boiler reference baseline of 212.63 kg/MWh, all analyzed configurations allow for a reduction in CO_2 emissions of over 45%. Specifically, the Liquid Cooled system proves to be the most sustainable solution with an average production of 55.82 kg/MWh, reducing the carbon footprint by approximately 21% compared to Air Cooled technology (70.80 kg/MWh) and by 50% compared to the stand-alone SAHP solution (112.11 kg/MWh).

Case study	CO_2 produced [kg/MWh]	CO_2 baseline [kg/MWh]	CO_2 not emitted [kg/MWh]
MI_001	112.82	212.63	99.81
MI_003	113.41	212.63	99.22
MI_004	111.90	212.63	100.73
MI_005	112.00	212.63	100.63
MI_006	111.78	212.63	100.85
MI_007	111.87	212.63	100.76
MI_017	112.13	212.63	100.50
MI_019	111.82	212.63	100.81

Table 4.30: Summary of CO_2 specific emissions across all case studies for stand-alone heat pump technology.

The analysis conducted, while focusing on operational emissions (tank-to-wheel phase) and not constituting a full Life Cycle Assessment (LCA), provides unequivocal indications of the environmental mitigation potential inherent in this technological integration. The results highlight how transforming a Data Center from a mere "energy sink" into a proactive supplier of waste heat can radically alter its sustainability profile.

In particular, thermal recovery coupled with a district heating network allows for a drastic reduction in the indirect environmental impact of the Data Center. Since heat production via natural gas boilers has historically represented one of the primary sources of urban emissions, replacing this baseline with recovered heat generates an operational "carbon credit" that partially offsets the DC's own electrical footprint. The transition to Liquid Cooling, by significantly improving the COP of the heat pumps and reducing auxiliary electrical demand for circulation, maximizes this compensation effect. It can therefore be foreseen that, from a circular economy perspective, integration with city infrastructure not only decarbonizes the residential sector but also acts as a powerful corrective for the digital sector's environmental impact, rendering Data Centers symbiotic and functional elements of the urban energy transition.

4.3. Specific design parameters

The analysis, through the identification of specific project parameters, aims to provide a benchmark for future designers of district heating networks coupled with data centers.

The objective is to define parameters that allow for the correct sizing of future district heating networks based on the thermal capacity of the DCs and the specific cooling technology adopted (e.g., air or liquid cooling).

Through a methodological approach based on these parameters, it is possible to predict the heat recovery potential of newly built data centers and ensure efficient integration with civil infrastructure.

The data obtained are reported below and refer to buildings with thermophysical characteristics and consumption profiles similar to those analysed in Chapter 3.

The analysis employs four Key Performance Indicators (KPIs) to evaluate the sizing and integration efficiency of the Data Center (DC) and Thermal Energy Storage (TES) within each urban case study:

- P_{DC}/S_{heated} [W/m^2] represents the installed Data Center electrical power per unit of heated floor area. It indicates the "density" of the waste heat source available relative to the building surface to be served.
- V_{TES}/S_{heated} [L/m^2] measures the capacity of the thermal storage tank relative to the heated surface. This KPI defines the specific volume required to buffer the thermal energy demand of the buildings.
- P_{DC}/E_{th} [W/kWh] relates the Data Center power to the annual thermal energy requirement of the case study. Similar to the first indicator, it differs in that instead of defining the power available per square meter, it defines it per unit of energy consumed in order to provide a parameter independent of the type of building but only of annual consumption.
- V_{TES}/E_{th} [L/kWh] correlates the storage volume with the annual energy demand. Like the previous parameter, it is based on the energy consumed and not on the heated surface.

Case study	Heated surface [m ²]	Thermal requirement [MWh/y]	P_{DC}/S_{heated} [W/m ²]	V_{TES}/S_{heated} [L/m ²]	P_{DC}/E_{th} [W/kWh]	V_{TES}/E_{th} [L/kWh]
MI_001	149 013	23 180	9.92	52.27	0.064	0.336
MI_003	60 786	10 328	10.94	57.74	0.064	0.340
MI_004	87 295	13 330	9.59	50.76	0.063	0.332
MI_005	31 075	4 811	9.98	51.06	0.064	0.330
MI_006	46 024	6 912	9.36	50.92	0.062	0.339
MI_007	59 734	9 078	9.56	51.30	0.063	0.338
MI_017	40 952	6 593	10.65	54.33	0.066	0.337
MI_019	64 816	9 780	9.45	50.01	0.063	0.331
Average	67 462	10 501	9.93	52.30	0.064	0.335

Table 4.31: Specific design parameters for the sizing of a district heating network starting from the characteristics of an air-cooled Data Center: specific power per heated surface and energy consumed and specific TES volume per heated surface and energy consumed.

Case study	Heated surface [m ²]	Thermal requirement [MWh/y]	P_{DC}/S_{heated} [W/m ²]	V_{TES}/S_{heated} [L/m ²]	P_{DC}/E_{th} [W/kWh]	V_{TES}/E_{th} [L/kWh]
MI_001	149 013	23 180	14.79	51.27	0.095	0.330
MI_003	60 786	10 328	16.80	57.91	0.099	0.341
MI_004	87 295	13 330	15.05	50.41	0.099	0.330
MI_005	31 075	4 811	15.34	51.46	0.099	0.332
MI_006	46 024	6 912	15.19	48.95	0.101	0.326
MI_007	59 734	9 078	14.91	49.81	0.098	0.328
MI_017	40 952	6 593	16.06	54.30	0.100	0.337
MI_019	64 816	9 780	15.25	50.24	0.101	0.333
Average	67 462	10 501	15.43	51.79	0.099	0.332

Table 4.32: Specific design parameters for the sizing of a district heating network starting from the characteristics of an liquid-cooled Data Center: specific power per heated surface and energy consumed and specific TES volume per heated surface and energy consumed.

Comparing the technical configurations, it is clear that the liquid-cooled scenario shows a higher P_{DC}/S_{heated} than the air-cooled one, with an average value increasing from 9.93 W/m² to 15.43 W/m². This difference is fundamentally linked to the temperature levels of the heat source: in the air-cooled configuration, the usable heat is lower because the lower evaporation temperatures at the heat pump require a greater electrical workload, with a consequent reduction in the coefficient of performance (COP). With the same installed electrical power of the data center, a larger heated surface can therefore be served than in the liquid-cooled case, considering a greater contribution of electrical work from the energy center heat pump. Similarly, the P_{DC}/E_{th} ratio increases from 0.064 W/kWh for the air-cooled case to 0.099 W/kWh for the liquid-cooled case, indicating the same

phenomenon recalculated for consumption. Interestingly, the specific storage requirements remain remarkably consistent across both technologies, averaging around 52 L/m^2 (or 0.33 L/kWh), indicating that the optimal thermal inertia is primarily determined by the building demand profiles rather than the thermal characteristics of the cooling system.

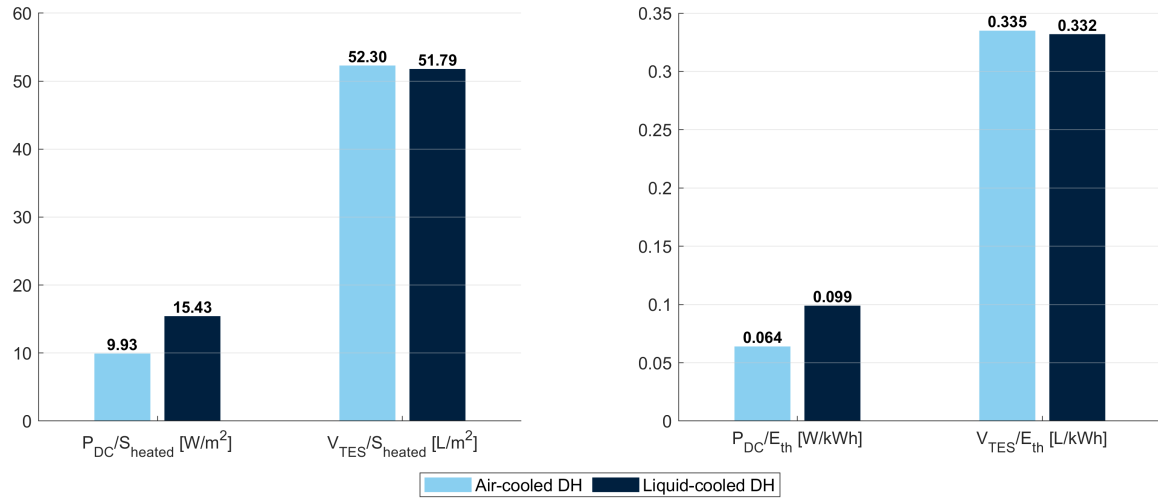


Figure 4.12: Comparison of case study average specific design parameters for air and liquid-cooled DC: specific power and specific TES volume per heated surface, specific power and specific TES volume per energy consumed.

5 | Conclusions

This research project outlined a rigorous and innovative methodological path to address the challenges of urban energy transition, focusing on waste heat recovery from data centers (DCs) as a key pillar for the development of fourth- and fifth-generation district heating (4/5GDHC) systems. By adopting a highly automated, bottom-up approach, it was possible to precisely map the thermal demand of complex building case studies, integrating geographic tools and dynamic weather APIs to reconstruct hourly load profiles that reflect the true variability of the metropolitan context. This level of granularity proved essential not only for the optimal sizing of network infrastructures, as demonstrated by the use of algorithms for defining the Minimum Spanning Tree in duct design, but also for understanding the thermal synergies between the constant waste heat production of servers and the seasonal fluctuations in end-user demand. The integration of heat pumps, both in centralized configurations and through distributed booster heat pumps, has emerged as the essential technological key to increasing the thermal potential of data center cooling water, making it fully compatible with the temperature requirements of modern networks while simultaneously ensuring improved overall efficiency parameters, leading to a significant reduction in Power Usage Effectiveness (PUE) and Total Usage Effectiveness (TUE) of the involved ICT sites. From an economic perspective, the thesis took the strategic perspective of an Energy Service Company (ESCO) to assess the long-term sustainability of investments, highlighting how the competitiveness of waste heat is closely related to the thermal density of the served district and the infrastructure's ability to operate at neutral temperatures to minimize energy losses along the route. The calculated financial indicators, including the Levelized Cost Of Heat (LCOH) and a detailed analysis of CAPEX and OPEX, suggest that the transition to hybrid grid models is not solely an environmental issue, but rather a resilient business strategy capable of mitigating risks arising from volatile fossil fuel prices and fluctuations in the National Single Price (PUN). At the same time, the ecological impact measured through primary energy savings and the drastic reduction in greenhouse gas emissions confirms that transforming data centers into urban energy hubs is one of the most promising paths for the creation of Positive Energy Districts (PEDs), fully aligned with European direc-

tives on decarbonization and the redevelopment of existing buildings. The robustness of the methodological framework presented here, however, paves the way for further scientific refinements, especially regarding the automation of decision-making processes and the intelligent management of complex heat flows through the use of bayesian optimization algorithms. These machine learning techniques could enable predictive regulation of power plants based on load forecasts and real-time weather conditions, reducing energy waste and optimizing operating cash flows through advanced control scenarios such as Upper Confidence Bound or Expected Improvement. Furthermore, a critical evolution of this research involves transitioning from the current operational emission analysis to a comprehensive Life Cycle Assessment (LCA). While the present study demonstrates significant "tank-to-wheel" carbon savings, a full LCA would allow for a rigorous evaluation of the "cradle-to-grave" impacts, accounting for the embodied energy and carbon footprint of the infrastructure—including heat pumps, district heating piping, and data center cooling retrofits. Such an approach is essential to verify the net environmental benefit over the entire lifecycle and to ensure that the operational gains are not offset by the environmental costs of manufacturing and decommissioning the integrated system. Additionally, a significant improvement in the modeling of network layouts could be achieved by moving beyond the current Minimum Spanning Tree (MST) algorithm. While the MST provides a mathematically optimal topology based on Euclidean distances, future iterations could integrate specialized GIS-based tools designed to generate network paths that strictly follow the urban street morphology. This transition would allow for a more realistic and precise estimation of trenching routes, accounting for existing road infrastructures, utility corridors, and physical obstacles. Such a refinement would lead to a more accurate calculation of pipe lengths and associated hydraulic losses, providing a higher level of consistency with real-world civil engineering constraints. Extending this model to different latitudes and climates would represent a further step forward in testing the scalability of the proposed solution, providing stakeholders and urban planners with a decision-making tool capable of guiding the development of integrated, smart, and sustainable infrastructure. In conclusion, the research not only validates the technical feasibility and cost-effectiveness of heat recovery from data centers, but also proposes a radical paradigm shift in which the digital industry and the civil energy sector cease to operate in isolated silos and collaborate to build an urban industrial symbiosis. Here, the waste from a technology-intensive process becomes a vital resource for the comfort and sustainability of citizens, ensuring systemic resilience and an ecological transition that is both fair, sustainable, and technologically advanced.

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A | Appendix A

A.1. Case studies

A.1.1. Case study MI 004

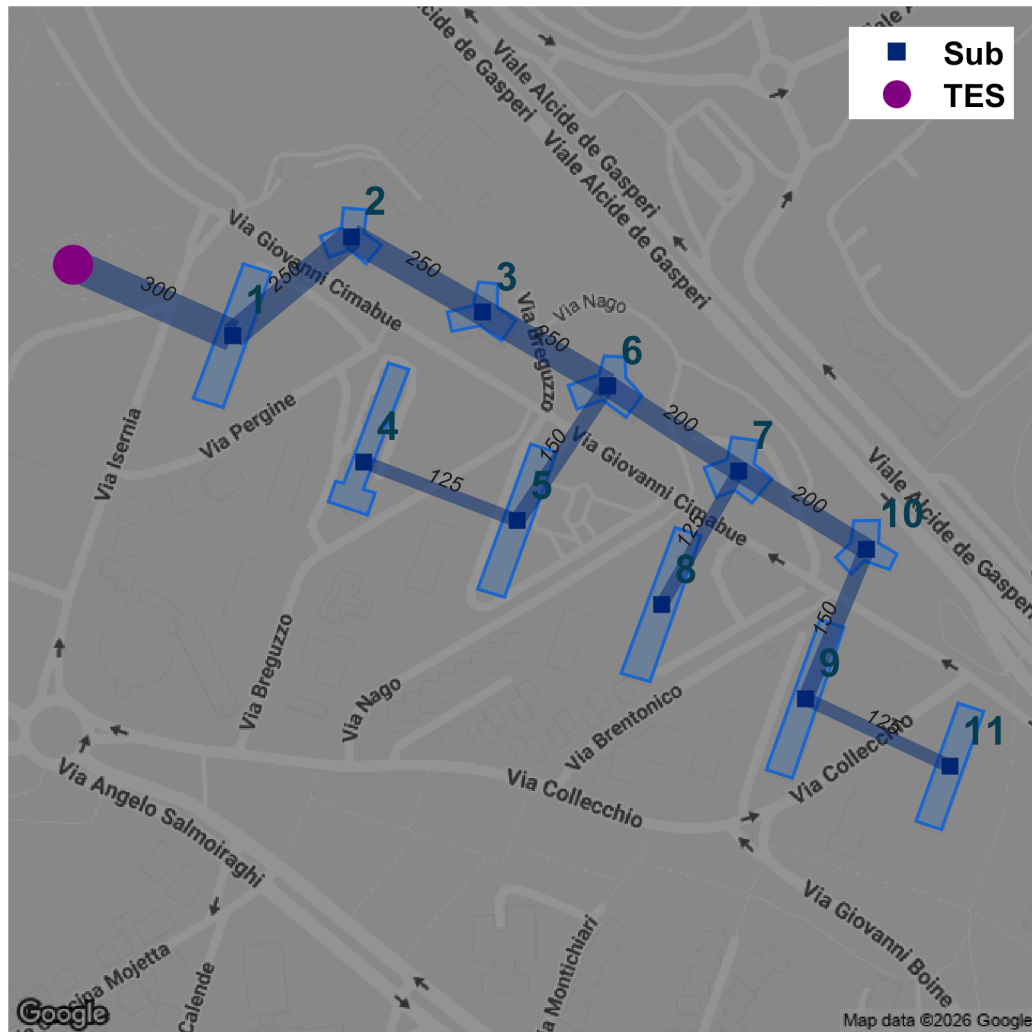


Figure A.1: Case study MI 004: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	11 571	34 714	8 074	615	241	855
2	3 834	11 502	3 686	231	80	311
3	4 246	12 738	3 981	253	88	341
4	9 635	28 906	8 375	559	201	760
5	11 426	34 279	8 334	617	238	855
6	5 144	15 431	4 320	292	107	399
7	5 390	16 170	4 368	301	112	414
8	11 898	35 694	8 481	637	248	885
9	11 225	33 675	8 430	613	234	847
10	3 872	11 617	3 644	231	81	312
11	9 053	27 158	6 885	497	188	686
Total	87 295	261 884	68 579	4 847	1 817	6 665

Table A.1: Detailed thermophysical characteristics of the MI 004 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	6 665
Specific Heating Demand per Floor Area	[kWh/m ² y]	55.53
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	76.35
Specific Demand per Volume	[kWh/m ³ y]	25.45
Peak Power	[kW]	3 157
Specific Peak Power per Floor Area	[W/m ²]	36.17
DH Network Length	[m]	~ 904
Specific Network Length (Linear Density)	[m/MWh]	0.14
Pumping Electric Power	[kW]	~ 31

Table A.2: Characteristic data of the MI 004 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.1.2. Case study MI 005



Figure A.2: Case study MI 005: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MWh]	DHW req. [MWh]	Total req. [MWh]
1	7 912	23 736	7 049	446	165	611
2	7 860	23 581	7 058	445	164	609
3	7 219	21 658	6 667	414	150	564
4	8 084	24 251	7 105	453	168	621
Total	31 075	93 226	27 878	1 758	647	2 405

Table A.3: Detailed thermophysical characteristics of the MI 005 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	2 405
Specific Heating Demand per Floor Area	[kWh/m ² y]	56.58
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	77.40
Specific Demand per Volume	[kWh/m ³ y]	25.80
Peak Power	[kW]	1 145
Specific Peak Power per Floor Area	[W/m ²]	36.85
DH Network Length	[m]	~ 249
Specific Network Length (Linear Density)	[m/MWh]	0.10
Pumping Electric Power	[kW]	~ 4

Table A.4: Characteristic data of the MI 005 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.1.3. Case study MI 006

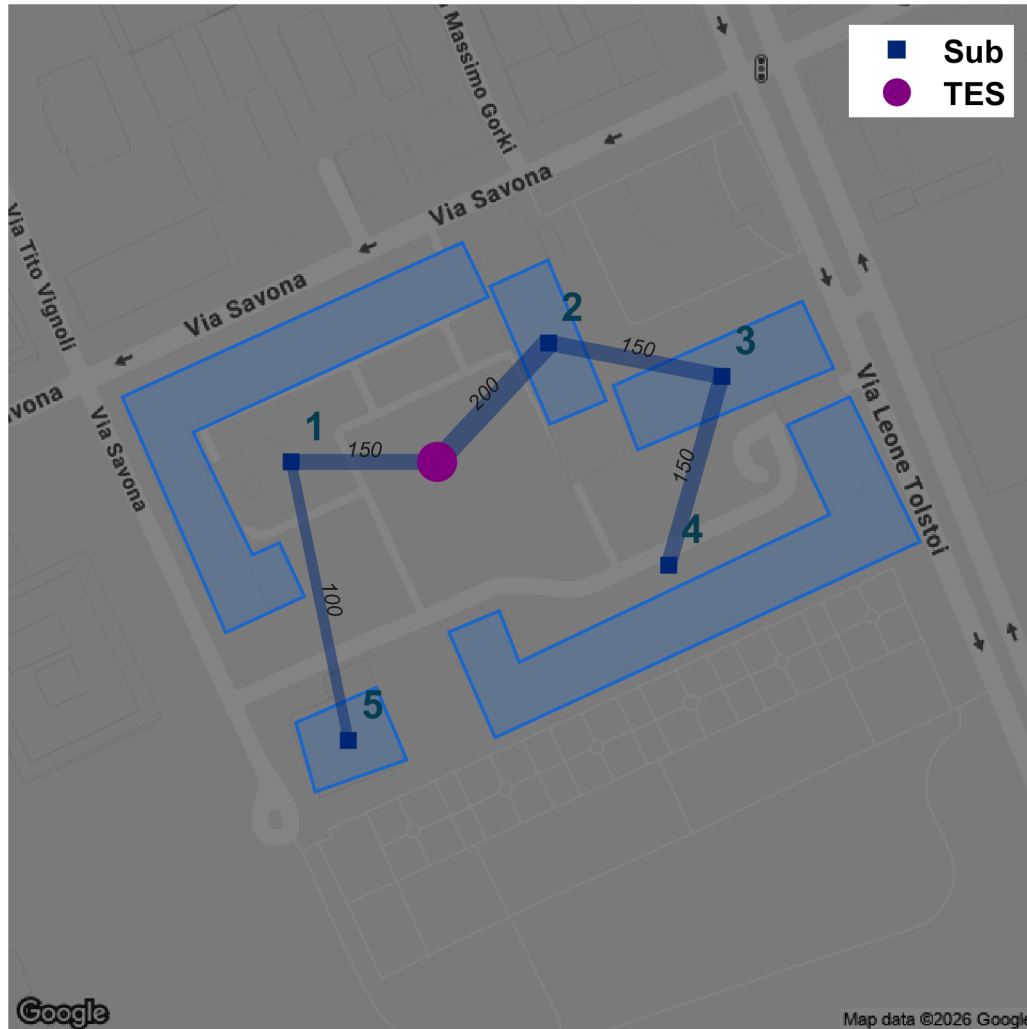


Figure A.3: Case study MI 006: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MWh]	DHW req. [MWh]	Total req. [MWh]
1	15 075	45 224	11 578	815	314	1 129
2	4 021	12 064	3 485	229	84	313
3	6 388	19 165	4 900	345	133	478
4	16 307	48 921	12 136	870	340	1 210
5	4 232	12 697	3 467	239	88	327
Total	46 024	138 071	35 567	2 498	958	3 456

Table A.5: Detailed thermophysical characteristics of the MI 006 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	3 456
Specific Heating Demand per Floor Area	[kWh/m ² y]	54.27
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	75.09
Specific Demand per Volume	[kWh/m ³ y]	25.03
Peak Power	[kW]	1 627
Specific Peak Power per Floor Area	[W/m ²]	35.35
DH Network Length	[m]	~ 252
Specific Network Length (Linear Density)	[m/MWh]	0.07
Pumping Electric Power	[kW]	~ 3

Table A.6: Characteristic data of the MI 006 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.1.4. Case study MI 007



Figure A.4: Case study MI 007: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	10 162	30 487	7 562	549	212	761
2	6 747	20 241	5 368	375	140	515
3	7 370	22 109	5 670	403	153	557
4	6 800	20 400	5 361	376	142	518
5	4 655	13 965	3 850	263	97	360
6	6 812	20 435	5 455	379	142	521
7	4 616	13 849	3 838	261	96	357
8	4 643	13 929	3 816	261	97	358
9	7 929	23 787	5 906	429	165	594
Total	59 734	179 203	46 825	3 296	1 244	4 539

Table A.7: Detailed thermophysical characteristics of the MI 007 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	4 539
Specific Heating Demand per Floor Area	[kWh/m ² y]	55.17
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	75.99
Specific Demand per Volume	[kWh/m ³ y]	25.33
Peak Power	[kW]	2 146
Specific Peak Power per Floor Area	[W/m ²]	35.93
DH Network Length	[m]	~ 406
Specific Network Length (Linear Density)	[m/MWh]	0.09
Pumping Electric Power	[kW]	~ 11

Table A.8: Characteristic data of the MI 007 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.1.5. Case study MI 017



Figure A.5: Case study MI 017: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	3 618	10 854	3 612	214	75	289
2	5 739	17 217	5 877	338	119	457
3	3 163	9 490	3 506	194	66	260
4	4 750	14 250	4 843	284	99	383
5	9 277	27 830	9 100	544	193	737
6	2 579	7 737	2 697	156	54	210
7	2 873	8 619	3 001	174	60	234
8	3 915	11 745	3 949	233	82	314
9	2 412	7 235	2 595	148	50	198
10	2 627	7 880	2 735	159	55	213
Total	40 952	122 856	41 915	2 444	853	3 296

Table A.9: Detailed thermophysical characteristics of the MI 017 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	3 296
Specific Heating Demand per Floor Area	[kWh/m ² y]	59.67
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	80.49
Specific Demand per Volume	[kWh/m ³ y]	26.83
Peak Power	[kW]	1 600
Specific Peak Power per Floor Area	[W/m ²]	39.08
DH Network Length	[m]	~ 455
Specific Network Length (Linear Density)	[m/MWh]	0.14
Pumping Electric Power	[kW]	~ 7

Table A.10: Characteristic data of the MI 017 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.1.6. Case study MI 019



Figure A.6: Case study MI 019: layout of buildings, indication of the location of the energy center (TES), representation of the district heating network with indication of the nominal diameters of the individual sections and substations (Sub).

Bldg.	Heat surf. [m ²]	Heat vol. [m ³]	Disp. surf. [m ²]	Heat. req. [MW h]	DHW req. [MW h]	Total req. [MW h]
1	6 043	18 130	4 939	337	126	463
2	6 309	18 927	5 057	349	131	481
3	6 509	19 526	5 090	357	136	492
4	7 235	21 705	5 419	390	151	540
5	7 868	23 603	5 670	417	164	581
6	5 118	15 353	4 361	291	107	397
7	5 647	16 942	4 585	314	118	432
8	6 141	18 423	4 853	338	128	466
9	7 085	21 255	5 218	379	148	527
10	6 861	20 584	5 031	367	143	509
Total	64 816	194 447	50 222	3 540	1 349	4 890

Table A.11: Detailed thermophysical characteristics of the MI 019 Case study for each building and heat requirement for heating, hot water and total and total demand.

Parameter	Unit	Value
Total Case study Demand	[MWh/y]	4 890
Specific Heating Demand per Floor Area	[kWh/m ² y]	54.62
Specific DHW Demand per Floor Area	[kWh/m ² y]	20.82
Specific Total Demand per Floor Area	[kWh/m ² y]	75.44
Specific Demand per Volume	[kWh/m ³ y]	25.15
Peak Power	[kW]	2 306
Specific Peak Power per Floor Area	[W/m ²]	35.58
DH Network Length	[m]	~ 472
Specific Network Length (Linear Density)	[m/MWh]	0.10
Pumping Electric Power	[kW]	~ 16

Table A.12: Characteristic data of the MI 019 Case study: specific heat requirements per heated surface and heated volume, consumption and peak power, characteristic quantities of the district heating network.

A.2. Optimization results

A.2.1. Case study MI 001

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	78.41	63.19	57.16	2.20	7777	1450
R2	78.53	63.30	57.25	2.35	7860	1447
R3	80.22	58.89	57.43	2.16	7658	1530
R4	78.63	63.09	57.41	2.30	7736	1449
R5	78.56	62.73	57.24	2.14	7686	1457
Avg	78.97	62.24	57.30	2.23	7743	1467

Table A.13: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 001 - WCS Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	58.86	61.54	57.58	2.07	7980	1476
R2	58.45	61.56	57.23	2.19	7790	1479
R3	59.32	58.87	57.43	2.34	7651	1530
R4	60.73	57.74	58.82	2.15	7706	1538
R5	62.19	51.02	57.75	2.22	7748	1718
Avg	59.97	58.14	57.76	2.19	7775	1548

Table A.14: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 001 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	77.24	46.61	57.08	2.18	7713	2308
R2	77.11	48.74	57.94	2.02	7843	2210
R3	77.46	48.04	57.41	2.00	8215	2243
R4	77.51	46.84	57.97	2.12	7669	2292
R5	77.59	50.17	59.86	2.56	7647	2134
Avg	77.06	48.08	58.05	2.18	7817	2238

Table A.15: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 001 - WCS Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	58.13	46.46	59.49	2.96	7654	2290
R2	57.85	45.96	58.85	2.19	7649	2325
R3	56.78	48.88	57.69	2.38	7640	2204
R4	57.50	45.89	57.81	2.04	7700	2338
R5	57.16	47.39	57.59	2.52	7708	2267
Avg	57.24	46.92	58.29	2.42	7670	2285

Table A.16: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 001 - BCS Scenario (Liquid Cooled).

A.2.2. Case study MI 003

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	86.87	59.53	57.22	2.03	3618	678
R2	87.09	60.16	57.88	2.51	3570	670
R3	86.60	60.48	57.42	2.30	3596	669
R4	86.45	60.84	57.60	2.22	3531	665
R5	87.26	58.86	57.57	2.07	3547	683
Avg	86.50	59.97	57.54	2.23	3572	673

Table A.17: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 003 - WCS Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	65.21	58.88	57.54	2.00	3549	683
R2	65.52	57.51	57.44	2.15	3510	696
R3	64.13	61.15	57.04	2.08	3509	665
R4	66.75	58.54	58.35	2.34	3934	681
R5	66.29	59.03	59.12	2.50	3529	673
Avg	65.30	59.02	57.90	2.21	3606	680

Table A.18: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 003 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	84.03	48.90	58.05	2.27	3512	981
R2	85.18	44.85	57.57	2.36	3519	1064
R3	83.57	49.61	57.52	2.05	3519	970
R4	85.05	46.00	57.99	2.76	3512	1036
R5	85.05	48.85	59.89	2.47	3522	975
Avg	84.20	47.64	58.20	2.38	3517	1005

Table A.19: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 003 - WCS Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	63.53	45.38	57.60	2.23	3524	1053
R2	63.74	46.18	58.57	2.62	3510	1031
R3	62.95	46.99	57.20	2.05	3520	1021
R4	63.67	46.38	58.68	2.10	3534	1028
R5	63.56	45.53	57.75	2.13	3539	1049
Avg	63.23	46.09	57.96	2.23	3525	1037

Table A.20: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 003 - BCS Scenario (Liquid Cooled).

A.2.3. Case study MI 004

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	86.58	63.01	57.93	2.13	4506	831
R2	85.60	63.26	57.24	2.15	4414	832
R3	86.76	60.73	57.48	2.12	4409	858
R4	86.61	61.78	57.82	2.27	4382	845
R5	86.52	60.99	57.41	2.35	4392	856
Avg	86.41	61.96	57.57	2.20	4420	844

Table A.21: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	75.73	61.60	57.49	2.06	4491	849
R2	75.61	62.80	58.03	2.42	4395	833
R3	76.01	59.60	57.28	2.21	4376	872
R4	78.81	52.35	57.11	2.17	4446	972
R5	74.76	63.55	57.24	2.11	4407	829
Avg	76.18	59.98	57.43	2.19	4423	871

Table A.22: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	65.00	59.36	57.07	2.03	4393	877
R2	64.63	62.04	57.66	2.42	4374	843
R3	65.41	59.10	57.54	2.11	4394	877
R4	64.24	62.80	57.26	2.23	4431	837
R5	67.96	54.60	58.53	2.80	4381	925
Avg	65.45	59.58	57.61	2.32	4394	872

Table A.23: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	83.82	50.21	57.90	2.12	4401	1236
R2	84.76	45.73	57.12	2.01	4395	1352
R3	84.15	49.00	58.11	2.05	4366	1264
R4	85.68	45.78	58.75	2.52	4386	1340
R5	83.67	49.91	57.36	2.25	4397	1245
Avg	84.41	48.13	57.85	2.19	4389	1287

Table A.24: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	74.44	46.52	58.37	2.39	4369	1323
R2	75.27	47.08	59.50	4.31	4363	1295
R3	74.05	48.43	58.40	2.71	4399	1274
R4	74.94	48.27	60.60	2.12	4387	1269
R5	73.73	47.56	57.31	2.13	4413	1302
Avg	74.49	47.57	58.84	2.73	4386	1293

Table A.25: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	63.68	46.44	58.00	2.71	4371	1325
R2	63.16	47.12	57.16	2.16	4400	1314
R3	63.37	46.25	57.11	2.00	4433	1338
R4	63.85	46.92	58.90	2.16	4409	1311
R5	64.51	45.75	59.76	2.10	4422	1338
Avg	63.71	46.49	58.19	2.23	4407	1325

Table A.26: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 004 - BCS Scenario (Liquid Cooled).

A.2.4. Case study MI 005

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	88.43	61.87	57.78	2.16	1602	304
R2	88.03	61.32	57.05	2.05	1615	308
R3	88.19	61.72	57.57	2.25	1592	305
R4	88.17	62.67	57.71	2.23	1615	301
R5	88.61	60.73	57.68	2.25	1583	309
Avg	88.29	61.66	57.56	2.19	1601	306

Table A.27: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	78.09	58.81	57.62	2.22	1598	317
R2	77.09	62.76	58.11	2.40	1589	300
R3	78.28	60.19	58.35	2.25	1602	310
R4	78.34	58.33	57.37	2.02	1643	320
R5	76.88	61.61	57.40	2.13	1585	306
Avg	77.74	60.34	57.77	2.20	1603	310

Table A.28: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	66.56	62.03	58.44	2.03	1632	302
R2	66.50	59.41	57.66	2.23	1594	314
R3	68.03	54.30	57.30	2.16	1598	339
R4	67.16	59.12	58.43	2.15	1594	314
R5	66.27	60.32	57.80	2.89	1587	310
Avg	66.90	59.04	57.93	2.29	1601	316

Table A.29: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	86.37	46.64	57.08	2.18	1598	478
R2	86.36	50.42	59.45	2.33	1587	441
R3	85.39	51.97	58.32	2.53	1586	431
R4	86.32	47.83	57.69	2.74	1584	466
R5	86.70	49.06	59.40	2.02	1594	453
Avg	86.23	49.18	58.39	2.36	1590	454

Table A.30: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	76.02	45.98	57.91	2.80	1583	482
R2	75.38	47.99	58.15	2.08	1588	464
R3	75.53	46.58	57.27	2.17	1600	479
R4	75.69	46.94	57.93	2.53	1588	474
R5	76.31	45.13	57.87	2.22	1607	492
Avg	75.79	46.52	57.83	2.36	1593	478

Table A.31: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	65.79	45.55	59.42	3.30	1589	483
R2	65.44	45.68	59.13	2.04	1602	484
R3	65.00	45.86	58.20	2.42	1588	484
R4	64.48	46.76	57.38	2.06	1599	477
R5	64.81	46.08	57.93	2.25	1587	482
Avg	65.10	45.99	58.41	2.41	1593	482

Table A.32: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 005 - BCS Scenario (Liquid Cooled).

A.2.5. Case study MI 006

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	85.23	62.44	57.68	2.30	2275	434
R2	85.21	62.91	57.85	2.36	2278	431
R3	85.25	62.12	57.54	2.20	2283	436
R4	87.49	55.64	57.00	2.05	2289	478
R5	83.97	64.13	57.09	2.12	2254	427
Avg	85.43	61.45	57.43	2.20	2276	441

Table A.33: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	75.23	58.44	57.02	2.06	2297	460
R2	76.62	55.45	57.20	2.12	2295	479
R3	74.54	59.94	57.08	2.09	2255	450
R4	75.21	58.83	57.13	2.07	2311	457
R5	74.27	61.49	57.34	2.11	2255	440
Avg	75.18	58.83	57.15	2.09	2283	457

Table A.34: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	64.04	59.96	57.32	2.25	2344	449
R2	62.98	63.35	57.10	2.07	2344	431
R3	63.14	62.15	57.36	2.20	2250	437
R4	64.28	61.62	58.66	2.08	2259	435
R5	65.56	57.17	58.43	2.17	2251	463
Avg	64.00	60.85	57.77	2.16	2289	443

Table A.35: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	82.33	51.06	57.67	2.25	2259	631
R2	84.07	46.02	57.97	2.00	2286	694
R3	83.44	47.86	58.17	2.23	2251	669
R4	82.79	48.55	57.15	2.07	2269	662
R5	83.57	50.45	59.85	2.52	2249	633
Avg	83.24	48.79	58.16	2.21	2263	658

Table A.36: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	73.42	46.24	58.24	2.12	2293	690
R2	72.35	48.98	57.81	2.23	2256	655
R3	72.61	48.17	57.80	2.21	2269	665
R4	72.71	47.97	57.93	2.60	2251	667
R5	72.94	48.74	58.82	2.10	2286	656
Avg	72.81	48.02	58.12	2.25	2271	667

Table A.37: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	62.82	46.75	59.29	2.41	2252	680
R2	63.02	45.71	59.16	2.31	2253	695
R3	62.37	45.72	57.56	2.07	2253	699
R4	62.52	45.78	57.71	2.56	2259	697
R5	62.94	45.69	58.43	3.22	2255	695
Avg	62.73	45.93	58.43	2.51	2254	693

Table A.38: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 006 - BCS Scenario (Liquid Cooled).

Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for

A.2.6. Case study MI 007

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	85.39	63.51	58.24	2.27	2998	561
R2	85.21	62.20	57.66	2.35	2972	572
R3	85.20	61.74	57.36	2.32	3014	577
R4	84.65	63.43	57.38	2.42	3025	565
R5	85.39	63.00	58.15	2.46	2979	565
Avg	85.17	62.78	57.76	2.36	2998	568

Table A.39: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	75.29	59.79	57.75	2.64	2999	590
R2	76.42	56.22	57.22	2.10	3029	622
R3	74.53	62.68	58.13	3.02	2970	567
R4	74.48	62.94	58.05	2.28	2980	566
R5	74.58	61.27	57.55	2.07	2971	580
Avg	75.06	60.58	57.74	2.42	2990	585

Table A.40: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	64.18	58.54	57.18	2.19	2975	603
R2	63.46	62.49	57.42	2.29	3064	571
R3	65.95	54.25	57.47	2.13	2997	640
R4	65.28	58.93	58.80	2.10	2980	592
R5	63.94	61.72	58.20	3.14	2975	574
Avg	64.56	59.19	57.82	2.37	2999	596

Table A.41: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	82.72	48.95	57.26	2.06	2975	863
R2	83.18	50.33	58.79	2.03	3012	837
R3	81.95	52.41	57.56	2.10	2968	810
R4	83.65	46.06	57.15	2.14	3004	913
R5	83.75	50.84	60.27	2.47	2970	824
Avg	83.05	49.72	58.21	2.16	2986	850

Table A.42: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	73.58	45.45	58.20	2.20	2972	922
R2	72.94	47.24	57.84	2.36	2976	890
R3	72.13	49.66	57.57	2.02	2974	851
R4	72.70	47.85	57.63	2.18	2994	880
R5	73.17	48.33	58.77	2.09	3038	869
Avg	72.90	47.71	58.00	2.17	2991	882

Table A.43: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	63.03	46.37	59.08	2.81	2970	900
R2	62.68	47.37	58.86	2.02	3026	885
R3	62.55	46.26	57.98	2.12	2996	907
R4	61.92	47.36	57.07	2.10	2975	891
R5	63.12	45.66	58.62	2.97	2993	914
Avg	62.66	46.60	58.32	2.41	2992	899

Table A.44: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 007 - BCS Scenario (Liquid Cooled).

A.2.7. Case study MI 017

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	87.82	60.38	57.27	2.13	2203	428
R2	87.89	61.82	57.79	2.52	2234	418
R3	92.12	52.46	57.85	2.09	2223	477
R4	89.87	57.00	57.67	2.04	2230	446
R5	88.39	59.39	57.10	2.14	2275	434
Avg	89.22	58.21	57.54	2.18	2233	441

Table A.45: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	76.97	60.60	57.60	2.21	2210	426
R2	78.75	56.33	57.58	2.16	2224	451
R3	76.10	62.28	57.19	2.13	2218	418
R4	77.73	60.92	58.68	2.90	2210	420
R5	76.96	60.13	57.40	2.12	2206	429
Avg	77.30	60.05	57.69	2.31	2214	429

Table A.46: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	66.59	57.99	57.42	2.02	2226	441
R2	66.74	58.85	58.09	2.05	2220	434
R3	67.56	54.75	57.32	2.06	2207	463
R4	66.42	58.75	57.60	2.16	2225	436
R5	66.58	57.77	57.31	2.02	2235	443
Avg	66.78	57.62	57.54	2.06	2223	443

Table A.47: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	84.09	54.43	57.85	2.03	2207	568
R2	84.50	51.72	57.23	2.03	2210	596
R3	85.71	48.60	58.07	2.32	2206	630
R4	85.57	49.10	58.22	2.06	2201	624
R5	85.73	47.70	57.23	2.32	2228	642
Avg	85.12	50.31	57.72	2.15	2210	612

Table A.48: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	74.81	49.37	58.22	2.52	2201	620
R2	76.14	46.52	59.48	2.37	2204	652
R3	75.42	47.88	58.81	2.24	2210	637
R4	74.89	51.35	59.47	2.40	2207	596
R5	75.05	46.62	57.18	2.14	2201	657
Avg	75.26	48.35	58.63	2.34	2205	632

Table A.49: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	64.74	45.31	57.45	2.57	2213	672
R2	64.93	45.21	58.12	2.10	2220	673
R3	64.37	46.50	57.48	2.03	2224	658
R4	64.46	46.92	58.01	2.26	2211	651
R5	66.23	44.22	60.40	2.38	2231	681
Avg	64.94	45.63	58.29	2.27	2220	667

Table A.50: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 017 - BCS Scenario (Liquid Cooled).

A.2.8. Case study MI 019

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	85.72	63.35	57.98	2.22	3218	606
R2	86.48	61.88	58.26	2.39	3212	616
R3	86.38	60.23	57.55	2.22	3195	633
R4	84.89	63.65	57.29	2.23	3209	607
R5	85.67	62.68	57.74	2.25	3203	612
Avg	85.83	62.36	57.76	2.26	3207	615

Table A.51: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - WCS Scenario (Air Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	74.92	62.21	57.76	2.26	3187	616
R2	75.50	63.27	58.81	2.42	3199	603
R3	76.32	58.73	58.02	2.13	3193	643
R4	75.00	61.99	57.62	2.32	3234	618
R5	74.95	61.81	57.37	2.04	3270	621
Avg	75.34	61.60	57.91	2.23	3216	620

Table A.52: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - BAU Scenario (Air Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	66.28	54.07	57.24	2.03	3245	693
R2	63.98	62.70	57.75	2.06	3242	612
R3	65.51	56.14	57.11	2.22	3208	671
R4	65.21	59.77	58.47	2.09	3192	632
R5	66.12	56.03	57.99	2.05	3197	669
Avg	65.42	57.74	57.71	2.09	3217	655

Table A.53: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - BCS Scenario (Air Cooled).

WCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	83.16	49.72	57.49	2.47	3187	915
R2	83.87	47.24	57.29	2.01	3246	961
R3	84.13	48.81	58.86	2.70	3192	926
R4	83.13	49.96	57.62	2.09	3210	912
R5	84.05	50.72	59.84	2.53	3193	891
Avg	83.67	49.29	58.22	2.36	3206	921

Table A.54: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - WCS Scenario (Liquid Cooled).

BAU	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	74.66	45.88	58.91	2.81	3298	979
R2	72.86	49.52	58.05	2.33	3195	917
R3	73.54	46.70	57.87	2.22	3200	969
R4	73.63	47.00	58.17	2.49	3193	962
R5	73.78	46.00	57.88	2.00	3226	983
Avg	73.69	47.02	58.18	2.37	3222	962

Table A.55: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - BAU Scenario (Liquid Cooled).

BCS	LCOH [€/MWh]	Rec. [%]	T _{set} [°C]	ΔT [°C]	V _{acc} [m ³]	P _{DC} [kW]
R1	63.79	45.32	59.09	2.61	3227	990
R2	63.54	45.51	59.02	2.17	3196	989
R3	63.05	46.65	58.17	2.28	3251	969
R4	62.99	45.79	57.41	2.09	3256	989
R5	63.59	45.57	58.60	3.22	3196	985
Avg	63.39	45.77	58.46	2.47	3225	984

Table A.56: Results of five Bayesian optimization processes for LCOH minimization: optimized grid east point temperature, optimized temperature delta, optimized TES volume and optimized DC power for Case study MI 019 - BCS Scenario (Liquid Cooled).

B | Appendix B

```

1 %% Bayesian Optimization Script - Data Center District Heating
2 clear;
3 close all;
4 clc;
5
6 ris = 'risultati3';
7 c_ee = 0.15; %    /kWhe
8 c_gas = 0.38; %    /smc
9
10 % --- 0. IMPOSTAZIONI CICLI ---
11 N_cycles = 5;
12 MaxEvals = 500;
13 NumSeeds = 200;
14 ExplorationRatio = 0.65;
15 filename = 'MI_001';
16
17 for k_scen = [1.15, 1, 0.85]
18
19 % Loop esterno per tipo di DC
20 for type_DC = [0, 1] % 0 = air cooled / 1 = liquid cooled
21
22     rootFolder = 'G:\Il mio Drive\TESI\edifici';
23     saveFolder = fullfile(rootFolder, filename);
24
25     % --- 1. CONFIGURAZIONE E CARICAMENTO DATI ---
26     fprintf('--- INIZIO SESSIONE MULTI-CICLO (Type DC: %d) ---\n',
27         type_DC);
28     fprintf('Caricamento dati statici in memoria...\n');
29
30     dataPath = fullfile(saveFolder, [filename '.mat']);
31     resPath = fullfile(saveFolder, [filename '_res.mat']);
32     retePath = fullfile(saveFolder, [filename '_rete.mat']);
33
34     % Caricamento
35     DataStatic.Edifici = load(dataPath).Edifici;

```

```

35 DataStatic.Edifici_res = load(resPath).Edifici_res;
36 DataStatic.Rete = load(retePath).Rete;
37 TT = readtable('Edifici_cat.xlsx');
38 DataStatic.Edifici_cat = table2struct(TT);
39 DataStatic.k_scen = k_scen;
40
41 [~, nSub] = size(DataStatic.Edifici.volume);
42
43 % Parametri fissi
44 DataStatic.c_ee = c_ee*k_scen;
45 DataStatic.c_et = c_gas*k_scen/(9.6*0.92); % /kWh
46 DataStatic.anni_pdc = 15;
47 DataStatic.anni_imp = 50;
48 DataStatic.r = 0.05;
49 DataStatic.rho = 995;
50 DataStatic.cp = 4.186;
51 DataStatic.type_DC = type_DC;
52 DataStatic.T_terreno = 15;
53
54 En_fab_par = sum(DataStatic.Edifici_res(nSub+1).Q_tot);
55 Min_Recupero = 0.40;
56
57 maxID = 0;
58 for k = 1:length(existingFiles)
59     tokens = regexp(existingFiles(k).name, '_(\d{3})\.mat$', 'tokens
60 ');
61     if ~isempty(tokens), val = str2double(tokens{1}{1}); if val >
maxID, maxID = val; end; end
62 end
63 startOffset = maxID;
64 fprintf('Ultimo ID trovato: %03d. Nuovi file da %03d.\n', maxID,
maxID + 1);
65
66 % --- 2. VARIABILI ---
67 if type_DC == 0
68     vars = [
69         optimizableVariable('T_set', [10, 80], 'Type', 'real'), ...
70         optimizableVariable('delta', [2, 12], 'Type', 'real'), ...
71         optimizableVariable('V_acc', [En_fab_par*0.0009, En_fab_par
*0.0015], 'Type', 'real'), ...
72         optimizableVariable('P_DC', [En_fab_par*0.00017, En_fab_par
*0.00025], 'Type', 'real')
73     ];
74 else

```

```

74     vars = [
75         optimizableVariable('T_set', [10, 80], 'Type', 'real'), ...
76         optimizableVariable('delta', [2, 12], 'Type', 'real'), ...
77         optimizableVariable('V_acc', [En_fab_par*0.0009, En_fab_par
*0.0015], 'Type', 'real'), ...
78         optimizableVariable('P_DC', [En_fab_par*0.00022, En_fab_par
*0.00028], 'Type', 'real')
79     ];
80     end
81
82
83     % Preallocazione
84     ResultsStruct(N_cycles) = struct('Cycle_ID', [], 'LCOH', [], 'T_set',
, [], 'delta', [], 'V_acc', [], 'P_DC', []);
85
86     if isempty(gcp('nocreate')), parpool; end
87
88     tic;
89
90     % --- 3. LOOP PARALLELO ---
91     parfor cycle = 1:N_cycles
92
93         currentID = startOffset + cycle;
94         fprintf('[START] Avvio worker per ID %03d\n', currentID);
95
96         fun = @(x) obj_fun_simulation(x, DataStatic, Min_Recupero);
97
98         % --- TRUCCO PER STAMPARE AVANZAMENTO ---
99         % Creiamo una funzione anonima che passa anche l'ID e il Totale
iterazioni
100         plotFn = @(results, state) stampaAvanzamento(results, state,
currentID, MaxEvals);
101
102         results = bayesopt(fun, vars, ...
103             'IsObjectiveDeterministic', true, ...
104             'AcquisitionFunctionName', 'expected-improvement-plus', ...
105             'NumSeedPoints', NumSeeds, ...
106             'ExplorationRatio', ExplorationRatio, ...
107             'MaxObjectiveEvaluations', MaxEvals, ... % Usa la variabile
definita sopra
108             'Verbose', 0, ... % Silenzia output standard
MATLAB
109             'UseParallel', false, ...

```

```

110         'PlotFcn', plotFn);           % <--- USA LA NOSTRA FUNZIONE DI
STAMPA QUI
111
112         bestParams = results.XAtMinObjective;
113         minLCOH = results.MinObjective;
114
115         ResultsStruct(cycle).Cycle_ID = currentID;
116         ResultsStruct(cycle).LCOH = minLCOH;
117         ResultsStruct(cycle).T_set = bestParams.T_set;
118         ResultsStruct(cycle).delta = bestParams.delta;
119         ResultsStruct(cycle).V_acc = bestParams.V_acc;
120         ResultsStruct(cycle).P_DC = bestParams.P_DC;
121
122         % Salvataggio
123         cycleFilename = sprintf('%s_bayesopt_PC_G_%03d.mat', filename,
currentID);
124         fullSavePath = fullfile(targetFolder, cycleFilename);
125
126         CycleData = struct();
127         CycleData.Results = ResultsStruct(cycle);
128         CycleData.BayesOptObject = results;
129         parsave(fullSavePath, CycleData);
130
131         fprintf('[END] ID %03d completato.\n', currentID);
132     end
133
134     totalTime = toc;
135
136     % --- 5. OUTPUT ---
137     BatchResults = struct2table(ResultsStruct);
138     fprintf('\n--- FINE ---\nTempo totale: %.2f min\n', totalTime/60);
139     disp(BatchResults);
140 end
141 end
142
143 %% --- FUNZIONI AUSILIARIE ---
144
145 function stop = stampaAvanzamento(results, state, id, maxEvals)
146     stop = false;
147     switch state
148         case 'iteration'
149             iter = results.NumObjectiveEvaluations;
150             % Stampa ogni 10 iterazioni (per non intasare troppo) o alla
fine

```

```

151         if iter == 1 || mod(iter, 10) == 0 || iter == maxEvals
152             perc = (iter / maxEvals) * 100;
153             % Stampa formattata: ID | Iterazioni | % | LCOH Corrente
154             fprintf('[ID %03d] Progresso: %3d / %d (%5.1f%%) -
Miglior LCOH: %.4f\n', ...
155                     id, iter, maxEvals, perc, results.MinObjective);
156         end
157     end
158 end
159
160 function parsave(fname, data)
161     save(fname, 'data');
162 end
163
164 function LCOH_out = obj_fun_simulation(params, D, min_rec_threshold)
165
166     T_set = params.T_set;
167     delta = params.delta;
168     V_acc = params.V_acc;
169     P_DC = params.P_DC;
170     rete_esistente = D.Edifici.rete_esistente;
171
172     Edifici = D.Edifici;
173     Edifici_res = D.Edifici_res;
174     Rete = D.Rete;
175     type_DC = D.type_DC;
176     [~, nSub] = size(Edifici.volume);
177
178     if type_DC == 0
179         T_DC = [20, 15];
180     else
181         T_DC = [45, 40];
182     end
183
184     if T_DC(1) - 5 - delta * 0.98 > T_set
185         no_PdC = 1; % no PdC in energy center
186     else
187         no_PdC = 0; % PdC in energy center
188     end
189
190     T_acc = zeros(1, 8760+1);
191     T_acc(1) = T_set + 0.98*delta;
192
193     R_D_h = 1; s_isolante = 0.2; lambda_iso = 0.04;

```

```

194     h_cyl = ((4 * V_acc) / (pi * R_D_h^2))^(1/3);
195     D_cyl = R_D_h * h_cyl;
196     Sup_acc = 2*(pi/4) * D_cyl^2 + pi * D_cyl * h_cyl;
197     R_th = s_isolante/(Sup_acc*lambda_iso);
198
199     % Preallocazione vettori (velocizza notevolmente)
200     Q_load = zeros(1, 8760); Q_load_net = zeros(1, 8760); W_load = zeros
(1, 8760);
201     Q_acs = zeros(1, 8760); Q_acs_net = zeros(1, 8760); W_acs = zeros(1,
8760);
202     W_ec = zeros(1, 8760); Q_loss_tes = zeros(1, 8760); Q_in = zeros(1,
8760);
203     Q_out = zeros(1, 8760); B = zeros(1, 8760); Q_int = zeros(1, 8760);
204     W_tot = zeros(1, 8760); Q_dis = zeros(1, 8760); Q_dc = zeros(1,
8760);
205
206     % Loop
207     for i = 1:8760
208         % Inizializza step
209         Q_load_step=0; W_load_step=0; Q_acs_step=0; W_acs_step=0;
210
211         for j = 1:nSub
212             curr_Q_load = Edifici_res(j).Q_tot(i);
213             curr_Q_acs = Edifici_res(j).Q_acs(i);
214
215             if Edifici.tm(j) < T_set-5-delta*0.95
216                 curr_W_load = 0;
217             else
218                 curr_COP_load = COP_WWB(T_acc(i)-2, T_acc(i)-7, Edifici.
tm(j), Edifici.tm(j)-5);
219                 curr_W_load = curr_Q_load / curr_COP_load;
220             end
221
222             if T_set-5-delta*0.95 > 48
223                 curr_W_acs = 0;
224             else
225                 curr_COP_acs = COP_WWB(T_acc(i)-2, T_acc(i)-7, 65, 60);
226                 curr_W_acs = curr_Q_acs / curr_COP_acs;
227             end
228
229             Q_load_step = Q_load_step + curr_Q_load;
230             W_load_step = W_load_step + curr_W_load;
231             Q_acs_step = Q_acs_step + curr_Q_acs;
232             W_acs_step = W_acs_step + curr_W_acs;

```

```

233     end
234
235     Q_load(i) = Q_load_step; Q_acs(i) = Q_acs_step;
236     W_load(i) = W_load_step; W_acs(i) = W_acs_step;
237     Q_load_net(i) = Q_load_step - W_load_step;
238     Q_acs_net(i) = Q_acs_step - W_acs_step;
239
240     Q_dc(i) = P_DC;
241
242     if no_PdC == 0
243         curr_COP_ec = COP_WWB(T_DC(1), T_DC(2), T_acc(i)+2, T_acc(i)
-3);
244         W_ec(i) = Q_dc(i)/(curr_COP_ec - 1);
245     else
246         W_ec(i) = 0;
247     end
248
249     Q_loss_tes(i) = (T_acc(i) - D.T_terreno)/(R_th*1000);
250     Q_in(i) = Q_dc(i) + W_ec(i);
251     Q_out(i) = Q_load_net(i) + Q_acs_net(i);
252
253     B(i) = Q_in(i) - Q_out(i) - Q_loss_tes(i);
254     T_next = T_acc(i) + B(i)*3600/(V_acc*D.rho*D.cp);
255
256     if T_next > T_set + delta
257         Q_in(i) = 0; W_ec(i) = 0;
258         B(i) = Q_in(i) - Q_out(i) - Q_loss_tes(i);
259     elseif T_next < T_set - delta
260         Q_int(i) = max(0, Q_out(i) - Q_in(i));
261         B(i) = Q_in(i) - Q_out(i) - Q_loss_tes(i) + Q_int(i);
262     end
263
264     T_acc(i+1) = T_acc(i) + B(i)*3600/(V_acc*D.rho*D.cp);
265     W_tot(i) = W_ec(i) + W_load(i) + W_acs(i);
266     Q_dis(i) = Q_dc(i) - Q_in(i) + W_ec(i);
267 end
268
269 % KPI e Vincoli
270 En_dc = sum(Q_dc);
271 En_ec = sum(W_ec);
272 En_del = sum(Q_out);
273 En_int = sum(Q_int);
274 En_ee = sum(W_tot);
275

```

```

276     En_rec_ratio = (En_del - En_ec) / En_dc;
277     EB_ratio = (T_acc(8761) - T_acc(1))/(delta*2);
278
279     % Costi
280     if rete_esistente == 1
281         parametriCosto.tubazioni_costo_specifico_DN = readmatrix('
parametriCostobis.xlsx', 'Sheet', 'Tubazioni').*(D.k_scen);
282         T = readtable('parametriCostobis.xlsx', 'Sheet', 'Parametri', '
TextType', 'string');
283     else
284         parametriCosto.tubazioni_costo_specifico_DN = readmatrix('
parametriCosto.xlsx', 'Sheet', 'Tubazioni').*(D.k_scen);
285         T = readtable('parametriCosto.xlsx', 'Sheet', 'Parametri', '
TextType', 'string');
286     end
287
288     for i = 1:height(T)
289         parametriCosto.(T.Parametro{i}) = T.Valore(i).*(D.k_scen);
290     end
291
292     [Costi] = stimaCostiReteTLR(Rete, Edifici_res, parametriCosto);
293     c_acc = costo_accumulo(V_acc).*(D.k_scen);
294
295     P_HP_ec = (no_PdC == 0) * max(Q_in);
296
297     P_pdc_load = zeros(1, nSub); P_pdc_acs = zeros(1, nSub); is_pdc_hx =
zeros(1, nSub); is_pdc_hx_dhw = zeros(1, nSub);
298     for k = 1:nSub
299         P_pdc_load(k) = max(Edifici_res(k).Q_tot)*1.1;
300         P_pdc_acs(k) = max(Edifici_res(k).Q_acs)*1.1;
301         if Edifici.tm(k) < T_set-5-delta*0.95
302             is_pdc_hx(k) = 0;
303         else
304             is_pdc_hx(k) = 1;
305         end
306         if T_set-5-delta*0.95 > 48
307             is_pdc_hx_dhw(k) = 0;
308         else
309             is_pdc_hx_dhw(k) = 1;
310         end
311     end
312
313     if type_DC == 1
314         rimborso = 0;

```

```

315     else
316         rimborso = D.c_ee*En_rec_ratio*En_dc/6; %SCOP = 6
317     end
318
319     LCOH_out = LCOH(Costi, c_acc, P_HP_ec, P_pdc_load, is_pdc_hx,
320     P_pdc_acs, is_pdc_hx_dhw, ...
321         D.anni_pdc, D.anni_imp, D.r, En_del/1000, D.c_ee
322         *1000, En_ee/1000, rimborso, D.k_scen, D.c_et, En_int);
323
324     % Vincolo 1: Integrazione
325     if En_int > 1e-3
326         LCOH_out = LCOH_out + (En_int/En_del) * 50;
327         return;
328     end
329
330     % Vincolo 2: Recupero
331     if En_rec_ratio < min_rec_threshold
332         LCOH_out = LCOH_out + 2 + (min_rec_threshold - En_rec_ratio)*10;
333         return;
334     end
335
336     % Vincolo 3: Bilancio Termico
337     if EB_ratio < -0.1
338         LCOH_out = LCOH_out + 10;
339         return;
340     end
341
342     end
343
344     function COP = COP_WWB(T_source_in, T_source_out, T_load_in, T_load_out)
345         Tsrc_ref = [35, 45]; COP_ref = [3.48, 4.22];
346         Tload_ref = 74;
347         Tsrc_mean = mean([T_source_in, T_source_out]);
348         Tload_mean = mean([T_load_in, T_load_out]);
349         COP_interp = interp1(Tsrc_ref, COP_ref, Tsrc_mean, 'linear', 'extrap
350         ');
351         COP = min(COP_interp * (1 - 0.02*(Tload_mean - Tload_ref)), 5.5);
352     end
353
354     function costo = costo_accumulo(V)
355         c0 = 1000; b = 0.80;
356         costo = c0 * (V.^b);
357     end
358
359     function [Costi] = stimaCostiReteTLR(Rete, Edifici_res, parametriCosto)
360         costo_tubi_tot = 0;

```

```

356     costo_table = parametriCosto.tubazioni_costo_specifico_DN;
357     segmenti = Rete.segmenti;
358     for i = 1:height(segmenti)
359         DN_i = segmenti.DN_mm(i); L_i = segmenti.Length_m(i);
360         if L_i == 0 || DN_i == 0, continue; end
361         costo_m = interp1(costo_table(:,1), costo_table(:,2), DN_i, '
linear', 'extrap');
362         costo_tubi_tot = costo_tubi_tot + (costo_m * L_i * 2);
363     end
364     costo_pompe_tot = Rete.summary.pumping_power_elec_kW *
parametriCosto.pompe_costo_specifico_kW;
365     CAPEX.tubazioni_euro = costo_tubi_tot;
366     CAPEX.pompe_euro = costo_pompe_tot;
367     CAPEX.totale_euro = costo_tubi_tot + costo_pompe_tot;
368
369     Q_car_orario_kWh = Edifici_res(end).Q_tot;
370     Q_car_picco_kW = max(Q_car_orario_kWh);
371     P_pompa_picco_kW = Rete.summary.pumping_power_elec_kW;
372     rapporto_carico_orario = Q_car_orario_kWh / Q_car_picco_kW;
373     rapporto_carico_orario(isnan(rapporto_carico_orario)) = 0;
374     P_pompa_oraria_kW = P_pompa_picco_kW * (rapporto_carico_orario .^ 3)
;
375     Energia_pompa_anno_kWh = sum(P_pompa_oraria_kW);
376     costo_pompaggio_anno = Energia_pompa_anno_kWh * parametriCosto.
costo_elettricit _kWh;
377     costo_manutenzione_anno = CAPEX.tubazioni_euro * parametriCosto.
perc_manutenzione_tubi_anno;
378
379     OPEX.pompaggio_euro_anno = costo_pompaggio_anno;
380     OPEX.manutenzione_euro_anno = costo_manutenzione_anno;
381     OPEX.totale_euro_anno = costo_pompaggio_anno +
costo_manutenzione_anno;
382
383     Costi.CAPEX = CAPEX; Costi.OPEX = OPEX;
384     Costi.dettaglio_OPEX.energia_pompaggio_kWh_anno =
Energia_pompa_anno_kWh;
385 end
386
387 function LCOH = LCOH(Costi_Rete, C_buf, P_hp_central, P_heat_vect,
is_pdc_hx, P_dhw_vect, is_pdc_hx_dhw, N_hp, N_resto, r, E_del, p_el,
E_el_HP_totale, rimborso, k_scen, c_et, En_int)
388     p_incentivo = 0.36; f_fix = 0.025; alpha_inst = 0.15; c_centrale =
600*k_scen;

```

```

389     c_he_spec_base = 120*k_scen; margine_he = 0.15; c_he_spec_effettivo
      = c_he_spec_base * (1 + margine_he);
390
391     P_heat_tot = 0; P_pdc_heat = 0; CAPEX_hp_heat = 0; CAPEX_hp_dhw = 0;
392     for i = 1:length(is_pdc_hx)
393         P_heat_tot = P_heat_tot + P_heat_vect(i)*(1-is_pdc_hx(i));
394         P_pdc_heat = P_pdc_heat + P_heat_vect(i)*is_pdc_hx(i);
395         CAPEX_hp_heat = CAPEX_hp_heat + 20000*k_scen*(P_heat_vect(i)*
is_pdc_hx(i)/50)^(0.65);
396         CAPEX_hp_dhw = CAPEX_hp_dhw + 20000*k_scen*(P_dhw_vect(i)*
is_pdc_hx_dhw(i)/50)^(0.65);
397     end
398     P_dhw_tot = sum(P_dhw_vect);
399     CAPEX_hp_ec = 20000*k_scen*(P_hp_central/50)^(0.65);
400     P_hp_totale = P_hp_central + P_dhw_tot + P_pdc_heat;
401
402     CAPEX_network = Costi_Rete.CAPEX.tubazioni_euro;
403     CAPEX_pompe = Costi_Rete.CAPEX.pompe_euro;
404     CAPEX_hp_lordo = (CAPEX_hp_ec + CAPEX_hp_heat + CAPEX_hp_dhw +
P_hp_totale * (c_centrale)) * (1 + alpha_inst);
405     CAPEX_he = P_heat_tot * c_he_spec_effettivo;
406     CAPEX_resto_lordo = C_buf + CAPEX_network + CAPEX_he + CAPEX_pompe;
407     CAPEX_totale_lordo = CAPEX_hp_lordo + CAPEX_resto_lordo;
408     Incentivo = CAPEX_hp_lordo * p_incentivo;
409     CAPEX_hp_netto = CAPEX_hp_lordo - Incentivo;
410     CAPEX_resto_netto = CAPEX_resto_lordo;
411
412     CRF_HP      = r * (1 + r)^N_hp / ((1 + r)^N_hp - 1);
413     CRF_Resto = r * (1 + r)^N_resto / ((1 + r)^N_resto - 1);
414     OPEX_pompaggio_annuo = Costi_Rete.OPEX.pompaggio_euro_anno;
415     OPEX_fix = f_fix * CAPEX_totale_lordo;
416     Ammortamento_annuo = (CRF_HP * CAPEX_hp_netto) + (CRF_Resto *
CAPEX_resto_netto);
417     annual_cost = Ammortamento_annuo + OPEX_fix + OPEX_pompaggio_annuo +
(p_el * E_el_HP_totale) - rimborso + En_int*c_et;
418     LCOH = annual_cost / E_del;
419 end

```

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List of symbols

Variable	Description	SI unit
U	Thermal transmittance	W/(m ² K)
$T_{setpoint}$	TES target temperature	°C
ΔT	Temperature deviation threshold	°C
Q_{TES}	Thermal energy stored in TES	MWh
Q_{DC}	Waste heat from Data Center	MWh
W_{EC}	Electrical work of the Energy Center	MWh
Q_{dist}	Heat delivered to the district network	MWh
Q_{loss}	Thermal energy losses	MWh
T_{acc}	Storage temperature	°C
V_{acc}	Storage volume	m ³
ρ	Fluid density	kg/m ³
c_p	Specific heat capacity	J/(kg K)
R_{th}	Thermal resistance	K/W
T_{ground}	Ground temperature	°C
$Q_{load,net}$	Space heating demand	MWh
$Q_{acs,net}$	Domestic Hot Water demand	MWh
$\dot{m}$	Mass flow rate	kg/s
$\dot{V}$	Volumetric flow rate	m ³ /s
Δp	Pressure drop	mmca/m
η	Efficiency	-
P_{DC}	Recovered DC power	kW
S_{heated}	Heated surface area	m ²
E_{fab}	Thermal energy demand	MWh
E_{int}	Integration energy	MWh

Variable	Description	SI unit
$C_{EE,dom}$	Domestic electricity cost	€/kWh
$C_{EE,ind}$	Industrial electricity cost	€/MWh
C_{gas}	Natural gas cost	€/Smc
C_{sub}	Substation cost	€/kW _t
C_{HP}	Heat pump cost	€/kW _t
C_{hex}	Heat exchangers cost	€/kW _t
C_{TES}	Storage cost	€/m ³
C_{pump}	Pumps cost	€/kW _e
FE_{el}	Electricity emission factor	kgCO ₂ /kWh _{el}
FE_{gas}	Gas emission factor	kgCO ₂ /kWh _{th}
r	Interest rate	-
N_{sub}	Substation lifetime	years
N_{net}	Network lifetime	years
T_{ext}	Outdoor ambient temperature	°C
RH	Relative humidity	%
$f_{defrost}$	Defrost correction factor	-

List of abbreviations

Abbreviation	Description	SI unit
PUE	Power Usage Effectiveness	-
TUE	Total Usage Effectiveness	-
COP	Coefficient of Performance	-
LCOH	Levelized Cost Of Heat	€/MWh
CAPEX	Capital Expenditure	€
OPEX	Operational Expenditure	€/year
4GDH	4th Generation District Heating	-
5GDHC	5th Generation District Heating and Cooling	-
APE	Energy Performance Certificate	-
ASHP	Air-Source Heat Pump	-
AWHP	Air-to-Water Heat Pump	-
BAU	Business As Usual	-
BCS	Best-Case Scenario	-
BHP	Booster Heat Pump	-
BO	Bayesian Optimization	-
CIW	Cold Inlet Water	-
DC	Data Center	-
DHW	Domestic Hot Water	-
EI	Expected Improvement	-
EPBD	Energy Performance of Buildings Directive	-
ESCo	Energy Service Company	-

Abbreviation	Description	SI unit
GP	Gaussian Process	-
GSHP	Ground-Source Heat Pump	-
GWHP	Groundwater Heat Pump	-
HP	Heat Pump	-
ICT	Information and Communications Technology	-
KPI	Key Performance Indicator	-
LCA	Life Cycle Assessment	-
LCC	Life Cycle Cost	-
MST	Minimum Spanning Tree	-
PED	Positive Energy District	-
PHE	Plate Heat Exchanger	-
PUN	Prezzo Unico Nazionale	-
TES	Thermal Energy Storage	-
UCB	Upper Confidence Bound	-
WCS	Worst-Case Scenario	-
WHR	Waste Heat Recovery	-

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