# BUILDING ENERGY FLEXIBILITY AS AN ASSET IN SYSTEM-WIDE DISTRICT HEATING OPTIMIZATION MODELS

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## Abstract

The ratio of renewable electricity production is currently increasing which introduces an increased need for energy storage and flexibility. One solution for accommodating this need is an increased interconnection between district heating (DH) systems and the electricity grid; if orchestrated right, DH systems can act as a ‘buffer’ by converting excess renewable electricity production into heat and store this in the thermal mass of the DH system, leading to a reduced energy need during times where renewable production is scarce. In this paper, we propose a new methodology of including the utilisation of the thermal mass of buildings as a potential asset in a techno-economic optimization. The methodology relies on clustering techniques to condense a bottom-up representation of the buildings in an area to a highly reduced number of archetype models, thus significantly reducing the computational burden associated with including the energy flexibility potential of groups of buildings as an asset in techno-economic optimization problems. In an urban expansion/densification case study, we demonstrate the accuracy of the archetype representation and include the building models in a techno-economic optimization to investigate whether energy-flexible buildings have an impact on the optimal investment strategy. The results indicate that energy-flexible buildings may reduce the amount of additional production capacity required for urban expansion/densification – in this case, 8% of the total peak production. The total savings of including energy-flexible buildings is probably not sufficient for a viable investment; however, future studies should capitalise other system benefits before any sound conclusion on the viability of energy-flexible buildings can be made.

## Introduction

The increasing interconnection between the electricity grid and district heating (DH) systems leads to new opportunities for DH companies to improve the efficiency of their production and lower the cost of district heating. The viability of different options for interconnection when designing DH networks and production portfolios can be assessed using techno-economic optimization methods. These methods provide DH companies with an optimization-based framework for optimizing investments in production units, storage capacity, as well as pipe systems. In this optimisation, a modeller represents the network in its current form as well as potential investment options through sets of variables and constraints in an optimization problem. The resulting optimization problem incorporates a simulation of the DH network for a given period – typically a design reference year that reflects the typical operating conditions of the network. In this simulation, the optimization solver identifies the optimal configuration of the network (the investments) minimising or maximising a specified objective function. Similarly, the solver identifies the optimal control strategy of all available assets including both production and storage units in the portfolio.

These optimization-based methods thereby allow DH companies to identify strategic investments that help them take advantage of various opportunities for lowering production costs or increasing revenue streams. One of these opportunities is to exploit cheap electricity from wind or solar power in the district heating production through large-scale heat pumps and electric boilers. However, the fluctuating nature of solar and wind (renewable) electricity production often means that increased thermal energy storage capacity is needed in the DH system to increase the share of renewable production that can be utilized in the DH system. The large investment costs and space requirements associated with centralized heat storage tanks have prompted several researchers to investigate the potential of utilizing the thermal mass inherent to buildings for thermal energy storage through so-called DR schemes. These schemes provide flexible consumers with economic incentives in exchange for them adopting their consumption in benefit of the grid – e.g. to achieve peak shaving or increase the temporal match between production and demand. Previous studies have investigated the potential of DR on the scale of individual buildings by implementing model predictive control (MPC) schemes capable of exploiting the thermal mass of the building [1–5]. The control problems solved in MPC schemes can be readily incorporated in the techno-economic optimization problem, thus allowing the building to act as a storage unit in the simulation.

Given a sufficiently accurate model of a DH system, techno-economic optimization thereby provides DH companies with a highly flexible framework on which they can base their investment strategy on that is capable of incorporating demand response initiatives alongside conventional assets. A challenge, however, is that the resulting optimization problems can become computationally infeasible to solve consistently as the number of assets increases. This issue is enhanced by the fact that the modeller is often forced to incorporate binary variables in the optimization problem to represent various discrete variables or discontinuous phenomena. In addition to the discrete variable of whether to invest in a given piece of DH infrastructure, binary variables are also needed to include start-up costs of cold production units or to specify operating ranges of plants that require a non-zero lower boundary of heat production to sustain the operation. The presence of binary variables transforms the problem from the class of computationally cheap class of linear optimization problems to the much more difficult class of mixed-integer linear problems. This computational burden significantly limits the number of constraints and variables that are available to incorporate DR in buildings in the optimization problem.

Overall, there are two options for incorporating DR in techno-economic optimization schemes: 1) Reduce the number of buildings, 2) reduce the complexity of the DR representation. The latter includes the use of simplified building models and comfort constraints [6,7], use of pre-simulated consumption profiles [8], or the use of top-down models and assumptions [9,10]. While the use of simplified building models may reduce the computational cost, there is also a risk that these models lead to inaccurate results due to oversimplification of the thermodynamic phenomena that is exploited to enable the structural thermal mass of buildings as energy storage. The use of pre-simulated profiles has the advantage that they can be generated using complex simulation models to ensure a proper representation of the involved thermodynamics. The main disadvantage relates to the pre-defined structure of the DR actions, which imposes an unnecessary upper limit on the indicated DR potential. Finally, the top-down approaches lack appropriate representation of the thermodynamic phenomena that is exploited when using the structural thermal mass of buildings energy storage, which makes the results highly dependent on the employed assumption and thereby subject to more uncertainty.

With these limitations in mind, this paper presents a methodology that combines a bottom-up modelling approach that ensures a high model accuracy with a clustering approach that reduces the number of building models to lower the computational burden with minimal impact on the accuracy of the DR representation.

The paper is structured as follows: First, we briefly introduce the applied bottom-up modelling and validate the performance of the resulting models. The clustering approach is then introduced and validated similarly. We then briefly describe a techno-economic optimization of a case study in which we incorporate an archetype representation of 1157 residential buildings obtained with the clustering approach. Finally, we present the findings of the techno-economic optimization and discuss the general applicability of the proposed method for obtaining an accurate and computationally efficient representation of DR in buildings.

## Methodology

Before the application of the suggested approach is demonstrated in a case study, the following sections briefly introduce the methods used to 1) establish the bottom-up representation of the buildings in an area, 2) cluster the buildings and derive representable archetype models, and 3) include the archetype representation in a techno-economic optimization scheme.

### Bottom-up modelling approach

In this study, we adopt the bottom-up modelling approach proposed in [11] that allows for modelling the DH demand in buildings through basic weather measurements, publicly available building meta-data and consumption data from remotely read smart meters. Since the latter includes both the space heating and domestic hot water components of DH consumption, we use a simple switching model to represent the DHW component. The switching model consists of 24-hour tapping profiles that are uniquely determined for each building. The 2-profile DHW model originally proposed in [11] was further refined in [12], where a move to the 4-profile model also used in the present study was found to improve predictive performance.

The thermal dynamics of the building (and thus the space heating component) is represented by a reduced-order model. Previous studies have demonstrated reduced-order models to be suitable for a range of applications in buildings including representing the thermal indoor climate [13–15], identifying the thermal dynamics of buildings [16–18] and for model-driven control purposes [2–5]. Regardless of the specific application, it is always desirable to reduce the complexity of the employed models as much as possible taking the application of the model into account. In the context of utilizing buildings for structural thermal energy storage (STES), a critical aspect is to ensure that the model can describe the interaction between the indoor environment (indoor air) and the thermal mass of the building. Since first-order models lump these two bodies together despite their significantly different time-constants, these models are considered too simple for describing the thermal dynamics that are exploited for STES and may significantly overestimate the actual storage potentials. In a trade-off between model accuracy and complexity, we, therefore, represent the thermal dynamics of buildings with a physics-based second-order model structure, where the structure of the model is an extension of the model used in the *simple hourly method* of ISO 13790:2008. The parameters of both the DHW and building models are calibrated in parallel in a Bayesian calibration scheme, where priors are incorporated in an attempt to compensate for the relatively low information-content (excitation) of the smart-meter training data. The calibration parameters of the DHW model are all entries of the 24-hour tapping

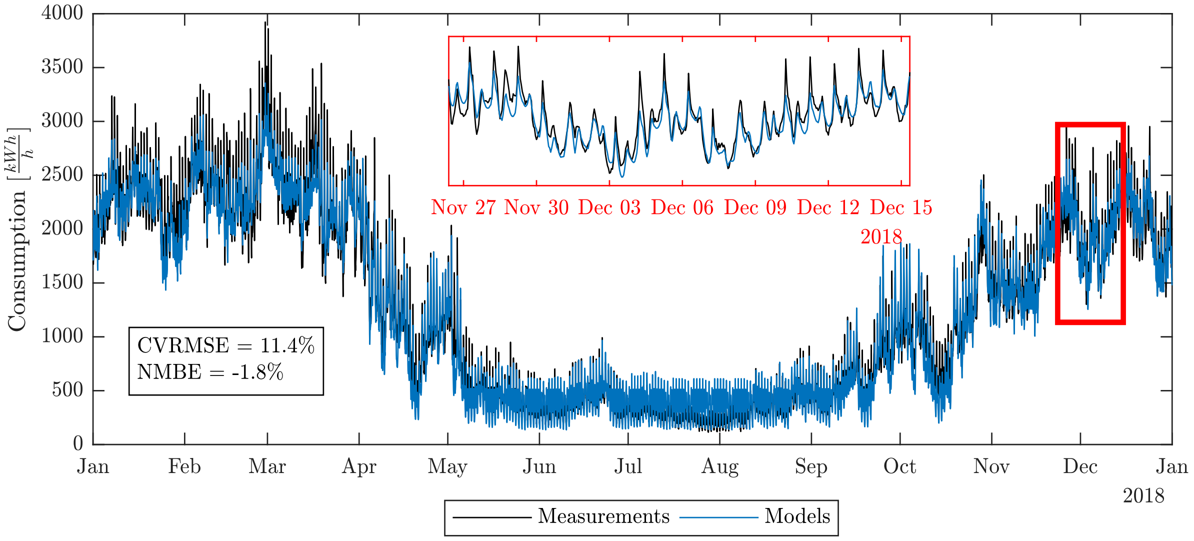


*Figure 1 Evaluation of the bottom-up model performance for 755 residential buildings (Node 1 in area). The time-series depict a validation period (2018) that was not a part of the training data set (2017).*

profiles, while the calibration parameters for the building model remains the same as in [11] and includes the 1) window-to-floor ratio, 2) infiltration rate, 3) average envelope U-value, 4) the number of occupants, and 5) the effective thermal capacity of heavy building components.

Figure 1 depicts a comparison of the measured and predicted consumption aggregated for 755 single-family houses featured in the case study introduced later in the paper. The depicted period was not used for training the models. The figure indicates that the combined output of the DHW and building models are capable of reproducing the aggregated consumption of the buildings. The stochastic nature of especially DHW consumption means that the performance of the models on the scale of individual buildings is typically lower than the aggregated comparison. For a more in-depth validation of the modelling method, we refer to the original works [11,12].

## Clustering approach

The goal of the clustering approach is to reduce the number of building models to be included in a techno-economic system model while ensuring a minimal loss of accuracy for the resulting archetype representation of the DR potential associated with the original building sample. To achieve this, the clustering should identify buildings with similar DR characteristics and not buildings with similar steady-state consumption levels. Therefore, the clustering is not based on the overall heat loss coefficients or solar aperture of the models, but rather on metrics that quantify the DR capability of the buildings. Several researchers have developed methods for quantifying the energy flexibility of buildings [19–21]. In this analysis, we apply an approach inspired by the method of using a series of optimal control problems to derive so-called flexibility cost curves as suggested by De Coninck & Helsen [22]. In addition to a reference scenario, 10 optimal control problems were solved for each building model - each with a predefined peak event with durations spanning from one to ten consecutive hours. In each scenario, the optimal control problem is defined such that it minimizes consumption during the peak event as much as it is possible without violating predefined comfort constraints. This causes the solver to preheat each building before the event by up to 4°C to allow it to be thermally autonomous during the peak. Since the act of storing energy in the thermal mass is associated with increased heat losses, the resulting heating consumption is larger than the reference case. Several metrics that can be derived from the solutions of the optimal control problems may facilitate a suitable clustering of buildings based on their DR characteristics. In this study, the buildings were clustered by the on-peak energy price that was necessary to make it profitable for the given building to engage in DR. Figure 2 depicts an example of the average break-even price for each building cluster as a function of the duration of the peak event.

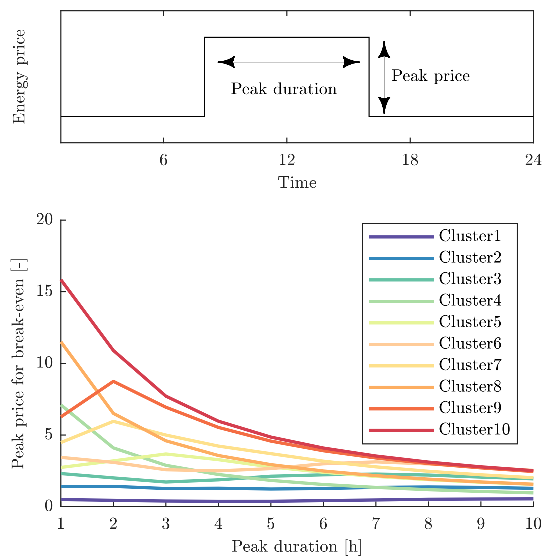


*Figure 2 Data used for clustering of buildings. Top) Definition of peak duration and price. Bottom) Cluster-average peak price necessary to make load shifting economically viable as a function of peak duration.*

For the clustering itself, a simple k-means clustering scheme was adopted. However, this approach can lead to an undesirable grouping of buildings e.g. due to the presence of outlier buildings that perform significantly different than the remaining pool of buildings. Such issues can be remedied by combining certain clusters and re-clustering the remaining buildings. In doing so, one can improve the homogeneity of the remaining clusters, thus ensuring a lower loss of model accuracy when moving to an archetype representation of the original building sample. Furthermore, it may be desirable to prioritize the homogeneity of building clusters with high DR performance, as the buildings in these clusters will generally be more actively engaged in DR activities. In this study, the buildings in each node of the DH system model was divided into 10 clusters. Of these, the three clusters with the poorest DR performance were combined, while the remaining seven clusters were re-clustered into nine new clusters.

Once the buildings were clustered, the task is to derive the archetype model that represents each cluster. If the physical interpretation of the models is to be preserved, the parameters of the archetype model can be obtained by taking simple or area-weighted averages of the models belonging to the cluster. If no physical interpretability is necessary (e.g. if black-box models are used), then the task of identifying the average model is simply to average the matrices containing the parameters of the models. Incorporating the resulting archetype model in a techno-economic optimization is then not different from incorporating a single building – with the exception that the energy consumption in the building should be multiplied with the number of buildings that the model represent. An evaluation of the loss-of-fidelity resulting from the archetype representation is depicted in Figure 3. Here, the first three plots are a separate evaluation of different clusters, while the final plot compares the consumption levels of the 755 individual building models and the much more compact archetype representation consisting of the 10 building models that represent each cluster. Each plot depicts a reference scenario (no price increase) along with two scenarios with a moderate and high price increase, respectively. The scenarios with peak-price thereby emulate a price-based DR scheme that causes a share of the buildings to engage in preheating before the event to lower exposure to the higher on-peak prices. As indicated in Figure 3, the response of the archetype models is almost identical to that of the bottom-up models except for the initial pickup in consumption caused by the buildings starting to preheat the thermal mass before the peak. Here, the inevitable heterogeneity within each building cluster makes some buildings in the bottom-up representation initiate preheating before others. This varied response cannot be captured by the archetype representation as it relies on a single building model to represent all buildings in the cluster. This discrepancy between the two representations of the buildings is seen to be much less pronounced when the response of all clusters are combined as shown in the bottom plot of Figure 3.

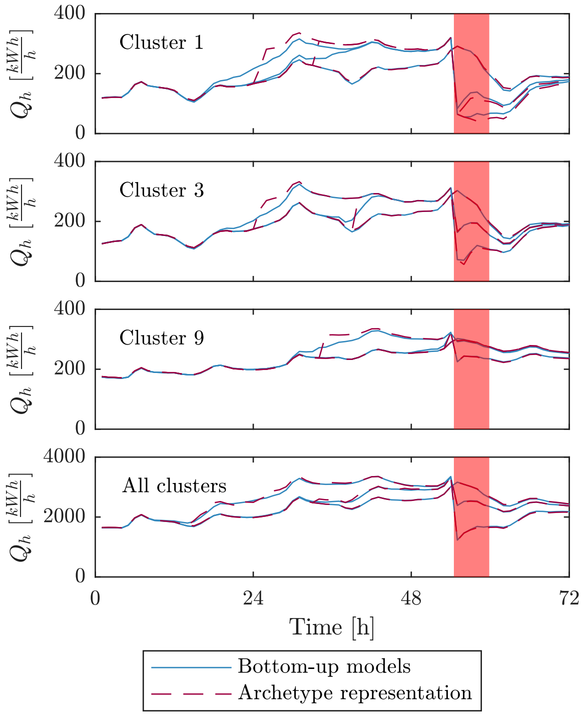


*Figure 3 Comparison of DR actions in response to increased prices during a hypothetical peak event with increased prices (red rectangles) as indicated by the bottom-up models and the archetype representation.*

**Techno-economic optimization scheme**

This section provides a brief description of the DH system modelling approach used to develop the techno-economic optimization model. The first part of a techno-economic optimization problem is the objective function, which in our case is to minimize the net present cost (NPC) of operating the DH system for a given period ($T$) as defined by Equation (1).

$$\min \text{NPC} = \text{CAPEX} + \text{OPEX}^{\text{fix}} + \sum_{t \in T} \text{OPEX}_t^{\text{var}} \quad (1)$$

Where capital expenditure (CAPEX) refers to the annualized investment cost of any new infrastructure that is part of the optimal configuration of the DH network. The operating expenditure (OPEX) features a fixed and variable component. The fixed component includes e.g. running maintenance on production or storage units, while the variable component can represent fuel costs, start-up costs, as well as taxes and tariffs. For the latter, $t$ refer to the time step of the simulation.

The actual model of the DH network, including production plants, storage units and consumers, are incorporated in the optimization through a series of constraints. Depending on the applied modelling approach, the modeller may represent the DH network as a set of interconnected nodes. Within each of these nodes, it is assumed that energy may flow freely. The number and configuration of nodes can thereby be chosen to represent the presence of bottlenecks in the system. A common modelling approach is to impose an energy balance constraint for each node in the model, see Equation (2).

$$\Phi_t^{\text{passive}} + \Phi_t^{\text{flexible}} = \sum_{u \in U} \Phi_t^u + \sum_{s \in S} \Phi_t^s + \sum_{c \in C} \Phi_t^c \quad (2)$$

Where lowercase $u$, $s$ and $c$ refer to production units, storage units and interconnections to other nodes, respectively. Similarly, uppercase $U$, $S$ and $C$ are the sets of production units, central storage units and inter-nodal connections that belong to the current node.

The passive demand for DH in each node ($\Phi_t^{\text{passive}}$) refers to the DHW consumption in all buildings in the node, as well as the space heating consumption of all buildings in the node that are not engaged in the DR scheme. Contrary to the passive demand, the flexible demand ($\Phi_t^{\text{flexible}}$) of the buildings engaged in the DR scheme is incorporated as an optimization variable. This allows the solver to modify the consumption of these buildings to achieve supply-side benefits as long as it does not violate any specified comfort constraints. The DH production term ($\Phi_t^{\text{u}}$) is always positive, while the energy flow to and from both centralized storage units ($\Phi_t^s$) and other nodes ($\Phi_t^c$) may be both positive and negative.

Equation (3) relates the aggregated flexible demand to the space heating consumption in each building ($u$), which Equation (4) then relates to the temperature conditions in the building model ($T_{\text{i},t}$). Here, matrices $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{C}$ and $\boldsymbol{E}$ contain the parameters describing the thermal dynamic characteristics of each building, where subscript $t$ indicate the presence of time-varying parameters in the model. The vector $\boldsymbol{x}_t$ contain the internal states of the model, while $u_t$ denotes the control input (space heating) and the vector $\boldsymbol{d}_t$ contains any uncontrollable phenomena (disturbances) that affect the model such as weather conditions. Equations (5) – (7) constrain the space heating capacity available in each building, the lower and upper temperature boundaries, and the highest allowed temperature gradient between time steps, respectively. Note that we for the sake of readability have dropped a subscript $b$ to indicate differences between buildings in Equation (4) – (7).

$$\Phi_t^{\text{flexible}} = \sum_{b \in B^{DR}} \boldsymbol{u}_{b,t} \quad (3)$$

$$T_{\text{i},t} = \mathbf{C}(\boldsymbol{A}_t \boldsymbol{x}_t + \boldsymbol{B} u_t + \boldsymbol{E}_t \boldsymbol{d}_t) \quad (4)$$

$$0 \leq u_t \leq P_{\max} \quad (5)$$

$$\mathrm{T}_{\mathrm{i}}^{\min} \leq T_{\text{i},t} \leq T_{\mathrm{i}}^{max} \quad (6)$$

$$\Delta T_{\mathrm{i}} \leq \Delta T_{\mathrm{i}}^{\max} \quad (7)$$

Due to space limitations, we omit to state the series of constraints that specify limits the production capacities and ramp rates of production units, the storage capacity and heat losses for storage units as well as the limitations on heat transfer between the nodes of the model. Similarly, we have omitted several equations elaborating the connections between the objective function and the variables of the optimization problem.

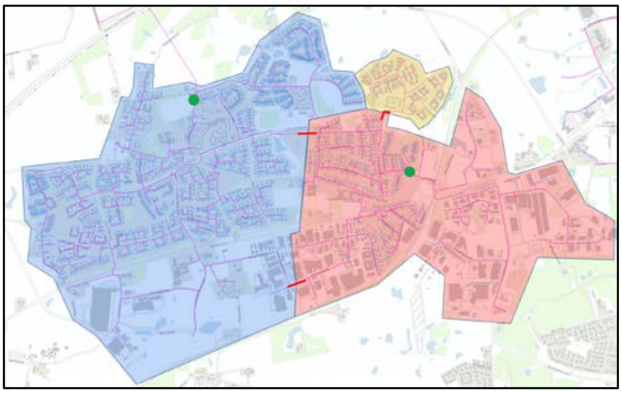

*Figure 4 Depiction of the DH network of the case study. The network was divided into three nodes due to the presence of bottlenecks (indicated as red lines between coloured areas). Green markers indicate the locations of existing production units.*

## Case study

This section provides a demonstration of the proposed approach to include building heating energy flexibility as DR assets in techno-economic optimization problems through a relatively simple case study provided by the local DH company in Aarhus, Denmark. The case involved the DH network supplying the suburban area depicted in Figure 4. The area, which includes both residential and industrial DH consumers, is expected to undergo significant development in the coming years which increases the current peak demand from approx. 25 MW to approx. 62 MW. As indicated in Figure 4, the area was divided into three nodes. The two larger nodes representing the red and blue areas have existing DH production infrastructure in the form of an oil-fired boiler to cover peak demand as well as a heat exchanger station coupled to a larger DH transmission network of Aarhus. Therefore, in addition to the electricity spot market price used to represent fuel costs of heat pumps and electric boilers, the techno-economic optimization also includes the cost of heat from the larger transmission network of Aarhus. The solver identifies the set of infrastructure investments that yields the lowest costs for the utility company. Practical concerns regarding the available space for production and storage units limited the investment options that were considered to heat pumps, electric boilers and water-based storage tanks. The optimization was run both with and without flexible demand to investigate how the inclusion of DR assets affects the optimal solution.

DR-enabled buildings were modelled for the two larger nodes of the model (the red and blue areas of Figure 4), where ten building clusters in each node were represented by archetype models. Figure 5 depicts time-series of the coldest period of the simulation, where the DR-enabled buildings are actively engaging in load shifting to lower the peak demand of the whole area (the upper part of the figure). The lower part of the figure depicts the

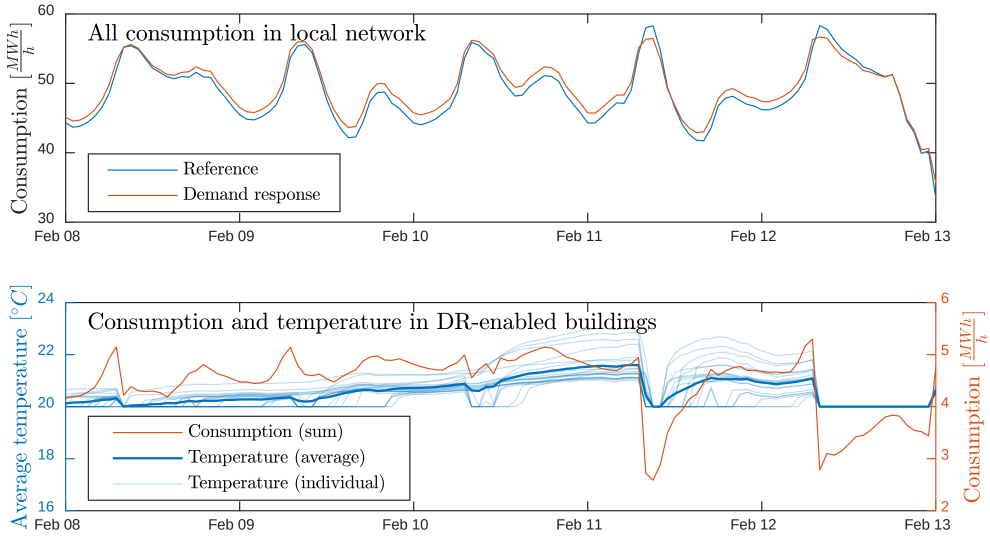


*Figure 5 Time-series obtained from the techno-economic optimization. Top) Comparison of demand in scenarios with and without DR-enabled buildings. Bottom) Time-series depicting the operation of DR-enabled buildings (temperature and space heating consumption).*

consumption and temperature conditions in these buildings. The temperature profiles show how some of the more energy-efficient building clusters are moderately preheated for several days before the two largest consumption peaks (design peaks) occurring on February 11 and 12, respectively. During each of these events, the DR assets lower their consumption for space heating and the indoor air temperature drift until the lower boundary of the comfort range was reached. Furthermore, the optimisation also utilises the DR assets at other times throughout the year to reduce daily peaks even though they are not design peaks (Figure 6).

In both the reference and the DR scenario, the optimization results indicated that a buildout of the existing DH substation from 25 to 37 MW was a part of the optimal investment strategy. This investment was inexpensive since the current substation could be readily upgraded without requiring the substation building itself or the associated pipe system to be upgraded. Also in both scenarios, the remaining demand was to be covered through investments in large-scale heat pumps (HP). The results indicated that utilization of DR led to a 22% reduction in the necessary new HP-based production capacity (from 22.4 MW to 17.5 MW). For reference, the demand for the DR-enabled buildings only accounted for 7.7% of the total demand in the area after the expected buildout. The optimization indicated that the optimal investment strategy both with and without DR assets involved investment in heat pumps combined with a 100 MWh storage tank, which was the largest tank size allowed in the optimization due to space considerations. The lower heat pump capacity needed when DR assets were utilized reduced the annualized capital expenditures for this investment by approximately 20%. Most of these savings, however, was lost due to increased operational costs of running the system. One of the factors contributing to this increase in costs was that the lower available heat pump capacity also lowered the ability of DH operators to exploit cheap electricity prices, thus leading to a higher average cost of heat. Another reason is tied to the comfort-related constraints imposed on the operation of DR models, which meant that while the buildings could be heated further up before a DR event, the temperature could never drop below the reference temperature. This meant that the utilization of DR resulted in higher overall consumption. In this case, the overall consumption increased by 375 MWh (2.3%) in the DR-enabled buildings, i.e. 0.18% of the total consumption in the area. Table 1 summarizes the economic impact of including the DR assets in the optimization. Since the cost of enabling DR in the residential buildings is subject to high uncertainty, this cost was left out of the optimization. This cost should, therefore, be subtracted by any savings achieved as a result of the DR initiative. As indicated by Table 1, the optimization indicated these savings to be 140.000 DKK per year which, considering that 1107 buildings were involved, is unlikely to cover the costs of enabling DR in the buildings.

*Table 1 Comparison of costs from techno-economic optimization of reference scenario (Ref.) and the scenario with DR-enabled buildings (DR). All costs are reported with the unit [mill. DKK/year].*

| | **Ref.** | **DR** | **Diff.** |
|---|---|---|---|
| HP capacity [MW] | 22.4 | 17.47 | 4.93 |
| Investment cost | 5.41 | 4.29 | 1.12 |
| Operational cost | 39.0 | 40.08 | -1.08 |
| Maintenance cost | 0.36 | 0.29 | 0.07 |
| Total costs | 44.8 | 44.66 | 0.14 |

However, it is not unlikely that a viable business case for utilizing building heating energy flexibility for DR in the case study could be obtained through capitalisation of

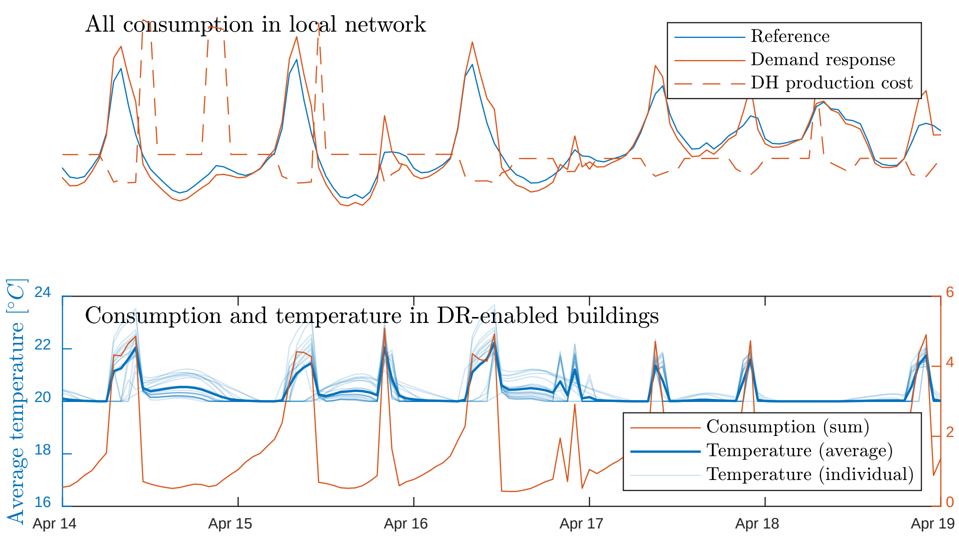


*Figure 6 Time-series showcasing DR operation during period with warmer weather. In this case, load shifting occurs to exploit variations in DH production prices (depicted on upper plot), whereas the load shifting depicted in Figure 5 was with the intent of reducing design peaks to lower the need for production capacity.*

other system benefits that were not quantified in our study. An example of such a benefit is that the DH operators through the utilization of DR can reduce the fluctuations in the supply temperature that is currently necessary to supply peak demand without upgrading pipe dimensions. Maintaining a low and stable supply temperature is desirable for several reasons, including improved efficiency of production units and reduced strain on old pipes caused by repeated temperature expansions. The same temperature expansions also present a challenge due to the expanding water mass in the network, which requires the DH operator to collect overflow and refill the system as the supply temperature is lowered again.

The large differences between individual DH networks and the challenges they face make the business case for a DR scheme highly case-specific. Although the featured DH network was divided into nodes to explore the potential of utilizing DR to solve bottleneck issues, the simulations indicated little or no impact of the bottlenecks, thus removing one of the areas where DR may be utilized to avoid costly upgrades from the equation. Furthermore, it is worth considering whether the assumptions made in the analysis had a significant influence on the viability of the DR scheme. It is, for instance, worth considering whether most of the benefits achieved through the DR scheme could have been realized with a lower number of buildings, thus increasing the savings per DR-enabled building. It would, therefore, be interesting to map how the supply-side benefits of DR scale with the number of buildings enrolled in a given DR scheme – perhaps for a case study with more nuances and details than the one considered in this simple demonstration.

## Conclusion

In this paper, we proposed a method for including heating energy flexible buildings in urban areas as DR assets in techno-economic optimization problems. The method relies on building models generated using a bottom-up modelling approach to estimate the DR capacity of the buildings in a neighbourhood from their DH smart meter consumption data. The building models were divided into clusters of buildings with similar DR characteristics leading to a low number of archetype models that can readily be incorporated in techno-economic optimization schemes.

The method was applied to a case study featuring a real DH network that required new production capacity to accommodate expected growth in demand. The proposed method was used to include 1107 residential buildings as DR assets in the techno-economic optimization, and the ability of the derived archetype models to represent these buildings were validated. The results of the optimization indicated that the DR assets lowered the need for production capacity in the area by 8% after the DH area has gone through an urban expansion/densification. The majority of the investment cost savings associated with this was lost due to the lower HP capacity available for exploiting cheap electricity prices; however, the study should be expanded to also include capitalisation of other system benefits of the investigated type of DR before any sound conclusion on its viability can be made. Nonetheless, the case demonstrated the applicability of the proposed approach, which can be readily adapted to support other model structures if need be.

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