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Published in:
Applied Energy

Link to article, DOI:
10.1016/j.apenergy.2023.121442

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Applied Energy 347 (2023) 121442

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

A decision support system for green and economical individual heating resource planning

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ARTICLE INFO

Keywords:
Decision support system
Decentralized heat sources
Long-term strategic planning

ABSTRACT

The heat sector accounts for almost half of the world's energy consumption, making it a crucial component in meeting decarbonization targets. One of the biggest challenges of heat energy decarbonization arises at the household level, which collectively has a substantial impact on decarbonization. Individual households commonly rely on decentralized heat sources (DHS). Different technologies can be used as a DHS, each of which leads to different overall (Capex and Opex) costs and carbon emissions. Households choose their DHS technologies freely, though typically influenced by the recommendations from their local city planners who use historical data and analyze the respective economical and environmental consequences. Therefore, developing a decision support system (DSS) that guides individuals in their DHS investment choices is a high priority for city planners as it can help evaluate the role of different policies in aligning economical and environmental concerns. This is becoming more important as both the economical and environmental concerns are increasing, respectively, due to recent energy price spikes and the growing urgency of decarbonization. However, developing such a comprehensive DSS is challenging due to the complexity of accounting for all DHS constraints and the uncertainties in demand, prices, and policies. In this study, we present a reliable and comprehensive DSS that provides a range of optimal strategies including the most cost-efficient and the most environmentally friendly ones. These strategies identify the optimal type, installed capacity, and year of investment of DHS technologies, as well as the expected yearly heat generation of each technology. Our DSS accounts for the uncertainties of heat demand, fuel prices, investment, and operation and maintenance costs. We apply our DSS to a typical household in the municipality of Lyngby-Taarbæk under different policy scenarios. We show that between the most environmentally friendly and most cost-efficient solution only a gap of 9%–15% in cost needs to be bridged. We also demonstrate that current energy taxation policies in Denmark do not provide a level playing field between different heat technologies. Under different policy scenarios, we show that heat pumps integrated with PV have the highest potential for minimizing CO2 emissions for a Danish household.

1. Introduction

According to Ref. [1], global carbon emissions are expected to increase significantly by 2050, primarily due to economic growth and increasing energy demand, which outweigh future improvements in energy efficiency. To combat this, reducing greenhouse gas emissions, especially carbon dioxide, has become a clear policy goal for many countries over the past decade. As a result, all energy sectors worldwide are taking steady steps toward decarbonization to reduce their carbon footprint, promote the renewable-based generation, and create an environmentally friendly system. In 2021, the building sector accounted for 37% of energy-related CO2 emissions globally [2], with residential buildings accounting for 75% of this total [3]. Since most residential energy consumption is due to heat consumption, decarbonizing individual heat consumption is a crucial step in meeting national or international carbon emission reduction targets [4].

City planners play a pivotal role in decarbonizing the heat sector by developing sustainable and efficient heating strategies that reduce greenhouse gas emissions, integrate energy efficiency measures, and support the uptake of renewable energy resources (RES) [5–9]. One clear pathway for decarbonization that city planners can take is implementing district heating (DH) systems, which generate the heat supply

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https://doi.org/10.1016/j.apenergy.2023.121442
Received 11 January 2023; Received in revised form 20 April 2023; Accepted 10 June 2023
Available online 26 June 2023

centrally and then distribute it through hot water to individuals for their hot water and space heating needs. DH is an ideal pathway for decarbonizing heat demand and a critical tool for achieving significant carbon emissions reductions. However, legal or geographical restrictions often hinder building new DH stations for the purpose of heating urban districts, or in some cases, the connection cost might be too high, making DH economically infeasible.

Districts without current or future access to district heating (DH) rely on small-scale decentralized heating sources (DHS) for thermal energy. There is a wide range of DHS technologies that vary in costs, emissions, and operational restrictions. To serve their heat demand, households freely choose their DHS technology, but they may prioritize economic concerns over environmental ones without a clear understanding of the consequences. This is due to the wide range of DHS types and fuels, as well as the difficulty of predicting future heat demand and supply matching. As a result, households often seek advice from city planners on the economic and environmental impacts of each DHS. Depending on household preferences and existing and future regulations, solutions could range from the most cost-effective to the most environmentally friendly. This difference is becoming more crucial as energy prices become volatile and sustainability goals become more critical. City planners can act as smart agents by providing informed decision support to guide households towards economical, low-carbon heating solutions. Thus, they actively seek reliable and comprehensive Decision Support Systems (DSS) to bridge the gap between their sustainability goals and the households' need for a reliable and efficient heat supply. Policymakers can also use such a DSS to investigate the impact of different policies on the long-term sustainability of the heat supply.

While there is a dire need for a reliable and comprehensive DSS for city planners, this is currently missing in practice because of multiple sources of complexity. Firstly, DHSs are composed of various types of technologies with different operational and physical restrictions, investment costs, fuel types, carbon footprints, and lifetimes. Incorporating all of these diversities in an inclusive DSS is complex. Secondly, the desirable DSS should account for multiple and often conflicting objectives, such as minimizing the overall carbon emissions and minimizing the energy investment and operation costs for the individual. Thirdly, the DSS should factor in several stochastic processes (such as heat demand, solar power, fuel and electricity prices, taxes, etc.) and their projections for the future. Fourthly, the decision support model must be flexible and extensible to other local or district areas, reflecting their local regulatory framework conditions and energy orientations. Lastly, the DSS should be generalizable and applicable to a wide range of heat supply technologies, different sustainability targets, heat demand and price profiles, regulatory projections, etc. Our study aims to develop a DSS that can address all of these challenges successfully.

This study addresses a growing need for city planners to promote the heat energy transition of citizens in areas where DH solutions are not available. Additionally, it helps policymakers investigate the impact of various policy scenarios on DHS choices and the collective heat energy transition. Our work falls into the category of model-driven decision support systems that focus on quantitative mathematical modeling as the main component [10], while still using some limited data to tune the model to particular cases [10–12].

Our proposed DSS addresses four key aspects that have not been studied simultaneously before. First, we account for a vast number of uncertainties (e.g., supply, demand, and price) in the optimization calculation and include detailed operational restrictions of the underlying DHS technologies to achieve robust, inclusive, and practical solutions. Second, we use an extended time frame that accounts for the entire lifetime of technologies, allowing us to define the optimal DHS mix on a yearly basis and anticipate heating equipment replacement. Third, we incorporate important policy and restriction scenarios to enable examining their impact on the DHS choice for households. Finally, we subject all of the above parameters to a multi-objective function that minimizes both heating cost and carbon emissions. This approach explores and informs on the trade-offs between the least cost and least carbon emissions and allows us to strike the optimal balance between private budgetary and societal environmental objectives. To the best of our knowledge, this study enhances the existing state-of-the-art DSS models for optimal DHS investments and planning by considering multiple technologies, accounting for demand uncertainties, and representing regulatory risks over an extended period.

We apply our proposed DSS to a practical Danish case. Denmark has a long tradition of involving municipal actors in the choice of heating infrastructure – and mix – at the city level. A large share of the population (63% in 2022) is connected to DH and 15% to natural gas networks. The rest of the heating demand is historically supplied by oil and gas furnaces. The Danish political agreement on heating targets a phaseout of 120,000–170,000 (out of 350,000) gas boilers by 2030 and targets a progressive complete phasing out of oil and gas boilers, replaced by rolling out district heating and clean heating equipment such as heat pumps [13]. Projections indicate that 30%–50% of households will have district heating by 2028 and 20% of households will have heat pumps by 2030, creating a gap in fossil fuel heating replacement in the announced time frame [14]. This discrepancy, combined with the rising prices of hydrocarbons since 2022, puts increasing pressure on municipalities, which are the main actors in guiding households' energy choices until they are connected to district heating. Therefore municipalities are in need to obtain a concrete assessment of the situation to be able to inform and encourage households who do not have direct access to DH in the transient time, to efficiently choose their heating technology. We, particularly, focus on the municipality of Lyngby–Taarbæk as a representative of many other municipalities that face the challenge to cope with expanding urban development and carbon emissions mitigation requirements. Lyngby–Taarbæk has set a target of a minimum of 20% reduction in carbon emissions during the forthcoming decade. Additionally, the municipality's climate partnership with the Danish Society for Nature Conservation requires 2% carbon emissions reduction yearly from the building sector. These goals cannot be achieved without steering the DHS in a sustainable way (as it accounts for 48% of the overall demand in the municipality) and this cannot happen without having an efficient DSS. Applying our DSS model to this case, we have provided them with some interesting observations and new insights.

Our key contributions can be summarized as follows:

1. **Theoretical/Methodological contribution:** To the best of our knowledge, the model we developed for our DSS stands out from the existing ones, in terms of comprehensiveness, inclusiveness, and generalizability. Moreover, this DSS allows a comparison of the impacts of a selection of policy and regulatory factors on households' possible choices of technologies.
2. **Real-world data and an actual case:** By applying our model to real-world data and the case of Lyngby–Taarbæk in Denmark, we gain valuable insights into the optimal choices of DHS technologies and how they are influenced by underlying policies.
3. **Policy/Managerial implications:** Our DSS can be used by the city planners and policymakers which can, respectively, affect individual heat decarbonization and recognize the impact of different policies on heat decarbonization. Our results also provide insights into the effectiveness of existing policies. For example, we demonstrate how some policies and regulations may overlap, reinforce, cancel each other out, or have a limited impact.

The paper is organized as follows: In the next section, we provide a review of the relevant literature. We present our DSS model formulation in Section 3. Section 4 outlines the details of the case study for our numerical investigations. In Section 5, we show the results and provide new insights. We conclude the paper and discuss the limitations of the work in Section 6.

2. Related literature

Decision support systems for long-term planning of heating systems have gained much attention among industry and researchers in recent years. Ref. [15] provides a comprehensive review of different modeling approaches for energy systems at the district level. Ref. [16] reviews urban energy system modeling approaches, challenges, and opportunities in five key practice areas: technology design, building design, urban climate, systems design, and policy assessment.

Most studies use Mixed-Integer Linear Programming (MILP) while modeling single- or multi-objective functions. A large share of prior literature focuses on single-objective optimizations, only considering either cost minimization or carbon emission minimization [17,18]. Some others only consider the minimization of investment cost, but include the taxation of carbon emissions [19–22]. Indeed, long-term planning requires multi-objective optimization to offer some balance between cost and carbon emission minimization. Only a few studies have accounted for such a multi-objective design. Morvaj et al. use a mixed integer linear programming model to minimize total cost and carbon emissions [23]. Their model considers 288 time steps representing one day per month for a single year. Karmellos et al. present two multi-objective models with the aim of designing distributed energy systems to satisfy the heat demand [24]. Their multi-objective MILP framework compares two main approaches for design when minimizing the total cost and carbon emissions as objective functions. They consider a single year for planning considering six periods per day for three typical days for every season in the year. In another work, Testi et al. provide a model that incorporates a multi-objective stochastic optimization of the expected performance of the system and the risk index measured to achieve a low percentile of the annualized cost-saving percentage [25]. Their model incorporates demand and fuel costs uncertainties and makes a simplifying assumption that all technologies have the same lifetime (20 years). Another multi-objective framework aiming to balance cost and emission minimization is presented in [26]. The authors focus on household-scale systems to promote green technologies such as solar heat collectors and heat pumps. The model considers a one-year planning horizon in a deterministic setting. In another work, Moret et al. use a simple model for demand uncertainty to propose a DSS for long-term strategic planning for the choice of technology in energy systems using robust optimization [27].

There are also some studies that focus on the role of regulations in decarbonizing heating sources and equipment. At the electricity–heat interface, two recent studies [28,29] list the regulatory barriers in detail, distinguishing at which stage of the project life cycle each obstacle occurs and describing its level of origin. Essentially, tax exemptions and the tariff structure for electricity transmission are identified as two fundamental barriers affecting the competitiveness of some green technologies (e.g., biomass) and electricity for heating [28,30–34]. These studies also indicate that the generalized omission of network tariffs in the calculation of the marginal cost for electricity – or gas – tends to achieve results often too optimistic regarding the future investment of electricity-based heating, often at the benefit of biomass-based heating [33]. Although most of these studies focus on district heating, the substitution effects triggered by these regulations can be found in individual heating. Concerning individual heating in dwellings, past studies assess and demonstrate that subsidies for the replacement of heating equipment are a powerful driver to accelerate the technological shift, especially from gas or fuel boilers to heat pumps or wood stoves [35–37]. Krützfeldt et al. reveal that the costs linked to regulation are often missing from studies using similar MILP approaches, which tend to drift results away from the optimum [38]. Other studies [39,40] include grid tariffs and taxes in their respective cost estimate, allowing more policy-oriented recommendations. These studies highlight the gap between the *socio-economic optimum* (where only the operating and capital costs are considered), and the *political optimum* (which also incorporates subsidies associated with energy solutions).

While these prior studies shed light on the optimal decisions for the heating sector decision, a reliable and comprehensive DSS for individual heating is still missing for multiple reasons. First of all, most existing models consider a single objective function, which is mainly cost minimization, and factors in carbon emissions as carbon taxes. This simple model cannot capture the trade-off between cost and sustainability, which are often conflicting objectives. Secondly, most previous work has limited time horizons for planning, for example taking sample days for the planning of a single year. This limitation prohibits the realistic consideration of the actual lifetime of the technologies being invested in and used, which leads to an inaccurate or incorrect recommendation. Consequently, previous literature that considered longer planning time frames, up to 10 or 20 years, rarely offers insight into the optimal year in which investments should take place. Thirdly, existing studies fall short in accounting for uncertainties in long-term planning. It is evident that there are multiple uncertain factors, such as heat demand, fuel prices, and investment costs that have a direct impact on the optimal results and strategies. Fourthly, the effects of policy and regulation on energy technologies, cost, carbon footprint, and ultimately, heating technology choice are often disregarded. Finally, because of the fundamental differences in the operational restrictions of different heat technologies, prior studies mostly build their model for a specific choice of technology. In this study, we fill this gap by providing a reliable and comprehensive DSS that accounts for all of these shortcomings.

3. Decision support system

In this section, we elaborate on the optimization formulation and the solution approach used in the proposed decision support system (DSS) for long-term strategic planning of distributed heating sources. We formulate a multi-objective optimization and cast it as a mixed-integer linear programming (MILP) problem. The first objective function concerns the minimization of the total DHS investment and operational cost. The second objective function focuses on minimizing the carbon emissions from the invested DHS. Considering both objectives allows us to investigate the trade-off between the cost and carbon emission minimization, which leads to a range of potential long-term planning strategies extending from the least total investment and operational cost (cost-optimal) to the least carbon emissions (environmental-optimal) portfolios.

Fig. 1 summarizes the inputs and the outputs of the proposed decision support model. The DSS takes as input the desired planning horizon, all costs related to investment, operation, and fuel for all considered DHS technologies, the lifetime of such technologies, and their carbon emission factors. The output is a range of potential long-term strategies that is illustrated as a Pareto front, where every point on the Pareto front on the graph represents a different optimal strategy at a given carbon emission target. Every strategy produces a different set of decision variables values: (1) the optimal types of DHS technologies to be purchased; (2) the optimal size and yearly heat generation of each DHS, and (3) the optimal year at which every DHS investment should take place. Our model ensures the total heat demand of the individual is served and the peak heat consumption does not violate the available heat supply capacity of the operational DHSs.

The proposed DSS is designed for long-term planning, (e.g., 10–30 years ahead), and accounts for the uncertainty of key parameters such as heat demand development, and costs for investment, operation, and fuel (see Section 3.2). A unique feature of the proposed DSS is its generalizability. The DSS can be used in different settings, technologies, jurisdictions, and even scales. While our focus is on the household level, the DSS can also be used for district-level decision-making, treating the district as one large individual. This offers valuable insights to policy-makers to better understand the impact of new policies on society. In the following, we explain the detail of the model.

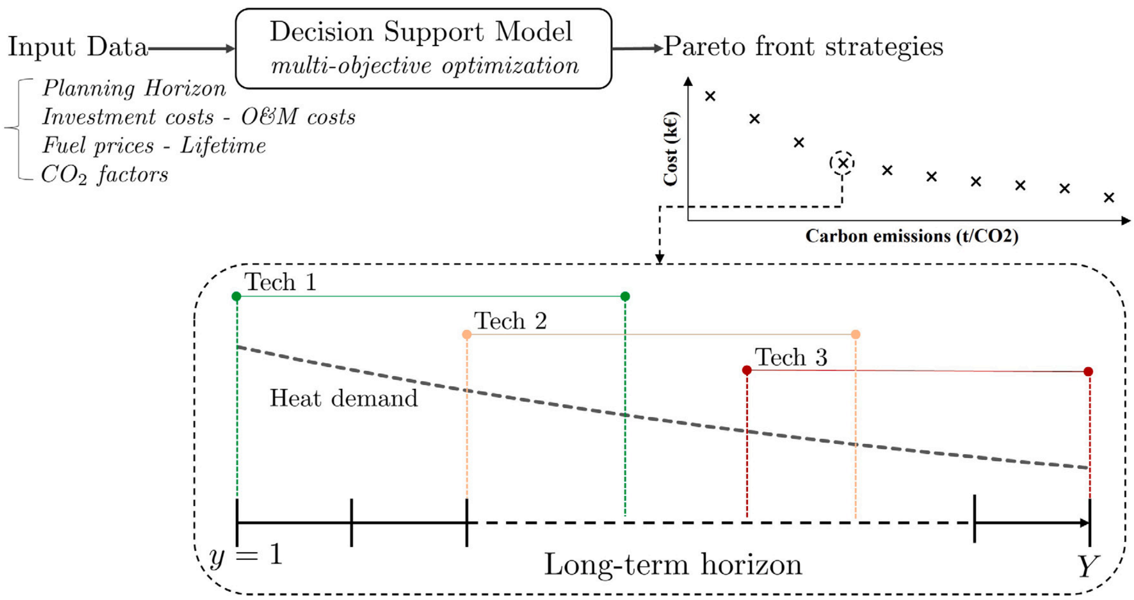

Fig. 1. The inputs and outputs of our proposed DSS.

3.1. Multi-objective optimization problem

We consider a discrete-time model for the planning of the next Y years, where new investments can only happen at the beginning of each year. A monthly time granularity for capacity sizing is modeled since yearly calculations cannot capture seasonal variations. To be more precise, each year y (where $1 \leq y \leq Y$) is subdivided into 12 months denoted by m (where $1 \leq m \leq 12$). Our model ensures that the monthly peak heat demand does not violate the heat supply capacity. We further use the notation T to represent the set of all feasible DHS technologies and t ($\in T$) to refer to any technology in the feasible set. Refer to Table 3 for the nomenclature of all parameters and variables.

3.1.1. Objective function

We consider two objective functions for the DSS and we separately formulate them. The first objective function, denoted Θ in Eq. (1), aims to minimize the total cost of the mix of DHS used at any time and summed over the entire long-term planning horizon. The total cost of each technology $t \in T$ consists of three main components; the investment cost I_t^y, the operation and maintenance costs (O&M) OM_t^y, and the fuel price with grid tariff δ_t^y, and taxes τ_t^y. The investment cost I_t^y of a technology $t \in T$ purchased at the beginning of year y is a function of the installed capacity of the DHS, denoted by C_t^y. The operation and maintenance OM_t^y cost for any technology $t \in T$ in each year y, denoted by OM_t^y. Both cost components, I_t^y and OM_t^y, linearly scale with the installed capacity C_t^y. The fuel prices with grid tariff δ_t^y, and the taxes τ_t^y linearly scale with the total amount of heat energy generated by each technology t in every month m in year y, denoted $Q_t^{y,m}$.

Some DHS technologies rely on the electricity grid to generate heat. For these technologies, additional rooftop solar photovoltaic (PV) panels can be used to serve part of the electricity need, thus saving cost and carbon emission. For example, heat pumps can be integrated with PV panels to help reduce the cost and/or emission of their heat generation. In this case, both technologies will be invested in at the same time. Therefore, for every technology $t \in T$, we use subscript t, pv to refer to the supplementary solar panel installations. As such, a DHS technology can further invest to buy a total capacity of $C_{t,pv}^y$ in year y, which costs $I_{t,pv}^y$ per unit of capacity, but this can cover part of the heat energy demand, reducing fuel (electricity) costs and carbon emission. Solar PV panels have negligible O&M costs thus it is neglected in Eq. (1).

Since the proposed DSS focuses on long-term planning, we assume that investment decisions can only occur at the beginning of each year, i.e. $m = 1$. Furthermore, we incorporate the discounted rate of d throughout the lifespan of the DHS technologies. Combining all the above notation, the first objective, which is the total cost of heat investment and generation, is expressed as

$$\Theta = \sum_{y=1}^{y} \frac{1}{(1+d)^y} \left[\sum_{m=1}^{M} \sum_{t \in T} (I_t^y + OM_t^y) C_t^y + (\delta_t^y + \tau_t^y) Q_t^{y,m} + I_{t,pv}^y C_{t,pv}^y \right] \tag{1}$$

The second objective function formulates the total carbon emission, denoted Φ. Let λ_t denote the carbon emission factor per unit of heat generation from any given technology t. The amount of electricity procured from the grid to supply DHS technologies that rely on the electricity grid is denoted $P_{grid}^{y,m}$. Then, the second objective function can be expressed as

$$\Phi = \sum_{y=1}^{Y} \sum_{m=1}^{M} \sum_{t \in T} \lambda_t^y Q_t^{y,m} + \lambda_t^y P_{grid}^{y,m} \tag{2}$$

Accounting for both objective functions forms our multi-objective optimization problem. In order to solve this problem, the ϵ-constraint method, adopted from Ref. [41], is used. In this method, the optimization problem is solved by minimizing a primary objective, while formulating the secondary objective function as an upper bound constraint that is limited to a value $\epsilon \geq 0$. This method produces a non-dominated set of feasible solutions, namely called trade-off solutions, that collectively form a Pareto front. The primary objective function is the cost function Θ described in Eq. (1), while the secondary objective function is the emission function Φ in Eq. (2). The latter can be considered as the carbon emission allowance set by the municipality, where the optimal technologies identified by Θ should meet. Thus, we can write $\underline{\epsilon} \leq \Phi \leq \overline{\epsilon}$, where $\overline{\epsilon}$ is the maximum allowable carbon emission, or mathematically expressed as

$$\min \Theta \tag{3}$$

$$s.t., \quad 0 \leq \Phi \leq \overline{\epsilon} \tag{4}$$

This means that at different carbon emissions limits, the optimization model produces a set of different optimal investment strategy plans. This set of feasible solutions ranges from the minimum possible carbon emissions at the maximum total cost, to the maximum possible carbon emissions at the minimum feasible total cost.

3.1.2. Optimization constraints

In the following, the underlying constraints for both optimization functions are explained.

• **Heat demand balance:** The sum of all heat generated from all DHS technologies must satisfy the expected demand throughout the planning horizon. In long-term planning, and because of the typical form of data availability in the heat sector, we consider a monthly time resolution for heat demand and supply matching in order to account for the seasonality of heat demand over the year. Let us denote the heat demand during month m of year y by $Q_D^{y,m}$. To balance the heat supply and demand during that month, we must have

$$\sum_{t\in T}(Q_t^{y,m} + Q_{t,pv}^{y,m}) = Q_D^{y,m} \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{5}$$

Besides balancing the heat supply and demand, the sum of all DHS capacities must be sufficient to meet any future peaks. Given the assumption that new capacity investments take place at the beginning of each year, capacity constraints only need to be examined on an annual basis. Let us denote by K_D^y, the peak heat demand over the entire year y. Then, the following constraint ensures that the sum of all installed capacities is larger than the peak demand,

$$\sum_{t\in T}(C_t^y + C_{t,pv}^y) \ge \eta_{sys} K_D^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{6}$$

where $\eta_{sys} > 1$ is the over-sizing margin factor to account for potential heat losses in the system.

• **Capacity and heat generation bounds:** For any given technology t, the installed capacity C_t^y, and amount of heat generation $Q_t^{y,m}$ are bounded between maximum and minimum limits. This is mathematically expressed as

$$v_t^y \underline{C}_t \le C_t^y \le v_t^y \overline{C}_t \qquad \forall\ 1 \le y \le Y \tag{7}$$

$$0 \le C_{t,pv}^y \le v_t^y \overline{C}_{t,pv} \qquad \forall\ 1 \le y \le Y \tag{8}$$

$$u_t^y \underline{Q}_t \le Q_t^{y,m} \le u_t^y \overline{Q}_t \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{9}$$

where we have used two binary variables: v_t and u_t, which are referred to as the capacity variable and the operation variable, respectively. The capacity variable indicates 1 if a given technology is invested in, and 0 otherwise. Similarly, the operation binary variable gives 1 if the technology is committed to generation during a specific month m and year y, and gives 0 otherwise. Note that the superscript m is only used with heat generation and not installed capacity, since the former can have different values during the months of the operational years, while the latter can only have a single value during its lifetime of operation.

The amount of heat generation for every technology is also bounded by its installed capacity. This is formulated as

$$0 \le Q_t^{y,m} \le \alpha_t^{y,m} C_t^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{10}$$

$$0 \le Q_{t,pv}^{y,m} \le \alpha_{t,pv}^{y,m} C_{t,pv}^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{11}$$

These constraints ensure that the maximum heat generation coming from every DHS technology is linearly proportional to the installed capacity of that technology. The multiplying factor $\alpha_t^{y,m}$ for a technology t is dependent on the efficiency of the energy that technology is generating. For the case of solar PV panels, the multiplying factor $\alpha_{t,pv}^{y,m}$ is a random variable per month that apart from the efficiency of the technology, also incorporates the solar energy availability during that month. Note that since every technology can be invested in once, it is vital that the optimization model only accounts for the investment cost only once when the technology is selected. Therefore, the amount of heat generation in Eq. (10) is bounded by the vector sum of all C_t^y (see Eq. (15) which bounds the capacity variable to a maximum of 1, thus there can be only a single value in that vector).

• **DHS lifetime:** A unique feature of the proposed optimization is being able to identify the optimal year in which the optimally selected technologies should be purchased, accounting for the lifetime of each technology. This is done by means of establishing a relation between the investment and operation binary variables. To give an example, an investment in technology t in year y with a lifetime of two years only, then $v_t^y = 1$ and $v_t^k = 0$ for any $k \ne y$, while $u_t^y = u_t^{y+1} = 1$ and $u_t^k = 0$ for any $k \ne y$ or $k \ne y+1$. Using these two binary variables, we can incorporate the lifetime of DHS technologies through the following constraints:

$$\sum_{i=y}^{y+L_t-1} u_t^i \ge v_t^y L_t \qquad \forall y \in \{1, \dots, Y - L_t + 1\}, \forall t \in T \tag{12}$$

$$\sum_{i=y}^{L_T} u_t^i \ge v_t^y L_t \qquad \forall k \in \{Y - L_t + 2, \dots, Y\}, \forall t \in T \tag{13}$$

$$\sum_{i=1}^{Y} u_t^i \le L_t \qquad \forall t \in T \tag{14}$$

$$\sum_{i=1}^{Y} v_t^i \le 1 \qquad \forall t \in T \tag{15}$$

where Eq. (12) ensures that an investment in a specific technology t in year y will consequently allow the operation of such technology until the end of its lifetime. Eq. (13) ensures that no investment takes place in which its lifetime extends beyond the time planning horizon Y. Furthermore, the operation duration of any technology is restricted to its corresponding lifetime as modeled in Eq. (14). Finally, Eq. (15) ensures that every technology can be purchased only once during the next Y years.

• **Rooftop area:** Technologies such as solar thermal collectors or solar PV panels occupy space on households' rooftops. However, these rooftop areas are limited, thus it is key to account for the permissible rooftop area when on capacity sizing and investments in such technologies. Let us denote by A_t^y and $A_{t,pv}^y$, respectively, the total rooftop area occupied by technology t and its supplementary rooftop solar PV panels (if any) in year y. If a technology is not installed on the rooftop in year y, then $A_t^y = 0$. Similarly, if there are no PV panels needed for technology t in year y, then $A_{t,pv}^y = 0$. If A_{roof} represents the total rooftop area, then we have the following constraints

$$\sum_{t\in T}\left[A_t^y + A_{t,pv}^y\right] \le A_{roof} \tag{16}$$

The total area occupied on the rooftop by each technology is typically proportional to the capacity of the technology. This means that

$$A_t^y = \beta_t C_t^y \tag{17}$$

$$A_{t,pv}^y = \beta_{t,pv} C_{t,pv}^y \tag{18}$$

for some technology-dependent multiplier $\beta_t \ge 0$ and $\beta_{t,pv} \ge 0$. The special case that a technology does not need any space on the rooftop, we have $\beta_t = \beta_{t,pv} = 0$.

3.2. Parameters uncertainty

Long-term strategic planning must properly account for the time evolution of the underlying parameters and variables. In our setting, we deal with multiple of such variables: solar energy production in month m in year y for each technology t (reflected in $\alpha_{t,pv}^{y,m}$), investment costs in year y for technology t (I_t^y), O&M costs in year y for each technology t (OM_t^y), fuel prices in year y used by technology t (δ_t^y), the heat demand in month m in year y ($Q_D^{y,m}$), the peak demand in year y (K_D^y), fuel costs for technology t in year y (δ_t^y), and the tax values applied to technology t in year y (τ_t^y).

To account for the uncertainty in projected values of these variables, we create several time-series trajectories per variable, according to an autoregressive model [42]. To be more precise, we assume we are given the values for these variables (for each month) of the year before the start of the long-term decision-making. We use these values to create the projected values for (each month of) the upcoming years, recursively as follows. For a given random variable $x^{m,y}$ for the month

Table 1
Parameters of DHS technologies.

DHS	$\underline{C}_t$	$\overline{C}_t$	$\overline{C}_{t,pv}$	$\underline{Q}_t$	$\overline{Q}_t$	$\alpha_t^{y,m}$	β_t	$\beta_{t,pv}$
b	0	$\overline{C}_b$	$\overline{C}_{b,pv}$	0	∞	$\eta_b r_b^{y,m}$	0	0
h	0	$\overline{C}_h$	$\overline{C}_{h,pv}$	0	∞	$r_h^{y,m}$	0	$\frac{1}{\eta_{pv}}$
s	0	$\overline{C}_s$	0	0	$\gamma_{hot}^y Q_D^y$	$\alpha_t^{y,m}$	$\frac{1}{\eta_s}$	0

b: Heat boiler, h: Heat pump w/wo PV, s: Solar thermal collector.

m in year y, we generate the value of x for the same month in the next year $(y+1)$, according to

$$x^{m,y+1} = \phi_x x^{m,y}(1+\theta_x^{m,y}), \tag{19}$$

where $\phi_x \in \mathbb{R}$ reflects the level at which random variable x is attenuated or amplified compared to its value in the last year. The values of the parameter ϕ_x are pre-determined and are functions of the random variable x. The other term, $\theta_x^{m,y}$, is the multiplicative noise with a truncated normal distribution with zero mean, standard deviation σ_x, and larger than -1 (to ensure $x^{m,y+1}$ is non-negative), mathematically expressed as $\mathcal{N}(0,\sigma_x,-1,\infty)$, where σ_x reflects the variability of the realized value of x with respect to its average forecast.

For random variables that we only need their annual values (such as the investment costs I_t^y and the annual peak demand K_D^y), we remove the month index in Eq. (19). Moreover, if we have reliable forecast values for a variable f (such as fuel costs δ_t^y and tax τ_t^y), we replace $\phi_x x^{m,y}$ in Eq. (19) with the forecast values in year $y+1$ and keep θ^{y+1} to still account for forecast errors.

In our problem formulation, we have several random variables, which we group into a single set, $\mathcal{R}$. To generate multiple realizations for each random variable, we use Eq. (19). We assign a realization index, ω, to refer to one instance of the bundled trajectories of all random variables in $\mathcal{R}$. These trajectories for a given ω are created randomly and mutually but independently. We use $\mathcal{R}_\omega$ to represent the set of the trajectories of all random variables for the specific realization index ω; i.e., $\mathcal{R}_\omega = \{\alpha_{t,pv,\omega}^{y,m}, I_{t,\omega}^y, OM_{t,\omega}^y, \delta_{t,\omega}^y, Q_{D,\omega}^{y,m}, K_{D,\omega}^y, \delta_{t,\omega}^y, \tau_{t,\omega}^y\}$. To solve the optimization problem, we use a Monte Carlo simulation considering multiple realizations ω. For each realization ω, we determine the optimal solution of the optimization problem deterministically. After obtaining all solutions, we average the objective function across all the solutions, assuming that all scenarios are equiprobable.

3.3. Applying the model to common DHS technologies

This section outlines technology-specific constraints for a selected set of widely-used technologies. We specify the parameter values of our DSS for each technology and this is also summarized in Table 1. Note that more existing and future technologies can be included in our proposed DSS, by similarly specifying the model parameters to those technologies.

• **Heat boilers:** Heat boilers heat up the water in a boiler for space heating and hot water consumption. They rely on different energy sources to generate heat, natural gas boilers being the most common type. There are also other common types of boilers such as green-source (e.g., biomass and biomethane) boilers as well as electric boilers. We denote any heat boiler technology with the index b. For non-electric boilers, PV panels cannot help $\overline{C}_{b,pv} = 0$, while the electric ones can be equipped with PV panels of capacity $\overline{C}_{b,pv} > 0$. There is no physical upper bound on heat supply $\overline{Q}_b = \infty$, apart from the one imposed by the installed capacity of the boiler

$$0 \le Q_b^{y,m} \le \eta_b r_b^{y,m} C_b^y \tag{20}$$

where η_b is the operation efficiency of the boiler and $r_b^{y,m}$ is the number of hours during month m of year y that the boiler is operating. Comparing Eq. (20) with Eq. (10), we find that $\alpha_t^{y,m} = \eta_b r_b^{y,m}$. Finally, boilers are typically not installed on the rooftop, therefore, $\beta_b = \beta_{b,pv} = 0$, which enforces that the occupied roof area by the technology becomes zero i.e., $A_b = A_{b,pv} = 0$.

While formulation can be extended to any type of heat boiler, in this study, we consider four of the most widely-used types of boilers: Biomass wood boiler (BWM), Natural Gas Boiler (NGB), Biomethane Gas Boiler (BMB), and Electric Boiler (EB). The costs and emission characteristics of these technologies are listed in Table C.4.

• **Heat pumps with/without solar photovoltaic panels:** Heat pumps are known for low primary energy consumption compared to boilers or traditional electrical heating. Heat pumps are denoted by the index h.

The amount of heat that can be generated from heat pumps depends on the so-called coefficient of performance (COP), denoted COP_h, and the amount of electricity consumed by the heat pump, denoted $P_h^{y,m}$. The COP describes the efficiency of the source, which is the ratio between the electricity input and the useful heat output. Thus, we can describe $Q_h^{y,m}$ as in Eq. (21). Furthermore, the heat generation that can be obtained from heat pumps is restricted by the installed capacity of the heat pump and the number of monthly hours $r_h^{y,m}$, which is given in Eq. (22). Comparing Eq. (22) with Eq. (10), we find $\alpha_t^{y,m} = r_h^{y,m}$.

$$Q_h^{y,m} = P_h^{y,m} COP_h \qquad \forall y \in Y, \forall m \in M \tag{21}$$

$$Q_h^{y,m} \le r^{y,m} C_h^y \qquad \forall y \in Y, \forall m \in M \tag{22}$$

Since primarily heat pumps are connected to the electricity grid, we can write $P_h^{y,m} = P_{grid}^{y,m}$, where $P_{grid}^{y,m}$ is the total electricity consumed from the grid. As a result, the calculation of the running electricity cost for heat pumps in the objective function in Eq. (1) can be written as $(\delta_h^y + \tau_h^y)P_{grid}^{y,m}$ to reflect the cost of procuring energy from the grid to run the heat pump.

Heat pumps are commonly complemented with solar PV panels to reduce their electricity consumption and carbon emissions. Let us denote $P_{pv}^{y,m}$ the energy generated from the PV panels, thus we can write

$$P_h^{y,m} = P_{pv}^{y,m} + P_{grid}^{y,m} \qquad \forall y \in Y, \forall m \in M \tag{23}$$

which ensures that the total electricity consumed by the heat pump is the sum of the electricity generated by the PV panels and the electricity procured from the grid.

The amount of electricity that can be generated from the PV panels $P_{pv}^{y,m}$ is calculated as

$$P_{pv}^{y,m} \le \eta_{pv} A_{pv} \rho^{y,m} \qquad \forall y \in Y, \forall m \in M \tag{24}$$

where η_{pv} is the efficiency of the PV panels, A_{pv} is the panel size in m^2, and $\rho^{y,m}$ is the monthly sum of solar radiation energy hitting 1 m^2 of a PV panel, measured in kWh. Finally, Eq. (25) computes the installed capacity for the PV panel system.

$$C_{h,pv}^y = \eta_{pv} A_{pv} \qquad \forall y \in Y \tag{25}$$

Comparing Eq. (25) with Eq. (18), we find $\beta_{t,pv} = \frac{1}{\eta_{pv}}$. Heat pumps can also have different types. In this study, we consider a widely-used type of heat pump: air-to-air heat pump with and without solar photovoltaic panels (PV), respectively, referred to as HP/PV and HP. The costs and emission characteristics of these technologies are listed in Table C.4.

• **Solar Thermal Collectors:** Solar heating collectors for dwellings use solar radiation to heat water to supply the hot water demand during the summer period. However, they are rarely used for space heating due to their low efficiency. Given the index s, their capacity is linearly proportional to the area of thermal collectors; here denoted by A_s. The efficiency factor η_s reflects how much of the solar radiation energy hitting 1 m^2 is converted to heat. Combining all, the solar thermal collector capacity can be expressed as

$$C_s^y = \eta_s A_s^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{26}$$

Comparing Eq. (26) with Eq. (18), we find $\beta_s = \frac{1}{\eta_s}$.

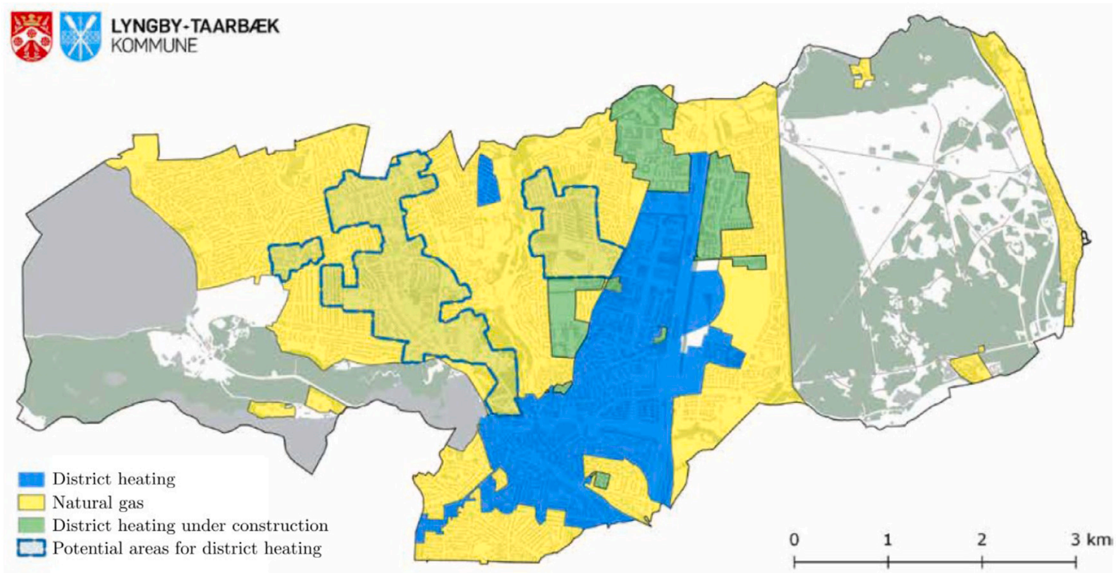

Fig. 2. Heat supply map for Lyngby–Taarbæk [43].

Given the capacity of the solar thermal collector, the amount of heat generation of this technology in month m of year y is constrained by

$$0 \le Q_s^{y,m} \le \rho^{y,m} C_s^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{27}$$

Comparing Eq. (27) with Eq. (10), we find that $\alpha_{t,pv}^{y,m} = \rho^{y,m}$.

Following practical reasons, we assume solar collectors are only used for hot water demand. We denote γ_{hot} as the ratio of the hot water demand to the total heat demand. Then, the following constraint ensures that the amount of heat generated by the solar thermal collector supplies only the hot water demand

$$0 \le Q_s^{y,m} \le u_s \gamma_{hot}^y Q_D^y \qquad \forall\ 1 \le y \le Y, \forall\ 1 \le m \le M \tag{28}$$

Comparing Eq. (28) with Eq. (9), we find that $\underline{Q}_t = 0$ and $\overline{Q}_t = \gamma_{hot}^y Q_D^y$. The costs and emission characteristics of the solar thermal collector (ST) are listed in Table C.4.

4. Case study

In this section, the proposed DSS model is used for a practical case in the municipality of Lyngby–Taarbæk in Denmark. The objective of this case study is to (1) demonstrate how our decision support system can help city planners offer consumers a range of long-term strategies for investing in DHS technologies, and (2) show how the DSS can be used to evaluate the impact of different policies on the choices of technologies on the long run. The solution helps individuals to have a solid understanding of their investment decisions and their consequences. It also helps city planners to plan their strategies according to the underlying policies they are subject to. Finally, it informs policymakers on the impacts of policies and regulation packages to incentivize consumers' choices and steer them in favor of environmental concerns. Below, we describe the case, the policies under study, and the data.

The proposed DSS is implemented using MATLAB software [44], with the 'intlinprog' solver. The model consists of 3818 continuous variables and 2732 integer variables. For the Monte Carlo simulation, we generate 1,000,000 independent realizations ω. For each realization, we generate trajectories of all underlying random variables in $\mathcal{R}\omega$, as described in Section 3.2, where $\mathcal{R}\omega = \alpha_{t,pv,\omega}^{y,m}, I_{t,\omega}^y, OM_{t,\omega}^y, \delta_{t,\omega}^y, Q_{D,\omega}^{y,m}, K_{D,\omega}^y, \delta_{t,\omega}^y, \tau_{t,\omega}^y$. With these specifications, the DSS takes approximately 2400 s to run and produce the output.

4.1. Lyngby–Taarbæk municipality

The municipality of Lyngby–Taarbæk is situated in the northern suburbs of Copenhagen in Denmark. With 55,500 inhabitants, the municipality is obligated to reduce CO2 emissions by 20% at least during the coming 10 years, and even more in 30 years. In efforts to realize these sustainability goals, Lyngby–Taarbæk has signed the climate partnership of the Danish Society for Nature Conservation, which obligates them to reduce the CO2 emissions of its own buildings by 2% per year. In Lyngby–Taarbæk, there is a high reliance on waste incineration-based district heating as the main heat supply source covering almost 52% of the total heat demand as illustrated in Fig. 2. The remaining areas rely on individual heating solutions, mainly natural gas boilers. Therefore, the outcomes of the optimization may support action in the areas marked in yellow in Fig. 2.

The ongoing new urban development in some areas of Lyngby–Taarbæk is exerting pressure on the municipality to offer the best decision support to the new household owners concerning their heat supply. Furthermore, households are prohibited from investing in natural gas boilers, or any other type of fossil fuel-based heating system, from 2030 according to the Danish Climate Agreement of 2020 [7]. Therefore, to meet its sustainability goals, the municipality is encouraged to offer the new consumer tailor-made long-term investment plans for sustainable and efficient DHS technologies.

4.2. Policy/taxation scenarios

We use our DSS to investigate the impacts of multiple policies on the availability of heating equipment in Lyngby–Taarbæk, their relative cost, and competitiveness. These policy scenarios are selected based on the likelihood of occurrence, determined by cross-referencing three types of sources, the legal corpus that constitutes the climate agreement enacted in 2020 [7], empirical studies reviewing the long-term strategic energy plans implemented in several Danish cities, and direct exchanges with the city planners in Lyngby–Taarbæk municipality. We elaborate on these scenarios one by one below and summarize them in Table 2.

• **Socio-economic case:** The socio-economic case includes all the technology and fuel costs plus the costs related to electricity and gas grid tariffs but in the absence of taxes and additional policies. In doing so, we introduce all the costs affecting the marginal cost of electricity

Table 2
Overview of investigated policy/taxation scenarios.

	Socio-economic case	Policy case			
		Typical	Scenario 1	Scenario 2	Scenario 3
Technology cost (I_t^y&OM_t^y)	✓	✓	✓	✓	✓
Grid Tariff (δ_t^y)	✓	✓	✓	✓	✓
Taxes (τ_t^y)	–	✓	✓	✓	✓
Additional regulation	–	–	Biomass ban	Biomass ban & Biomethane price increase	Biomass ban & Heat pumps subsidy

and gas, which is relevant when investigating substitution effects between heating technologies. Thus, the socio-economic scenario leaves aside the regulatory factors affecting consumers' choices.

• **Typical policy case:** In this case, the taxes associated with different heating technologies are added to the socio-economic case (see Table C.6). Therefore, the difference between the socio-economic scenario and the policy scenario illustrates how energy taxes distort consumers' decisions from the optimal allocative efficiency reached with the socio-economic case. As this case only includes the most typical form of energy taxes and excludes any other type of taxation and regulation, we call this the typical policy case, which also serves as the benchmark for other policy scenarios that have additional taxation or regulation.

• **Scenario 1 – Biomass boilers ban:** In this scenario, a biomass ban regulation is added on top of the typical policy scenario. Despite the fact that there is no clear indication that a ban on biomass energy for heating in individual households will be implemented, several factors indicate that biomass, mainly biomass wood, will decrease in individual heating. Dyhr-Mikkelsen et al. [45] present 14 strategic energy plan projects carried out in 6 large Danish municipalities and 8 smaller partnerships, biomass is considered a transition energy solution for households to migrate from fossil fuel-based heating to electric heating. Besides, biomass energy is subject to sustainability requirements defined in the Climate Agreement [7] that specifies that security of supply and renewal of wood should be considered in the long-term use of the resource, as confirmed in [46]. Finally, several municipalities are raising concerns about the rising particle emissions associated with the multiplication of wood stoves in densely populated areas. Due to the aforementioned factors, the study includes a scenario where biomass energy is banned, which allows us to observe how other energy sources substitute it.

• **Scenario 2 – Biomass boilers ban and increase in biomethane price:** In this scenario, apart from the energy taxation introduced in the typical policy scenario and the biomass boiler ban, introduced in Scenario 1, we also raise the biomethane fuel price by 10% to represent stronger competition from other sources. This is to account for the fact that future biomethane prices face significant uncertainties [47]. Due to increased sector coupling, prices are increasingly dependent on, e.g., the transport or industrial sector. Therefore, this scenario raises the biomethane fuel price by 10% to represent stronger competition from other sources.

• **Scenario 3 – Subsidies on heat pumps:** In this scenario, apart from the energy taxation introduced in the typical policy scenario, we also introduce a 30% subsidy on the investment cost of heat pumps. This subsidy scheme runs along with the decommissioning of gas-heated homes and is a stepping stone in the Danish policy to support electricity-based heating outside district heating areas. The policy framework provides a financial subsidy scheme aiming at covering a third of heat pump costs and allocates DKK 20 million per year between 2021–2024 [46], to be renegotiated in the next period. A recent Danish survey showed that already 83% of the households who expect to replace their gas boiler in the coming years would convert to another form of heating, and 42% of the consumers willing to replace their installation within the next two years plan to apply for the financial subsidy scheme [48].

4.3. Data

We use real-world data and documented industry-based projected values for solar power, heat demand, energy prices, taxes, and stochastic scenarios. For some cases where this information is not available, we use well-justified data traces based on practical assumptions. A detailed description of all data used for the case study is elaborated in the Appendix.

5. Results

In this section, we apply our proposed DSS to the case of Lyngby–Taarbæk (see Section 4) to gain some insights into the optimum long-term heating mix and the impact of different policy scenarios, described in Section 4.2. We include the set of all technologies discussed in Section 3.3 as possible choices: biomass wood boiler (BWM), natural gas boiler (NGB), biomethane gas boiler (BMB), electric boiler (EB), air-to-air heat pump with and without solar photovoltaic panels, respectively, referred to as (HP/PV) and (HP), and solar thermal collector (ST). As discussed in Section 3.2, there are multiple sources of uncertainty, and we use a Monte–Carlo simulation to account for them. While we primarily focus on the average result over all realizations, it is also important to examine how results might vary for different realizations. As such, we present the results under three different projections, called the *average*, *high*, and *low* realizations, respectively, referring to the optimal average across all realizations, the 95% highest, and the 95% lowest solution across all realizations.

5.1. The trade-off between the cost and carbon emission

To study the trade-off between the cost and carbon emission, we consider the range between two extreme cases; the zero-emission budget ($\overline{\epsilon} = 0$) and the unrestricted carbon emission budget ($\overline{\epsilon} = \infty$), which we refer to as the *environmental-optimal* and the *cost-optimal* strategies, respectively. This range forms a Pareto front, which presents the minimum cost configuration (Θ; Y-axis) for each given maximum allowable carbon emission budget (Φ; X-axis). Focusing on the city planner perspective, in this section, we only include the socio-economic and the typical policy cases. Fig. 3 illustrates the Pareto front for the socio-economic case (left figure) and the typical policy case (right figure).

An observation from Fig. 3 is that the Pareto front in this example has only a limited feasible region in terms of long-term solutions. This is due to the current high share of renewable energy in the electricity mix in Denmark, which makes electricity-based technologies such as HP relatively green. Additionally, Denmark has set a hard target to reach 100% renewable electricity by 2030 [49]. Apart from the electricity decarbonization targets, fossil fuel-based heating systems are also prohibited for households from 2030 according to the Danish Climate Agreement of 2020 [7]. This means that all fuels will be carbon neutral by 2030 even in the cost-optimal scenario. Thus, the cost-optimal strategy should still guarantee carbon neutrality after 2030 and hence, cannot deviate substantially from the environmental-optimal strategy. As a result, the DSS outcome does not offer a wide range of optimal solutions in this case. It is, however, important to note that the Pareto front graph differs per case and could lead to a large range of

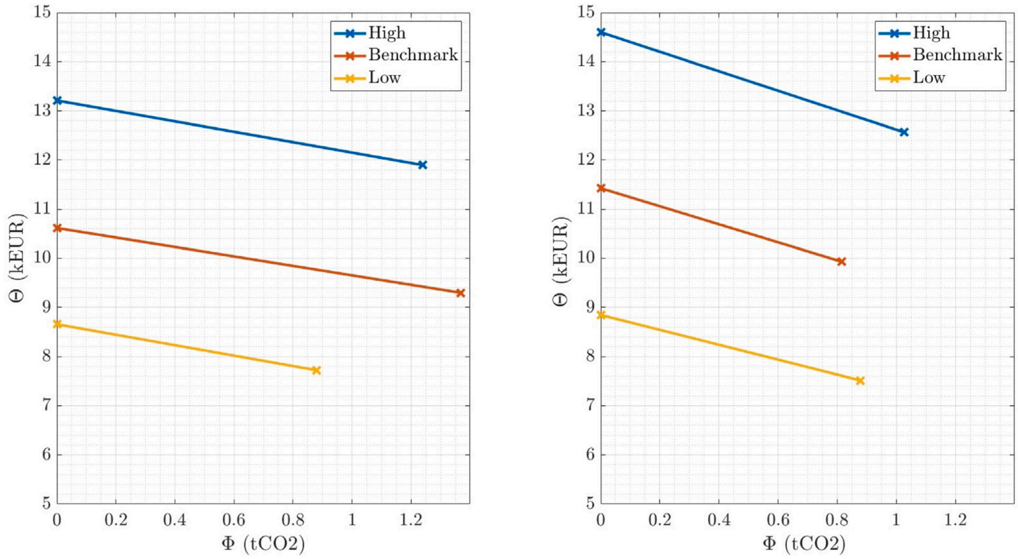

Fig. 3. Pareto front: Socio-economic case (left), typical policy case (right).

solutions where the share of renewables is low and there are no hard restrictions on decarbonization.

According to Fig. 3, in the socio-economic case for the environmental-optimal strategy, the minimum total cost ranges between €8.66k and €13.21k, accounting respectively, for the high and low realizations. Similarly, for the cost-optimal strategy, the minimum total cost ranges between €7.72k and €11.90k, and the total expected carbon emission ranges between 0.88tCO2 and 1.3tC02. The typical policy case shows a slightly higher range of total cost for the environmental-optimal scenario than the socio-economic one. With taxes included, the total cost ranges between 8.89k€ and €14.60k for the low and high realizations. The cost-optimal case produces a range of emissions between 0.88tCO2 and 1.03tC02 and a total cost between €7.51k and €12.56k, respectively, for the high and low realizations. An interesting observation is that compared to the cost-optimal case, the environmental-optimal strategy increases the total cost by only 9% to 15% depending on the statistical realizations. This means that households can opt for an entirely carbon-neutral investment strategy with a slight increase in their investment and operation costs over the 30 year horizon. We emphasize again that this might not be the case for other places where the share of renewables is not as high as Denmark or there is no hard restriction on decarbonization.

5.2. The optimal technology investments

In this section, we investigate the optimal choices of technologies over the planning horizon for the statistical average solution. For this experiment, we consider the socio-economic case (for both cost-optimal and environmental-optimal scenarios) to exclude the impact of policies, i.e., creating a level playing field between different technologies. In all experiments and as also indicated in Fig. 4, we identify three non-overlapping phases, namely the *initial phase*, the *decision phase*, and the *end phase*. The initial phase commences at the beginning of the planning horizon in 2021 and continues until the year when the customers decide to invest in new technologies. The decision phase starts when the customers choose to invest/add a new technology while the initial technologies are still operational. Finally, the end phase starts when all of the initial technologies reach their lifetimes. The end phase continues until the end of the planning horizon, i.e. 2050. For the sake of simplicity of presentation and to facilitate gaining insights, in the rest of this section, we will represent the choices of technologies per phase (instead of a year) over the planning horizon.

Fig. 4 shows the optimal installed capacity per technology and the year in which these technologies are invested and operated. This figure also allows a comparison between the long-term solutions of the environmental-optimal (top figure) and the cost-optimal (bottom figure) strategies. The environmental-optimal strategy relies heavily on the HP/PV during the initial and the decision phases along with the biomethane boiler to cover peak loads. The biomass wood boiler is invested in during the decision phase, which is then complemented with a regular HP during the final phase of planning. Since Denmark is planning a 100% renewable electricity generation by 2030, then investing in HPs only, without PVs, will be a carbon-neutral solution. The cost-optimal solution follows a similar strategy to the latter, with the difference of pushing forward the BMB investment during the end phase of planning instead of the HP since BMBs have a lower investment cost compared to HPs.

Fig. 5 further expands the experiment in Fig. 4 to the statistically high and low realizations to examine the impact of different realizations of random variables. Figs. 4 and 5 collectively show that the forefront technologies in all optimal strategies are hybrid HP combined with PV, biomass wood boilers, and biomethane boilers. The HP only appears on two occasions. A common observation for the high and low realizations is the secondary technology invested in besides the hybrid HP/PV. The cost-optimal scenario for both high and low realizations shows that the optimal technologies within the initial phase are the hybrid HP/PV alongside the biomass wood boiler or the biomethane boiler. This is because BWB and BMB have zero carbon emissions, which is essential in the environmental-optimal strategy. On the other hand, the cost-optimal strategy in both low and high realizations solely relies on the HP/PV solution since it has the highest efficiency. The environmental-optimal scenario results in early investment in biomethane boilers, while this investment is deferred if the carbon constraint is relaxed. Finally, applying a solid carbon policy tends to promote the competitiveness of heat pumps against biomethane boilers in the long term.

The figures also indicate that natural gas boilers, electric heating, and solar thermal heating, are the three technologies never invested in. This can be attributed to the following reasons: (1) According to Denmark's carbon-neutral target by 2030, natural gas for households is expected to phase out by then. As a result, it is not economical or carbon-efficient to invest in a new gas boiler that will eventually phase out. (2) Electric boilers have high investment costs. (3) Solar thermal heaters can only supply hot water demand, which is a small percentage of the total household demand. Besides, solar heaters have

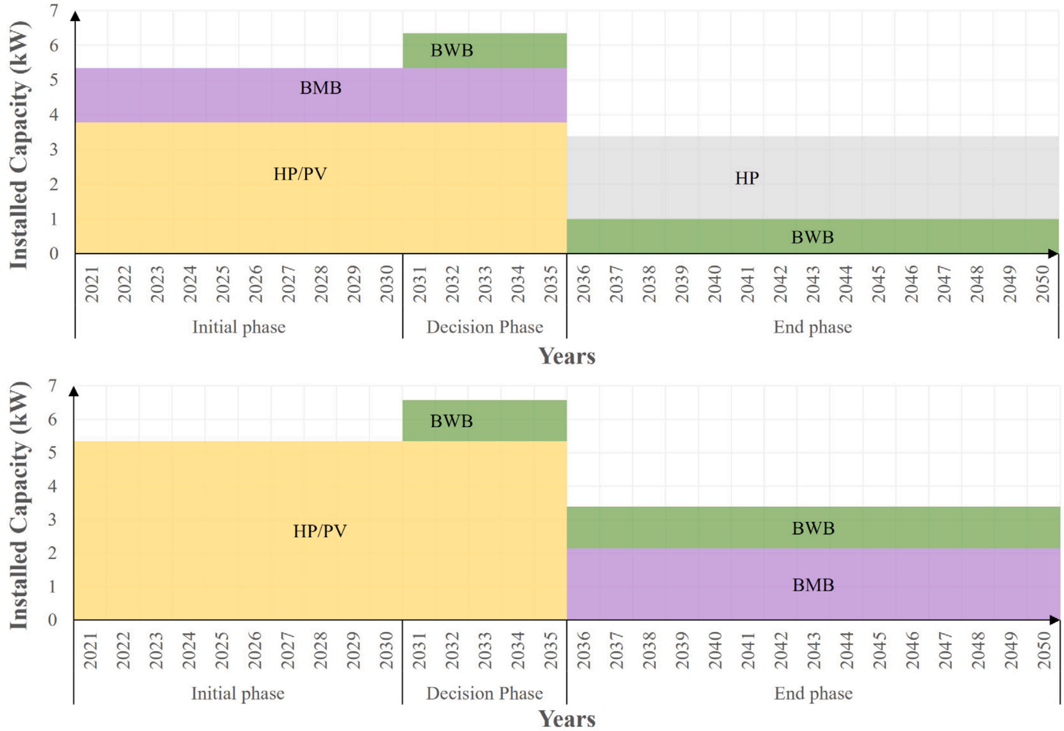

Fig. 4. Installed capacity of optimal technologies in the socio-economic case for the environmental-optimal (top figure) and the cost-optimal (bottom figure) strategies.

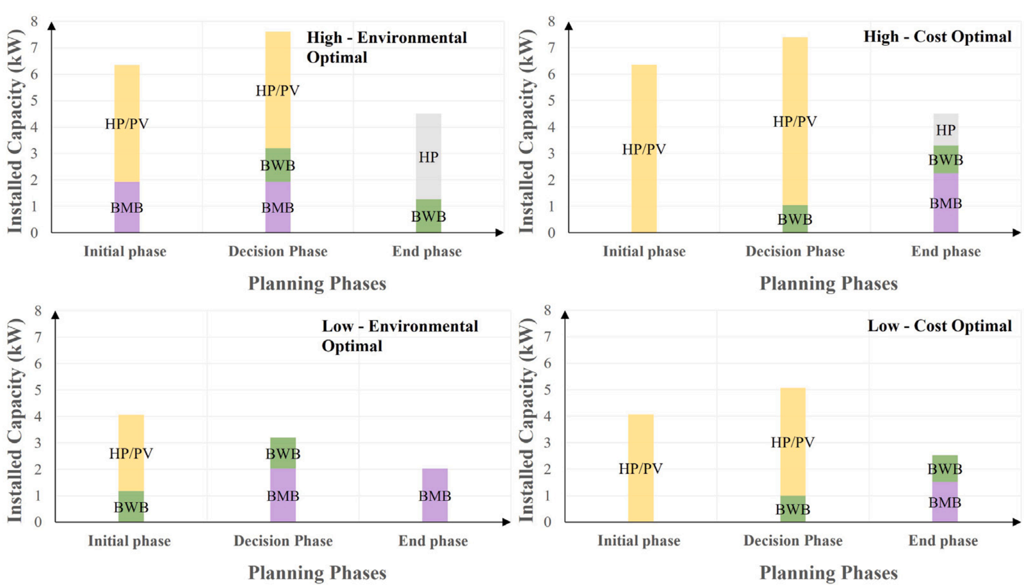

Fig. 5. Installed capacity of optimal technologies per decision phase in the socio-economic case for the environmental-optimal and cost-optimal strategies for the high and low statistical realizations.

low efficiency, which makes them an economically inefficient solution for households. Finally, Denmark is not a sunny country, thus, the total solar energy collected through solar thermal heating might not justify its overall cost.

5.3. The role of policy and regulation

In this section, we investigate the role of policy and regulations on optimal investment decisions. We start by comparing the typical policy case with the socio-economic case. This comparison reflects the extent to which current energy taxes affect the optimal investment choice. We make this comparison through Fig. 6, which shows the percentage change in installed capacity induced by the energy taxes in the typical policy case compared to the socio-economic case. A positive (negative) percentage indicates an increase (decrease) in the installed capacity in the policy case compared to the socio-economic case. This figure suggests that despite a limited impact in the initial phase, current energy taxes are likely to move investment choices away from the optimum during the decision phase and end phase. Biomass boilers benefit the most from the existing tax framework with an investment increase of up to 20%, regardless of the CO_2 budget. Conversely, HPs and biomethane gas boilers are negatively affected by existing taxes, especially and respectively, in the environmental-optimal and the cost-optimal strategies. Note that all technologies do

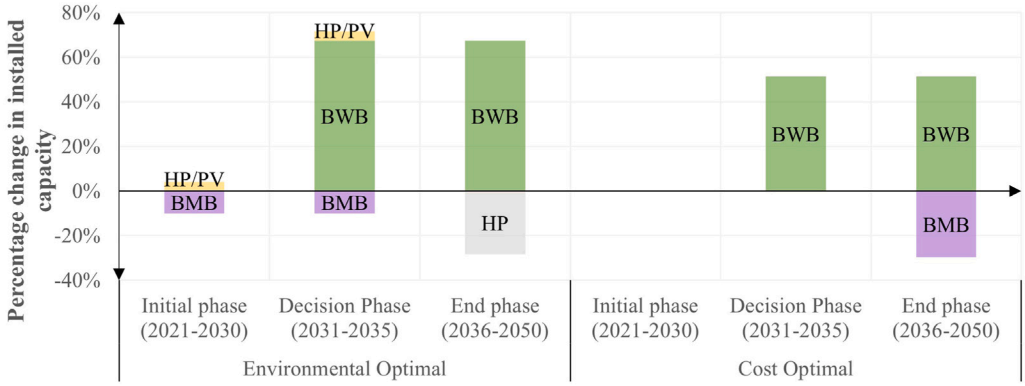

Fig. 6. Percentage change in capacity between the socio-economic case and the policy case for the environmental-optimal and cost-optimal strategies.

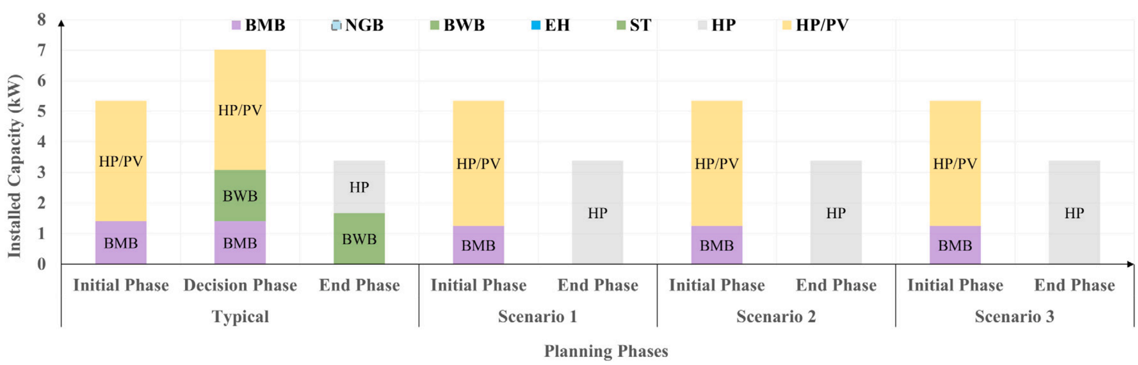

Fig. 7. Optimal technologies/capacities: Policy case, planning/end phases, environmental-optimal strategy.

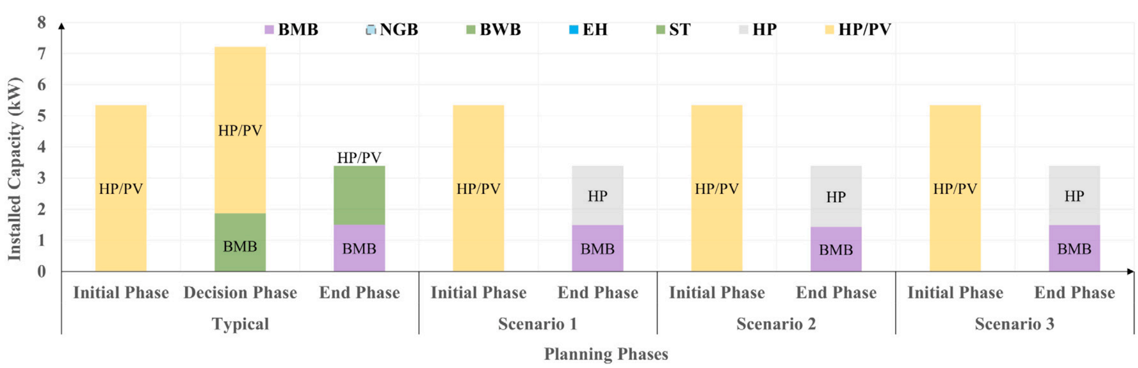

Fig. 8. Optimal technologies/capacities: Policy case, planning/end phases, cost-optimal strategy.

not appear in Fig. 6, which indicates that the energy taxes did not affect the optimal investment. Thus, policymakers have to take into account the skewed tax framework represented by the differences between our socio-economic and policy cases that does not provide a level playing field between biomass wood versus electricity even though lower tax rates have already been applied for HPs.

Figs. 7 and 8 summarize how the regulatory scenarios affect the investment choice made in the typical policy case in the low and high statistical realizations for the cost-optimal and environmental-optimal strategies. The primary trend in the environmental-optimal strategy in Fig. 7 indicates that all regulatory framework conditions lead to relatively identical changes in investment decisions in the initial phase of planning; hybrid heat pumps with PV replace biomass wood boilers. The decision and end phases overlap for all policy scenarios except for the typical scenario. Thus, these phases show a more apparent distinction between the effect of the biomass ban on the one hand and the increase in the price of biomethane and the heat pump subsidy, on the other hand. Banning biomass benefits heat pumps and disfavors biomass boilers.

Fig. 8 illustrates the impact on investment decisions under the cost-optimal strategy. Hybrid heat pumps with PV are the only optimal technology choice in the initial phase, although the tested regulatory frameworks result in a slight 2%–3% decline in installed capacity. In the end phase, the results show a complete shift in all tested policy scenarios from hybrid heat pumps with PV to heat pumps, supplemented again by biomethane gas boilers.

In summary, hybrid heat pumps with PV appear to be the optimal technology in the 2035 time frame to minimize CO_2 emissions at a low cost to the household, regardless of the case tested and the sensitivities analyzed. This makes it the most feasible investment choice for households in Denmark. Energy taxes and regulatory framework conditions have the main effect of further improving the investment conditions for this technology and disfavoring investment in biomass boilers. The only difference in impact between the regulations tested in the policy scenarios appears from 2035 onward, where the increase in biomethane price and the implementation of the heat pump subsidy reach the same results in terms of technology choice and investment magnitude. In such a case, the optimal technology choice is shared at 25%–75% between biomethane gas boilers and hybrid heat pumps with PV. The CO2 allowance combined with the regulatory framework conditions is a boost for heat pumps, but only in the long term. Assuming a growing demand results in opening up prospects for biomethane boilers both in the short and long term.

6. Discussion and conclusions

6.1. Concluding remarks

This work is motivated by the heat energy transition challenges. In particular, households choose their distributed heat supply technologies without a full understanding of the future economical consequences and often with disregard for the environmental consequences. Thus, city planners are in need of a decision support system that assists households in their future heat energy development while providing solutions that are both economic and sustainable. Policymakers also need to know the impact of their policies on the collective long-term heat decarbonizations of households.

In this paper, we used a model-driven decision support approach to show how relevant data and proper analysis can help in this direction. We developed a decision support system (DSS) that is inclusive by incorporating a large range of distributed heat supply technologies (DHS). It is comprehensive by implementing the operational details, physical constraints, data projections, etc. It is also generalizable in the sense that it can be used for any municipality and even at a community level instead of an individual level. Our DSS can also be used by regulators to ex-ante evaluate the impact of regulations and taxation on heat energy decarbonization. This in turn provides leeway for municipalities and households to anticipate the effects of such policies and regulations and adopt the best-suited solution.

We use our DSS for the municipality of Lyngby–Taarbæk in Denmark as a case to show how this DSS can be useful for both city planners as well as regulators. In terms of aligning cost-optimal and environmental-optimal solutions, we found that the difference between these two objectives is not significant in a country like Denmark with an ambitious electricity and heat decarbonization strategy. Compared to the cost-optimal case, the environmental-optimal strategy increases the total cost only by 9% to 15% depending on the projected head demand. This means that households can opt for an entirely carbon-neutral investment strategy with a slight increase in their investment and operation costs over the 30 year horizon.

In terms of optimal choices of DHS technologies, we made several interesting observations for the Lyngby–Taarbæk case. We found that some technologies are more favorable. The forefront technologies in all optimal strategies are hybrid HP combined with PV, biomass wood boilers, and biomethane boilers. Conversely, some other technologies are not attractive under any scenario. This includes natural gas boilers, electric heating, and solar thermal heating. This indicates that these technologies cannot beat others in either cost-effusiveness or CO_2 emission, at least in the case of Lyngby–Taarbæk.

In terms of the impact of policies and regulations, we investigated policy scenarios and regulations, which correspond to the primary measures currently in place in Denmark or likely to be implemented. Our results show that energy taxes induce a sharp increase in investment in biomass boilers from 2031 until 2050. This outcome is consistent with the past research results on the DHS technology mix, especially in the Nordic region. The results also indicate that, despite the special tax regime that heat pumps benefit from until 2024, the tax exemption has a marginal impact on the uptake of heat pumps with PV, which indicates that this measure alone will not bring about the massive replacement of oil and gas boilers desired. Energy taxes penalize both biomethane boilers and heat pumps. In this study, the effect of the tax exemption on heat pump demand beyond 2024 is not tested to be in line with the current regulatory framework. The decision by parliament to prolong this measure could affect our results and lead to more investment in heat pumps in the two latter phases. The results show the reinforcing effect between energy tax exemption and carbon restrictions for heat pumps with PV in the first phase and the beneficial effect of CO2 restrictions on heat pumps over the long term. By counterbalancing effect, CO_2 emissions restrictions limit biomass boilers

Table 3
Nomenclature.

Notation	Indices
b	Heat boiler
h	Heat pump
m, y	Index of month and year
pv	Photovoltaic solar panel
s	Solar thermal collector
ω	A realization of random variables
Notation	**Abbreviations**
BWB	Biomass wood boiler
BMB	Biomethane Boiler
EB	Electric Boiler
HP	Electric Heat pump (air-to-air)
NGB	Natural Gas boiler
PV	Photovoltaic Panels
ST	Solar thermal collector
Notation	**Sets**
M	Number of months per every year in the planning horizon, i.e. 12.
T	Set containing all DHS technologies considered within the planning horizon
Y	Number of years in the planning horizon
$\mathcal{R}_\omega$	Set of trajectories of all random variables for the realization ω
Notation	**Parameters**
A_{roof}	Rooftop area size for household (m^2)
$\underline{C}_t, \overline{C}_t$	Lower and upper limit for installed capacity size for technology T (kW)
COP_h	Coefficient of performance for heat pumps: (electricity input/useful heat output)
d	Discount rate (%)
I_t^y	Capital cost for investing in any technology T in year y (€/kW)
K_D^y	Peak heat demand of entire year Y (kW)
L_T	Lifetime in years for a given technology T
OM_t^y	Operation & maintenance cost for any technology T in year y (€/kW)
$Q_D^{y,m}$	Heat demand during every month in M of year Y (kWh)
$\underline{Q}_t, \overline{Q}_t$	Lower and upper limit for heat generation for technology T (kWh)
$\mathcal{R}$	Set of bundled trajectories for random variables
$r_t^{y,m}$	Number of hours that technology t can operate in month m during its lifetime (hrs)
γ_{hot}	Ratio of the hot water demand to the total heat demand (%)
δ_t^y	Fuel price with grid tariff for any technology T in year y (€/kWh)
δ_t^y	Taxes for any technology T in year y (€/kWh)
η_{sys}	Over-sizing factor to account for system losses (%)
η_T	Operation efficiency of technology T (%)
λ_t	Carbon emission factor per unit of heat generation from any given technology T (ton/CO2)
$\rho^{l,m}$	Monthly sum of solar radiation energy hitting 1 m^2 of a PV panel (kWh)
Notation	**Variables**
$A_{t,pv}^y$	Optimal PV panel area size (m^2)
A_s	Optimal solar thermal heating area size (m^2)
C_t^y	Optimal installed Capacity for any technology T in year y (kW)
P_t^y	Amount of electricity consumed from the grid (kWh)
$P_h^{y,m}$	Total amount of electricity consumed by the heat pump (kWh)
$P_{pv}^{y,m}$	Amount of electricity generated from PV panels to supply the heat pump (kWh)
$P_{grid}^{y,m}$	Amount of electricity bought from the grid to supply the heat pump (kWh)
$Q_t^{y,m}$	Optimal heat generation energy for every technology T in month m in year y (kWh)
u_t	Operational binary variable: 1 if technology t is operating, and 0 otherwise
v_t	Capacity binary variable, 1 if technology t is invested in, and 0 otherwise

investment in the medium and long term and therefore exacerbate the substitution effect between the two technologies and, to some extent, between biomass and biomethane. Finally, it is important to point out that the policies and regulations only have a marginal effect on the heating mix. All policy scenarios reach the relatively same impact in terms of technological choice leading to a mix based on heat pumps and biomethane and showing growth potential for biomethane along with demand growth. Ultimately these outcomes create knowledge to refine the use of regulatory packages, both in their nature and in their temporal scope.

6.2. Limitations and future work

The presented work has some limitations, which provide directions for future research. Firstly, the long-term planning of energy systems is inherently uncertain and can be impacted by unforeseen disturbances such as wars. While the proposed model accounts for statistical changes, long-term patterns, and policy scenarios, it does not address disturbances. To accommodate such disruptions, the proposed DSS can be periodically updated with current information or revisited after a disturbance. Secondly, the model does not consider factors such as reselling second-hand heat technologies, decommissioning decisions, or decommissioning costs. We assume that technologies invested within the planning horizon must run their lifetime before the end of the planning horizon and can be disposed of without cost. Future work could investigate the impact of including these factors. For example, exploring the potential role of reselling opportunities in the future or considering decommissioning costs. Another limitation of this study relates to the time resolution of the analysis, which is monthly in this work. Indeed, in this paper, we decouple long-term planning and investment decisions from short-term operational decisions and focused on the latter. Dealing with inter-hourly operational decisions is equally interesting but not the main focus of this study. These types of operational decisions can be optimized with, for example, short-term heat/electricity storage devices. Therefore, an interesting extension of this study is to optimize the short-term operational decisions, given the long-term planning decisions (or even concurrently), choosing (sub-)hourly time resolutions and considering the inclusion of heat/electrical storage systems. Finally, while we assume a fixed efficiency factor for heat pumps and solar panels throughout the year, future models can improve accuracy by accounting for the impact of ambient temperature on these factors.

CRediT authorship contribution statement

Ayman Esmat: Conceptualization, Formal analysis, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Yashar Ghiassi-Farrokhfal:** Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Philipp Andreas Gunkel:** Conceptualization, Formal analysis, Validation, Writing – review & editing. **Claire-Marie Bergaentzlé:** Conceptualization, Formal analysis, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request

Acknowledgments

This article was partly funded by the FlexSUS project (nbr. 91352) that received funding in the framework of the joint programming initiative ERA-Net/NWO, with support from the European Union's Horizon 2020 research and innovation programme under grant agreement No 775970.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.apenergy.2023.121442.

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