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Multi-stage optimal design of energy systems for urban districts

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ABSTRACT

Urban districts develop in a dynamic manner over multi-year horizons with new buildings being added and changes being made to existing buildings (*e.g.* retrofits). Nevertheless, optimization models used to design urban district energy systems (DES) commonly consider a single, "typical" year for the design. This practice, however, does not allow for energy design decisions to be made in multiple phases in order to reflect a district's development phases. This paper addresses this issue and presents a novel optimization model that allows the multi-stage optimal design of urban DES. The model identifies the cost-optimal technology investment decisions across a horizon that spans multiple years, while also calculating the energy system's optimal operating patterns in order to meet the district's energy demands. The evolution of the district's energy demands and aspects like the evolution of technology costs and energy carrier prices are considered in the model. The model is applied to a new urban district in Zurich, Switzerland, for which 5 development stages are considered with new buildings of various types constructed in each phase. A multi-stage DES design plan is developed for the period 2021-2050, which includes large energy technology investments for each new development phase, but also smaller ones in the intermediate years between 2021 and 2050. The model specifies the amount of energy generated by each technology installed in each year, as well as the contribution of renewable energy in covering the district's energy demands.

KEYWORDS

Urban energy systems, District Energy Systems, Multi-stage energy planning, Optimization

INTRODUCTION

District energy systems (DES), incorporating multiple efficient energy technologies and locally available renewable sources, have the potential to sustainably transform the energy supply of existing and new urban districts. Designing DES is commonly performed using mathematical optimization models. These models aim to identify the optimal set of technologies that need to be installed in a DES, their capacities, and their operating patterns in order to cover the building energy demands and optimize a specific criterion (*e.g.* total system costs, CO_2 emissions etc.).

In these models, the DES design investment is typically assumed to occur in one stage, at the beginning of the project, without the possibility of further investments in later stages. Moreover, the design is usually performed for a "snapshot" in time, which corresponds either to the district's current state or to the final state of a district. Multiple studies have presented such DES design models (see *e.g.* (Orehounig et al., 2015; Weber and Shah, 2011)).

This DES design paradigm, however, fails to consider the dynamic character of existing and new urban districts, which dynamically develop as buildings are getting retrofitted and/or new buildings are being added. Energy planning for urban districts should instead be able to account

for the developments in an urban district and involve multiple investment phases. This would allow the energy system plan to not only reflect the changes in the district, but also to take advantage of future investment opportunities *e.g.* due to reducing technology costs.

Therefore, this paper presents an optimization model, which enables the multi-stage design of urban DES. More specifically, the model outputs a multi-year investment plan for the DES design and calculates the system's optimal operation for each year. Additionally, the model is able to perform these tasks taking into account the evolution of a district's characteristics, as well as, the evolution of other external factors like energy prices and technology costs.

FORMULATION OF A MULTI-STAGE OPTIMAL DES DESIGN MODEL
In this section, the formulation of the multi-stage DES design model is presented. In order to be able to make DES design decisions in multiple stages, the model's horizon needs to include multiple years $y = \{1 \ldots \mathcal{Y}\}$. Each year y is then represented with a set of days $d = \{1 \ldots \mathcal{D}\}$, which are in turn represented with 24 hourly time steps $t = \{1 \ldots 24\}$.

The developments considered in the model's multi-year horizon are: (i) the district's heating and electricity demands, (ii) the solar radiation availability, (iii) the energy carrier prices, (iv) the electrical grid's carbon factor (due to grid mix changes), and (v) the future technology costs.

The set of candidate energy generation and storage technologies for the DES are given in Fig. 1 and include a gas and a biomass boiler, a CHP engine, a ground-source heat pump (GSHP), PV panels, a thermal storage and batteries for the storage of electricity. Note that the connection to the electrical grid is maintained and accounted as a "generation technology" in the model.
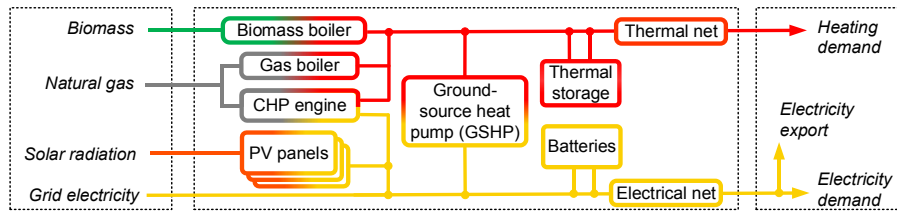

Figure 1. Candidate energy generation and storage technologies for the synthesis of a DES

The model aims to minimize the total DES cost, *TC,* over the modeled horizon. *TC* is expressed as the sum of the discounted annual costs (AC_y), which include an investment (Inv_y) and an operating expenditure (Op_y). All the relevant cost metrics are given in Eq. (1)-(3) (bold symbols indicate model variables).

$$TC = \sum_y (\boldsymbol{AC_y}) \cdot (1+DR)^{y-1} = \sum_y (\boldsymbol{Inv_y} + \boldsymbol{Op_y}) \cdot (1+DR)^{y-1} \tag{1}$$

$$\boldsymbol{Inv_y} = FC_{i,y} \cdot \boldsymbol{d_{i,y}} + LC_{i,y} \cdot \boldsymbol{ncap_{i,y}} + (L_y^{net} - L_{y-1}^{net}) \cdot LC_{net,y}, \ \forall y \tag{2}$$

$$\boldsymbol{Op_y} = \sum_{j,d,t} (\boldsymbol{P_{j,y,d,t}} \cdot OC_{j,y}) - \sum_{d,t} (\boldsymbol{L_{y,d,t}^{exp}} \cdot FiT_y), \ \forall y \tag{3}$$

In all terms of Eq. (1)-(3), the indices *y*, *d*, and *t* signify that a term is indexed per year, day, and/or time, respectively. In Eq. (1), *DR* is the discount rate used for future expenditures. In Eq. (2), $FC_{i,y}$ and $LC_{i,y}$ are the fixed and the capacity-dependent costs of technology *i*, $\boldsymbol{d_{i,y}}$ is a binary variable denoting the installation of technology *i*, while $\boldsymbol{ncap_{i,y}}$ is the newly installed capacity of technology *i*. L_y^{net} is the length of the thermal network and $LC_{net,y}$ is the investment cost per *m* of network. These two variables form the *design decisions* of the model. In Eq. (3), $\boldsymbol{P_{i,y,d,t}}$ is

the input energy flow to energy generation technology j, $OC_{j,y}$ is the price per kWh of the energy carrier used by generation technology j, $L_{y,d,t}^{exp}$ represents exported electricity to the grid, and FiT_y is the feed-in tariff for exported electricity. The variables $P_{j,y,d,t}$ and $L_{y,d,t}^{exp}$ are indexed per y, d, and t to calculate the system's operation for each year, day, and time step considered.

The carbon emissions, $Carb_y$, resulting from the system's operation in year y are defined in Eq. (4), in which $C_{j,y}$ is the emission factor [gCO$_2$/kWh] of the carrier used in technology i.

$$Carb_y = \sum_{j,d,t}(P_{j,y,d,t} \cdot C_{j,y}), \ \forall y \tag{4}$$

An additional variable is needed in the model to track the total capacity of technology i in each year considering not only the introduction of new capacity, which is represented by $ncap_{i,y}$, but also the retirement of capacity that has reached the end of its lifetime. This variable is noted as $tcap_{i,y}$ and is defined in Eq. (5), in which $life_i$ represents the lifetime of technology i in years.

$$tcap_{i,y} = \sum_{max(0,y-life_i+1)}^{y} ncap_{i,y}, \ \forall y \tag{5}$$

An additional important set of model constraints are needed to ensure that the DES covers the district's energy demands in each time step. Eq. (6) expresses the energy balances for the heating and electricity demands of the district.

$$P_{j,y,d,t} \times \Theta_j + Q_{l,y,d,t}^{dis} - Q_{l,y,d,t}^{ch} = \eta_{net}^{dem} \cdot L_{y,d,t}^{dem}(+L_{y,d,t}^{exp}), \ \forall y, d, t, dem \in \{Heat, Elec\} \tag{6}$$

In Eq. (6), Θ_j is a matrix of conversion efficiencies for each generation technology, $Q_{l,y,d,t}^{dis}$ and $Q_{l,y,d,t}^{ch}$ represent the charging/discharging flows from storage of type l, $L_{y,d,t}^{dem}$ are the district's heating/electricity demands, η_{net}^{dem} is the efficiency of the thermal/electrical network connecting the DES to the buildings, while $L_{y,d,t}^{exp}$ is only included in the electricity demand balance.

Additional constraints are included in the model to express the energy balance for the storage technologies, non-violation of capacities and charging/discharging rates, and other technical and operational constraints. These constraints have similar formulation to the constraints included in previous models that performed one-stage DES design. The difference, though, is that these constraints must also be indexed per year y instead of just per day d and time step t.

CASE STUDY
The developed model can be applied for both existing districts and new developments. In this paper, a hypothetical new urban district in Zurich, Switzerland is taken. New buildings of various types are added to the district every five years from 2021 to 2040. The analysis horizon is taken as 2021-2050 in order to analyze the DES operation for ten years after the district's construction is complete. The evolution of the district's building stock is shown in Fig. 2.

A centralized DES is envisioned for the district that will generate and distribute energy to the buildings using local thermal and electrical networks. The DES's location and thermal network are also shown in Fig. 2. Each new building of the district is assumed to be built with the newest standards defining U-values for the building envelope parts. The hourly heating and electricity demands and solar radiation patterns for each building and year are calculated using the software EnergyPlus. Future climate projections are sourced from the CORDEX project (Giorgi et al. 2009). The resulting annual district energy demands are shown in Fig. 3.

The evolution of energy carrier prices and the grid's emission factor are taken according to the New Energy Policy (NEP) scenario in the Swiss Energy Strategy 2050 (Prognos, 2012) and are shown in Fig. 3. The *FiT* is taken as 9 Rp./kWh for 2021 and is assumed to be linearly phased out until 2050. The evolution of technology prices is described using the approach of Gahrooei et al. (2006). The cost of technology i in year y, $C_{i,y}$, is described as: $C_{i,y} = C_{i,0}e^{-\gamma_i y}$, where $C_{i,0}$ is the price in 2021 and γ_i determines how fast future costs are reduced (this equation is applied to both $FC_{i,y}$ and $LC_{i,y}$). Base costs for year 2021 are taken from (Mavromatidis, 2017). A γ_i value equal to 0.01 is then used for the thermal storage and district heating network pipes, 0.02 for the GSHP and gas and biomass boilers, and 0.03 for PV panels and batteries.
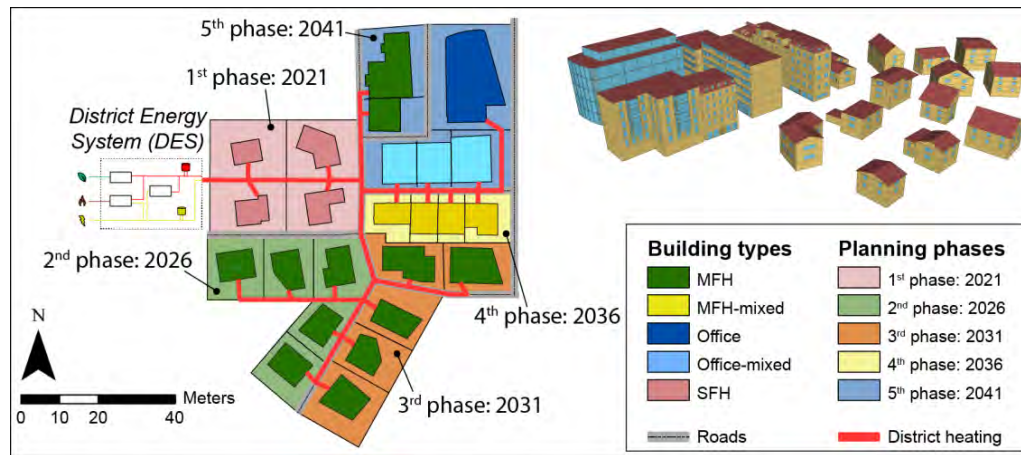

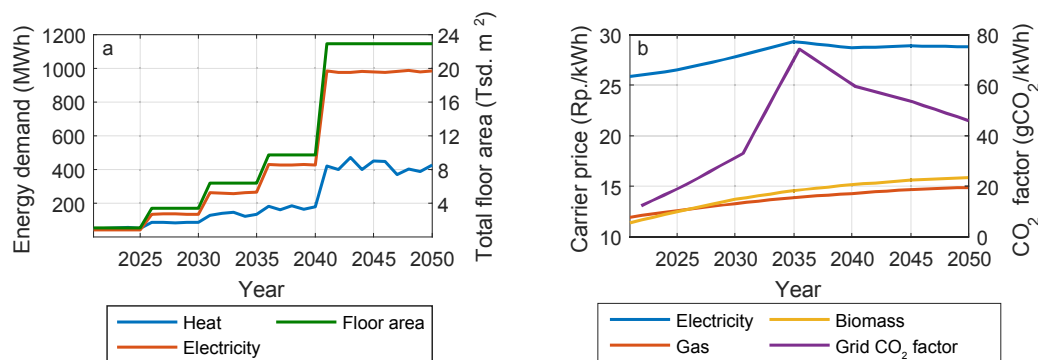Figure 2. Evolution of urban district from 2021-2040

Figure 3. a. Evolution of district energy demands and total floor area, b. Evolution of energy carrier prices and the grid's emission factor

RESULTS

The first set of model results shown in Fig. 4a pertain to each year's operating and investment expenditures for the optimal DES design. The energy plan involves investments in primarily 5 stages, matching each development phase of the district. However, smaller investments are also necessary during the horizon (*e.g.* in year 2029). On the other hand, expenditure for the system's operation is necessary in each year and its evolution reflects the evolution of the district's energy demands and of the energy prices, leading to gradually increased costs in the future.

Fig. 4b presents the evolution of the system's CO_2 emissions along the modeled horizon. Initially, the emissions exceed the 10 tCO_2 per year during each year of the district's first phase. Then, during the second phase, the emissions reduce significantly only to increase again during

2031-2040. Finally, during the district's final phase after 2041, the emissions show a sharp increase. Despite the grid's CO_2 factor getting lower from 2041 on (see Fig. 3b), the district's increased floor area (see Fig. 3a) and the resulting increase in the total energy demands (see Fig. 2) offset this benefit and lead to higher CO_2 levels. Nevertheless, the CO_2 emissions per total floor area for the district remain at the same levels as the previous years.
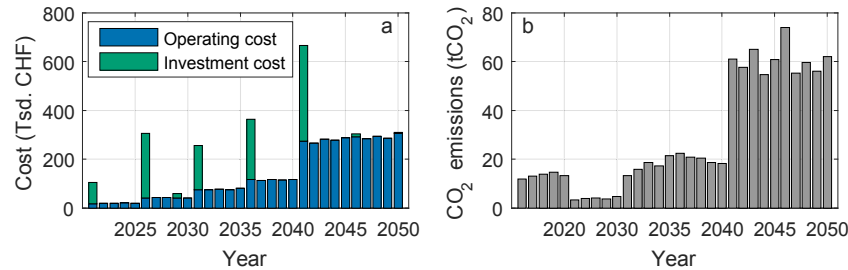

Figure 4. a. Investment and operating cost expenditures per year, b. CO_2 emissions per year

The evolution of the system's composition in terms of the energy generation and storage technologies and their capacities is shown in Fig. 5. On the generation side, the DES in the first phase consists of only a gas boiler of small capacity. A GSHP is first introduced in year 2026 and then in year 2036, while additional gas boilers are introduced in 2031, and, finally, a much larger boiler is added in year 2041. The evolution of the PV capacity is also shown in the figure with the first panels installed in 2026 and the maximum capacity being reached 2041. The figure also shows the generation capacity reduction when a device reaches the end of its lifetime (see *e.g.* year 2046 when the GSHP from year 2026 is retired). On the storage side, thermal storage capacity is added in two phases – in year 2026 and then in year 2036, reaching eventually a total capacity of approx. 560 kWh. Finally, in 2046 some storage capacity is retired and replaced in the final year of the modeled horizon.
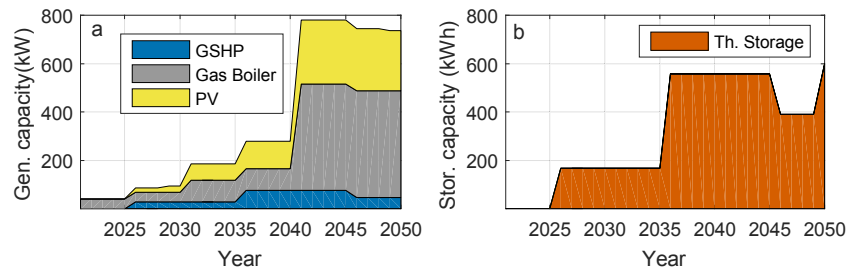

Figure 5. Total installed capacity for energy generation (a) and storage (b) technologies

The installed capacities, however, do not necessarily reflect the utilization of each technology. Thus, Fig. 6 shows the total annual heat and electricity supplied by the different technologies. During the first phase of the district, the heat demands are only covered by the gas boiler. After year 2026, though, the GSHP emerges as the main heat supply technology, and the utilization of the gas boiler remains low until 2040 and is only increased after 2041. These patterns can also explain the system's emissions in Fig. 4. Initially, when the system relies mostly on gas, the emissions are high. During the period 2026-2040 the emissions remain low as the GSHP is mainly used. Finally, from 2041 onwards the emissions increase due to both higher gas consumption, but also due to higher district energy demands.

On the electricity side, grid electricity is the primary source for covering the district's electricity demands, as well as the electricity needed by the GSHP. In the first 5 years, it is the only source

of electricity; however, as more PV capacity is installed after 2026, the contribution of PV electricity increases and reaches 28% of the total electricity supply in 2050.
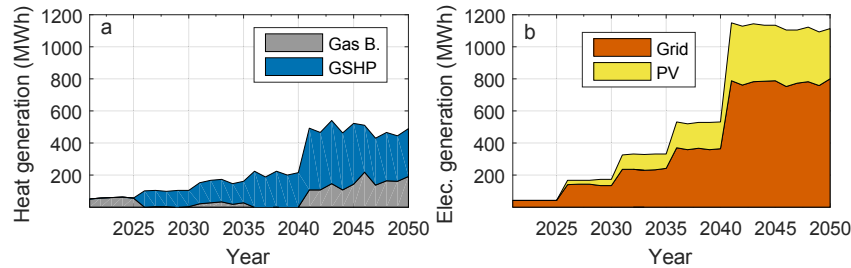

Figure 6. Heat (a) and electricity supply (b) by technology

CONCLUSIONS

In this paper, a model for the optimal multi-stage design of urban DES is presented and applied to a hypothetical urban district in Switzerland. The model is able to identify optimal energy technology investments and their timing along a multi-year horizon. Moreover, it calculates the system's optimal operation in each year and quantifies the contribution of each technology in meeting a district's energy demands.

The model's formulation is very flexible, as it can accommodate any number and type of energy technologies and be applied in urban districts of different scales. Moreover, the model can also be valuable for urban planning. Currently, urban DES are typically designed only after the district's development is finalized. By integrating the model in the urban planning process, the concurrent design of a district and its energy system can be performed, leading to potentially better solutions.

As future work, additional aspects like the efficiency improvements of energy technologies will be introduced. Additionally, the issue of uncertainty is very important, as predicting accurately the long-term evolution of energy demands, prices etc. can be very difficult. By introducing uncertainty considerations in the model, more robust DES strategies can be obtained.

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