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Forecasting and optimization of the heat demand at city level

Abstract: Computational methods have been developed for the predictive optimization of the heat demand to increase energy efficiency in heating by taking into account the point of view of both the energy producers and consumers. Research methods included the modelling of the individual buildings indoor temperature and heat demand, which can then be expanded to a larger scale to optimize the heat demand at the city level. The developed models are accurate and easily adaptable enabling the city level predictive optimization of the heat demand. This makes it possible to better adapt to and prepare for future changes in the outdoor temperature while at the same time ensuring the normal living conditions and optimized energy efficiency, also enabling the demand side management in the heating network. However, the full realization of the concept requires proper real-time and two-way information flow through the whole energy chain.

Keywords: district heating, modelling, prediction, demand side management, optimization

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1 Introduction

Energy Efficiency Directive (EED) [1] sets binding measures for EU countries to improve energy efficiency by 20% at EU level by 2020. In 2016, an update to EED was proposed setting a new 30% energy efficiency target for 2030 [2]. At the same time, buildings represent 20–40% of the total energy consumption and half of this energy is used for heating, ventilation and air conditioning (HVAC) [3]. Furthermore, for 15 of the 28 EU countries the annual heat demand in buildings is larger than electricity and cooling demands [4]. Also, fossil fuels are still used to produce most of the heat [5]. For the aforementioned reasons, the implementation of new energy efficiency measures for the heating and building sectors is of utmost importance.

As the requirements for energy efficiency are becoming stricter, it is no longer sufficient to consider buildings as isolated elements in energy systems [6]. They have to be treated as active participants having storage capabilities and even their own energy production. Therefore, buildings have to be taken into consideration when developing new control and optimization schemes for district heating systems. A concept for optimizing the heat demand in district heating systems has been proposed by the authors [7] and is presented in Fig. 1. The concept approaches the subject by predicting the heat demand and then optimizing the heat production utilizing demand side management (DSM). DSM refers to the change in energy consumption by the end user in response to the changes in the price or the production of the energy [8]. However, city level consumption forecasts can be extremely time-consuming if the simulations are done on a single building level, due to data gathering, simulation and monitoring efforts and the estimation of uncertainties [9]. Consequently, forecast models are widely used for individual buildings, but their application at the large scale is lacking [9–11]. It has been even stated that it is impossible to model every building separately, one of the main reasons being the lack of real measurement data [12]. However, today many buildings are equipped with smart meters that record heat consumption in intervals of an hour or less. Furthermore, model predictive control (MPC) has been one of the most studied control strategies for buildings during the last decade, offering an efficient way to perform demand response actions in buildings, but the amount of modelling work required makes the implementation expensive [13–15]. Ease of modelling would make the forecasting of heat demand and the implementation of predictive control strategies at the building and city level more cost-effective. In this regard, the applied models have to be easily reproducible for multiple buildings. This sets requirements for the simplicity and ease of parametrization of the models. The straightforward implementation in real applications should also be kept in mind. In modern automation, the cost of implementation work plays a key role while the cost of the hardware is decreasing.

In this work, the developed modelling approaches are presented to realize the predictive optimization

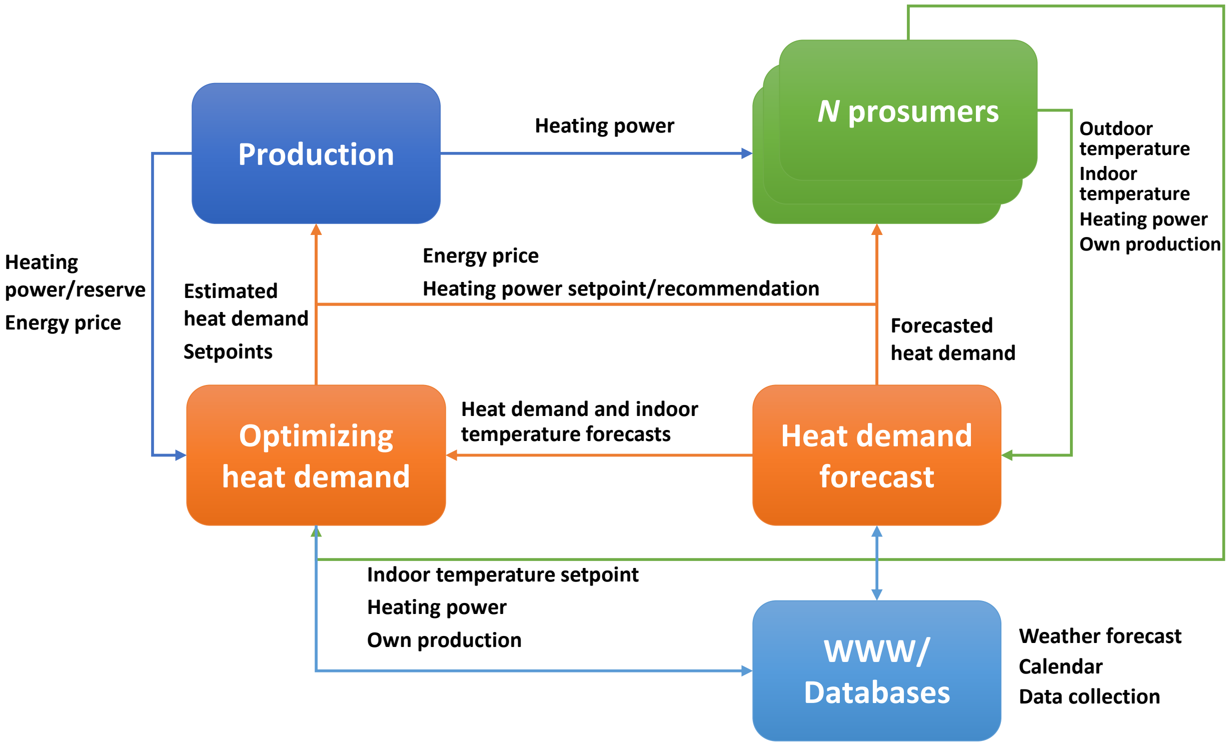

Fig. 1. Concept for the predictive optimization of the heat demand.

concept illustrated in Fig. 1. Then, the application of the developed modelling methods to optimize the heat demand at city level are discussed.

2 Modelling

Models are the basis for any MPC. Straightforward modelling methods would enable MPC to be implemented in buildings at city level. The concept presented in Fig. 1 builds on the forecast of the heat demand of individual buildings thus enabling DSM. Many of the previous works have considered only the total heat demand forecast of a district heating system. These approaches would not enable DSM actions as forecasts for the heat demands of individual buildings are not included. Furthermore, when optimizing the heat demand utilizing DSM, maintaining the indoor temperature at an acceptable level in buildings is important as the control actions should ensure the quality of the living conditions for the residents. Therefore, a mathematical model for the indoor temperature of a building is critical for enabling control and optimization strategies aiming at higher energy efficiency [16].

2.1 Forecasting the indoor temperature

For wide use of any indoor temperature model, it should be applicable to different types of buildings with minimum extra implementation work. However, most of the research have focused on a single building for the development and testing of the models. Furthermore, many of the models found in the literature need detailed information about the building properties and large amount of representative measurements together with many parameters. All of this would increase the complexity and the implementation work of the models thus limiting their application to different buildings in real environments. If the models are only tested in one building, it is very much possible that they cannot be transferred directly to another building. Then it comes to the amount of work needed to transfer these models into the different buildings. If the model is to be used only to control an individual building, the implementation time will not necessarily be an issue. However, as the intention of the authors is to perform the optimization of the heat demand at district and city level, the short implementation time for the model is crucial. When the model is implemented in hundreds or thousands of buildings, days of modelling work on one building is not acceptable.

To overcome these modelling issues, a new dynamic modelling approach was developed to predict and optimize the indoor temperature in large buildings [17]. To ensure the model generalizability to the whole building stock with reasonable prediction accuracy, the modelling approach combines easily available, existing measurements, building information and tabular values while minimizing the number of model parameters and inputs. A low number of parameters, easily available measurements and generalizable model structure make the parameter identification of the model easy in comparison to present modelling methods. The average relative modelling error of the developed model was below 5%. The results confirmed that the model can be used to predict and optimize the indoor temperature in large buildings. A low number of needed measurements and generalizable model structure would allow the implementation and adaptation of the model to a wide variety of different buildings as a part of city level energy optimization concepts.

2.2 Forecasting the heat demand

Most of the studies that have considered heat demand forecast in individual buildings have had only one building for the model development and testing. Application of the models to a larger building stock using the same model structure would not necessarily result in the same accuracy. Some studies have also utilized data from simulated buildings. Then the model performance in real buildings may remain questionable. Although, there are studies that have considered more than one real building, there appears to be no study where hourly heat demand for a large district heating system has been forecasted utilizing models for real individual buildings.

Considering the above, two different straightforward modelling approaches were developed to forecast the hourly heat demand at city level considering more than 4000 individual buildings [18]. The proposed modelling approaches forecast the heat demand for individual buildings and at city level, enabling DSM. The results showed that the relative error was 4% for the city level heat demand forecast. Low amount of estimated parameters reduced the calculation time and easily attainable measurement data facilitates the implementation of the models for thousands of buildings.

3 Optimization of the heat demand

Today the heat demand for district heating is forecasted based on the outdoor temperature. This forecast is for the production of the heat and does not take into account the real heat demand of the buildings that the heat is being provided to. This result in non-optimal heat production. Furthermore, the lack of information from the consumption side prevents any DSM actions that could provide flexibility for the heat production. Heat demand forecast based on the forecasted heat demand of individual buildings together with the information on the indoor temperature of the buildings would enable different DSM action as presented in Fig. 2. These include peak load cutting, the minimization of the heat demand and timing of the energy production.

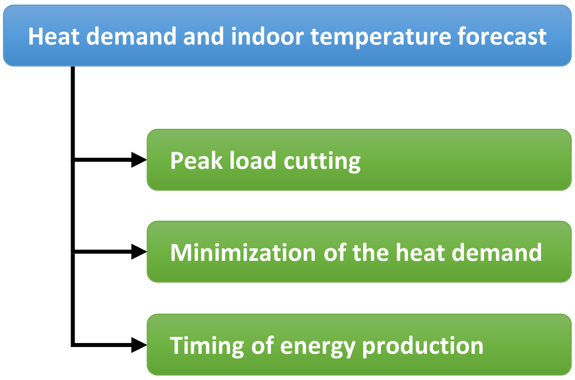

Fig. 2. Different optimization strategies for heat demand enabled by the demand side forecast.

3.1 Peak load cutting

Peak loads refer to times of high energy consumption that exceeds the production capacity of the power plant. The heat demand forecast would be used to identify these peak loads before they happen and the thermal mass of the buildings could be used to cut them. Fig. 3 shows an example of the peak load cutting by utilizing the thermal mass of buildings by preheating them thus lowering the heat demand during the forecasted peak load. It should be noted that the total heat demand remains similar in both cases. So there are not necessarily any direct benefits to building owners, rather the benefits are for the heat producer for not needing to start auxiliary power plants which would increase the production costs. However, it should be noted that this is highly case dependent and there could be energy savings when applying peak cutting. This could happen if buildings are already overheated or the outdoor temperature profile is favorable. This is also highly dependable on the allowed indoor temperature limits.

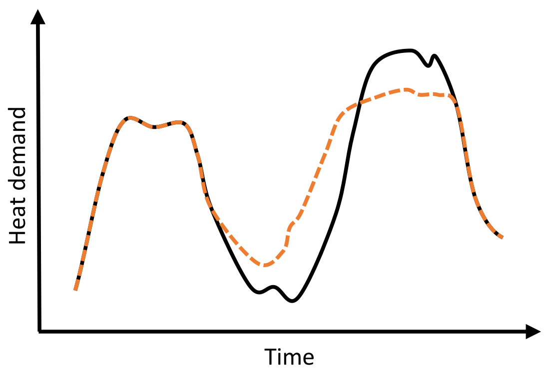

Fig. 3. An example of the peak load cutting. The black line is the heat demand without peak load cutting and the red dashed line is the heat demand with peak load cutting.

Simulations of different peak load cutting scenarios have been performed in two apartment buildings by utilizing the developed indoor temperature model [19]. One building was built in 1972 and the other in 2011. The results showed that the studied buildings had very different heat storage capacities. In the newer building, even 70% peak load cuts were possible without compromising the indoor temperature. However, in the older building 30% peak load cuts decreased the indoor temperature below the desired level. The results confirmed that the system level effect of peak load cutting cannot be concluded based on the results of a single building. Only by investigating systems with multiple buildings, the city level peak load cut capacity utilizing heat storage in buildings can be reliably evaluated.

3.2 Minimization of the heat demand

Optimization strategy that would have direct benefit for the building owners would be the minimization of the heat demand. This requires knowledge about the indoor temperature inside the building and its future projections. The minimization of the heat demand would be enabled by more stable indoor temperature control taking better into account the future outdoor temperature for example avoiding overheating when the outdoor temperature is rising. Fig. 4 illustrates what the result of minimization of the heat demand could be at city level. Again, to have an effect on the city level, the method would need to be implemented in multiple buildings.

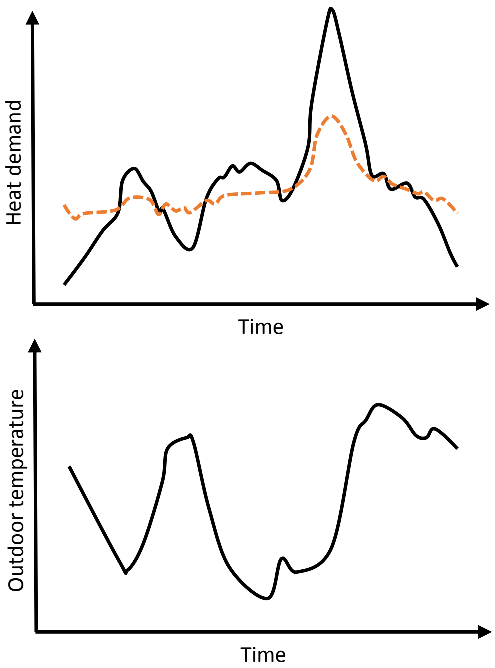

Fig. 4. The minimization of the heat demand. The black line is the heat demand without minimization and the red dashed line is the heat demand with minimization.

Preliminary results from a field test, where the optimization of the heat demand was performed in a school building, showed that significant savings in heat consumption and reduction in peak loads are possible [7]. Compared with the reference day, 14% energy savings were achieved in one day by optimizing the heat demand. It meant 1 MWh reduction in the heat consumption and additionally an average of 25% cut in peak loads. This demonstrates that there is a huge energy saving potential in the heat demand of buildings.

3.3 Timing of energy production

The timing of energy production refers to the timing of electricity production in combined heat and power (CHP) plants. At favorable times, electricity production could be increased and the extra heat could be stored in the buildings. As the trading in the Scandinavian electricity market is performed one day in advance, the predictive information on the heat demand and indoor temperature of the buildings is crucial.

3.4 Realization of the concept

In the context of the concept in Fig. 1, all the aforementioned predictive optimization strategies would utilize buildings as short term heat storages which is an effective and efficient way to store heat [20, 21]. It is well known that the peak loads can be cut, the indoor temperature swings can be reduced and the time of the heat demand can be shifted by utilizing buildings as short term heat storage [22–26]. As the heat storage capacity of buildings is already existing, only proper ways to utilize it are needed. The easily adaptable models discussed in Section 2 [17, 18] would enable the application of the predictive optimization methods to the whole building stock providing predictive information on the heat demand and indoor temperature in buildings. The optimization could be implemented as a continuous process where the buildings minimize their own heat consumption while maintaining the living comfort. On the other hand, the heat demand forecast model could also be used to provide predictive information on the future heat demand and DSM actions could then be executed when needed. This could be related to peak load cutting or timing of electricity production in case of CHP plants. Of course these two approaches could be combined. In any case, the full realization of the concept would require proper real-time and two-way information flow through the whole energy chain.

4 Conclusions

Computational methods for the predictive optimization of the heat demand to increase energy efficiency in heating have been developed. Models for the indoor temperature and heat demand have been developed. The developed indoor temperature model can predict the indoor temperature in buildings with under 5% relative error. The average relative error of the total heat demand forecast was 4%. The utilization of buildings as short term heat storages to optimize the heat demand have been discussed. Simulations and the performed field test have shown that the buildings can be used for short term heat storage to achieve significant reduction in peak loads and an increase in energy efficiency by applying the developed modelling methods.

In conclusion, the presented modelling approaches enable the city level optimization of the heat consumption due to their reproducibility and accuracy. However, the realization of the concept requires proper real-time and two-way information flow through the whole energy chain. In addition, although the simulations with real data give valuable information on the feasibility of the developed methods, more actual testing in the real environment would be crucial to commercialize the results.

Acknowledgements

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