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Municipal energy system modelling – A practical comparison of optimisation and simulation approaches

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A B S T R A C T

This paper investigates the impact of applying optimisation and simulation approaches for energy system modelling and scenario design in a municipal context. In doing so, the previous understanding of what constitutes "optimisation" and "simulation" is expanded with further distinctions and it is documented how the outlined modelling approaches are applied in the existing literature. In a practical comparison, it is tested how the choice of modelling approach influences the design of future energy system scenarios for a municipal case study. The energy system scenarios and results obtained from a proposed stepwise simulation approach are compared to an established multi-objective optimisation approach. The results show that for the investigated municipal case it is possible to obtain results with a simulation-based approach that are comparable to the results obtained from multi-objective optimisation. Ultimately, the choice of modelling approach is a complex issue in which modellers must consider the necessary degree of modelling freedom, stakeholder involvement, and available system knowledge. Modellers need to consider not only what tool to use, but also how it is used; a tool can be used for both optimisation and simulation, and both can be valid approaches for developing future energy system scenarios.

1. Introduction

Energy system scenarios are increasingly a part of energy planning on all scales ranging from the national level [1] to the regional and municipal level [2], and even at an urban scale [3]. The use of scenarios for national energy planning is a well-established practice, and many relevant tools and models exist for developing such scenarios [4]. It however varies significantly how scenarios are used, as seen in the study by Braunreiter and Blumer [5], where it is found that two distinct types of users exist; sailors and divers. Sailors predominantly use scenarios as guidance toward a possible energy future, whereas divers use the scenarios as a deep dive into quantitative assumptions which can be applied in their calculations and scenarios.

Energy system scenarios are typically developed based on modelling of the associated energy system. Energy system modelling approaches can generally be divided into simulation-based and optimisation-based approaches, each with different modelling characteristics and resulting outcomes. Lund et al. [6] compare these two approaches, further defining the two approaches as archetypes of energy modelling, and arguing that optimisation aims to establish a *"prescriptive investment optimisation or optimal solutions approach"*, and simulation is an *"analytical simulation or alternatives assessment approach"*.

In their comparison of simulation and optimisation approaches, Lund et al. [6] clarify differences between the models applied, the results produced, and provide a theoretical foundation for interpreting results. It is argued that one of the fundamental differences between the models is how investment optimisation is implemented. Therefore, what in short in the present study is referred to as "optimisation models", are models which include endogenous investment optimisation, as seen in models such as HOMER [7], TIMES/Markal [8], and Balmorel [9], meaning that investment optimisation is done within the model. Simulation models, such as EnergyPLAN [10] or energyPRO [11] are instead based on exogenous investment optimisation, where investment optimisation is done outside of the model.

Optimisation methodologies are generally by nature very structured in their approach to arriving at optimal scenarios, but the underlying

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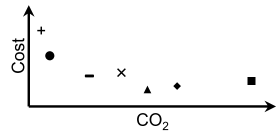
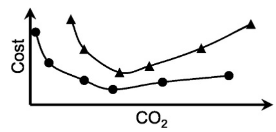
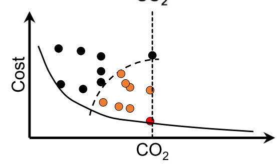
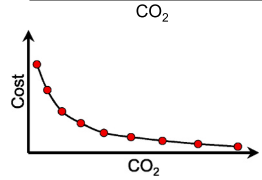
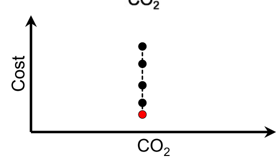
Table 1
Simulation and optimisation modelling approaches applied for modelling future scenarios.

Degree of freedom of approach	Approach	Illustration	Participatory processes	Examples
High	Expert-based simulation		Early and ongoing participation is needed to determine objectives.	[24–26]
	Stepwise simulation		Early and ongoing participation is needed to align design principles and objectives.	[22,27,28]
	Near-optimal solutions		Participation in post-processing and filtering based on additional criteria.	[29,30[a],31],[a]
Low	Multi-objective optimisation		Participation in post-processing is needed for weighing the value of objectives.	[32–35]
	Single-objective optimisation		Limited participation is needed during objective selection; no filtering is needed.	[36,37]

● Optimal solutions.
● Near-optimal solutions.
● X – ▲ ◆ Other solutions.
[a] Only considers modelling of the electricity system.

process is not necessarily obvious to the user, and intermediate steps in the calculation sequence do not necessarily reflect distinct energy system choices. Simulation approaches on the other hand may appear more unstructured as the energy system modelling is guided largely by the modeller. This also means that the steps towards the optimum scenario will reflect actual distinct energy system choices.

Municipal and city energy system modelling is an area of increasing interest from both energy practitioners and modellers and is becoming an important part of strategic energy planning in municipalities [12]. While cities and municipalities show an interest in developing energy scenarios, as part of their energy planning, there is a lack of appropriate tools and methods for doing so [13]. It is not that tools do not exist that can conduct municipal energy system analysis, they do, but Weinand et al. [14] argue that these are generally targeted at energy system modelling experts and a central planning perspective, as opposed to energy planning practitioners in cities and municipalities. Furthermore, in addition to the practical knowledge needed to operate existing tools, substantial know-how is required to develop meaningful scenarios and results, as generalised methodologies are not well-established [15].

To provide an overview of challenges commonly experienced in energy system modelling, Prina et al. [16] present a classification scheme for bottom-up energy system modelling. In this, the authors present a matrix of challenges within the fields of resolution in time, space, techno-economic detail, and sector coupling. In the study it is concluded that no current models achieve high resolution in all fields, leaving users and planners with important decisions both in terms of model or tool selection and methodology when modelling energy scenarios.

Simoes et al. [12] determine challenges found specifically within urban energy system modelling, arguing that planning efforts so far in cities have been fragmented and that integrated planning is not widely applied for energy planning. The authors find that determining the extent to which cities can implement measures for transitioning the energy system is a challenge, as several systemic changes e.g., on the supply side or in the industrial sector are beyond the scope of what a city is reasonably able to influence. To negate these challenges the INSMART approach based on the TIMES model and multi-criteria decision analysis is presented as an optimisation model combining qualitative and quantitative criteria.

Ferrari et al. [17] present the main features of a selection of 17 tools including a combination of simulation and optimisation tools. The study focuses on six tools relevant for urban energy planning based on their user-friendliness and summarises technical characteristics of these tools. A similar study by Klemm and Venneman compare 145 different energy system models for urban districts, finding a general lack of tools suitable for multi-energy systems [18]. However, the studies do not provide practical insights into how the tools should be applied for developing future scenarios in a municipal or urban context and do not discuss differences in the applicability of simulation and optimisation approaches.

It is common for both simulation and optimisation-based energy system modelling case studies to present their general methodology and the applied modelling tool, but rarely are alternative approaches considered, especially alternatives belonging to a different school of modelling. This is exemplified in both optimisation-based case studies employing multi-objective optimisation (MOO) methods [19,20], and in simulation-based case studies [21,22]. Some researchers have attempted to correlate optimisation-based scenarios to simulation-based scenarios established by other researchers, finding that the two approaches can arrive at similar results [23]. However, the authors only compare the final simulation-based scenario to the Pareto front established by MOO and do not provide insights into the process through which the simulation scenario was established.

1.1. Scope and structure

Existing literature on energy system scenarios in a municipal context contains several reviews and technical classifications of existing tools, supplemented by an array of literature with case-specific scenarios. Limited comparison and discussion on the applicability of simulation and optimisation approaches exist, and authors do not appear to explicitly consider potential consequences of their choice of modelling approach.

This paper compares two distinctively different approaches to energy system modelling in the context of municipal energy system scenarios – i.e., the optimisation and the simulation approach. This expands on previous work with an emphasis on tool reviews and case studies with limited attention to the modelling approaches applied for developing future scenarios. Defining modelling approaches is a topic that extends beyond individual tools, as it is largely a process guided by the user and modeller.

In this paper we first conduct a review of existing modelling and scenario design approaches, expanding the concept of simulation and optimisation models to include sub-categories of the two archetypes. We then apply a proposed stepwise simulation approach and an established MOO approach to a case study, to uncover practical implications of the choice of modelling approach when developing future energy system scenarios.

In Section 2 an overview of existing energy system modelling approaches is presented, followed by the proposal of a stepwise simulation-based scenario development approach. In Section 3 the primary methods of the study are presented, including an introduction to the modelled case area, the modelling tool and approaches applied, and the investigated decision variables. In Section 4 results are presented for the case area for both the stepwise simulation approach and the MOO approach, and the two approaches are compared. In Section 5 the applicability of simulation and optimisation methods is discussed followed by the conclusion of the study in Section 6.

2. Simulation and optimisation approaches

Different approaches to energy system modelling exist, even if these are generally not explicitly defined and differentiated in literature. Therefore, we establish five specific approaches to energy system modelling in Table 1, functioning as a framework for categorising approaches. Naturally, not all studies are solely committed to one specific approach and may apply several approaches, or even a combination of the outlined approaches. Nevertheless, we believe that the five approaches presented below serve as a general outline of applied approaches and as a suitable framework for further discussion of scenario design, approaches, and principles. The examples below are categorised based on our assessment; the authors have not necessarily within the studies positioned themselves as part of a specific approach.

In Table 1 several defining characteristics for the five determined modelling approaches are shown. The concept "degree of freedom" is introduced as a measure of the extent to which the modelling approaches are based on defined rules and constraints, sorting the approaches from "high" to "low" relative to each other, not based on an absolute quantification.

In single-objective optimisation, the degree of freedom for policymakers or participatory processes with modellers is low, as the output is only one optimal solution. Multi-objective optimisation allows modellers to establish participatory processes with policymakers when choosing between scenarios, and thereby a higher degree of freedom compared to single-objective optimisation. The near-optimal solution approach is the optimisation approach with the highest level of freedom as it allows modellers to establish an open participatory process with policymakers who can make decisions based not only on costs and CO_2 emissions but also on other indicators through which is possible to filter the cloud of near-optimal solutions. In the simulation approaches (both stepwise and expert-based) the level of freedom is even higher because the participatory processes can be executed with multiple and different iterative steps between the modellers and the policymakers.

The five established modelling approaches are presented in greater detail in the following.

2.1. Expert-based simulation

In the expert-based simulation approach, modelling and scenario design are generally based on prior knowledge, "rules of thumb", and otherwise established principles of energy system modelling. These are then combined and applied in a "trial and error"-approach where different energy system scenarios are compared and explored. This makes it possible to investigate vastly different scenarios with a relatively limited number of simulations ($n < 50$) due to the number of changes that can be implemented with each simulation.

The modelling approach may be documented in the form of general principles which have formed the basis of the established scenario(s); however, it can be difficult to replicate the exact process undergone by the modeller from reference to the suggested future scenario. This is not to say, that suggested future scenarios cannot be well-documented and replicable – it most often is – but the path undergone to reach a suggested future scenario is typically not transparent. This is also in Table 1 illustrated by the high degree of freedom of the model, a characteristic of the expert-based simulation approach.

The expert-based approach may need inputs from local stakeholders, i.e., planners and policymakers, in outlining the primary objectives for the scenarios. This is necessary, as many intermediate decisions are left to the modeller (expert), and the post-processing participation is used for discussions on the suggested future energy scenarios.

2.2. Stepwise simulation

The stepwise simulation approach is a multi-step process for designing and, to some extent, "optimising" a future scenario. It is widely applied for all scales of the energy system and is based on a series of steps undergone to reach a future energy system scenario. This increases the number of simulations done compared to the expert-based simulation approach, however, the number remains relatively low and within the range of what is feasible to conduct manually ($n < 250$).

The stepwise priority simulation approach is an umbrella term for capturing different stepwise simulation approaches – there is no such thing as a general approach that can be applied everywhere. However, a general essential characteristic is that the procedure (steps) undergone by the modeller is documented afterwards. The extent and details of this documentation can vary significantly, but ideally, the level of detail should allow other researchers to replicate the work and go through the same logical process of scenario design. In Table 1 only two "steps" are shown in the illustration, but the process would likely consist of more steps before a scenario is finalised. A step in this context could be implementing energy savings, variable renewable electricity production (VRE), or district heating (DH), and through a process of testing different implementation rates or capacities to find an optimum. These are, as implied in the name, implemented in separate steps, thereby providing the modeller with insights into how the energy system responds to the various changes.

Like in the expert-based approach, early involvement and participation from local stakeholders are important, mainly for outlining the modelling steps to be investigated and the principles guiding the modelling. Because the stepwise priority simulation approach is based

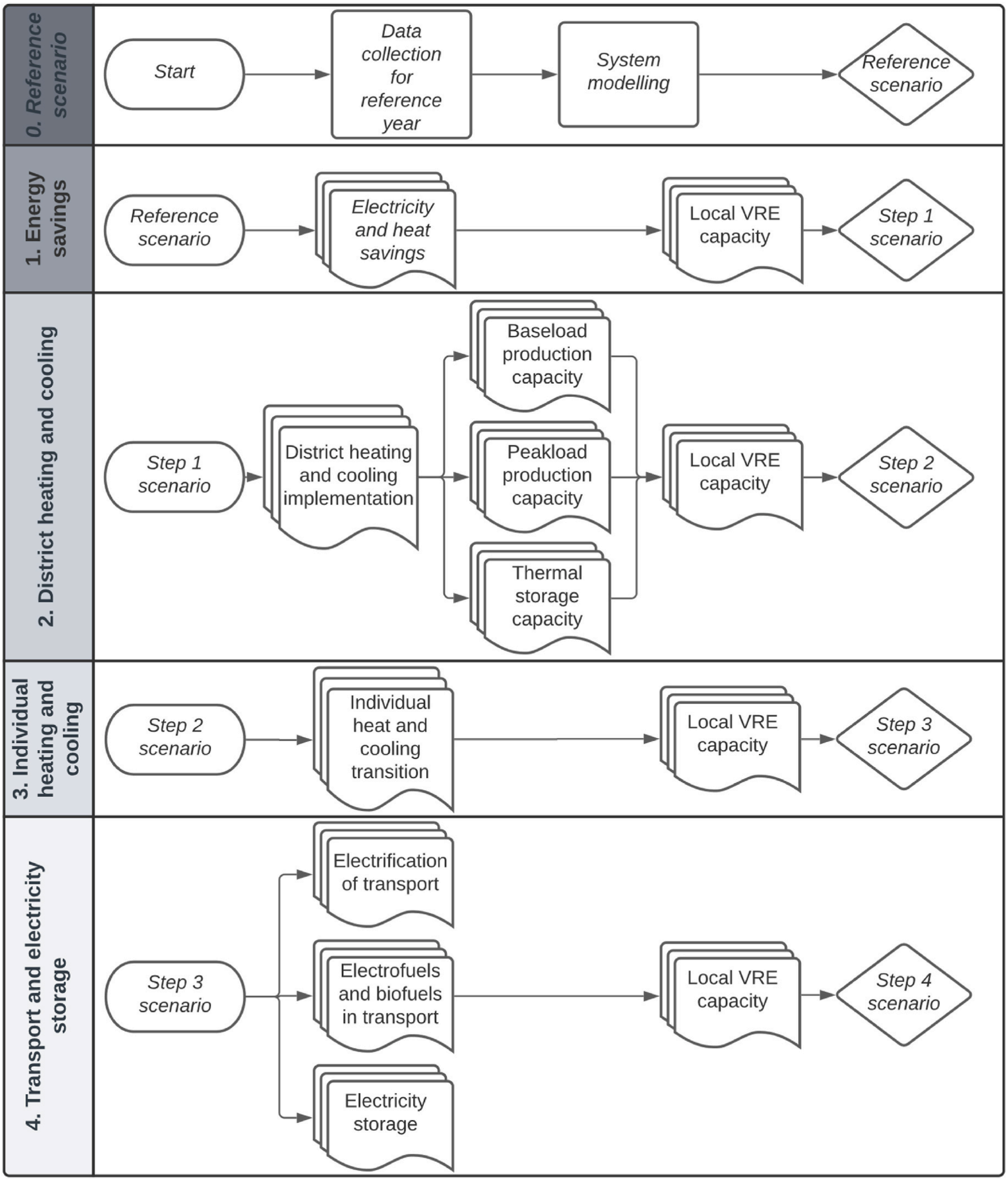


Fig. 1. A general stepwise simulation framework for developing energy system scenarios in a municipal context.

on these established principles, the degree of freedom is lower than for the expert-based simulation, however, because these are often only general guidelines the degree of freedom remains high compared to optimisation approaches.

2.3. Near-optimal solutions

The concept of near-optimal solutions is an emerging but so far not widely applied approach to energy system modelling. The idea is that solutions with similar results, in terms of costs and CO_2 emissions, may be very technologically diverse. Therefore, presenting an array of feasible (near-optimal) solutions may in some instances be preferable, as it would allow modellers and decision-makers to evaluate scenarios on additional criteria than, e.g., minor differences observed in cost and CO_2 emissions.

The near-optimal solutions approach is an extension of optimisation approaches. In simulation studies considering alternatives based on multiple criteria is an ingrained part of the evaluation process, even if it is not generally referred to as an assessment of near-optimal solutions. This is not generally the case for the outputs of an optimisation approach, where there may be only one optimal solution or a series of optimal solutions in the case of a Pareto front, and hence also considering near-optimal solutions (based on additional criteria) could provide a greater depth to such optimisation studies.

2.4. Multi-objective optimisation

MOO approaches are widely applied in energy system modelling studies through different methods and tools. While MOO could refer to the optimisation of any number of objective functions, most studies are limited to two objectives, CO_2 emissions and system costs (e.g., regional applications to South Tyrol [32] or Niederösterreich [38]). The optimisation model will seek to minimise or maximise the objectives within an allowed decision space defined by a number of decision variables. With the decision variables, the modeller defines boundary values for the optimisation model, generally based on physical limitations. There is no strict limit on the number of decision variables that can be included in a MOO model, however, depending on the range of values to be investigated, the decision space can quickly increase beyond what is feasible to optimise based on brute-force optimisation (simulating all possible system combinations). Instead, advanced search heuristics are often needed such as, e.g., genetic algorithms or particle swarm optimisation due to the large number of simulations required ($n > 1{,}000$). The output of a MOO model is generally in the form of a Pareto front, consisting of scenarios with the lowest costs and CO_2 emissions.

The degree of freedom of a MOO approach is low due to the rule-based nature of optimisation approaches where the model will include a set of pre-established rules for conducting the optimisation process, allowing a model to independently arrive at an optimal solution (or a series of optimal solutions). Some participation with local stakeholders, i.e., planners and policymakers may be needed in post-processing, as the output by nature is not one optimal scenario, but a series of optimal solutions found on the Pareto front.

2.5. Single-objective optimisation

Single-objective optimisation is not widely applied in energy system modelling due to the multi-criteria nature of most problems related to energy systems, for which MOO would generally be applied instead. Single-objective optimisation may be combined (in post-processing) with other boundary criteria, e.g., maximum CO_2 emissions, which to some extent would allow for additional criteria to be considered in single-objective optimisation models.

Like in MOO models, many simulations are required ($n > 1{,}000$), and the degree of freedom of the approach is low due to the pre-established set of rules for conducting the optimisation process. There is less need (and room) for participatory processes in the post-processing of results, as the output is one optimal scenario, based on optimisation of a single objective.

2.6. Proposing a stepwise simulation approach

Simulation modelling approaches are generally guided by some more or less well-defined principles, but no actual framework exists for stepwise simulation approaches. This is particularly a challenge in simulation approaches as the development of future scenarios relies significantly on the decisions of the modeller and the prior knowledge and understanding of energy system interactions. Therefore, based on the review of existing approaches, a stepwise simulation approach is proposed, as illustrated in Fig. 1.

The purpose of the proposed stepwise simulation approach is first to explore system solutions that can reduce both CO_2 emissions, and total system costs. Secondly, a weighing of these needs to occur, generally based on a politically set emission reduction target. This is possibly a target that cannot be achieved without compromising the total system economy as it may not be the cheapest solution, hence the second aim of the stepwise simulation approach is to fulfil the political target at the lowest possible total system cost. The approach outlined in Fig. 1 consists of four main steps to consider when developing energy system scenarios in a municipal context, starting from a reference scenario.

In Step 1 the potential for energy savings is explored for all relevant energy sectors by testing different levels of savings, after which a preliminary assessment of local VRE potential can be done. The resulting preliminary scenario with energy savings and local VRE production then serves as starting point for Step 2.

In Step 2 the potential for conversion to DH and cooling is explored. The feasible potential is a result of multiple factors such as building density, heat and cooling demands, and local heat and cooling sources, therefore the modeller needs to consider multiple system solutions. Depending on the extent to which electrification and storage capacity is included in DH and cooling, the potential VRE capacity may be affected and can therefore be reassessed. The resulting scenario with DH and cooling then serves as starting point for Step 3.

In Step 3 conversion of the remaining individual heat and cooling demand is investigated, e.g., through a shift to individual heat pumps. Again, increased electrification may have occurred which could impact the potential for installing VRE capacity, hence this should be tested again. The resulting scenario with complete or partial transition of the individual heating and cooling sector then serves as starting point for Step 4.

In Step 4 electrification of the transport sector and the potential for electricity storage are investigated. Depending on the local demands and the scope of the energy system modelling electrofuels for heavy transport may be needed. Lastly, local VRE potentials are tested again.

The process outlined in Fig. 1 should be considered recursive and may need to be repeated in case targets are not met in the first iteration. However, after the first iteration, the modeller will have a general understanding of the marginal costs of further CO_2 reductions for each of the initiatives in Steps 1–4, and hence be able to prioritise certain areas for further developments.

3. Methods

This section presents the selected case study where the established simulation and optimisation approaches are applied to compare how such modelling approach decisions affect the resulting future municipal energy scenarios.

3.1. Case selection and reference scenario

Oud-Heverlee is one of 300 independent municipalities in the Flemish region of Belgium. In 2015 the municipality developed a climate action plan for 2020 [39] as part of the Covenant of Mayors initiative [40] and has also joined the 2030 Covenant of Mayors initiative, committing to 40% CO_2 reductions by 2030.

Oud-Heverlee has approximately 11,000 inhabitants, and an energy system based mostly on fossil fuels, with electricity being supplied mainly from the national electricity grid. Oud-Heverlee already has a small amount of rooftop photovoltaics (PV), some electric vehicles, and some households have heat pumps for heating.

Oud-Heverlee consists primarily of single-family houses (88% in 2020), with the remaining housing facilities being mostly apartments. The municipality has experienced a slight growth in population from 2011 to 2020 by 0.9%, and a gradual increase in housing facilities, increasing by 5.4% in the same period. Both growth rates are however lower than the average of the Flemish region. The building stock consists of 44.3% of buildings from before 1970, 20.5% of buildings from the period 1971–1981, and the remaining 35.2% being buildings constructed after 1981.

Energy consumption, for both heat and electricity, has been decreasing slightly from 2011 to 2020, and as a result, so has CO_2 emission. Total energy consumption has decreased by approximately 12.6%, and CO_2 emissions by 7.6% - thus failing to reach the previous Covenant of Mayor target of a 20% reduction by 2020. Reductions in energy demand and CO_2 emissions are a result of house renovations enabling heat savings, a gradual replacement of oil boilers with natural gas boilers, and in a few cases, the installation of electric heat pumps.

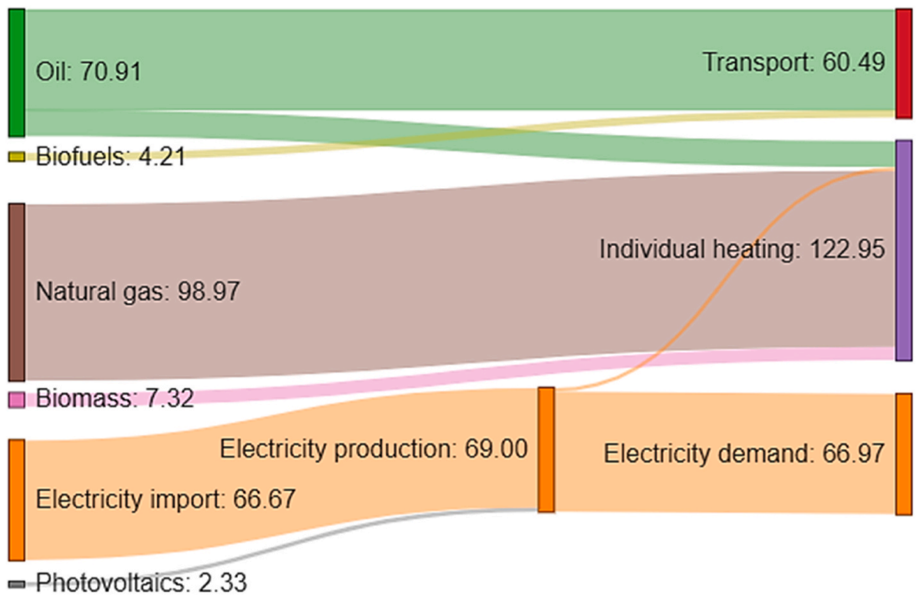


Fig. 2. Reference scenario energy flows for Oud-Heverlee (2020).

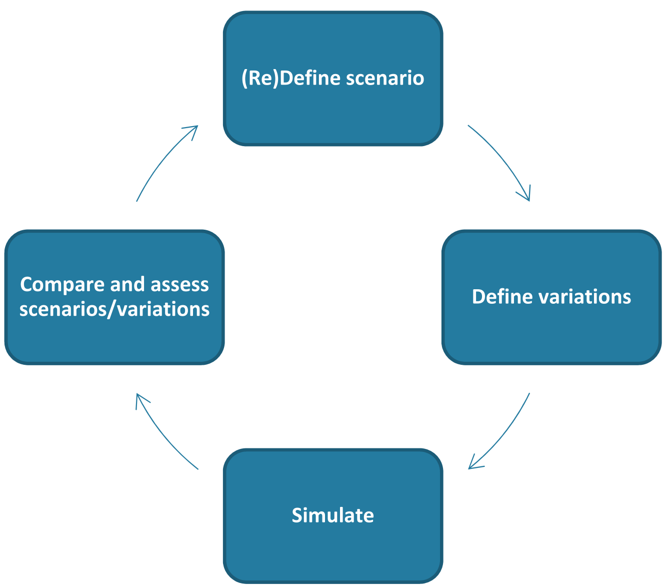


Fig. 3. Scenario development process of the stepwise simulation approach.

The transportation sector is largely unchanged in the same period. Industrial activity in Oud-Heverlee is limited, and there are no local power plants. A reference scenario for 2020 was established, functioning as a starting point for future scenarios - an overview of energy flows can be seen in Fig. 2.

Individual heating is by far the most energy-consuming sector with the majority of the heat demand being supplied by natural gas. Transport is overwhelmingly covered by fossil fuel-based personal vehicles relying on oil, and electricity is imported from the national grid except for a small local electricity production from PV.

Table 2
Decision variables investigated in energy system scenarios.

Decision variable	Unit	Minimum value	Maximum value	Interval
Onshore wind power	kW	0	100,000	1,000
PV	kW	2,000	100,000	1,000
Electricity storage	MWh	0	300	10
DH thermal storage	MWh	0	1,500	50
DH HP capacity	kW-e	0	25,000	250
DH share	%	0	100	10
Indiv. HP production	GWh	6	120	1

3.2. Modelling tools and approaches

In this study, energy system scenarios are modelled with the use of EnergyPLAN v16.1 [10] – a well-established tool for holistic modelling of energy systems and all related energy sectors with more than 300 references in the academic literature [41] EnergyPLAN is used as the calculation engine for both the simulation and optimisation-based approaches but is applied in different ways to accommodate both modelling approaches.

The stepwise simulation approach uses the Multiple Energy Grids Planning tool, an EnergyPLAN-based modelling tool designed specifically for municipal energy system scenarios [13]. This tool comes with additional functionalities for scenario modelling, allowing the user to develop multiple energy system scenarios more easily compared to the stand-alone version of EnergyPLAN. In Fig. 3 the inherent logic for scenario modelling in the Multiple Energy Grids Planning tool can be seen. This process aligns well with the stepwise simulation approach defined in Section 2.2 which, due to its nature with user-defined scenarios, considers scenario development an iterative activity.

The MOO approach also relies on EnergyPLAN for the actual energy system calculations to ensure consistency, but the optimisation of inputs is done by the EPLANopt model [32], a MOO model based on a genetic algorithm. The model, typically adopting total system costs and CO_2 emissions as objective functions, establishes a Pareto front of Pareto optimal solutions. These solutions are identified by the expansion capacity optimisation algorithm which varies the decision variables' values in their admissible ranges until convergence indicators are met.

The stepwise-simulation approach represents a categorical approach to simulation, relying on significant user input and careful selection of scenarios, as opposed to automated generation of thousands of systems. The applied MOO approach represents a broader optimisation-based modelling paradigm where the development from reference to future scenarios is done autonomously based on pre-defined boundaries.

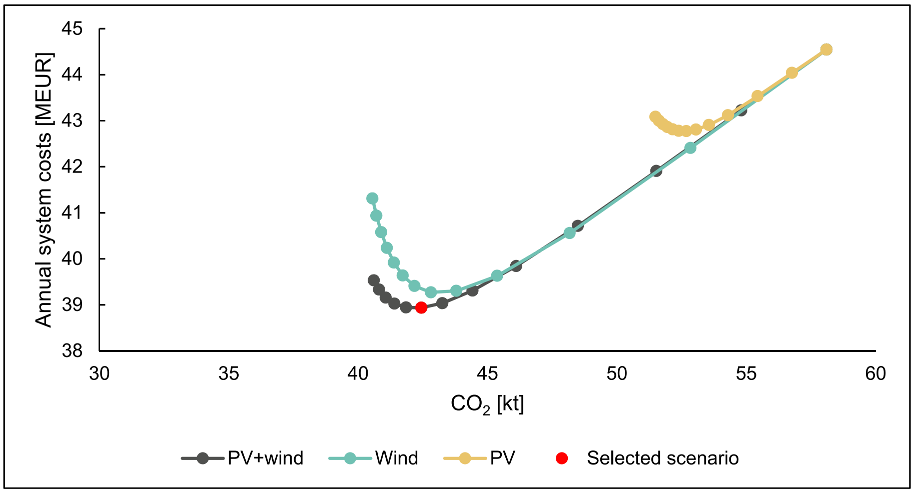


Fig. 4. Annual system costs and CO_2 emissions for different combinations of installed VRE production capacity for Oud-Heverlee (Simulation-based approach Step 1).

3.3. Decision variables

Seven decision variables are included in the energy system modelling conducted for this study. This is firstly to limit the scope of the modelling exercise, and to structure the variables included in the energy system scenarios so that comparable results can be obtained for the two applied modelling approaches. Secondly, the variables included are in areas of the energy system that are within the municipality's sphere of influence, hence aligning with the scope of municipal energy planning. In Table 2 the decision variables investigated can be seen with the assumed minimum and maximum boundary values.

The decision variables shown in Table 2 are investigated in both the stepwise simulation approach and the MOO approach, adhering to the minimum and maximum values and the intervals shown. Energy efficiency improvements and changes to the transportation sector are not included in the scenarios due to a lack of data and to limit the scope of modelling. Simulation-based approaches would typically not adopt the "decision variables" terminology, and instead refer to "system characteristics and technological changes", but for simplicity, these possible system changes will be referred to as decision variables going forward.

Most of the decision variables do not have correlated modelling impacts (i.e., onshore wind power, PV, electricity storage, DH thermal storage, and DH HP capacity), meaning that changing these variables does not strictly require changes to other model inputs. However, increasing the DH share does require additional model changes. Firstly, increasing DH inherently come with the assumption that the individual heat demand is decreased in parallel. It is therefore assumed that the individual heat demand is shifted from individual heat production technologies to DH, prioritising a shift away from fossil fuel technologies. Hence, the shifting is first done for the individual oil boilers, then the natural gas boilers, then the biomass boilers and finally, if needed, the individual electrical HPs.

Secondly, increasing DH demand needs to be accompanied by sufficient peak load production capacity. It is assumed that a peak load production capacity for DH is supplied by biomass heat-only boilers at a capacity equal to 120% of the peak load demand. For increased individual HP production, other individual heat production technologies are reduced concurrently, based on the same principles as described for DH.

Further details on the technical and economic assumptions for the decision variables can be seen in Appendix A.

4. Results

In this section, the results from the energy system modelling of Oud-Heverlee are presented. Results, with an emphasis on the modelling process, are presented for both the stepwise simulation approach and the

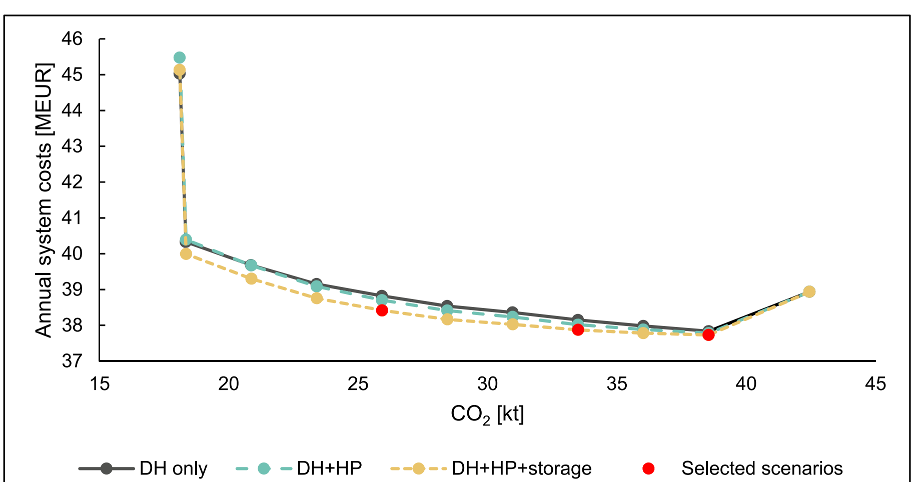


Fig. 5. *Annual system cost and CO_2* emissions for different levels of DH implementation, HP capacity, and thermal storage capacity *for Oud-Heverlee (Simulation-based approach Step 2).*

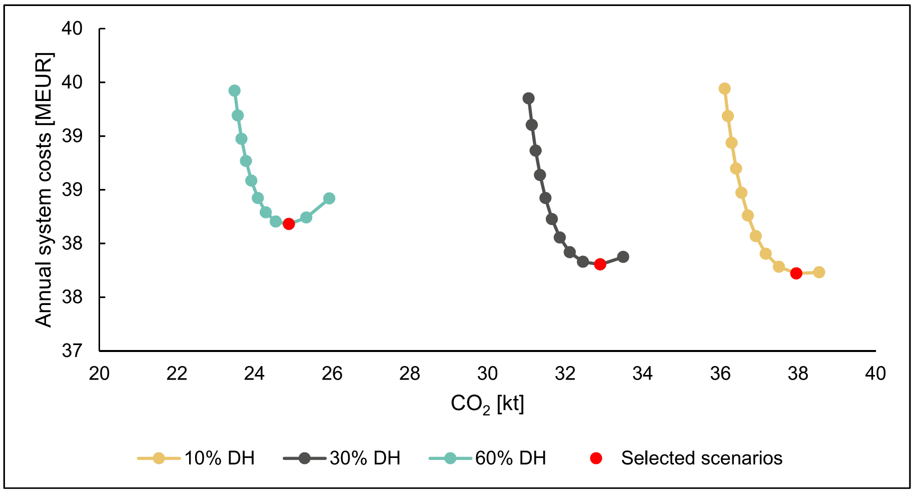


Fig. 6. Annual system cost and CO_2 emissions for different levels of DH implementation and increasing VRE capacity for Oud-Heverlee (Simulation-based approach Step 2).

MOO approach, followed by a comparison of the two approaches.

4.1. Stepwise simulation approach

Electricity and heat savings are omitted from the model, hence in a first step it is tested how the energy system in Oud-Heverlee responds to the implementation of VRE capacity by increasing the installed wind power capacity, PV capacity, and a combination of wind power and PV (Fig. 4). For all scenarios, the same trend emerges; both CO_2 emissions and total annual system costs (operation costs and annualised investment costs for all energy sectors) are decreasing up until a point after which system costs increase. The potential for CO_2 reduction is lowest for scenarios implementing PV only, a result of the natural temporal production profile of PV, while wind power comes with a more variable production profile. The highest potential for CO_2 reduction and the lowest system costs were however observed for the combination of PV and wind power – hence this option was selected for Step 2, with an installed capacity of 16 MW PV and 21 MW wind power.

In Step 2 (Fig. 5) DH is implemented, testing three different scenarios all with increasing DH implementation. A "DH only"-system where heat is supplied by large biomass heat-only boilers, a "DH + HP" system where the boilers are supplemented by an electrical HP capacity, and a "DH + HP + storage" system where thermal storage capacity is also included. DH is implemented based on a cost curve which can be seen in Appendix A, which also includes the methodology for establishing the particular DH cost curve.

Differences are generally minor across the three scenarios, and the same trend is observed – cost and CO_2 emissions are reduced for the first 10% of the DH cost curve (i.e., the densest areas), but for any additional DH implementation the annual system costs increase. CO_2 emissions continuously decrease with increasing DH because of the transition from fossil fuel-based individual heating to renewable DH. A complete conversion to DH results in a significant increase in system costs due to the very scattered housing found towards the end of the cost curve. While the difference is small, the DH + HP + storage scenario is selected for the next step due to it providing the lowest system cost. Only a 10% conversion to DH resulted in a reduction in system costs, however, for comparison, and because of the CO_2 emission reductions from further DH conversion, also 30% and 60% DH variations are included in the following steps. In Fig. 6 it is shown whether the conversion to DH (and the electrification occurring because of it) makes it feasible to increase the installed VRE capacity. This is possible for all scenarios, but most prominently for the 60% DH scenario since naturally the largest electrification occurs here. The result is an installed capacity of 18 MW PV and 24 MW wind power for the 10% DH and 30% DH scenarios, and 20 MW PV and 27 MW wind power for the 60% DH scenario.

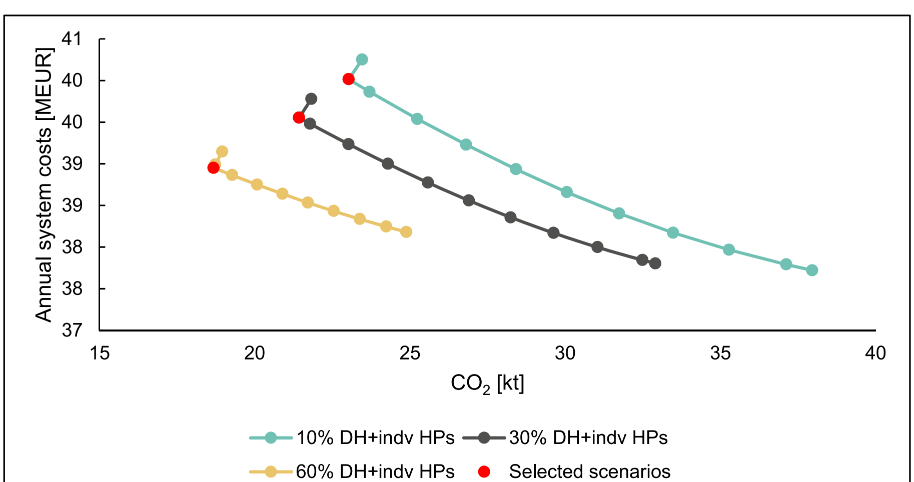


Fig. 7. Annual system cost and CO_2 emissions for increasing conversion to individual HPs with different levels of DH implementation for Oud-Heverlee (Simulation-based approach Step 3).

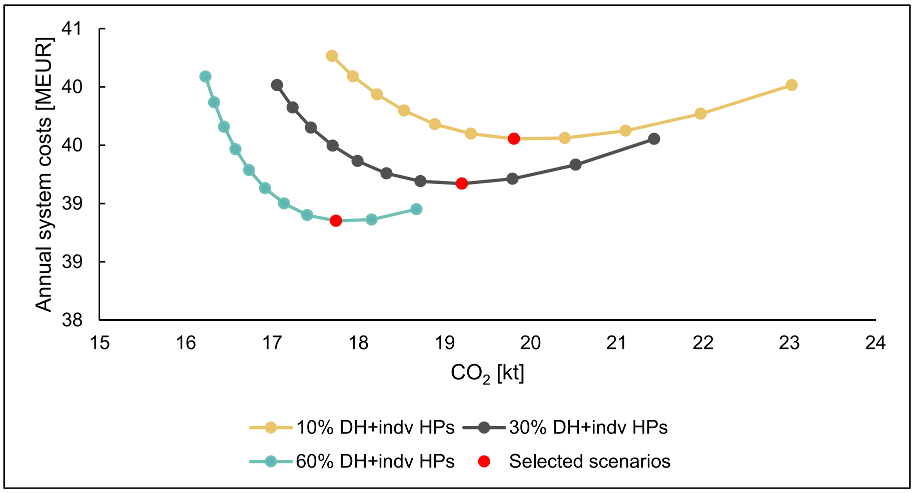


Fig. 8. Annual system cost and CO_2 emissions for increasing VRE capacity with different levels of DH and individual HP implementation for Oud-Heverlee (Simulation-based approach Step 3).

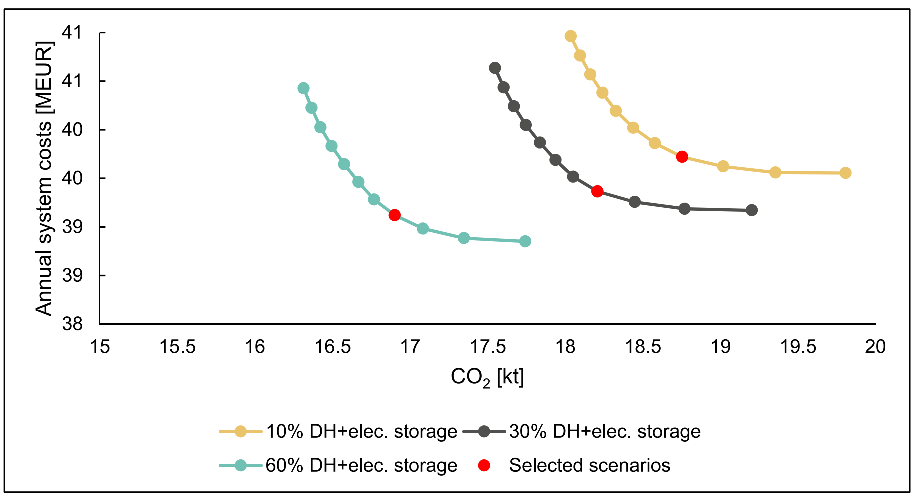


Fig. 9. Annual system cost and CO_2 emissions for increasing electricity storage capacity with different levels of DH and individual HP implementation for Oud-Heverlee (Simulation-based approach Step 4).

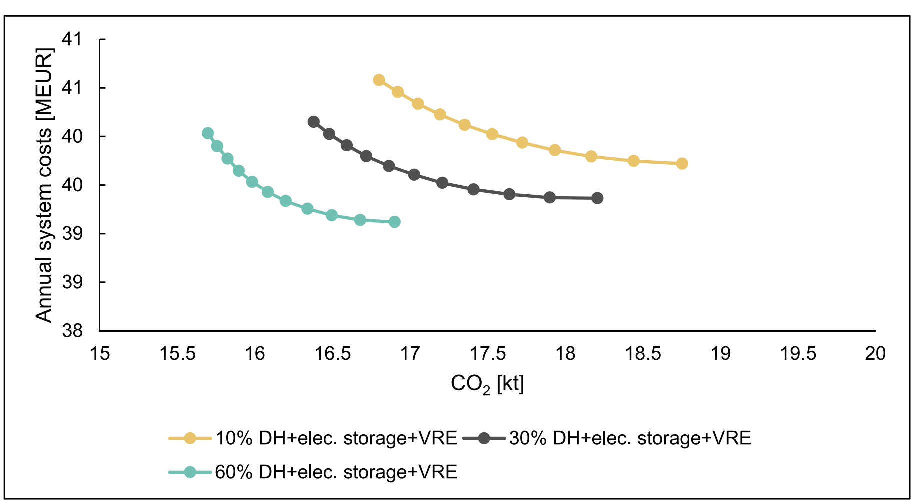


Fig. 10. Annual system cost and CO_2 emissions for increasing VRE capacity with different levels of DH and individual HP implementation and 30 MWh electricity storage for Oud-Heverlee (Simulation-based approach Step 4).

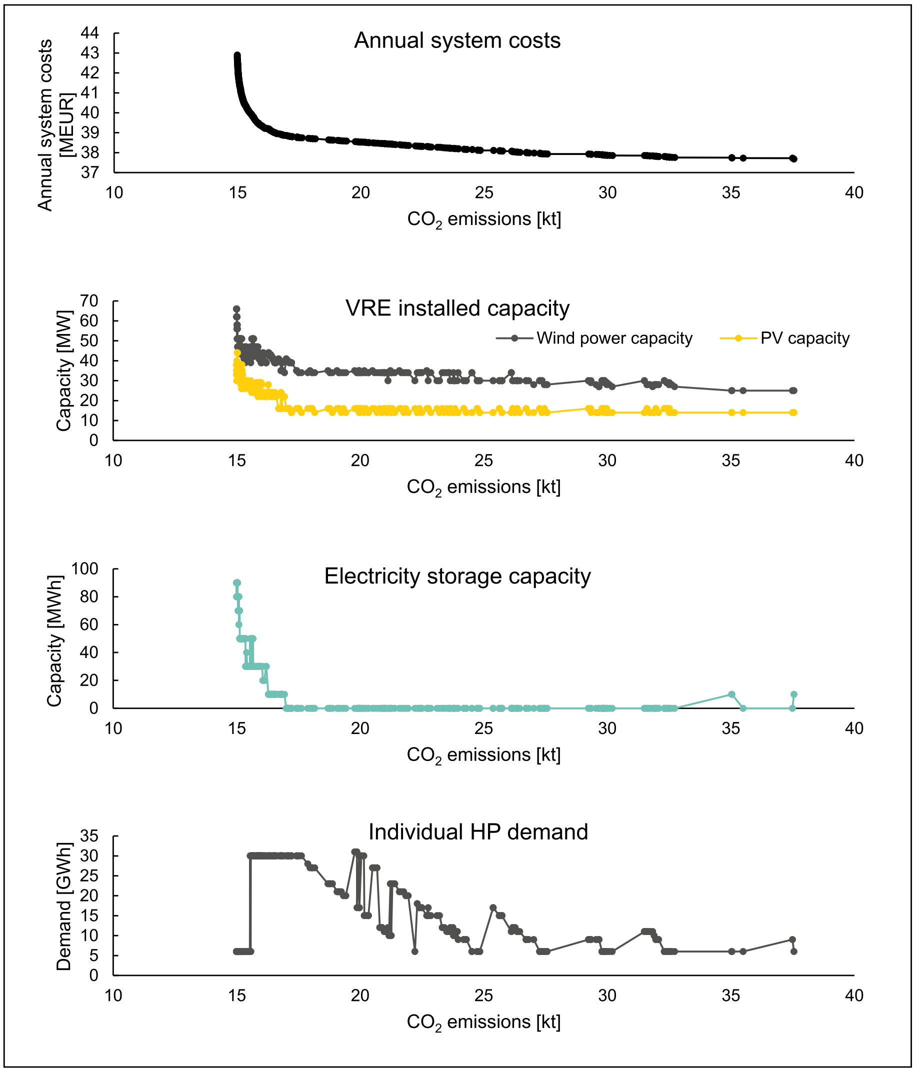


Fig. 11. Development of VRE capacity, electricity storage capacity, and individual HP demand relative to Pareto front for the Oud-Heverlee case.

In Step 3 a gradual conversion of the remaining individual heat demand to electrical heat pumps is investigated (Fig. 7). The gradual conversion to individual HPs results in an increased system cost but does reduce CO_2 emissions. For the final step, a variation with almost complete conversion to individual HPs is selected, only the already existing biomass boilers remain. With the increased electrification from the increased capacity of individual electrical HPs, it is now possible to further increase the VRE capacity while lowering both CO_2 emissions and system costs, as seen in Fig. 8. The result is an installed capacity of 26 MW PV and 36 MW wind power in the 10% DH scenario, and 24 MW PV and 33 MW in the 30% DH and 60% DH scenarios.

In Step 4 li-ion batteries are added for electricity storage, enabling further, however relatively minor, CO_2 emission reductions but with increased system costs, as seen in Fig. 9. For completeness, scenarios with 30 GWh of electricity storage capacity are tested with increasing VRE capacity (Fig. 10), but the added electricity storage capacity does not enable additional VRE capacity to be installed without incurring additional system costs.

4.2. Multi-objective optimisation approach

The optimisation model EPLANopt is applied to the case of Oud-Heverlee with the same decision variables as in the stepwise simulation approach. The model determines optimal system solutions for CO_2 emission and system cost reduction, resulting in a Pareto front of optimal solutions, as seen in Figs. 11 and 12. The results thereby do not determine a single optimal scenario, but rather a range of optimal scenarios for continuously decreasing CO_2 emissions.

In Fig. 11 it can be seen how the model determines the optimal capacity of PV to be around 14 MW–16 MW and for wind power to be around 27 MW–33 MW for most scenarios. This however increases significantly towards the end of the Pareto front as the CO_2 emissions decrease. Electricity storage is not included in most scenarios and is only included towards the end of the Pareto front where the system costs increase exponentially. The trend is less clear for the individual HP demand - the individual HP demand increases gradually before a steep drop to 6 GWh at the end of the Pareto front. The drop to 6 GWh occurs because a 90% conversion to DH allows for increased integration of VRE from storage capacity compared to individual heating and thereby reduced CO_2 emissions but results in a high system cost due to the required investment costs and resulting thermal losses.

In Fig. 12 it can be seen how the model determines that for optimal scenarios the DH share is gradually increased to reduce CO_2 emissions. This increase in DH comes with increasing installed capacity of HPs in DH is increasing and increased thermal storage capacity.

The general trends observed in Fig. 12 (increasing HP capacity and increasing thermal storage capacity) are intuitively relatively logical correlations to an increased DH deployment. The fluctuations observed

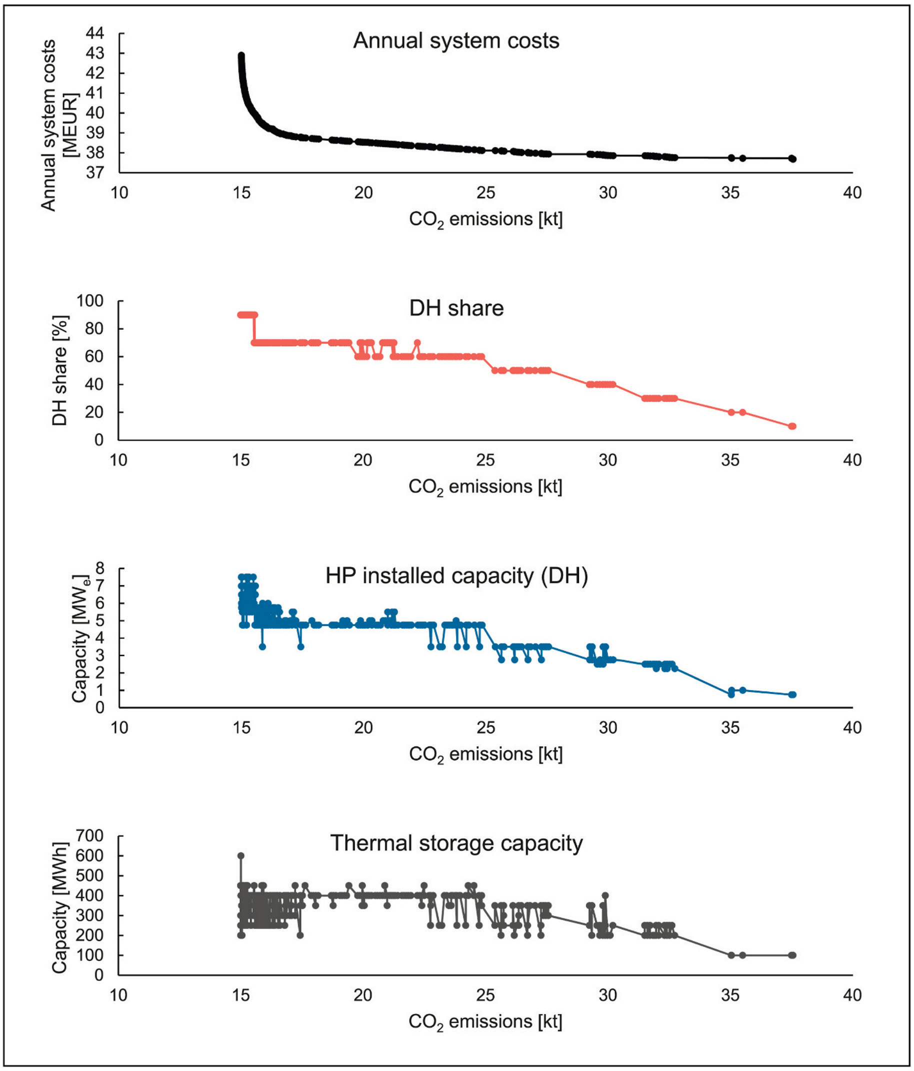


Fig. 12. Development of DH share, HP capacity in DH, and thermal storage capacity relative to Pareto front.

for the HP and thermal storage capacity indicates that there is some uncertainty on the exact optimal installed capacity, even if it is quite clear that some capacity is needed.

4.3. Simulation vs optimisation

Comparing the results of the stepwise simulation approach to the MOO approach in Fig. 13, it can be seen that the simulation results in all steps (1–4) are generally at least at one point very close to the Pareto front. Hence, the proposed stepwise simulation approach does enable the user to arrive at scenarios that are similar to those obtained from the MOO approach. The exception to this is Step 1 where it is not possible to arrive at results comparable to the MOO approach; that is however not surprising based on the limited options available for Step 1.

The structured nature of the proposed simulation approach of the user-guided stepwise simulation approach also leads to some system understanding of technological interactions obtained from the process of modelling. The MOO optimisation approach does however provide a much more complete picture of all possible Pareto optimal solutions, but without any inherent explanations or understanding of the conclusions to draw from the results. Instead, the modeller needs to establish this understanding of results in a post-processing phase.

To arrive at the results in Figs. 13, 9,000 simulations were done for the MOO approach, which due to the genetic algorithm applied is relatively few compared to the total decision space available. The results for the stepwise simulation approach required 219 total simulations, however, these results do not cover the same array of optimal solutions found with the MOO approach.

5. Discussion

Determining that distinctively different energy system modelling approaches exist is the first step towards greater awareness of how modellers approach energy system modelling, beyond contemplating what modelling tool to use, but also considering how it is applied. However, the aim of comparing energy system modelling approaches in this study has not been to establish whether one approach is superior to others, but rather to establish that a conscious decision is needed from modellers.

Energy systems are inherently complex due to consisting of multiple sectors and an abundance of technologies [42], and modellers could therefore be inclined to believe that MOO methods are required to obtain results even resembling optimality. It is however seen in this study that it is possible to arrive at energy systems for a municipality based on a general set of principles for simulation that is comparable in terms of CO_2 emissions and total system cost to energy systems derived from MOO. This is illustrated by the proximity of the results from the proposed stepwise simulation approach compared to the established

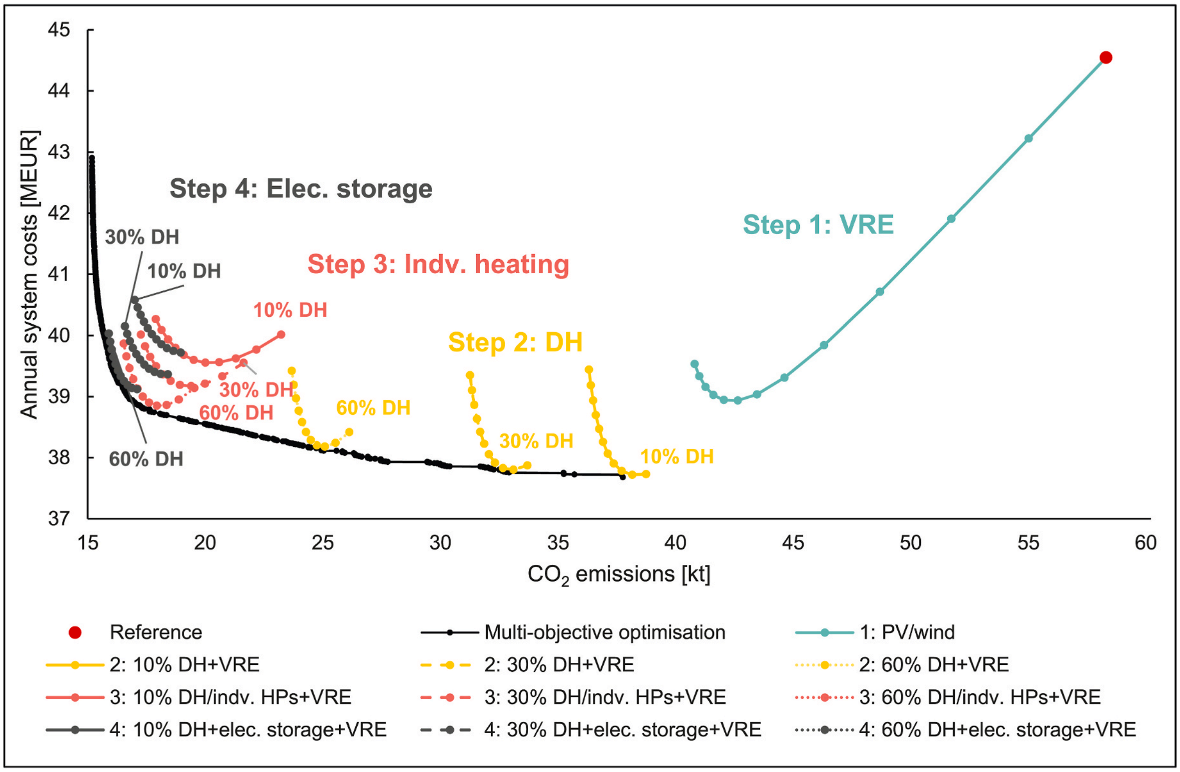


Fig. 13. Comparison of Pareto optimal solutions determined through MOO to selected stepwise simulation solutions for the Oud-Heverlee case.

Pareto front from the EPLANopt method. Hence, system complexity should likely not be used alone as a criterion to determine whether to apply simulation or optimisation-based approaches. Rather, such a decision should preferably be guided by the local challenges, recognising whether these can be translated to an optimisation problem.

The stepwise simulation approach relies on an iterative process guided by the modeller, thereby supporting a build-up of system understanding that may help in defining future scenarios and later in communicating the results of these scenarios. A downside to this user-guided process is the risk of overlooking relevant energy system configurations, as the process is naturally limited by the imagination of the modeller. MOO on the other hand, in this study implemented through the EPLANopt model, models a larger range of potential system configurations compared to what is feasible in a stepwise simulation approach. The downside of MOO is that significant post-processing of the results is needed to understand the occurring energy system interactions.

The emphasis on CO_2 emissions and total system cost present in this study is not embedded in simulation approaches and was perhaps in this study overemphasised to enable the comparison to optimisation approaches. This is however a general tendency seen in studies on decentralised energy system modelling as such scenarios often need to align to concrete national CO_2 emission targets [43,44].

Such emphasis on only CO_2 emissions and costs, and a strictly confined set of decision variables, disregards some of the opportunities provided by simulation approaches. This includes the potential to investigate fundamental or radical changes to the energy system that cannot be confined to an optimisation problem, or the potential to evaluate scenarios based on an additional set of parameters. Hence, for holistic energy system modelling, optimisation approaches may in some instances be unable to at the same time choose between savings in electricity, heat, electrification, DH or individual supply, production technologies for electricity and DH. In simulation approaches, such choices can be better understood and can be dealt with separately, while also addressing the different markets they act on.

Perhaps as a response to the general energy system complexity and challenges in evaluating scenarios, increasing attention to model coupling, model integration and multi-criteria approaches seems to be emerging. Muñoz et al. [45] argue for a general need for holistic modelling in integrated city energy modelling. They further propose a methodology for combining energy scenario modelling based on sectoral energy demands and present a framework for evaluating scenarios based on energy, environmental, and socioeconomic criteria. Underlining the emerging emphasis on integrated methods, Chang et al. [46] present an extensive review of the growing field of multi-model analysis practices in energy system modelling and model coupling. In this, the authors argue that simulation and optimisation methods are mutually complementary, and that model coupling can enable modellers and planners to explore a wider solution space and thus more robust scenarios. Chang et al. conclude that model coupling also occur across different model classes, i.e., coupling energy system models with demand side models, geospatial models, macroeconomic models, or life cycle assessment models, but that coupling to social dimensions is lacking. Future models for municipal energy system modelling could potentially develop in line with these trends, and to a larger extent function as “hybrid” simulation-optimisation models employing multi-criteria principles with less strict distinctions of simulation- and optimisation-based approaches.

6. Conclusion

This study defined five individual energy system modelling approaches, building on the previous simplified distinction of simulation and optimisation models in existing literature, and categorised existing applied approaches to energy system modelling. A stepwise simulation approach was proposed and compared to the EPLANopt MOO approach through an application to a municipal case study. The comparison exemplified how fundamental differences in modelling approaches influence the process of designing future energy systems.

The municipal energy system of Oud-Heverlee was used as a case for the practical comparison of stepwise simulation to a MOO approach. As a municipality, the energy system of Oud-Heverlee is delimited by political boundaries and due to its limited size relatively simple in terms of technologies and energy demands. Hence, there are no inherent barriers to applying the stepwise simulation approach or the MOO approach.

Modellers should consider their approach to energy system modelling concurrently with deciding on a modelling tool so that both can be aligned with their research problem. Both simulation and optimisation approaches are legitimate approaches to energy system modelling for scenario development, assuming that sound fundamental principles are applied.

Future research could consider investigating if the proposed stepwise simulation approach and principles herein can be transferred to national energy system modelling, with the increased system complexity entailed. While the proposed stepwise simulation approach would likely in principle be transferable, some further development may be needed to accommodate the increased array of technologies and energy sectors that must be captured in such national energy system models.

Credit author statement

Rasmus Magni Johannsen: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing **Matteo Giacomo Prina**: Conceptualization, Methodology, Writing – review & editing **Poul Alberg Østergaard**: Conceptualization, Writing – review & editing **Brian Vad Mathiesen**: Writing – review & editing **Wolfram Sparber**: 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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.energy.2023.126803.

Appendix A

Technical and economic assumptions for decision variables.

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