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A multi-objective optimization approach in defining the decarbonization strategy of a district heating network: A case study of Oslo

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ABSTRACT

This study investigates the decarbonization of the Oslo district heating network by, firstly, modeling its current framework using EnergyPLAN and, afterwards, exploring optimized solutions, in terms of CO_2 emissions and total annual cost, combining EnergyPLAN with a multi-objective evolutionary algorithm. Alternative scenarios are explored based on nine decision variables (energy technologies), each constrained by upper and lower boundaries defined by a specific set of criteria. In this work, the exploration of 20,000 solutions is performed following a four-step approach that starting from a broad availability of the decision variables, step by step adds new constraints. In the first step, heat pumps and waste heat recovery were recognized as the most cost-effective decarbonization solutions. The second step, avoiding the use of heat pumps, shifted the focus to more costly electric boilers. The third step, excluding also electric boilers, resulted in favoring biomass boilers, but with an additional cost increase. In the final step, carbon capture and storage became the only feasible decarbonization option and highlighted the difficult decarbonization with a steep Pareto front. Overall, this study confirms that, in line with recent system-oriented literature but extending beyond technology- or case-specific studies, waste heat recovery and electrification-based sector coupling emerge as the dominant cost-optimal decarbonization pathways at the system level.

Keywords

Decarbonization;
District heating;
Waste incineration;
Multi-objective evolutionary algorithm;
EnergyPLAN

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1. Introduction

The Kyoto Protocol of 1997 was the first major step in setting binding targets to address global warming [1]. The Paris Agreement in 2015 followed, focusing on limiting global temperature rise to 1.5 °C above pre-industrial levels [2]. Later, the European Green Deal of 2019 introduced the target of reaching net-zero emissions by 2050, emphasizing renewable energy, energy efficiency, and waste heat recovery [3]. These initiatives all aim to secure a sustainable future, but success requires action at individual, societal, national, and global levels. A key step in this process is reducing the carbon footprint, especially by moving away from fossil fuel use.

A district heating network (DHN) generates heat centrally and deliver it to buildings via insulated pipelines, using a range of energy sources including combined heat and power (CHP) plants, biomass, geothermal, waste-to-energy, and solar thermal systems [4,5]. Thermal storage balances daily and seasonal variations, with short-term solutions like tanks and long-term solutions like borehole or aquifer storage, the latter being less efficient. Over time, DHNs have evolved from high-temperature

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steam networks to low-temperature systems with high renewable integration, now referred to as fourth-generation district heating (DH) [6,7].

Globally, around 80,000 DHNs exist, with 6,000 in Europe, mainly serving buildings and industry, while district cooling is emerging in urban areas [5,8]. In Scandinavia, DHNs cover 14–16% of final energy use in Sweden and Denmark, but only 1% in Norway due to abundant hydropower and low electricity prices [9]. Despite this, Norwegian DHN has grown from 1.6 TWh in 2000 to 7.9 TWh in 2023, primarily sourced from waste incineration, biomass, electric boilers, and heat pumps [10].

Energy system optimization models and smart energy system approaches are widely used to explore pathways for decarbonization, emphasizing high renewable energy penetration, energy efficiency and sector coupling [11–15]. Modeling for Norway and cities like Oslo shows that expanding district heating networks using renewable sources, waste heat, bio-wood, and geothermal energy can surpass building-based heating by 2040 [16].

In addition to technology choices, the availability and cost of energy infrastructures-particularly electricity grids, DHNs and storage can strongly influence decarbonization pathways, and in fully renewable energy scenarios these infrastructure costs may even exceed the cost of renewable energy technologies themselves. Consequently, integrated smart energy systems approach that jointly consider infrastructure, sector coupling, and demand-side measures are essential for identifying least-cost transition pathways [17].

Decarbonizing district heating and district energy systems relies on renewable energy, waste heat utilization, electrification, and low-temperature district heating (LTDH). Studies highlight industrial decarbonization and urban energy planning, such as in Italian pharmaceutical facilities, the Giudicarie Esteriori Valley, Santa Chiara district, and Val di Non valley, showing the importance of integrating renewables, energy storage, electrification, and sector coupling to reduce costs and emissions [18–21]. Waste heat from industrial processes, wastewater, and waste-to-energy plants can supply substantial DH demand while lowering emissions [22–25]. Solar integration and thermal energy storage (TES) are essential for seasonal balancing and maximizing renewable use, while LTDH enhances efficiency and facilitates renewable integration [26–29]. Electrification through heat pumps and electric boilers is a primary strategy, though electricity price volatility and storage capacity must be managed [30].

GIS (Geographic Information Systems)-based mapping and advanced system modeling support DHN planning by identifying excess heat sources, urban demand, and optimal infrastructure investments [31–33]. Economic and regulatory factors, including carbon pricing, green hydrogen, and policy incentives, are critical to enable decarbonization and integrate renewable and waste heat sources [25,30,34]. Overall, achieving low-carbon DHNs and district energy systems requires combining technological solutions, system optimization, and strong policy frameworks to meet European Union (EU) and global climate targets.

Making energy systems more sustainable is central to the net-zero transition, and district heating networks can play a key role by integrating renewable energy and waste heat, thereby reducing fossil fuel dependence, as highlighted by previously mentioned studies. Despite this potential, district heating is still not widely adopted, and expanding coverage could enable greater efficiency and decarbonization.

This study focuses on the Oslo DHN, analyzing its current operation and exploring improvements for both decarbonization and cost reduction. The approach involves modeling the existing system to determine total annual CO_2 emissions and costs, followed by evaluating potential enhancements. EnergyPLAN [35] is used for the simulations, and a multi-objective evolutionary algorithm (MOEA) is integrated to assess how different technologies contribute to decarbonization. By applying capacity limits and constraints, the study identifies alternative solutions and provides recommendations for system operators, serving as a reference for similar-scale systems and supporting policy and planning decisions. The innovative and unique contribution of this paper lies in the use of real operational data from a district heating operator combined with innovative modeling techniques such as EnergyPLAN software combined with MOEA.

While existing research has extensively applied EnergyPLAN and other system models to investigate sector coupling and renewable integration, limitations remain when simulating heating-only configurations dominated by heat pumps and electric boilers. In the baseline scenario of this study, a dummy renewable electricity production is introduced to ensure electric boilers can operate, with the generated electricity fully self-consumed by boilers and heat pumps. For the decarbonization scenarios, however, the heat pump section of EnergyPLAN is repurposed to represent both heat pumps and electric boilers using imported electricity.

Their installed capacities are then derived through a simple linear post-processing approach, based on coefficient of performance (COP) values and the optimal capacities selected by the MOEA. This tailored adaptation of EnergyPLAN, combined with multi-objective optimization, enables a more realistic representation of district heating decarbonization pathways, highlighting cost–emission trade-offs that could not be captured with standard modeling practices.

The paper begins by introducing Oslo's district heating network, describing its components, operational principles, and supply-demand data. The methodology section outlines how the system is modeled in EnergyPLAN and how a MOEA is applied to explore decarbonization scenarios. The results and discussion present baseline outcomes and scenario analyses, highlighting potential implications for policymakers, and the conclusion summarizes the main findings while suggesting directions for future research.

2. The Case Study of Oslo

This section outlines the technical and operational characteristics of the current Oslo DHN using data provided by the operator Hafslund CELSIO [36], referred as company in this study, as part of the Horizon Europe USES4HEAT project [37]. The network integrates multiple heat generation technologies, including waste incinerators, fossil fuel boilers, biomass boilers, heat pumps, electric boilers, and waste heat recovery. Waste incineration takes place at two facilities: Klemetsrud and Haraldrud. The Klemetsrud plant operates as a CHP plant, while Haraldrud provides heating only. As a result, the operator supplies not only heat but also electricity, which is sold directly to the grid rather than prioritized for self-consumption. The electrically powered components are likewise connected to the grid. The overall configuration of these sources is illustrated in Figure 1.

This network representation is based on data provided by the operator Hafslund CELSIO, including the list of technologies at different locations. Installed capacities are reported in terms of thermal output. To differentiate between technologies, the company applies a unique naming convention, consisting of the first three letters of the location followed by an identifier (NXnumber). A comprehensive overview of all technologies, together with their unique tags, fuel type, thermal output capacity, and thermal efficiency, is presented in Table 1.

For Klemetsrud (KLE), three separate technologies are listed under the fuel type waste, corresponding to three incineration lines in the waste-to-energy (WtE) plant. Together, these lines provide a total thermal capacity of 107 MW_{th} dedicated solely to district heating. The Klemetsrud plant also includes two turbines with a combined electric capacity of 22 MW_{el}. At Haraldrud (HAR), a single waste incineration line supplies only district heating. In addition, the fuel type "waste heat" at Haraldrud

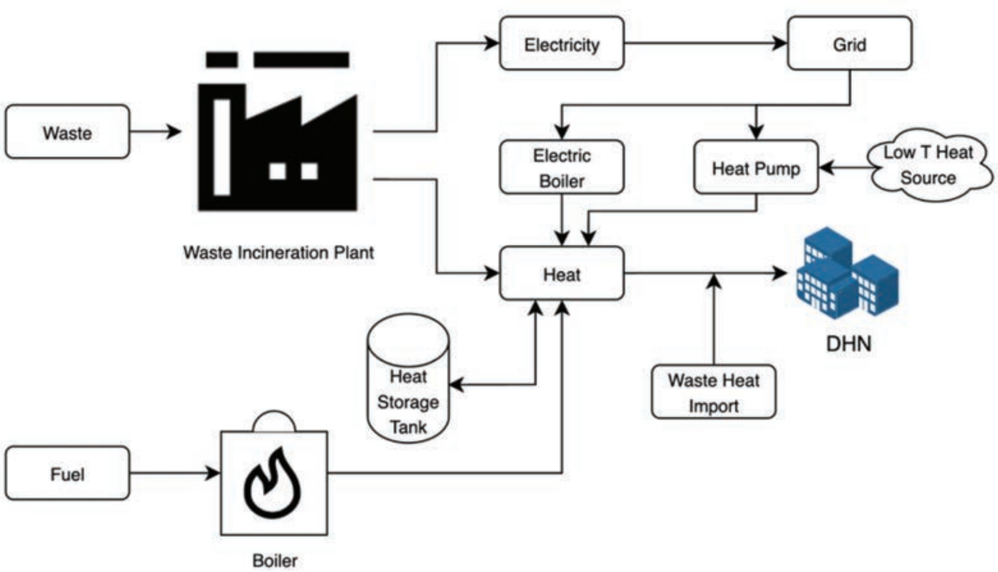

Figure 1: Overall schematic of the current district heating networkwith its connection to the grid operated by Hafslund CELSIO in Oslo.

Table 1: The list of technologies with their tags, fuel types, capacities, and efficiencies.

Tag	Fuel Type	Capacity [MW_{th}]	Efficiency [-]	Tag	Fuel Type	Capacity [MW_{th}]	Efficiency [-]
KLE_NX100	Waste	27	83%	ULL_NX100	Electric	10	99%
KLE_NX200	Waste	27	83%	ULL_NX200	Electric	10	99%
KLE_NX300	Waste	53	83%	ULL_NX300	Electric	10	99%
KLE_NX301	(Heat pump)	14	(COP = 4.95)	ULL_NX400	Biodiesel	8	90%
KLE_NX500	Biogas	2	90%	ULL_NX500	Biodiesel	10	90%
KLE_NX600	Oil	13	90%	ULL_NX600	Biodiesel	10	90%
HAR_NX100	Wood pellets	56	85%	ROD_NX100	Bio-oil	90	95%
HAR_NX200	LNG/Biodiesel	50	95%	HAS_NX100	Biodiesel	15	90%
HAR_NX300	LNG/Biodiesel	50	95%	HAS_NX200	Electric	8	99%
HAR_NX400	Electric	25	99%	ULV_NX110	(Heat pump)	5	(COP = 2.76)
HAR_NX500	Waste	30	83%	SKO_NX100	(Heat pump)	11	(COP = 2.86)
HAR_NX671	(Waste heat)	16	–	SKO_NX200	(Heat pump)	22	(COP = 3.17)
HAR_NX672	(Waste heat)	16	–	SKO_NX300	Electric	10	99%
VIK_NX100	Electric	27	99%	HOF_NX100	Biodiesel	50	95%
VIK_NX200	Biodiesel	25	90%	HOF_NX200	Biodiesel	50	95%
VIK_NX300	Biodiesel	25	90%	HOF_NX400	Electric	25	99%
VIK_NX400	Electric	35	99%	HOL_NX100	Electric	10	99%
VIK_NX500	Electric	25	99%	HOL_NX200	Electric	10	99%
VIK_NX600	Electric	40	99%	HOL_NX300	Biodiesel	26	90%
OKE_NX100	Biodiesel	15	90%	HOL_NX400	Biodiesel	13	90%
OKE_NX200	Electric	8	99%				

refers to a connection with another operator's waste heat recovery plant. The waste heat from this facility is injected into the district heating network operated by the company at the required supply temperature, with a fixed tariff applied per unit of energy delivered.

The reference year for this study is 2023. Hafslund CELSIO reports the hourly heat supply from all technologies to the network between 00:00 on January 1 and 23:00 on December 31, 2023. The total heat delivered to the district heating network amounts to 2.017 TWh/y in 2023, with the company estimating overall network losses at 8%. Consequently, the effective demand met by consumers is 1.856 TWh/y. This production level in 2023 accounts for nearly 20% of Norway's total district heating supply [10].

The demand profile is strongly seasonal, peaking in winter due to high heating needs and reaching its lowest levels in summer. The maximum demand is recorded at 681 MW_{th} in early December. Since the waste-to-energy plant operates year-round, except for short maintenance shutdowns, district heating production typically exceeds demand during the summer months. The surplus heat is dissipated into the ambient air using fans. As this dissipated heat is also produced through waste incineration, it is included in the overall production data. Monthly averages of overall production, including dissipated heat, production supplied to the district heating network, and demand are presented in Figure 2, along with their annual averages. A small share of excess heat is observed in winter, primarily due to inaccuracies in demand forecasting.

The total annual dissipated heat amounts to 0.113 TWh/y. If stored, this energy could be utilized during peak demand periods, reducing reliance on other technologies and lowering the network's carbon footprint.

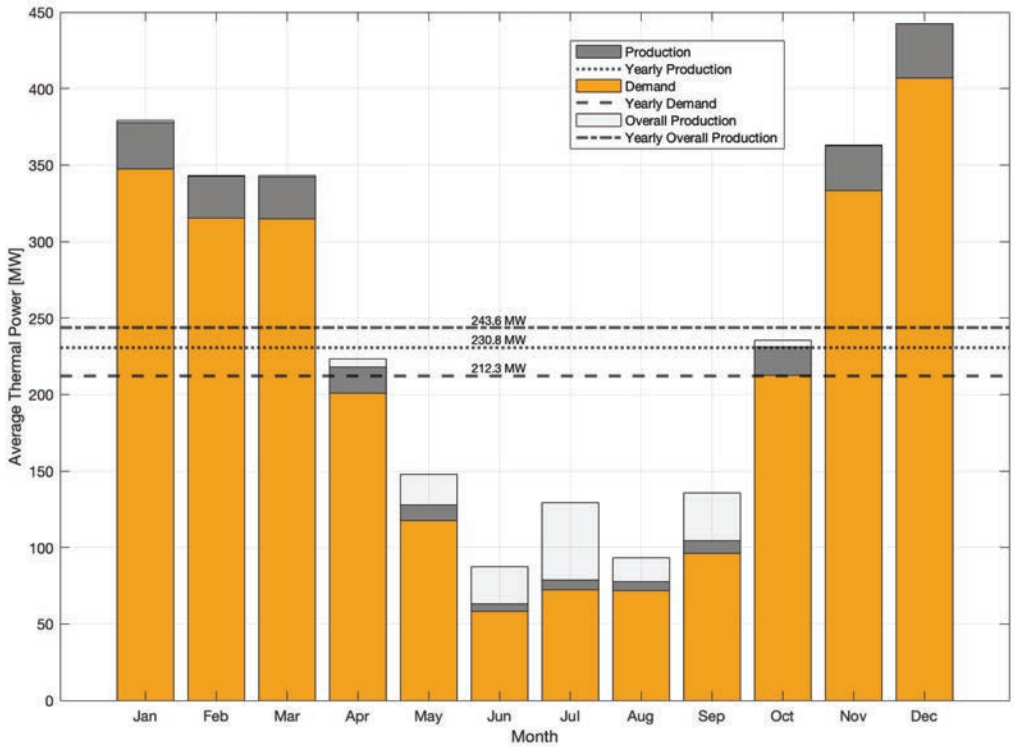

Figure 2: Monthly average thermal power overall production, production, and demand with annual average lines in 2023.

3. Methodology

The approach taken in this study can be summarized through the following key phases.

- Modeling the existing DHN in Oslo using EnergyPLAN, incorporating company-provided data and literature references to define system parameters and cost functions, to quantify total annual cost and CO_2 emissions.
- Integrating MOEA with EnergyPLAN to optimize system configurations for various decarbonization scenarios, considering trade-offs between total CO_2 emissions and total annual cost.
- Analyzing results to identify potential pathways for deep decarbonization of the DHN.

3.1. District Heating Network Modelling with EnergyPLAN

For this study, EnergyPLAN is utilized to model the DHN in Oslo and to analyze deep decarbonization scenarios. Its capability to integrate demands and productions from different energy sectors, renewable energy sources (RES) and waste heat utilization makes it well suited for evaluating optimized heating solutions and sector coupling strategies. The tool performs hourly simulations, capturing temporal variations in supply and demand, and has been widely adopted in academic and policy research for DHN analysis.

3.1.1. Baseline Scenario

Oslo DHN's primary technology is the WtE plant. In EnergyPLAN, this unit is defined in the waste subsection of the supply technologies, which requires three main inputs, total waste input, heating and electric efficiency, along with a distribution file. The total annual waste input ($\dot{Q}_{in,WtE}$) is determined as in Eq. (1).

$$\dot{Q}_{in,WtE} = \dot{m}_{total\ burned\ waste} \times LHV_{waste} \tag{1}$$

where, $\dot{m}_{total\ burned\ waste}$ is reported as 51.5 t/h × 8784 h = 452,376 t_{waste}/y and (LHV_{waste}) = 10,830 MJ/t_{waste}. This calculation yields 4,899.23 TJ/y annual energy input to the WtE plant, which is equal to 1.361 TWh/y. The output from this WtE plant is district heating ($\dot{Q}_{out,DH}$) and electricity ($\dot{E}_{out}$). Since these total production values are already provided, the district heating (η_{DH}) and electric (η_{EI}) efficiency can be found as shown in Eq. (2) and Eq. (3), respectively.

$$\eta_{DH} = \frac{\dot{Q}_{out,DH}}{\dot{Q}_{in,WtE}} \times 100\% \tag{2}$$

$$\eta_{EI} = \frac{\dot{E}_{out}}{\dot{Q}_{in,WtE}} \times 100\% \tag{3}$$

Thermal output values for the district heating and the electricity production are 0.975 TWh/ y and 0.152 TWh/y, respectively. The district heating thermal output also contains the amount dissipated and the district heating efficiency becomes 71.64%, while the electrical efficiency is 11.17%. The overall efficiency is then 82.81%, which is also reported in Table 1. For EnergyPLAN, the WtE plant is defined with:

- Total waste input: 1.361 TWh/y
- District heating efficiency: 71.64%
- Electric efficiency: 0%

Although the plant generates electricity, its efficiency is set to zero in the thermal balance. This ensures EnergyPLAN does not prioritize internal consumption of the electricity, which in practice is sold to the grid. The revenue from electricity sales is instead accounted later in post-processing and values are given in the section 3.1.3. The distribution profile applied in the WtE subsection is based on actual production data from four waste incinerators. It also incorporates wasted heat from fans, since this originates directly from the incineration lines.

The second technology defined is the boiler. The total boiler thermal output capacity, excluding electric boilers, is 508 MW_{th}. Since no separation by fuel type is available, an overall boiler efficiency is calculated using the weighted average method with the reported capacities and efficiencies in Table 1, resulting in 92.2%. For fuel assignment, all biogas, bio-oil, biodiesel, and wood pellets are grouped under biomass. The boiler fuel distribution is then set among oil, natural gas, and biomass in EnergyPLAN according to the data provided by the company. The final fuel mix for the district heating boiler system is defined as 2.56% oil, 10.85% natural gas, and 86.59% biomass.

The third technology is waste heat import, labeled as industrial excess heat in EnergyPLAN. The annual imported energy, provided by the company, is 0.190 TWh/y and its distribution is inserted directly into the model. Since EnergyPLAN does not allow assigning a specific cost to waste heat, this cost is incorporated during post-processing using the unit price provided by Hafslund CELSIO. The detailed calculation is presented in the section 3.1.3.

The next supply technology is the heat pump, which includes four units with different performance characteristics and a total thermal output of 52 MW_{th}. Hourly electricity consumption and thermal output data for each heat pump, provided by the company, are used to determine their hourly COPs. Only the operating hours are considered in the averaging to avoid skewing the results with zero values during non-operation. A weighted average across all four heat pumps is then calculated, yielding an initial average COP of 3.54. To ensure the annual thermal output matches the actual data, a correction factor of 0.958 is applied, resulting in a final average COP of 3.39 for the EnergyPLAN model. This average COP is used to define heat pump performance in the simulation.

Although electricity production is not explicitly modeled in this study, two components of the district heating system, heat pumps and electric boilers, require electricity. In EnergyPLAN, electricity can be supplied either from in-system production or via import with sufficient transmission capacity. By default, the software prioritizes feeding electricity to heat pumps first, which does not reflect the actual operation of the Oslo network. To address this, the electricity consumption for the studied year is defined as renewable electricity supply with an exact hourly profile. Although the Norwegian electricity mix is not 100% renewable [38], this approach is used as a modelling workaround to overcome EnergyPLAN's limitations regarding the treatment of imported electricity. The required corrections for both costs and emissions associated with this electricity use are therefore applied separately during the post-processing stage in the section 3.1.3. The total renewable electricity input ($\dot{E}_{total}$) is determined by summing the ratio of each electric boiler's thermal capacity ($\dot{Q}_{EB,i}$) to its efficiency ($\eta_{EB,i}$) and the ratio of the total heat pump thermal capacity ($\dot{Q}_{HP,i}$) to the average COP (COP_{avg}), as expressed in Eq. (4).

$$\dot{E}_{total} = \sum \frac{\dot{Q}_{EB,i}}{\eta_{EB,i}} + \frac{\sum \dot{Q}_{HP,i}}{COP_{avg}} \tag{4}$$

It is used to express the electrical input corresponding to the installed thermal capacities of electric boilers and heat pumps under peak-demand conditions and does not represent typical or simultaneous operational behavior, which is instead resolved through hourly simulations in EnergyPLAN.

In this study, the renewable electricity production defined in EnergyPLAN does not represent real generation but rather a modeling workaround to overcome the software's limitations when simulating heating-only scenarios. In EnergyPLAN, electric boilers are only activated when excess electricity is available. Therefore, a dummy renewable electricity supply is introduced to create the necessary excess production, which is then fully consumed by the heat pumps and electric boilers within the district heating network. This approach ensures that the heating system operation is represented correctly, while acknowledging that the modeled electricity production does not correspond to actual renewable generation. Accurately reproducing the operational behaviour of the district heating network is necessary to establish a reliable baseline, which is used to derive total annual cost and CO_2 emissions based on available operational data and literature-based emission factors and cost parameters, since these aggregated values are not directly provided by the system operator. These baseline results serve solely as a reference point for comparison. In contrast, the decarbonization scenarios do not rely on dummy electricity production, as electricity demand for heat pumps and electric boilers is supplied through grid imports enabled by a defined large transmission line capacity. Consequently, this modelling assumption does not influence dispatch behaviour or optimization outcomes in the decarbonization scenarios and does not affect the reliability of the comparative assessment.

The last definition that must be done is CO_2 content in the fuels so that EnergyPLAN can calculate emissions according to fuel usage. Default emission factors are used for oil and natural gas, while the emission factor for waste (EF_{waste}) is based on company data. The incineration of waste produces 1.115 kg CO_2 per kg of waste, but 45.02% of this originates from the organic fraction and is omitted to account only for fossil CO_2 emissions. Using the LHV_{waste}, the emission factor per unit of energy is calculated as in Eq. (5).

$$EF_{\text{waste}}\left[\text{kg}_{\text{CO}_2}/GJ\right] = EF_{\text{waste}}\left[\text{kg}_{\text{CO}_2}/kg_{\text{waste}}\right] / LHV_{\text{waste}} \times (1 - 0.4502) \quad (5)$$

In EnergyPLAN electric boilers are defined to incorporate them into the district heating system modeling. These boilers operate when there is excess electricity, as electricity production is not explicitly modeled. The electricity consumption of heat pumps and electric boilers is defined under the renewable electricity supply, generating an electricity surplus. This surplus is utilized by electric boilers through the critical excess electricity production (CEEP) regulation strategy number 4, with a thermal output of 253 MW_{th}. To ensure realistic distribution of electricity between heat pumps and electric boilers, the heat pumps' electricity input was adjusted using a correction factor of 0.78, resulting in a redefined input of 12 MW_{el}. This adjustment ensures accurate thermal output, considering that heat pumps operate with a COP of 3.39. The thermal storage tank, with a capacity of 550 MWh as provided by the company, is also defined in this part.

In the cost tab, the general section is used to define CO_2 prices and the national interest rate. The company reported Norwegian CO_2 prices in 2023 as 20.84 EUR per ton for emissions from the waste-to-energy plant and 77 EUR per ton for emissions from other fossil fuels. Since EnergyPLAN does not allow separation of these CO_2 sources, the CO_2 price is set to 0 EUR per ton in the software, and related costs for waste, oil, and natural gas are calculated in post-processing. The national interest rate is set to 3.6%. Investment, fixed, and variable operation and maintenance costs are not provided by the company. These values are instead based on literature references [39,40] and included in the model; the detailed calculation procedure will be explained in section 4.1.2. The additional section of the cost tab is used to define the district heating network infrastructure cost. Using the EnergyPLAN cost database [41], delivery is estimated at 144,000 EUR per TJ of district heating, with annual operation and maintenance costs of 1,100 EUR/TJ and a 40-year lifetime. Given Oslo's network demand of 1.856 TWh/year, the estimated investment cost is calculated approximately as 960 M EUR.

Fuel prices represent the next parameter defined for the financial calculations of the base case scenario. Table 2 summarizes the final fuel prices paid by the company in 2023, expressed per GJ of consumption. Notably, the price of waste is negative, as the company receives a gate fee of 75 EUR/t_{waste} for incineration rather than incurring a cost. Electricity prices are not included in this table, as the day-ahead market (DAM) prices are used for grid transactions. While electricity sales to the grid are based directly on the DAM prices, electricity purchases include additional costs, which increase the effective price by up to 5% according to

Table 2: Final fuel prices paid by the company in 2023.

Fuel	Price [EUR/GJ]
Waste	–6.925
Wood Pellet	13.418
Natural Gas	30.525
Biogas	9.616
Oil	39.226
Bio-oil	28.402
Biodiesel	37.570

company data. The average annual electricity prices calculated for 2023 are presented in the section 3.1.3, while hourly DAM prices are applied in this study for evaluating electricity costs and revenues.

Since EnergyPLAN does not provide separate input fields for different bio-based fuels, a single aggregated biomass fuel price must be defined. This value is calculated using a weighted average approach based on the installed boiler capacities of each biomass fuel type (wood pellet, biogas, bio-oil, and biodiesel). Applying this method yields a final biomass fuel price of 32.492 EUR/GJ.

The final steps in EnergyPLAN include choosing the technical simulation strategy to balance heat demands, selecting the output format, and defining emission factors. In this study, only CO_2 emissions are considered.

3.1.2. The Cost Calculation Technique

Since Hafslund CELSIO did not provide cost data, except for the carbon capture and storage (CCS) unit, which is currently under investment, two widely used literature sources were selected for investment and operation and maintenance cost calculations. The first is the Danish Energy Agency's technology catalog [39], a regularly updated reference that provides technical and economic data on electricity and district heating technologies, including investment costs, operation and maintenance expenses, efficiencies, lifetimes, and projections. The second is a report prepared by ILF Consulting Engineers Austria GmbH and the Austrian Institute of Technology GmbH for the Joint Research Centre of the European Commission [40], which offers similar data for large-scale district heating and cooling technologies in the EU with an outlook to 2050. Using both references, cost estimates for the relevant district heating technologies were calculated and compared, forming the basis for the values implemented in EnergyPLAN. The following Table 3 summarizes the investment and operation and maintenance cost values for the district heating technologies considered in this study as well as the district heating infrastructure cost suggested by EnergyPLAN. Only the final values necessary for the modeling are presented.

3.1.3. Post-processing EnergyPLAN Results

After running EnergyPLAN with the Oslo district heating baseline model, the obtained results serve as the starting point for the decarbonization scenarios; however, the total annual cost and the total CO_2 emissions must be corrected. In the EnergyPLAN model, the dummy electricity production associated with heat pumps and electric boilers is defined as renewable generation with no assigned cost. As a result, the system assumes electricity to be free in the current configuration. However, in reality, the hourly cost of electricity determines the actual expenses. While the model does not account for this cost, the company follows an hourly price distribution (average in 2023 is 71 EUR/MWh). Therefore, this price distribution must be considered in hourly electricity usage to accurately calculate the real cost of electricity, which will be added to the total annual cost during post-processing. On the other hand, there is also the electricity production from the WtE

Table 3: Cost parameters for EnergyPLAN district heating modeling in Oslo.

Technology	CAPEX	$OPEX_{fix}$	$\frac{OPEX_{fix}}{CAPEX}$	$OPEX_{var}$	Lifetime
Waste incinerator	1.931 M EUR/$MW_{fuel\ input}$	59,348 EUR/$MW_{fuel\ input}$/y	3.074 %	6.311 EUR/MWh_{th}	25 y
Heat pump	2.328 M EUR/MW_{el}	7,210 EUR/MW_{el}/y	0.310 %	6.102 EUR/MWh_{el}	25 y
Electric boiler	0.138 M EUR/$MW_{fuel\ input}$	500 EUR/$MW_{fuel\ input}$/y	0.362 %	0.200 EUR/MWh_{th}	20 y
Boiler	0.236 M EUR/$MW_{fuel\ input}$	2,482 EUR/$MW_{fuel\ input}$/y	1.050 %	0.300 EUR/MWh_{th}	25 y
Thermal energy storage tank	18.6 M EUR/GWh	5,000 EUR/GWh/y	0.261 %	0 EUR/GWh_{th}	25 y
Carbon capture and storage unit	2077 M EUR/Mt_{CO2}	26.271 M EUR/Mt_{CO2}/y	3.614 %	0 EUR/Mt_{CO2}	25 y
District heating infrastructure	0.144 M EUR/TJ_{th}	1100 EUR/TJ_{th}/y	0.764 %	0 EUR/TJ	40 y

plant which was excluded in the model to avoid the self-consumption in EnergyPLAN simulation. This electricity produced is sold to the grid with an hourly price distribution (average in 2023 is 67 EUR/MWh) and this amount must be deducted from total annual cost during post-processing.

Moreover, the total annual cost for the industrial excess heat definition is corrected to account for waste heat recovery. Since there is no cost assignment for this imported energy, the model now uses it as free source while in reality it has a fixed tariff over the year (average in 2023 is 27 EUR/MWh). This expense will be added on top of the total annual cost calculated so far. Finally, the CO_2 price must be corrected as a part of total annual cost since it was set as zero CO_2 price in the model. Due to usage of waste, natural gas and oil, and their corresponding CO_2 price (20.84 EUR/t_{CO2} for waste and 77 EUR/t_{CO2} for natural gas and oil), the additional cost will be calculated. The second type of correction pertains to total CO_2 emissions since the electricity is sourced from the grid. According to electricity production statistics from 2020 [38] the national grid in Norway is 98.6% renewable. It can be concluded that the emission factor for electricity is 0.0106 Mt_{CO_2}/TWh. This emission factor can be multiplied by the imported electricity to determine the specific emission contribution, allowing for a corrected total CO_2 emission value. There is no consideration of CO_2 emission correction caused by waste heat recovery plant modelled in this study.

There is also a post-processing need for decarbonization scenarios (how they are configured in EnergyPLAN is explained in the next section). For the cost correction, the amount of electricity produced by the WtE plant (fully sold to the grid) must be multiplied by the DAM price in 2023 from the NordPool, and the total amount must be added as revenue (while the cost for electrical import in this case is directly calculated by EnergyPLAN). The imported industrial excess heat must be calculated like the baseline scenario. For alternative scenarios that incorporate a CCS unit, this unit's total annual cost contribution must be post-processed, as EnergyPLAN does not provide an appropriate section to define such a cost. The CO_2 price must be calculated as in the baseline scenario. Lastly, the cost of heat pump and electric boilers must be calculated based on adopted capacity values by the MOEA. For the total CO_2 emissions correction, the imported electricity amount must be multiplied by the national grid emission factor given above and added on the reported value by EnergyPLAN.

3.2. A Model and an Algorithm for Decarbonization Scenarios

After establishing the baseline scenario and cost database for decarbonization scenarios, a MOEA is implemented to explore different decarbonization strategies over a large space of admissible solutions. Due to its effectiveness and long track of records [42], the NSGA-II (Non-dominated Sorting Genetic Algorithm) is selected to find sets of non-dominated solutions that were feasible with respect to energy system constraints. The fast non-dominated sorting technique based on the crowding distance calculation and selection elitism of the NSGA-II are its points of strength, which enabled fast convergence to a solution [43]. The integration of a MOEA with EnergyPLAN follows a structured optimization process.

First, a model of the problem is drafted, starting from the set of decision variables $\boldsymbol{x} \in \mathbb{R}^9$, which are mapped to the following list of technologies:

1. Waste-to-energy CHP plant (1.361 – 2.722 $TWh_{fuel\ input}$/y)
2. Industrial excess heat (0.19 – 0.38 TWh/y)
3. Boiler oil share (0 – 100%)
4. Boiler natural gas share (0 – 100%)
5. Boiler biomass share (0 – 100%)
6. Heat pump (HP) capacity (0 – 681 MW_{th})
7. Electric boiler (EB) capacity (0 – 681 MW_{th})
8. Thermal energy storage (TES) capacity (0 – 100 GWh)
9. Carbon capture and storage (CCS) capacity (0 – 0.278 $MtCO_2$/y)

The boiler capacity is not included in the list of variables since it is the designated technology for satisfying the peak demand supply. The capacity of the designated peak-load technology, the boiler, is deterministically derived from the maximum residual heat demand after accounting for baseload heat supply. Specifically, the installed capacity is fixed to fully cover the peak heat demand that cannot be met by baseload technologies, thereby guaranteeing satisfaction of the heat balance constraint in all simulated scenarios. For this reason, peak-load capacity is not treated as an independent decision variable within the MOEA, but rather as a dependent parameter ensuring the feasibility of the solution space. On the other hand, the type of fuel used in a scenario is determined by the algorithm as a consequence of decision variables. Next, a family of constraints is imposed to ensure technical feasibility and operational

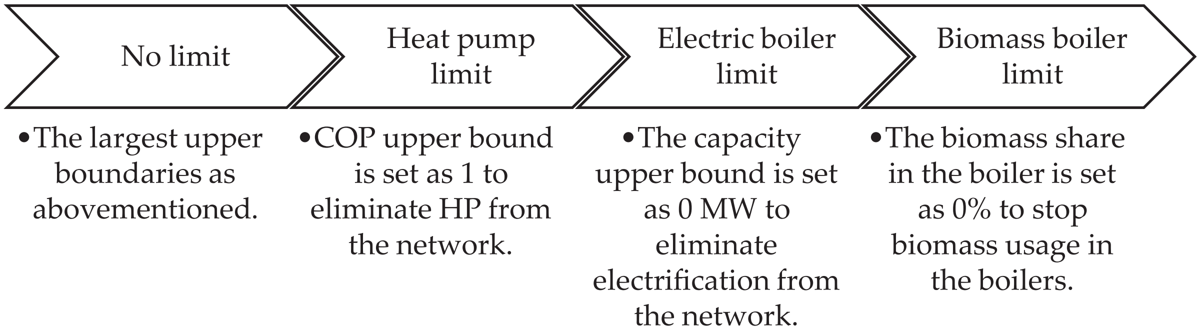

Figure 3: The summary of MOEA integration steps with EnergyPLAN.

limits within the district heating system. The two conflicting objectives to be minimized are $f_1(x)$ CO_2 emission and $f_2(x)$ total annual cost. A formal definition of the problem is as follows:

$$\min_x f_1(x)\ (\text{total } CO_2 \text{ emission})$$

$$\min_x f_2(x)\ (\text{total annual cost})$$

$$\text{such that}$$

$$x_i^{min} \le x_i \le x_i^{max}, \forall i = 1, 2, \ldots, 8, 9$$

Where x_i^{min}, and x_i^{max} are the lower and upper bound of variable i, respectively.

Through an iterative procedure, MOEA generates and refines solutions, exploring trade-offs between CO_2 emissions and total annual cost. During each iteration, after setting the value of decision variables, the required thermal power from the boiler to satisfy the demand all hours of the year will be set.

3.3. Scenarios Optimization and Analysis

A four-step numerical experiment is designed to see the different technologies' effects on decarbonization. Starting from the set of available technologies listed in the previous section, subsequent scenario optimization is carried out by progressively limiting the capacity of a technology as in Figure 3.

The progressive constraint sequence adopted in this study reflects both system-specific conditions and realistic decarbonization pathways. In the Norwegian context, the electricity grid is already almost fully renewable [38] and with low prices, making electrification-based solutions such as heat pumps and electric boilers the most natural and expected first-step options for reducing emissions. Heat pumps are prioritized due to their high efficiency, followed by electric boilers, which provide operational flexibility for peak demand coverage. Biomass boilers are constrained last, as biomass represents a zero-emission but cost-sensitive option in this case study. As discussed previously, after Table 2, the biomass fuel mix is dominated by biofuels rather than conventional wood pellets, resulting in higher fuel costs compared to typical literature values. Under these conditions, biomass-based solutions are not expected to emerge before electrification options in cost-optimal solutions. Importantly, each constraint step is modeled independently rather than cumulatively. Therefore, the sequence does not influence the resulting technology selection but instead provides a structured and transparent framework for comparing decarbonization scenarios under consistent boundary conditions.

Once the optimization process is completed, the resulting scenarios will be systematically analyzed and interpreted. The first step involves comparing the optimized solutions with the baseline case in order to quantify the cost reductions achieved for given levels of emission reduction. Beyond the numerical improvements, attention is placed on understanding how these outcomes are obtained—specifically, which technologies are selected, at what capacities, and under what operating conditions. Identifying realistic solutions is essential, as certain scenarios may offer low emissions but prove economically infeasible or technically impractical.

Building on these insights, the analysis aims to distinguish between feasible and unrealistic pathways, thereby strengthening the basis for actionable recommendations. The outcomes will outline the necessary steps for transitioning toward a decarbonized and cost-effective district heating system, while also providing guidance on the technological directions most suitable for implementation. In this way, the study not only supports local decision-makers in Oslo but also offers transferable insights for other existing networks and planned DHNs in comparable urban contexts.

4. Results and Discussion

In the baseline model, EnergyPLAN provided a total emission of 0.289 $MtCO_2$/y and a total annual cost of 106 M EUR/y. After performing the post-processing for the total annual cost and the total CO_2 emission mentioned previously, this DHN can be operated with 148.17 M EUR/y and 0.294 $MtCO_2$/y. This point will be highlighted in the MOEA results as the baseline scenario. The four-steps optimization experiment was implemented using the Python programming language and the PyMOO library for the NSGA-II. In each optimization run, a population of 100 individuals was considered, and the stopping criterion was set to 50 generations. A total of 5,000 scenarios were evaluated during each optimization run, resulting in 100 non-dominated solutions.

The results of the first step of the optimization process, called "no limit", are presented below in Figure 4. The resulting outcomes were plotted on a graph, with total carbon dioxide emissions on the x-axis and total annual cost on the y-axis.

A distinct slope change is observed in the Pareto front, corresponding to a transition in the optimal technological mix. After this inflection point, CCS technologies begin to dominate the solution space, as additional emission reductions can only be achieved through their larger deployment, leading to a steeper cost increase. Figure 5 illustrates the evolution of the Pareto front as the optimization algorithm progresses through the 50 generations. Each curve represents the set of non-dominated solutions at a given generation, highlighting how the trade-off between objectives improves over time. The final Pareto front is well-defined, indicating that the algorithm has effectively explored and optimized the solution space, yielding a good convergence with a robust set of trade-off solutions.

The hypervolume indicator was employed to show that the NSGA-II converged towards a set of solutions. Figure 6 depicts the evolution of the hypervolume indicator over iterations. A steady increase in hypervolume reflects progressive improvement of the Pareto front, while a plateau over successive generations indicates that the solutions have converged. It is important to note that the plateau value does not necessarily equal 1, as it depends on the reference point selection; the key indicator of convergence is the stabilization of hypervolume rather than its absolute value.

The key aspect at this stage is to examine the annual values of actual heat production and classify them technologically. In this optimization process, all individuals were simulated in EnergyPLAN, considering the selected

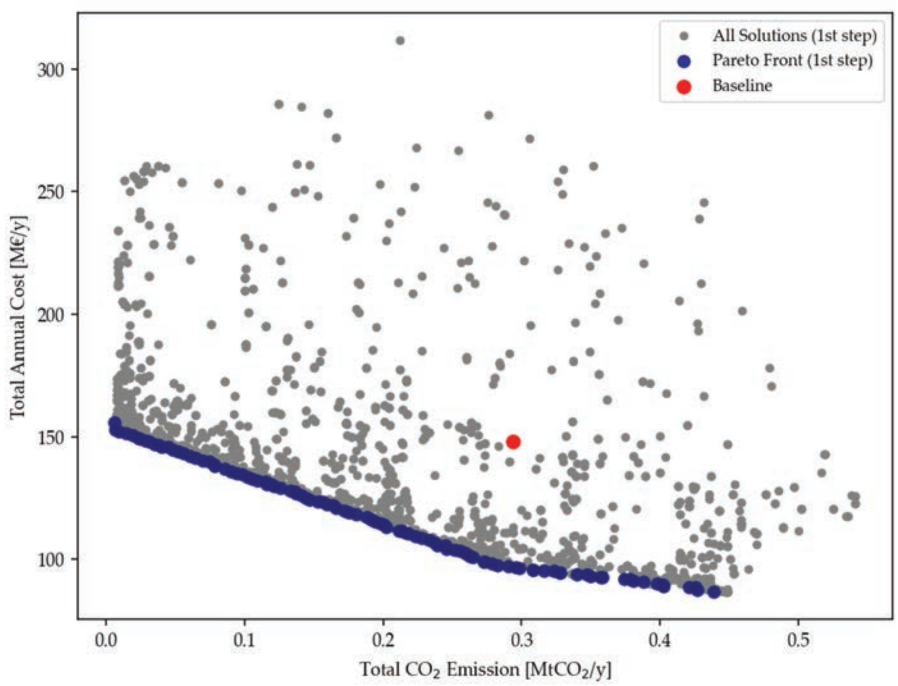

Figure 4: No limit scenario optimization results with 5,000 solutions and the baseline point.

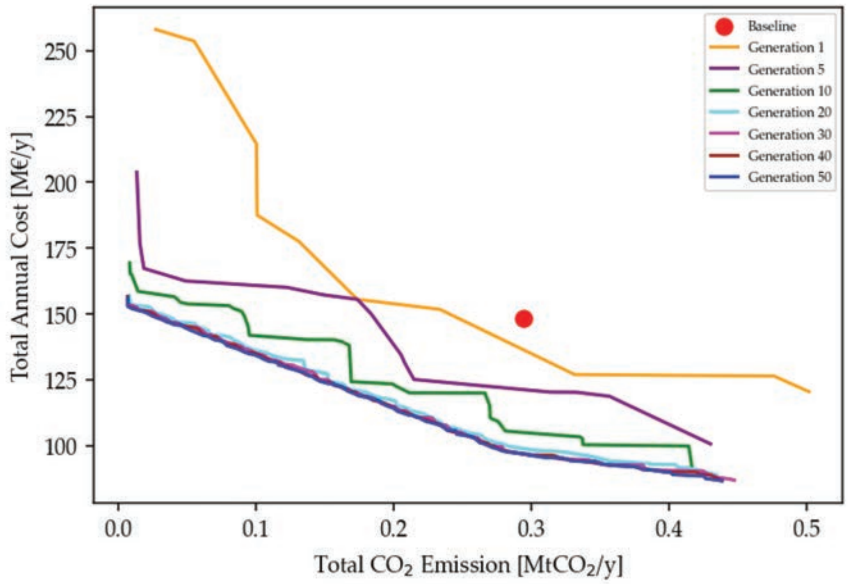

Figure 5: The Pareto front evolution from generation 1 to generation 50 in no limit optimization step.

decision variables and the corresponding boiler capacity needed to be sure that the demand is satisfied. As a result, both the size of the decision variables and the annual heat production values were obtained as outputs. Using these outputs in the final Pareto front of the 50 generation, the graph in Figure 7 illustrates total CO_2 emissions along with the technological breakdown of total heat production and the installed CCS capacity for the first optimization step.

The analysis of annual heat production shows that WtE plants, heat pumps, and industrial excess heat are the main contributors. WtE plants always operate at least at their minimum capacity, and expanding WtE (reducing costs but increasing emissions) reduces reliance on heat pumps while increasing off-demand heat dissipation.

A total of 77 decarbonization solutions were identified, 64 of which reduce emissions while lowering

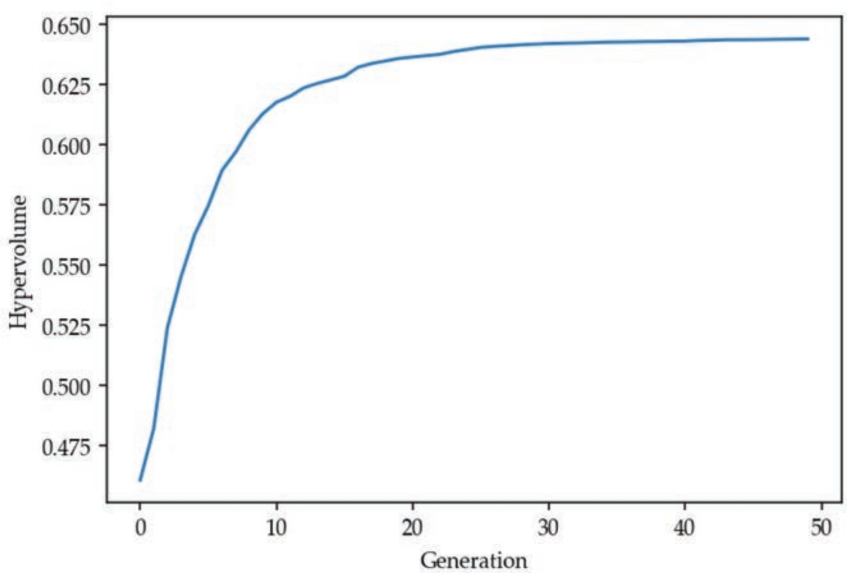

Figure 6: The hypervolume evolution over iterations, showing convergence and improvement of the Pareto front in the first optimization step.

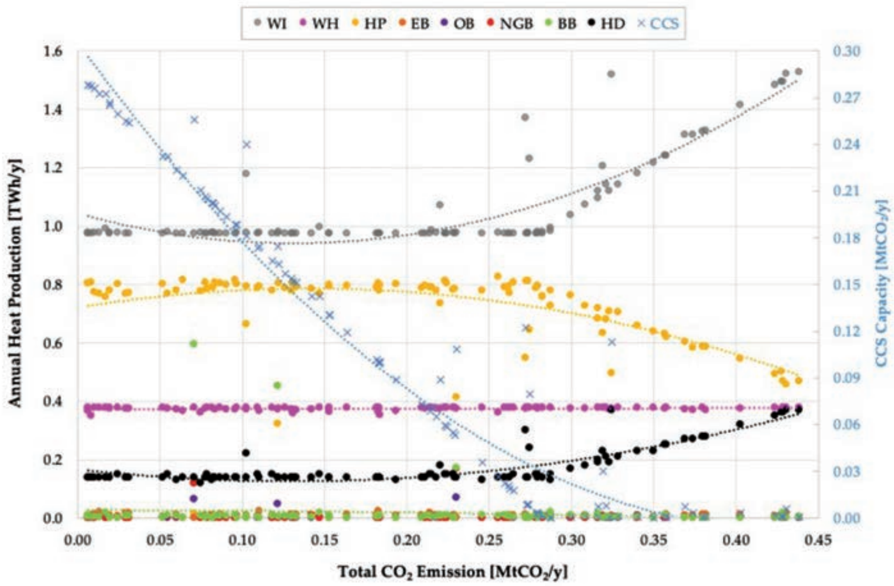

Figure 7: Total CO_2 emission values and technological distribution of the total heat production in each individual of the final Pareto front of the 50 generation with installed CCS unit capacity of the first optimization step (WI: waste incineration, WH: waste heat, HP: heat pump, EB: electric boiler, OB: oil boiler, NGB: natural gas boiler, BB: biomass boiler, HD: heat dissipation, CCS: carbon capture and storage).

annual costs (compared to the baseline). Heat pumps are consistently selected as peak suppliers alongside industrial excess heat because their higher thermal output makes them more cost-effective than electric boilers, despite higher investment costs. CCS adoption reduces emissions further but increases total annual costs, reflected in the slope change of the Pareto front.

The minimum emissions achievable without exceeding baseline costs is 0.031 $MtCO_2$/y (a 90% reduction), with 0.25 $MtCO_2$/y of CCS capacity. Nearly 34% cost reduction is possible using a better (than the baseline) combination of existing WtE, heat pumps, and waste heat without changing emissions. However, achieving maximum emission reductions relies heavily on the availability of significant CAPEX for investments in large-scale heat pumps which may be impractical currently. Overall, aside from heat pumps and waste heat, other technologies contribute little to total heat production, motivating the second optimization stage to explore scenarios without heat pumps.

In the second optimization step, heat pumps are removed from the system, and the focus is on electric boilers using imported electricity alongside other technologies. Figure 8 presents the resulting Pareto front of the 50 generation, showing total CO_2 emissions together with the technological breakdown of total heat production and the installed CCS capacity.

In the second-step optimization, the removal of heat pumps shifted the system toward electric boilers as the main decarbonization solution, complemented by waste heat operating at its maximum capacity. Biomass was considered but could not outperform electric boilers due to high fuel costs and the specific biomass composition, which included biodiesel.

A total of 48 solutions reduced CO_2 emissions compared to the current level, with only 9 achieving both decarbonization and slight reductions in total annual cost. In these solutions, waste heat remains fully utilized, the WtE plant continues operating at or above baseline capacity, electric boilers supply the remaining heat, and CCS is incorporated for deeper decarbonization. Overall, this step demonstrates that substantial emission reductions and modest cost savings are achievable even without heat pumps, highlighting the continued importance of electrification and waste heat integration.

In the third step of the optimization, the goal was to explore potential decarbonization outcomes by completely preventing electrification, removing not only the heat pump but also the electric boiler from the system. Figure 9 presents the resulting Pareto front of the 50 generation, showing total CO_2 emissions alongside the technological breakdown of total heat production and the installed CCS capacity.

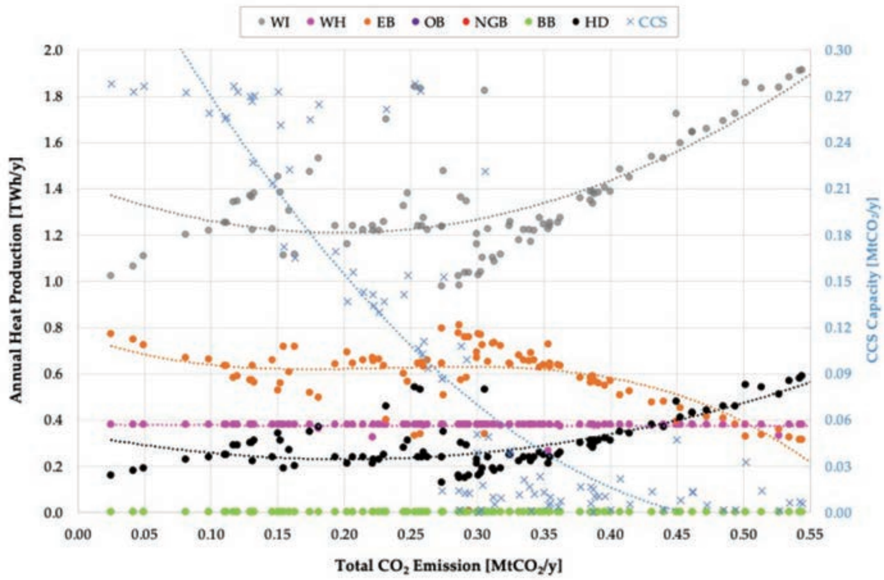

Figure 8: Total CO_2 emission values and technological distribution of the total heat production in each individual of the final Pareto front of the 50 generation with installed CCS unit capacity of the second optimization step.

In this step, waste heat remains fully integrated, while the remaining heat demand is met by biomass boilers. CO_2 emissions can be further reduced through CCS adoption. Increasing WtE plant capacity allows the system to operate at higher emissions while reducing costs, consistent with previous steps. Out of 100 non-dominated solutions, 57 achieve decarbonization but always with higher costs than the baseline. Full decarbonization requires costs above current levels, while are possible scenarios that maintain similar emissions at ~5% higher cost. For total costs of 150–170 M EUR/y (so close to the baseline value), solutions are dominated by CCS unit, a high-capacity WtE CHP plant, waste heat recovery plant, and biomass boilers.

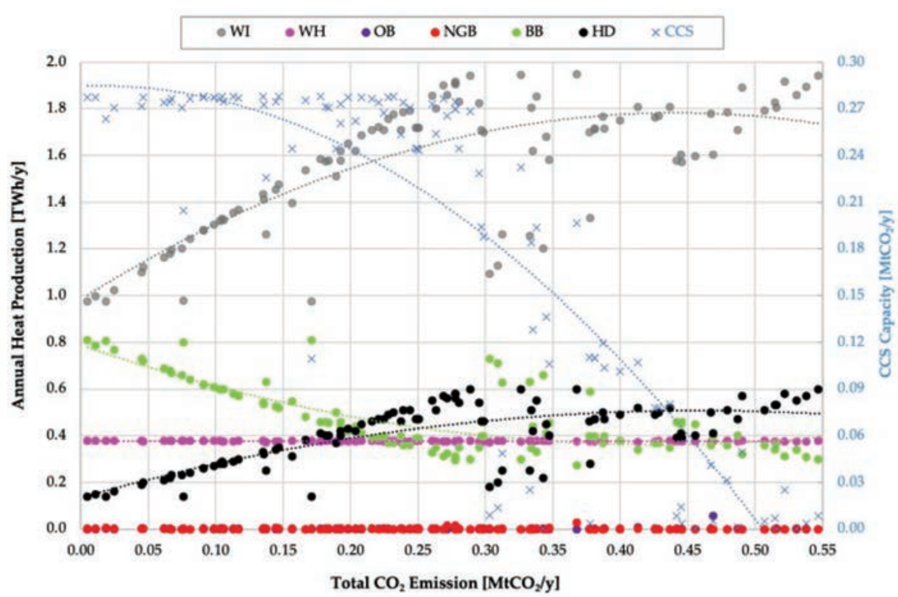

Figure 9: Total CO_2 emission values and technological distribution of the total heat production in each individual of the final Pareto front of the 50 generation with installed CCS unit capacity of the third optimization step.

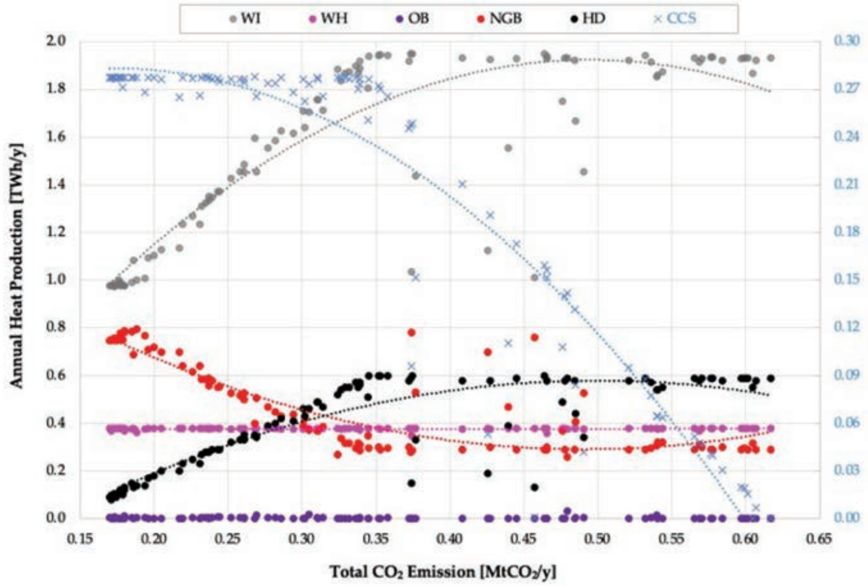

Figure 10: Total CO_2 emission values and technological distribution of the total heat production in each individual of the final Pareto front of the 50 generation with installed CCS unit capacity of the fourth optimization step.

In the final optimization step, the aim was to assess decarbonization potential and associated costs after removing the three main previous decarbonization technologies: heat pumps, electric boilers, and biomass boilers. Figure 10 presents the resulting Pareto front of the 50 generation, showing total CO_2 emissions alongside the technological breakdown of total heat production and the installed CCS capacity.

The upper limit for CCS was set to absorb emissions from the WtE plant in the current system. Therefore, no solutions with zero CO_2 emissions are observed in the results, as the technology required to meet the heating demand after the WtE plant and the waste heat is the high-emission natural gas boiler. In the minimum-emission solutions, maximum CCS capacities are present, while in the high-emission scenarios, this CCS adaptation decreases (because more costly than other technologies). When looking at the 100 non-dominated results, only 43 offer decarbonization solutions, and even the lowest-cost option is approximately 20% more expensive than the current annual cost in the baseline. All these decarbonization solutions have included CCS at the upper bound in the system, which further proves that no alternative decarbonization technology is available.

Figure 11 presents all Pareto fronts from the optimization steps on a single plot, allowing direct comparison of cost–emission trade-offs under different technology configurations. Each set of points represents the non-dominated solutions from one optimization step. As technologies are removed along optimization steps, the fronts shift towards higher annual costs and higher CO_2 emissions, starting with the no-limit scenario be the most attractive, and progressing to the final step without heat pumps, electric boilers, and biomass. This shift indicates that removing key decarbonization technologies increases costs for achieving similar emission reductions or limits the achievable emission reductions for the same cost.

5. Conclusion and Future Work

The main motivation of this study was to minimize the effects of global warming through decarbonization, with district heating systems offering an effective way to utilize waste heat and renewable energy sources. Despite their potential, these systems remain underutilized in Europe.

First, a baseline model of the Oslo DHN was created in EnergyPLAN using operator-provided data, and annual CO_2 emissions and costs were estimated, with literature references used where company financial data were unavailable.

Then, using EnergyPLAN, a set of decision variables and corresponding upper and lower limits were defined

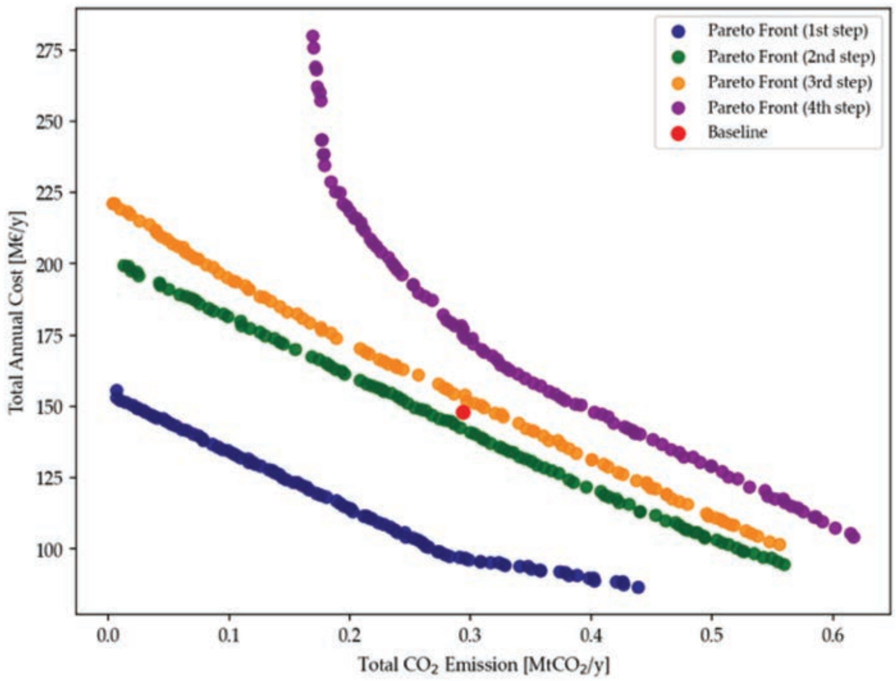

Figure 11: All optimization steps' Pareto fronts and the baseline point.

to integrate with the MOEA optimization process, which was carried out in four steps analyzing 5,000 scenarios per step. In the first step, heat pumps played a major role in decarbonization, complemented by maximum integration of waste heat. In the second step, with heat pumps removed, electric boilers emerged as the primary replacement technology due to their low investment cost and the high price of biomass fuel, while waste heat remained at its upper bound. In the third step, with electric boilers removed, biomass boilers supplied peak demand. Across all scenarios, achieving near-zero emissions required integration of a CCS unit, which however significantly increased annual costs. In the final step, with biomass boilers removed, even maximum CCS capacity (with upper limit set to absorb emissions from the WtE plant in the current system) could not achieve zero emissions due to the inclusion of natural gas boilers.

Overall, the findings indicate that, in the Oslo case study, waste heat recovery plants and sector coupling (electrification based firstly on heat pumps and secondly on electric boilers) are the most cost-efficient solutions for the district heating decarbonization, compared to biomass boilers and CCS unit. Moreover, this study confirms the key role of an energy system integration approach: linking sectors will allow a better cost-effective optimization of the energy system as a whole, rather than decarbonizing and making separate efficiency gains in each sector independently.

These findings are in line with recent system-oriented perspectives on the role of district heating in the energy transition. As highlighted by Lund et al. [44] and within the fourth-generation district heating framework [6], the future of district heating lies in low-temperature operation, sector coupling, and the integration of waste heat and large-scale heat pumps within smart energy systems rather than in single-technology solutions. At a more operational level, Lund et al. [45] demonstrate that low supply and return temperature levels required for fourth-generation district heating are technically feasible and beneficial for overall system efficiency. While these studies primarily focus on conceptual frameworks and consumer-side measures, the Oslo case study provides a quantitative system-level assessment, showing how such low-temperature and integrated operating conditions translate into cost-optimal technology portfolios dominated by waste heat recovery and electrification-based solutions.

Compared to previous case studies reported in the literature, which typically focus on specific technologies, individual urban or regional systems, or planning-oriented modeling approaches [16,18–33] the Oslo case study confirms at a full system scale that waste heat recovery and electrification-based sector coupling remain the dominant cost-optimal pathways for district heating decarbonization under realistic operational constraints.

Moreover, not only the findings of the case but also the joint tools and methodologies can be highlighted. Recent reviews of energy system modelling tools highlight a clear trend toward coupling specialized simulation models with optimization and decision-support frameworks, acknowledging that no single tool can adequately address the full complexity of energy transition pathways [46]. In this context, the combined use of EnergyPLAN and a multi-objective evolutionary algorithm in the Oslo case aligns with state-of-the-art modelling practice by enabling interpretable system-level insights under realistic operational constraints. Particularly, the consistency of the model structure, performance indicators, and system behavior with widely documented EnergyPLAN applications provides inferred validation of the approach, thereby enhancing the credibility of the results through alignment with outcomes reported in previous EnergyPLAN-based studies [47].

Finally, this study offers a replicable methodology for the cost-optimal decarbonization of a DHN and valuable insights for decision-makers and operators exploring similar decarbonization strategies.

Future developments could focus on integrating seasonal TES to reduce summer heat dissipation and utilize it in winter, potentially enhancing decarbonization. Currently, EnergyPLAN does not support seasonal TES modeling, but its inclusion in future versions could expand the study's technological scope.

Computational efficiency in the MOEA optimization could also be improved by introducing convergence criteria, as most steps converged early but all generations were still computed, increasing time and cost.

Regarding short-term storage, daily TES tank is not selected in any of the cost-optimal solutions, despite being included as a decision variable in the optimization framework. This outcome is primarily driven by the relatively high capital investment costs of TES compared to its marginal system benefits under the current system configuration. The Oslo district heating network exhibits a stable heat demand profile and a high share of baseload supply from waste-to-energy and industrial waste heat sources, which reduces the need for additional short-term load shifting. Peak demand is instead addressed more cost-effectively through heat pumps and electric or biomass boilers, which directly reduce operational costs and emissions within the applied objective functions. Nevertheless, future reductions in storage investment costs or significant changes in demand variability could improve the competitiveness of daily TES; however, such developments were beyond the scope of the present study and were therefore not explicitly assessed.

Additionally, environmental impacts and life cycle assessments were not considered here but incorporating them in future studies would provide a more comprehensive evaluation of decarbonization strategies for the Oslo DHN.

Data Availability

The data used in this study include operational and technical information provided by the district heating operator, Hafslund CELSIO, which are subject to confidentiality agreements and therefore cannot be publicly shared. Aggregated data and derived results supporting the findings of this study are included within the article. Additional non-confidential data may be made available from the corresponding author upon reasonable request.

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