A Concept for Cutting Peak Loads in District Heating

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ABSTRACT

In this article, a concept to make energy production and consumption more efficient in the future energy networks is proposed. The solution aims to minimize and schedule peak demand time and quantity based on the predicted heat storing capacity and total heat consumption of the building stock. By modelling the indoor temperature of a building predictions about the heat consumption can be made. This model can be further used to optimize energy consumption and to cut peak loads. The concept takes energy production as well as energy consumption into account by observing the whole system. In the tests, optimization of the heat consumption for 24 hour period utilizing the above mentioned concept was performed in a school building. Preliminary results show that at least 14% savings in the heat energy consumption can be achieved. In addition, significant reduction in peak loads was measured. Test results show great potential related to the proposed method and encourage to further develop the above mentioned concept.

1 INTRODUCTION

Heat represents nearly half of the world's final energy consumption /1/. In 2009, heat represented 47% of the final energy consumption when compared with electricity (17%), transport (27%) or 'non-energy use' (9%). Nevertheless, this form of energy is largely ignored in the climate change debate, although two-thirds of the fuels used to meet this heat demand consist of oil, coal and gas. Therefore, it is of the utmost importance to implement new energy efficiency measures in the heat sector. Cutting the peak loads in district heating system is one of such measures. In 2011, about 12% of Europe's and 23% of China's total heating energy came from district heating /2/. In Nordic countries the share of district heating in heat demand is even larger. In 2009, the share was 49% in Finland, 55% in Sweden and 47% in Denmark /3/.

Peak loads exist in a district heating system when the heating demand exceeds the capacity of power plants. Typically peak loads take place in the morning and evening when the heating control systems act simultaneously according to outdoor temperature. This especially applies to commercial buildings such as office buildings and schools. During the peak loads, oil powered reserve capacity is typically needed. This raises production costs for the energy company as oil is used as a fuel. This creates a strong economic incentive to find ways to cut peak loads and thus reduce the use of oil. In addition to economic benefits, reducing oil use has also environmental benefits as CO_2 emissions are reduced.

In this article a concept for cutting peak loads in district heating is proposed and preliminary results from the application of the concept are presented. In section 2, the idea of building's thermal mass is introduced and a survey on prediction of heating demand and building modelling is presented. The concept for cutting peak loads is presented in section 3. In section 4 preliminary results from the application of the concept are presented. Finally, conclusions and future work are discussed in section 5.

2 REVIEW

Building's thermal mass is one way to tackle peak loads. To use it efficiently predictions of heating demand and building models are needed. In this section the idea for utilising the building's thermal mass is discussed, including a survey on prediction of heating demand and building modelling. This gives a background for the concept to be presented in section 3.

2.1 Building's thermal mass

Heat can be stored into building structures that can be used as a short term heat storage to cut peak loads, to reduce indoor temperature swings and to shift the time of the heat load /4/. It is possible to construct large heat storage systems that allow heat to be stored for longer time periods, but the advantage of building's thermal mass is that it is already existing and only proper control strategies are needed to utilize it.

Conventional control strategies do not utilize thermal mass of the building, although it can significantly reduce operational costs by reducing overall heating demand and by cutting the peak loads as is presented in /5/. In his article, an overview of the building's thermal mass concept is given. Although cooling is discussed in the article the same applies to heating as well. There, also various simulation studies, laboratory tests and field demonstrations utilizing building's thermal mass are presented. Simulation studies show that even 50% cut in peak loads is possible when building's thermal mass is utilized. Furthermore, Braun et al. /6/ studied different control strategies utilizing building's thermal mass and showed that 20–40% savings in total cooling costs can be achieved. Other studies have also shown that significant cut in peak loads can be achieved by utilizing the thermal mass of the building /7,8/. Still, according to Braun /5/, quite little work has been done in developing general control solutions using building's thermal mass. For commercial solutions the implementation costs should be low. That means that the models and optimization methods would need to be relatively simple with small number of measured inputs.

2.2 Prediction of heating demand and building models

Cutting of peak loads can be implemented by reducing the heating demand or by moving the time of the heat consumption. Whichever way, prediction of the heat demand is needed to be able to perform peak cutting efficiently. Nowadays prediction of the district heating demand is mainly based on weather forecasts and utilized in the operation of the production side of the district heating network. For example, Dotzauer /9/ presented a simple method for heat load prediction that was based on the assumption that the heat load is mainly affected by the outdoor temperature and the social behaviour of the consumers. Predictions were comparable to those of more sophisticated methods, relative error being 6–15%, and the conclusion was that the research should focus more on improving the quality of weather forecasts rather than developing advanced heat load prediction algorithms. Other methods for heat load prediction include conditional Finite Impulse Response model /10/, grey-box model which combines physical knowledge with data-based modelling /11/, functional statistics /12/, recurrent neural networks /13/, partial least squares, artificial neural networks and support vector regression /14/.

Although above mentioned prediction methods may include some information from the demand side of the district heating network, they do not include models of individual buildings and do not have access to building control systems. Therefore these methods cannot utilize thermal mass of the buildings to optimize the heat consumption. To be able to effectively utilize building's thermal mass a model of the building is needed.

In their article, Kramer et al. /15/ review simple thermal and hygric building models. Zhao and Magoulès /16/ review models for the prediction of building energy consumption and state of the art in building modelling is discussed by Foucquier et al. /17/. These reviews are based on numerous research papers and it is not the intent of this paper to go through all of them, as the above-mentioned reviews do a great job in that, but to give a summary of different modelling approaches. Readers interested in more detailed discussion on publications on building modelling are referred to the above-mentioned reviews.

Based on the reviews, models can be generally categorized in three groups based on the modelling technique: white-box models, black-box models and grey-box models. White-box models (e.g. RC-models) are models based on physical principles and model parameters have clear physical interpretations. White-box models can be very elaborate and thus effective and accurate. However, they require detailed information on building and environmental parameters. This information is not easily available and also the operation of the simulation tools used requires expert work making it hard to perform cost inefficiently. The modelling work is usually high and models cannot be generalized. Furthermore, these complex and detailed models are not easily utilized for control purposes. Therefore, simplified models are favoured. /15,16,17/

In black-box models (e.g. linear parametric models, neural network models) parameters are estimated from experimental data and they have no direct physical interpretation. This is a huge advantage if no information is known about the physical properties of the building, but the disadvantage is that the building cannot be characterized by its parameters. Statistical black-box models are relatively easy to develop but can be inaccurate and lack flexibility. Common problem with neural network models is overfitting, which means that the model performs well with the training data but has a poor performance with unseen data. Neural networks and support vector machines give highly accurate results as long as model selection and parameter settings are well performed. However, they need sufficient historical data for training and can be extremely complex. Linear parametric models are also data driven and no information about the physical properties of the building is needed. Compared to neural network models there are several advantages: they are simpler, they are easier to deal with as the parameters could be connected to physical parameters of the system to build grey-box models, there is no parameter variation between trainings and they are easier to use for control purposes. /15,16,17/

Articles on black-box modelling approach include Kalogirou et al. /18/ who used artificial neural networks with minimum amount of input data to model heat load of a building and Mustafaraj et al. /19/ who studied black-box linear parametric models for indoor temperature and humidity using data collected over long periods. The latter is especially interesting as linear parametric models can be used to develop grey-box models.

Grey-box models are a mix between white-box and black-box models combining physical models and statistical methods. This brings forth a new scientific challenge as both physics and statistics is needed. While some disadvantages remain from these different techniques, advantage of grey-box models is that only estimation of building characteristics and thermal parameters is needed and physical interpretation is still retained. Combination of physical and statistical methods makes grey-box models especially efficient for monitoring and control applications. /17/

Plenitude of articles present models using grey-box modelling approach to predict heating load or indoor temperature /20,21,22,23/. Generally, these approaches take a simple physical model and use measurement data to identify its parameters. According to Berthou et al. /24/, grey-box models are better predicting the thermal behaviour of the building in the case of new control strategies compared to black-box models.

3 THE PROPOSED CONCEPT

In the section 2 it was shown that previous solutions in this field have typically derived from production side analysis or building modelling. In these solutions the optimisation of the whole system has been in lesser consideration due to demanding modelling work or fragmented general view because of distributed computation. For a commercial solution the implementation costs have to be low. This means that models have to be relatively simple with as few as possible measured inputs. Demand for simplicity comes also from the fact that for a commercial solution models have to be applied to hundreds or thousands of buildings and it is not feasible to spend much time on modelling each individual building, so models have to be generalizable. Complex models are also hard to use for control purposes. The concept described in this section tries to address these issues.

The overall aim here is to develop generic methods to make energy production and consumption more efficient in the future energy networks. Generalization of the methods makes it possible to reproduce the methods and automatize their implementation. The solution aims to minimize and schedule energy production so that the peak energy consumption time and quantity can be optimized centrally based on the predicted heat storing capacity and total heat consumption of the building stock. Research is focused on analysing measurement data and integrating modelling, control and optimization methods. Then, the object is to find general factors affecting the energy consumption in the building stock to enable the generalization of the results.

Multi-objective constrained optimization problem that emerges is a challenge for energy producers and automation system suppliers. For consumers this means poor possibilities to influence the cost of energy use. Due to all this, consumption of energy is partly unforeseeable and it cannot be affected effectively. At the same time society’s requirements for lowering buildings energy consumption are becoming more concrete. The research aims to provide methods to cost-effectively manage these situations in large scale. Analysis of individual buildings provides in advance information on building stocks behaviour, which enables the use of demand forecasts on consumer, automation system supplier and production levels. Consumers own heating energy production is also taken into account.

By modelling the indoor temperature of a building, predictions about the heat consumption can be made. Indoor temperature model is also used to make certain that indoor temperature stays between desired limits so that the quality of living is maintained. Model can be further utilised to optimize energy consumption and to cut peak loads. The concept takes into account energy production as well as energy consumption and examines the whole system. This is important as control measures done in a single building does not necessarily have the same effect at the district level.

In Figure 1, the concept is presented as a flowchart depicting all the different components. Consumers block presents all the buildings connected to the system and production block presents the district heating provider. As discussed earlier, the premise is that by predicting the buildings heating demand it is possible to minimize peak loads and optimize heat consumption. Prediction block has inputs from buildings' automation system including outdoor temperature, indoor temperature, heating power and own heat production. Also weather forecast and possibly additional calendar information as well as past data is needed for making predictions. Database block presents this in the figure and includes also data collection. Minimization block continuously minimizes the heat consumption by shifting the heating demand utilizing buildings' thermal mass especially when the predicted heating demand is higher than the power plant capacity i.e. during peak loads.

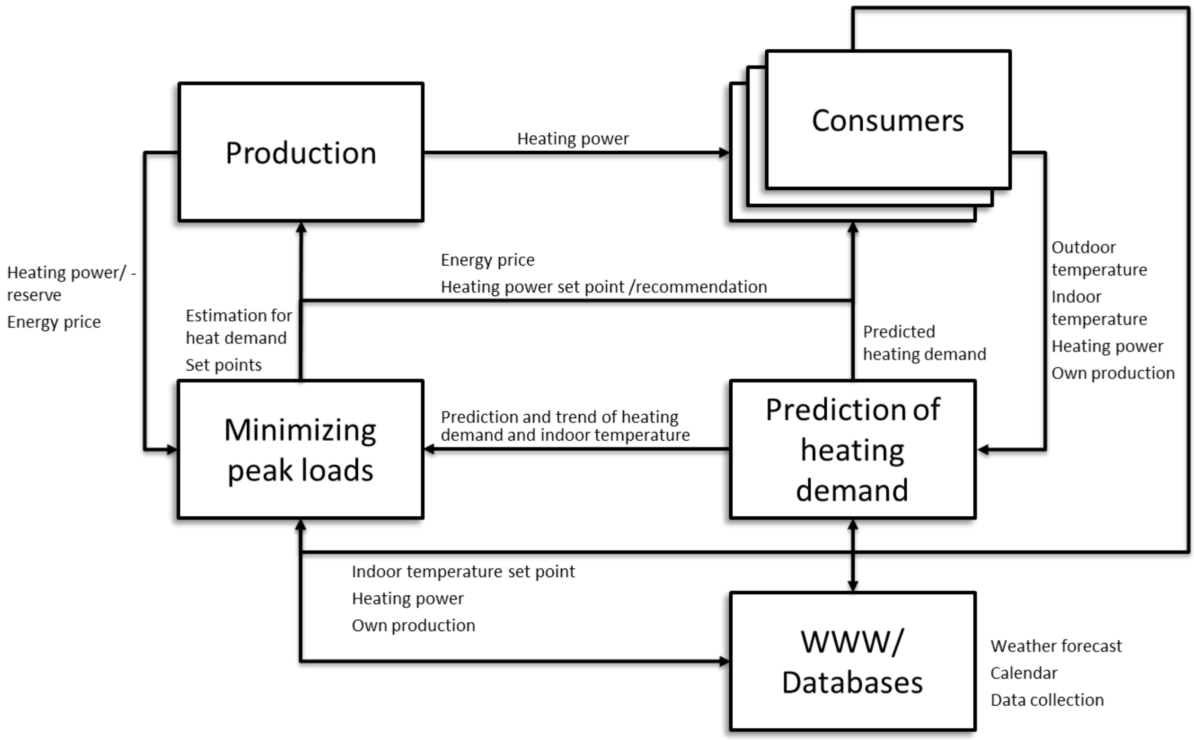

Figure 1. Concept for cutting peak loads in the district heating system.

4 PRELIMINARY RESULTS

Optimization of the heat consumption utilizing the concept described in section 3 was performed in a school building in March 2014. 24 hour period from March 20th 10.00 a.m. to March 21st 10.00 a.m. was chosen for the optimization. Using 24 hour weather forecast, optimization was performed off-line in MATLAB. Results of the optimization consisted of 24 heating power values which were manually entered into the building automation system.

Figure 2 shows the comparison between the optimized heat consumption and the reference day's heat consumption. Compared to the reference day 14% energy savings were achieved which in this case means 1 MWh reduction in energy consumption during the 24 hour period. However, the reference day was slightly warmer than the actual testing day so savings could be expected to be even more substantial. In addition to reducing overall energy consumption, an average of 25% cut in peak loads from 6.30 a.m. to 10.00 a.m. was achieved compared to reference day, although cutting peak loads was not as such defined in the optimization problem. There was also no unusual noticeable effect on the indoor temperatures during the test.

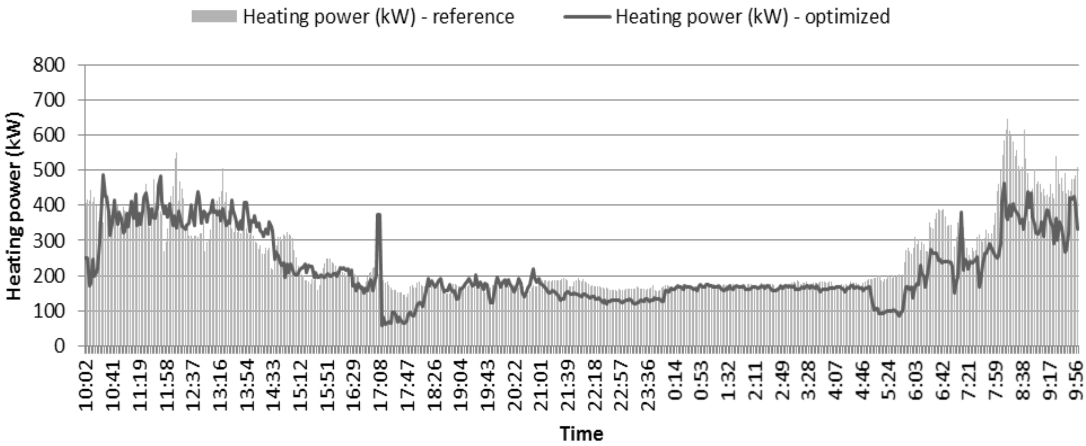

Figure 2. Optimized and reference day heat consumption.

5 CONCLUSIONS AND FUTURE WORK

Previous solutions in this field derived from building modelling or production side analysis have had the optimisation of the whole system in lesser consideration due to demanding modelling work or fragmented general view because of distributed computation. Though good results can be found in literature on predicting the heating demand or indoor temperature of buildings, models that are used need many inputs that are not easily available. This means that application of the models into practice is challenging as commercial solutions call for low implementation costs.

The solution presented in this paper aims to minimize and schedule energy production so that the peak energy consumption time and quantity can be optimized centrally based on the predicted heat storing capacity and total heat consumption of the building stock. Concept takes into account energy production as well as energy consumption and examines the whole system. Preliminary results are very promising showing that at least 14% savings in the heating energy consumption can be achieved using the concept to optimize building's heat consumption. In addition, significant reduction in peak loads can be achieved. This all gives further incentive to develop the concept described in the paper. However, the results presented here consider only the optimization of a single building. Optimization problem becomes more complex when multiple buildings are optimized simultaneously. Also, the energy saving potential in the case of multiple buildings cannot be derived from the optimization results of a single building. Therefore, future research will focus on the optimization of a system with multiple buildings.

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