Optimal indoor temperature flexibility for thermal peak shaving in buildings connected to the district heating network

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Abstract

Buildings are currently non optimally controlled, using a weather compensation controller that depends only on external temperature. A rich amount of real-time data is available and can be used for better control. This work is focused on developing a general and dynamic model for utilizing the building as an energy storage for a peak-shaving control strategy. A dynamic grey-box model is developed using industry standard operators data from a multifamily building, Building A, located in Västerås, Sweden. The training period is set to 408 hours, and the prediction horizon to 48 hours. The model is verified in 4 steps: prediction ability on the historic data, parametric verification on the time constant, simulation of heat supply separated from the historic data and model generality by implementing the model on a second multifamily building, Building B. The modelling errors over a two-month simulated period are 8 % for Building A and 9 % for Building B. To demonstrate the utilization possibilities, an optimizer is constructed to evaluate a peak shaving control strategy. Different flexibilities for the indoor temperature have been examined with a range yielding heat load peak shaving between 30 to 45%. Flexibility paves the way for improvement in pricing models for the heating sector. This work demonstrates the potential of utilizing building heat storage capacity to reduce peak consumption and costs.

1. Introduction

Currently, District Heating (DH) substations operate in sub-optimal conditions due to a lack of information about the supplied buildings, their future demand, and the operating parameters. The rich amount of real-time data available from new sensors implies saving potential if made available to the energy providers and buildings managers. Utilizing building thermal inertia as a short-term storage is a cheap and viable technology (Kensby et al., 2015), the concept consists of overheating or underheating the building. When overheating or underheating the building a change between the set indoor temperature and the actual indoor temperature occurs. This results in a divergence from the set temperature, and it is that temperature difference that functions as the energy storage in the building (Ståhl, 2009). By utilizing the internal heat transfer in buildings as heat storage the supply need can be reduced, assuming that the producers have knowledge of the relevant storage data. One of the main constraints in utilization lies in the comfort requirements of the occupancies (Renström et al., 2021). This work is focused on developing a general and dynamic model for utilizing buildings as energy storage for a peak-shaving control strategy. The work aims to determine how stored heat in buildings can be modelled using industry standard data streams. Furthermore, the work investigates the potential in controlling a building's heating system with consideration to stored heat and how a flexible indoor temperature affects different aspects of building thermal control.

2. Methodology

2.1. Problem setup

The building used for model development is a 9-storey multifamily building, called Building A, located in Västerås, built in 2017.

The thermal dynamics of the building consist of multiple different heat sources and heat losses from building components. The heat sources consist of two sources; heat supplied from the DH system, and heat delivered from unmeasured sources (passive heating). The main sources of heat loss are through the building envelope and the ventilation. The input data was originally supplied by the local DH company Mälarenergi (primary side) and a local landlord Mimer (secondary side). The data has a time step of one hour and consists of 1501 data points between 2019-12-01 and 2020-02-02. The temperature has been taken as an average over all the individual apartments to give an average temperature for the building itself, therefore the standard deviation on the indoor temperature is also given. The outdoor temperature was measured with a sensor installed on the building. Supply temperature, water mass flow and return temperature were all measured at the building's main heat exchanger.

The heat supply (calculated based on the supply-, return temperature and the mass flow from the main heat exchanger), average indoor temperature, and external temperature are used in this work. The data is presented in Fig. 1.

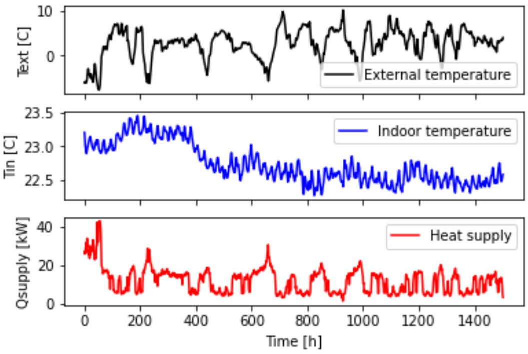

Figure 1: Historical data for Building A

2.2. Development of Building Model

The finalized model consists of three models that combine the strength of them all. The first is called First Order Thermal Model (FOTM) and is based on simple 1R1C models as described by Harb et al. (2016) or Monghasemi et. al (2022). The second is called Degree Day Model (DDM) and is a further development of the 1R1C model using the degree day method by Tabatabaei et al. (2017). The third is called Time Constant Model (TCM) and is based on Antonopoulos & Koronaki (2000). The cooperation between the different models is illustrated in Fig.2.

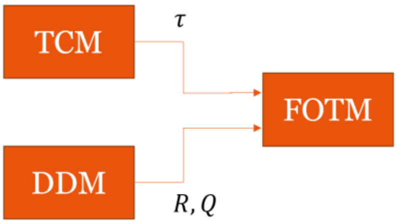

Figure 2: Model flow chart

FOTM is developed as an 1R1C model to ensure robustness due to the lower complexity. The typical 1R1C model is described with Eq. 1.

$$C\frac{dT}{dt} = R(T_{ext} - T_{in}) + Q_{supply} \quad (1)$$

FOTM includes an additional parameter to act as the heat from other sources then the heat delivered from the building's substation, $Q_{passive}$. This simulates heat from occupancies, electric appliances, solar radiation etc. The FOTM model is described with Eq. 2.

$$C\frac{dT}{dt} = R(T_{ext} - T_{in}) + Q_{supply} + Q_{passive} \quad (2)$$

The DDM is set up as a function called from the FOTM, it utilizes Eq. 2 with $\frac{dT}{dt} = 0$, resulting in Eq. 3**Error! Reference source not found.**.

$$R(T_{ext} - T_{in}) - Q_{passive} = Q_{supply} \quad (3)$$

Curve fitting (based on least squares) is then used to estimate $R_{passive}$ and $Q_{passive}$. The steady state heat loss of the building is represented by R. There are always some daily variations in the indoor temperature, but the general trend of the indoor temperature must be steady for R determination. $Q_{passive}$ is determined as an average of the passive heating during the training period and will therefore give an imperfect estimation on the hourly passive heating in the building.

TCM is also set up as a function called by FOTM. The equation used is Eq. 4 where the parameters C_{eff} & U are determined by optimizing for them using least squares from the SciPy optimize library with Eq. 5 as the cost function.

$$T_{in}(t) = T_{ext} - \\ -\left[T_{ext} - T_{in}(0) + \frac{Q_{supply}}{U}\right] e^{\left(-\frac{tU}{C_{eff}}\right)} + \frac{Q_{supply}}{U} \quad (4)$$

$$F(X) = T_{in,pred} - T_{in,real} \quad (5)$$

Given the resulting C_{eff} and U for the training period the mean of the values is taken to calculate the time constant according to Eq. 6.

$$\tau = C_{eff}/U \quad (6)$$

The time constant is then used to calculate a C based on the R value from DDM. In contrast to DDM, TCM requires variance in the indoor temperature to determine the effective heat capacity, C_{eff}.

The model detects the trend of the indoor temperature, thereby not capturing daily variations. The model is a dynamic model with accuracy dependent on the accuracy of the temperature data, as the temperature sensor most likely has the highest uncertainty. The temperature sensor is unknown; however a typical range is ± 1 K according to manufacturer specification data.

2.3. Verification of building model

The first verification step is to determine the prediction ability by implementing the model on the entire available data set and observing the model's ability to predict the indoor temperature for each time step over different prediction horizons. The model must replicate the trend rather than the actual values to avoid overfitting to variance caused by measuring the input data in the air. The next step is to verify the parameters. This is done by observing the resulting values of the time constant and comparing it to expected values from the literature, as presented in Tab. 1.

Table 1: Time constants presented by Johra et al. (2019)

Time constant τ [h]	Light	Medium	Heavy
1980's house	9	49	181
Passive house	135	169	626

The heat is then simulated using the historical outdoor temperature without access to the historical heat data. The generality of the model is also verified by implementing the model on a different building, Building B. The data available for Building B is of a similar character to that of Building A.

2.4. Optimizer

To highlight the utilization possibilities of using the building as a heat storage, an optimizer is developed to evaluate the future heat supply. It is developed in Gekko, which is an optimization library in python (Beal et al., 2018). The optimizer is based on a strategy presented by Saletti et al. (2021) that focuses on minimizing the variations in heat supply by controlling for the derivative of the heat supply.
To minimize the total variation in the heat supplied (Q_{supply}) the derivative squared is minimized to ensure that only positive values occur in the objective, this will assist the optimizer in flattening out the heat demand. The control objective (Q_{supply}) is controlled by manipulating the indoor temperature (T_{in}) within a set interval. By setting a fixed interval for the indoor temperature within the comfort interval, the comfort is still maintained. The optimization problem is stated below.

$Objective$:

$$\min\left(\sum_{i=1}^{i=forecast} dQ_{supply_i}{}^2\right)$$

$Constraints$:

$$T_{in_{min}} \leq T_{in_i} \leq T_{in_{max}}$$

$$Q_{supply_{min}} \leq Q_{supply_i} \leq Q_{supply_{max}}$$

$$Q_{supply_i} = \left(T_{in_{i+1}} - T_{in_i}\right)C - R\left(T_{ext_i} - T_{in_i}\right) - Q_{other}$$

Before the model can be utilized for peak shaving, the training period and the prediction horizon need to be determined by parametric analysis to yield the most accurate results. The training period is set to 408 hours/data points, and the prediction horizon is set to 48 hours. Different flexibilities in the indoor temperature are examined from Tin=22°C ± 0.25 to Tin=22°C ± 2.00. The baseline temperature is set to 22 °C to ensure that the indoor temperature is always within the Swedish health agencies recommended comfort interval (Folkhälsomyndigheten, 2014).

2.5. Normalized Economics

Currently, economically motivated peak shaving for customers is not the norm at the local DH company. The customers have the option to select a "baseload consumption" with a fixed price in SEK⁄kW,year and a "peak consumption" with a different fixed price in SEK⁄kW,year. But they can also allow the company to choose, and then no fixed cost is added if the consumption increases above the baseload level (Landelius & Åström, 2019). To highlight the economic benefits in peak shaving from a customer perspective a normalised economic analysis is developed. An initial baseload is calculated based on the average outdoor temperature for December 2019 using Eq. 3. The different parameters are estimated on an average of the first 408 data points.
The economic savings are then calculated by integrating the curves that exceed the baseload and comparing the integrals for the historic case and the new peak shaved case, as shown in Fig. 3.

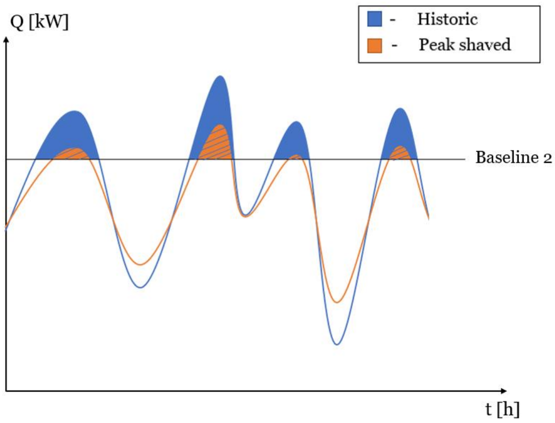

Figure 3: Normalized Economic Analysis

The savings are presented as a percentage and are calculated according to Eq. 7.

$$Savings = 100 - \frac{\int Peak_{new}}{\int Peak_{historic}} 100[\%] \qquad (7)$$

The baseload is then varied to illustrate the different savings achieved depending on the baseload level.

3. Results

3.1. Building model verification

The mean and max error over the entire prediction horizon for each time step when choosing the optimal prediction horizon and training set length is plotted in Fig. 4.

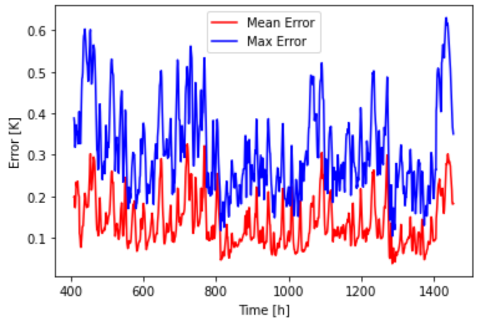

Figure 4: Mean and maximum error for Building A

The maximum error is 0.63K and the mean error of about 0.14K for Building A.

The heat capacity of Building A is 108 $[\frac{Wh}{Km^2}]$ respectively 124 $[\frac{Wh}{Km^2}]$ for Building B. The average time constant over the entire data set for Building A is 209 hours, and for Building B 120 hours. Compared to the values given in Tab. 1., these are reasonable.

As illustrated in Fig. 5. & Fig. 6., the simulated heat supply and indoor temperature generated by the model are reasonably well correlated to the historical data, as shown in Tab. 2.

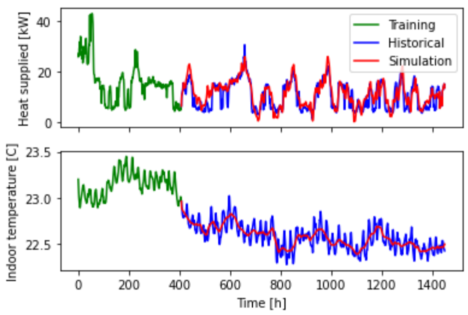

Figure 5: Verification of model for Building A

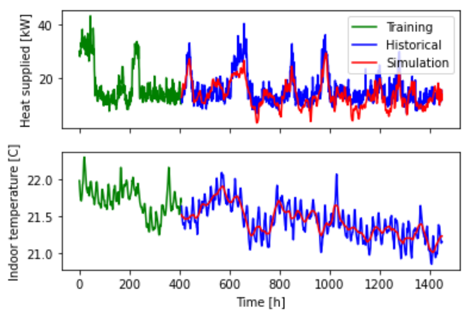

Figure 6: Verification of model for Building B

Table 2: Verification results: comparison between simulated and historical data for heat supply

	Building A	**Building B**
Correlation coefficient	85%	77%
RRMSE	8%	9%

The fact that the simulated heat supply and the historical heat supply do not match each other perfectly is not of concern, since it is the trend that is of interest.

3.2. Utilization potential

Fig. 7. shows the cumulative distribution of the heat supplied during the simulation period.

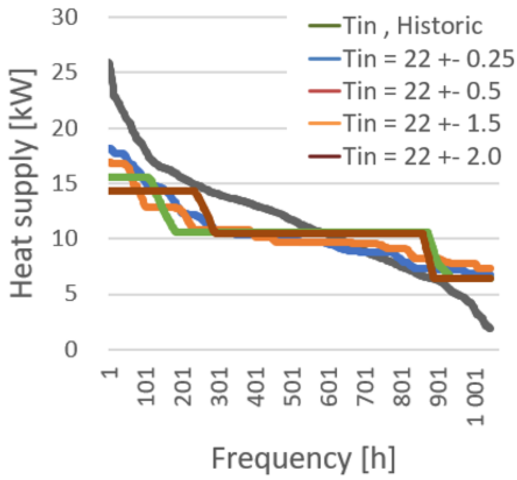

Figure 7: Load duration curve for peak shaving in Building A

The frequency describes how often (how many hours) the corresponding heat supply is reached for each investigated frequency. In general terms, by increasing the flexibility of the indoor temperature, less variation in the supplied heat and a lower peak power is achieved.

In Tab. 3. the results for different temperature flexibilities are presented. It shows that in general when implementing the peak shaving control strategy there is also an overall reduction in heat supply. However, this is mainly due to a reduction in the set indoor temperature as the simulated historical data has an average indoor temperature of 22.6 °C. Therefor it can't be concluded that utilizing peak shaving results in energy savings, it can however reduce emissions. If utilized by DH companies, peak shaving could reduce the need for a fossil fuel boiler during peak hours and thereby reduce overall emissions and the dependency on expensive and harmful fossil fuels.

Table 3: Results from peak shaving compared to the simulated historical data

Temperature flexibility [°C]	Peak power decreased	Energy consumption decreased	Average indoor temperature [°C]
±0.25	30	10	22
±0.50	35	10	22
±0.75	35	12	21.9
±1.00	36	9	22
±1.25	38	14	21.9
±1.50	40	7	22.2
±1.75	42	7	22.3
±2.00	45	6	22.3

As seen in Tab. 3. a temperature flexibility of ±1.25 $°C$ generates the most energy savings, however in a survey by Renström et al. (2021) including 88 respondents it was found that approximately 40 % of respondents thought they would not be affected by an variable indoor temperature of ±1 $°C$ whilst approximately 60 % thought they would be negatively affected by a variable temperature of ±1.5 $°C$. This might intel that even though the comfort impact will be minimal, it will be difficult to convince consumers to use the developed approach with higher variability. Renström et al. (2021) even found that 20 % of respondents believed they would be negatively affected already at ±0.5 $°C$.
To determine the appropriate flexibility a normalized economics analysis is done, the results are presented in Fig. 8.

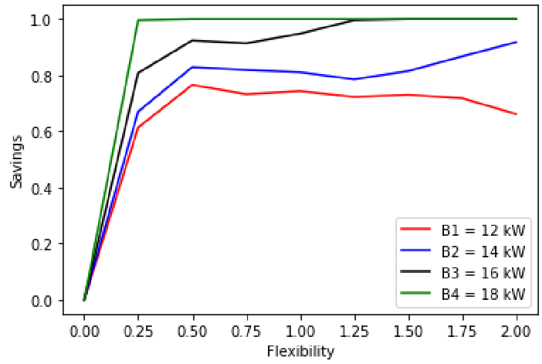

Figure 8: Normalized economics analysis results

As the percentage of the available area is made up of the difference between the historical peak and the shaved peak, the magnitude of the baseload is directly correlated to the possible savings. From the combined knowledge presented in Fig. 8.**Error! Reference source not found.** A higher baseload results in larger savings, this is demonstrated clearly in Fig. 9.

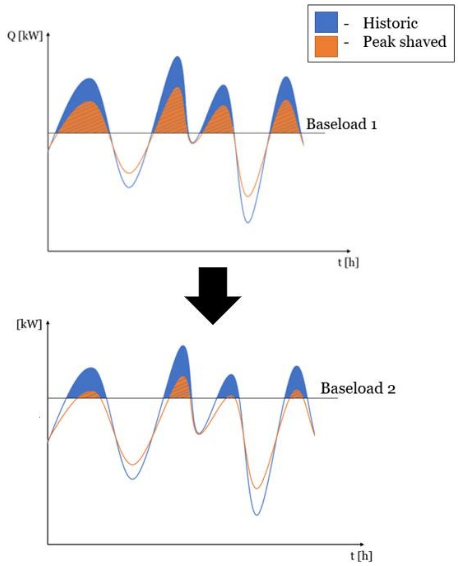

Figure 9: A moving baseload's impact on savings

In Fig. 9., one can determine that choosing an appropriate baseload is crucial when it comes to the economic benefits of peak shaving. The savings in the fixed cost of the peak consumption depends on how much of the peaks are above the baseload. Therefore, the higher baseload reaches savings of 100% since the new peak is below the baseload. In the lower baseloads, where the new peak never is below the baseload, the preferred choice of temperature flexibility is $\pm 0.5°C$. Due to this a temperature flexibility of $\pm 0.5°C$ is chosen as the preferred interval. Fig. 10. and Fig. 11. shows the potential of peak shaving by allowing a flexibility in the indoor temperature with ±0.5 $°C$ for Building A and B.

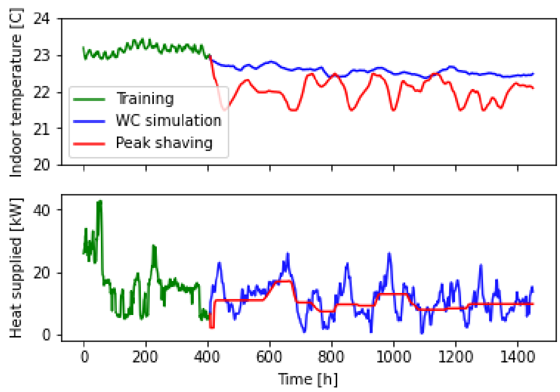

Figure 10: Peak shaving, Tin = 22°C ±0.5, prediction horizon = 48, Building A

Fig. 10. shows that the highest peak in the heat supply during the simulation decreased from 26 kW to 16 kW for Building A, and the total energy consumed during the simulation decreased from 12 100 kWh to 11 000 kWh.

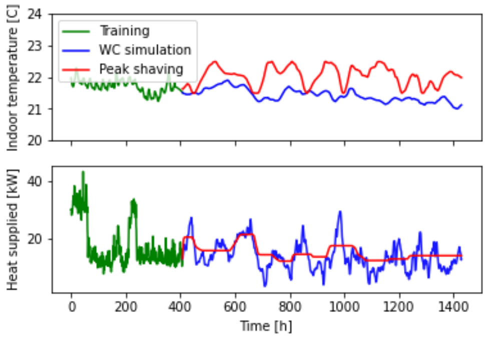

Figure 11: Peak shaving, Tin = 22°C ±0.5, prediction horizon = 48, Building B

For Building B as shown in Fig. 11. the highest peak was decreased from 29 kW to 22 kW, and the total energy consumed was increased from 14 700 kWh to 16 000 kWh.

4. Discussion and conclusions

4.1. Discussion

The FOTM and the constructed optimizer is a general model with a low execution time. Since the model was developed using the data from Building A and then also tested on data from Building B, the generality requirement was met. Execution time has not been an issue in the tests (448 seconds for a simulation period of 1085 hours). However, there are some concerns regarding the reliability when using online adaptation, since there are certain rules that must be considered for parameter estimation, which have not been developed. This have mainly been the parameter estimation of R and $Qpassive$. When estimating these parameters, the most important part is that the indoor temperature is stable and does not vary over time. When adapting peak shaving it is never stable. Vice versa if the indoor temperature is kept steady $Ceff$ is hard to estimate since it requires change within the indoor temperature to be determined. Examining how these issues might be solved belongs to the future works. For the results presented the parameters $R_{passive}$ and $Ceff$ has been determined on the training set and the assumed constant for the entire simulation period. This gives reliable results for the available data as shown.

By utilizing a control strategy similar to the one suggested in this work there is a possibility of increasing the amount of electricity produced in a CHP plant. A reduction in heat demand from the consumers yields a larger portion of the produced heat at the plant available for electricity production. Currently, most renewable sources cannot keep up with the higher electricity demand during the winter where DH companies normally can't produce any electricity due to the high heat demand. By decreasing the heat demand and increasing the electricity production the revenue can be greatly increased.

The authors suggest that a new subscription format is produced in which the customers subscribe to a certain comfort interval rather than a certain heat flux. The authors also believe that customer participation and engagement should be an integral part of future business models to ensure customer satisfaction. The authors also suggest adding a safety margin in the subscription range.

4.2. Conclusions

In this work a data driven physics-based model has been produced which directly quantifies the steady state heat loss, the heat capacity, the time constant and the passive heating. These parameters are essential for determining a building's thermal storage ability. The model has a RRMSE of 8% for Building A and 9% for Building B. By having access to the thermal dynamics of a buildings storage potential the buildings heating system can be controlled from a peak shaving perspective which utilizes over- and underheating to charge and discharge the building around peaks in heat demand generated by changes in the external temperature. Utilizing a peak shaving control strategy has been shown to generate savings in energy consumption of up to 14 % and 45 % in peak consumption (depending on the set indoor temperature and allowed flexibility). The authors suggest allowing the customers to choose their preferred flexibility to ensure their comfort, but also point out that a beneficial control can be found at an indoor temperature of 22 ±0.5 °C.

There are four aspects to be considered when allowing for a flexible indoor temperature, comfort, energy consumption, peak shaving, and economics. All aspects are correlated and to find an optimal strategy, compromises must be made. The authors have shown that economic savings and peak shaving can be achieved by allowing for small variations in the indoor temperature to the detriment of comfort and in some cases energy consumption.

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