ABSTRACT
In Denmark, 62% of the heating demand for private use is covered by district heating. As the climatic conditions have a major impact on the indoor temperature, the thermostatic radiator valves are one of the control strategies that is widely implemented for buildings connected to a district heating network. The weather compensation is the most important parameter in the performance of the weather compensation controller and affects the proper functioning of the district heating network. In this paper, the method of online parametric and structural learning is applied for creating an adaptive heat curve that can be used in a weather compensation controller.

The developed algorithm was successfully implemented and tested through a Matlab/Simulink simulation of a 75 m² building with an average energy consumption of 30 kW h m⁻² during a winter month. It is shown that the implementation of the building specific heat curve for this case study increases the thermal comfort in the building by adjusting the room temperature to be in a ±0.5 °C range around the desired temperature, and reduces the energy consumption by 5%, compared to a baseline study.

INTRODUCTION
District heating contributes to about 60% of the heating needs in Denmark. The tendency to use district heating is rapidly increasing due to its large potential and high efficiency in heating the buildings and supplying domestic hot water. Parallel to this, the industry is eager to increase the share of unconventional energy sources and combined heat and power plants to create an environmentally-friendly system that is fully automatized and well controlled (Rezaie and Rosen, 2012). Because of its flexibility, district heating offers a high potential for integration and facilitates the creation of sustainable cities (Lund et al., 2014).

To be able to improve the overall performance of the district heating network, it is important to optimize the demand side. In this paper, the focus is towards residential consumers through the development of an optimal control strategy that can reduce the energy used without diminishing the thermal comfort. The overall performance of the district heating network is directly affecting the proper functioning of the individual substations existing in buildings, and vice-versa. A local reduction of heat demand at the consumer side reduces the overall heat supply at the main district heating station (Fuchs et al., 2013). By reducing the energy needs, the peak periods can be reduced and balanced more efficiently.

Implementing a controller at the main station of district heating for setting the optimal set point of hot water supply can result in an energy saving of 19–32%, according to (Li and Zaheeruddin, 2004). Also, the frequency of adjusting this set point is important and influences the operating costs (Steer et al., 2011). In addition, it is shown that the price management can be used to reduce the heat load by decreasing the indoor temperature with 1 °C in the periods with high heat demand (Van Deventer et al., 2011). More accurate control can be achieved if the system uses the weather forecasts to predict the need of heat and adjust the flow temperature to compensate the future changes (Oldewurtel et al., 2012), (Dotzauer, 2002).

The controller has to recover in due time from different setbacks to achieve the desired room temperature for a specific period. In the same time, a soft recovery is desirable for district heating, so that the peak periods could be avoided, for example after the night setback. In general, model predictive control is rated as being the best solution in completing this task because of its possibility of using occupancy schedules and weather forecasts (Hazuyk et al., 2012), (Oldewurtel et al., 2010). Genetic algorithms (Kolokotsa et al., 2002), SCADA systems (Figueiredo and da Costa, 2012), visualization impact and human interaction (Bonino et al., 2012), kinetic awareness (Pallotta et al., 2008) are some of the approaches used lately for optimizing the control in buildings.

Energy savings based on implementation of a weather compensation controller in one family residential buildings are estimated to 10% (COWI, 2010), and in some cases up to 40% according to a COWI report (Prebensen et al., 1999). The role of the weather compensation in a heating installation is to adjust the supply of heat in order to help in maintaining a desired room temperature while lowering the energy costs, despite the weather conditions. It is known that one of the most important parameters in the performance of the weather compensation is the heat curve.

There are few studies regarding adaptation of the heat curve, and most of them are concerned with the adaptation to different desired room temperature as presented in (Saloky and Pitel, 2005). Another weather compensation controller provided by Vaillant (Vaillant, 2012), has implemented a self-learning heat curve. Their model is based on analysing the variations of the room temperature. The adaptation takes

SIMULATION OF AN ADAPTIVE HEAT CURVE FOR AUTOMATIC OPTIMIZATION OF DISTRICT HEATING INSTALLATION

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place by performing a parallel shift of the curve when the desired room temperature is changed.

An analysis on the influence of the supply temperature on the efficiency of a heat pump is presented in (Huchtemann et al., 2013). The adaptive control strategy takes into account different disturbances in addition to the thermal mass of the buildings. A feedback control for the supply temperature is applied based on the position of the automatic thermostatic radiator valve (TRV). The system is using a predefined heating curve that is assumed to be the optimal one. The corrections are implemented based on this curve.

A study described in (Tödtli, 1989) presents some algorithms for manual adjustments and also some initial ideas for self-adaptation of the heat curve.

Along with a wrong pre-setting of the TRVs or bad hydraulic balance of the heating installation, one reason for low performing heating installations is the complexity of configuring the settings in the electronic controller. One study has concluded that the district energy controllers are often incorrectly configured for optimal energy consumption (Danfoss, 2012). Especially the heat curve is either not changed from default settings or it is set in a way which ensures the consumer not to complain over too low temperature. Often, this choice increases the energy use.

As mentioned, the most important setting in this controller is the heating curve. Because it is manually set, and the installer seldom has the knowledge of the building dynamic behaviour for choosing the optimal heat curve, it is common that a sub-optimal heat curve is chosen. The advantage of using a self-optimizing heat curve is that there will be fewer manoeuvres of the TRVs and mixing valves and that will lead to increase the life time of the system components. The most important factor is that it will also greatly decrease the human interference, leading to higher energy efficiency.

**SYSTEM DESCRIPTION**

The model used for this study was part of an EFP project (Energi-forskningprogrammet), an energy research program under the Danish Ministry of Transport and Energy. Intelligent components with plug-and-play functionalities (Danfoss, 2007).

**Building model**

A small building was considered as a case study. It is connected to a district heating network and consists of three rooms, each one equipped with radiators and thermostatic valves. The layout of the building is shown in Figure 1. The building covers 75 m². The thermal behaviour of the rooms is based on a 4-capacity model, composed by the outer walls, inner walls, interior walls and room air. The model follows the nodal approach, describing the heat transfer with an electrical analogy (Fouquier et al., 2013).

**District heating system**

The district heating installation of the building, shown in Figure 2, is a standard one for small buildings like villas. It is a directly connected system where the primary side represents the hot water that comes from the district heating distribution grid along with the return, and the secondary side is composed of the mixing loop inside the building, distribution pipes and radiators. The mixing loop blends the supply hot water from the primary side with the return from the radiators by means of a valve. This is done for maintaining a secondary flow temperature that provides desired room temperature. The secondary flow temperature influences the room temperature despite the TRVs installed due to its P-band, as well as due to the uncontrolled heat emissions through the heating components like distribution pipes. A lower secondary flow temperature leads to a higher return temperature. Anyhow, due to operation below design load conditions for the majority of time, the return temperature from the radiators is only increasing to a small extent when reducing the flow temperature.

**Figure 2: Design of the considered district heating substation. (Taken from Danfoss Applications Handbook)**

The main components of the system are:

- M1 - motorized valve,
- P1 - circulation pump,
- S1 - outdoor temperature sensor,
- S2 - room temperature sensor,
- S3 - flow temperature sensor of the water on the secondary side,
- S4 - flow temperature sensor of the water on the primary side,
- S5 - return temperature sensor of the water on the secondary side.
Weather compensation controller

Depending on the outdoor temperature (S1) and on different settings that the customer provides at the installation of the controller (for example schedule, thermal preferences, night setback and others) the controller will automatically set the components of the system so that the required flow temperature is achieved. This temperature is set according to the heat curve that indicates the relationship between the ambient temperature and the flow temperature as shown in Figure 3.

If the curve H=1.4 is set, and outside temperature is -10 °C (S1), then the flow temperature sent to the radiators will be around 65 °C (S3). The controller has several such curves, and the installer manually chooses one of them.

For controlling the flow in the system through the mixing valve, a standard PI controller based on the error between the actual temperature of the flow and the set temperature obtained from the heat curve is implemented in the model.

CONCEPT OF ADAPTIVE HEAT CURVE

Methodology

According to (Tödtli, 1989), the two typical structures for designing adaptive algorithms are: ‘model reference adaptive systems’ (or Model Reference Adaptive Control (Brun et al., 2009)) and ‘self-tuning controllers’ (or Model Identification Adaptive Control (Brun et al., 2009)). Both approaches use a reference model to decide if the controller needs to be adjusted.

Taking into account the model reference adaptive systems (Figure 4), the theory of artificial neural networks is used to create an adaptive heat curve. Most of the learning methods that are studied in this area are based on parameter estimations. For this study, the on-line method is applied as described in (Miller et al., 1995). This approach presumes that the data is being processed once it is available for the system. At time step t, an estimate parameter that specifies the best model is calculated using the current input pattern. This parameter is then compared with the target output provided by the ‘teacher’ (the adaptation algorithm). After that, if needed, a new parameter estimate is calculated from the current estimate. This method is also called ‘parametric learning’. Further, the ‘structural learning’ is also used. This method implies multiple parameter adjustment. The detailed theory of these methods can be found in (Miller et al., 1995).

Design

In the proposed setup, the curve is divided into N = 61 points, covering a range from -40 °C to 20 °C for the outdoor temperature. Each point is characterized by the Tflow and Tamb value in the coordinate system as presented in Figure 5.

When the room temperature is different from the desired temperature value, an estimate for the new flow temperature is calculated, and the curve is adjusted by changing the set point.
The desired room temperature is set by the user, and represents the comfort temperature. If one of the points needs to be changed, this decision will affect a number of points adjacent to it, depending on how big is the error between the initial and the new value of the point, as illustrated in Figure 6. Here, ‘Δ’ represents the difference between the old and the new set of the point, and ‘e’ is the error value that influences the points near the setting.

Depending on the difference of the new set, a number of adjacent points will be affected with a pre-set value e.

![Flowchart for the adaptation of the heat curve](image)

The logic behind the adaptation of the heat curve and the learning steps are shown in Figure 7. If the room temperature does not meet the desired requirements, the controller will increase or decrease the set point for the flow temperature accordingly. After a time, specified by the user, the influence of this change will be evaluated. If the new setting improves the thermal comfort and the room temperature is now closer to the desired room temperature, the new data will be used for generating a new heat curve.

The available input data are:

- Tamb - ambient temperature,
- Troom - room temperature representing the average of the 3 rooms,
- Tdesired - desired room temperature,
- Tflow - the current setting of the flow temperature,
- Δ - the difference between the old and the new set point,
- Tf new represents the new flow temperature that is calculated.

**Implementation**

The whole system was implemented in Matlab/Simulink including the building model, the heating system and the controller with the initial settings of the heat curve (Danfoss, 2007). The new module added is the adaptive heat curve. The algorithm presented above was implemented in Simulink, using Interpreted Matlab Functions and Simulink Blocks. The old settings were kept as backup setup for restoring the controller at any time.

**INITIAL SETTINGS**

**Testing conditions**

The outdoor temperature for the simulations has a range between -12.5 °C and 11.5 °C as shown in Figure 8, for a typical winter period in Denmark. For simplicity, the solar radiation and wind are neglected. For these initial tests, the focus is on analysing the impact of a more accurate heat curve compared with an estimate one. The initial heat curve is set to be higher than required (H = 3.6).

**Update period and the number of points that are influenced**

An important factor is the time constant that needs to be set in order to grant the system with a sufficient reaction time to the changes. The adapted heat curve will have the same slope after the adaptation period. This adaptation period depends on the time interval when the update of points occurs (2 hours, 1 hour, 16 minutes). The learning process takes less time if the controller is updating the curve often.

The number of points that are influenced in the adaptation process at each time step is directly connected with the pre-set e value (see Figure 6). Several options were considered:

- e = 0.02 - a high number of points will affect all the points with a value higher than 0.5;
- e = 0.05 - average number of points will affect a maximum of 20 points in each direction;

![Figure 8: Ambient temperature](image)
e = 0.1 - small number of points will affect maximum 9 points in each direction.

After simulations, it was found that if a high number of points (e = 0.02) are influenced, the error around the desired room temperature is increasing and along with it, the time needed to achieve the optimal heat curve.

Table 1: Update parameter analysis

<table>
<thead>
<tr>
<th>e</th>
<th>2 h</th>
<th>1 h</th>
<th>16 min</th>
</tr>
</thead>
<tbody>
<tr>
<td>e 0.02</td>
<td>high overshoots</td>
<td>slow adaptation</td>
<td>energy efficient</td>
</tr>
<tr>
<td>e 0.05</td>
<td>less overshoots</td>
<td>better control</td>
<td>energy efficient</td>
</tr>
<tr>
<td>e 0.1</td>
<td>increased comfort</td>
<td>increased energy consumption</td>
<td></td>
</tr>
</tbody>
</table>

In Table 1 the analysis of the update period and number of points that are influenced are presented. The tests were performed using the same initial conditions and settings for different values of e. There is always a compromise between comfort and cost. The update of the curve was chosen to satisfy both to a reasonable extent. The curve is going to be updated each 1000 seconds (~ 16 minutes) to increase the speed of adaptation and an average number of points will be influenced (e = 0.05).

To eliminate overshoots in adapting the curve, a maximum limit of 1 °C that can be adjusted per time step is imposed. The comfort zone is defined as a band of ±0.5 °C around the desired room temperature specified by the user. In our case, this temperature was set to 20 °C. The adaptation will take place only if the room temperature is out of the comfort zone.

TESTS AND RESULTS

Evaluation of the standard heat curve

For this case study, the designers of the building model indicated that the optimal heat curve is the one having the slope H = 1.8. In Figure 9 the response for the room temperature to the ambient temperature (Figure 8), is presented. Clearly the desired room temperature is not achieved.

The temperatures in the 3 rooms are below the desired room temperature even if the heat curve is the optimal one.

An important point to consider is the setting of the thermostats that influences the response of the room temperature. For all simulations performed the thermostat is set at 20 °C.

If the heat curve is set lower, the temperature in the rooms drops considerably and the comfort is compromised. On the other hand, if a higher value is set the temperature tends to exceed the requirements. This difference will be corrected to some extent by the thermostat, and the temperature will be adjusted to fall in the acceptable range. This is why the installers set a higher value for the heat curve, to ensure the comfort. In this case, the energy consumption increases.

Adaptive heat curve using all 61 points

Figure 10 shows the result when simulating the system with N=61. It has a fluctuating behaviour, and the slope of the curve does not have a smooth shape. The main reason in having this response is the low complexity in filtering the data that are used for adaptation.

![Figure 10: Shape of the adaptive heat curve, using N=61 points approach (initial heat curve H = 3.6).](image)

Figure 11: Temperature variation in the rooms with N=61 points.

Apart from the shape of the curve, the thermal dynamics of the system has been improved. The adaptive algorithm is correcting the curve so that the room temperature is in the comfort zone as shown in Figure 11.
Adaptive heat curve using 6 points

In order to avoid the zigzag shape, the curve is fitted to 6 points. The new heat curve from which the flow temperature is calculated is shown in Figure 12.

![Figure 12: Basic principle for adapting the curve using the 6 points approach.](image)

Even if the system is learning by following the same algorithm based on the 61 points, by adjusting the curve to fit 6 points, a continuous and smoother slope is obtained, as shown in Figure 13. The resulting temperatures in the rooms are shown in Figure 14.

![Figure 13: Shape of the adaptive heat curve, using the 6 points approach (initial heat curve $H = 3.6$).](image)

The thermal comfort is improved, and the room temperature has less overshoots. Several other simulations were performed, having different weather data sets. It was observed that after a period of 3 weeks the changes in the shape of the heat curve become unnoticeable. When the outdoor temperature range starts to be very different from the initial one or the thermal comfort temperature is changed, the algorithm will start automatically to adjust the curve if the room temperature does not meet the requirements. After the adaptation period, all the heat curves obtained for the different data sets were similar, as shown in Figure 15.

![Figure 15: Shape of the adaptive heat curve, having different sets of inputs for the ambient temperature (using the 6 points approach).](image)

The algorithm was tested to be insensitive towards initial conditions. The adapted heat curve is almost the same for all sets of ambient temperature.

Solar radiation and wind influence

One of the issues in maintaining a constant room temperature is the solar radiation and wind. These factors cannot be taken into account by the weather compensation since it is controlled based on the ambient temperature. When adding solar and wind influence into the model the temperature inside the rooms increases with almost $4^\circ$C at high radiation, based on the simulation results.

The highest influence is due to solar radiation. For this aspect a more in depth analysis is needed. Without any correction for the solar factor, the controller would learn based on false assumptions leading to a wrong heat curve. So the first step is to find the best heat curve by enabling the adaptation during the nights or the days when there is no solar radiation, and then let the system perform at usual settings.

ENERGY SAVINGS POTENTIAL

There has to be a balance between costs and comfort. To evaluate the resulting heat costs for the heating installation with and without the adaptive heat curve, both situations were simulated. Because the best results for the thermal comfort comes after the adaptation period, the time of 3 weeks was selected to be the period with major changes seen in the heat...
thermal comfort is achieved. The heating costs are automated, the maintenance costs are reduced and the adaptive curve can improve the performance of the controller setting is eliminated. When performing this operation automatically, the maintenance costs are reduced and the same thermal comfort level.

**Initial heat curve set too high**

- maintaining this curve will result in having an increased comfort level with corresponding costs, and in some cases to exceed the desired room temperature;
- adapting the curve to fit the requirements will reduce the energy costs with 1 ~ 5% depending on how far from the right curve the initial heat curve is set. For the specific case presented in this study, this translates in reducing the monthly energy consumption with 112.5 Wh. In the same time the room temperature is maintained at the same thermal comfort level.

**Initial heat curve set too low**

If the heat curve is set too low there is no possibility to achieve comfort, so even if the costs are reduced, the installation is not fulfilling its duty. In this case, the re-configuration of the curve is a must, and by having the self-adaptive algorithm the controller will be automatically tuned. Thus, the need of the installer to perform this new setting is eliminated. When performing this operation automatically, the maintenance costs are reduced and the thermal comfort is achieved. The heating costs are increasing to an optimal level.

**FUTURE WORK**

The algorithm needs to be tested for longer periods of time, on different building layouts. Future work concerning the self-adaptation of the heat curve should include the disturbances caused by radiation, wind, as well as operation of the building. Corrections for solar and wind influence can be applied through equations using additional data provided by weather forecasts or new sensors installed for solar radiation and wind conditions.

Based on the different general weather condition aspects specific to each season it can be relevant to define seasonal heat curves characterizing autumn, winter, spring.

Due to the flexibility of the existing building energy simulation tools, the adaptive heat curve module presented in this paper can be easily imported and tested using co-simulation platforms (Wetter, 2011), (Nouidui and Wetter, 2014). An interesting aspect would be to investigate how the adaptive curve can improve the performance of the controller with respect to building refurbishment.

**CONCLUSIONS**

In this paper, an optimization for a house heating installation was presented. A self-adaptive heat curve was designed and implemented in order to increase the thermal comfort in buildings and to minimize the energy consumption.

The algorithm proposed follows the basis of artificial intelligence by using the on-line structural and parametric learning method. For this particular case, the results of the simulations revealed the capability of the system to adapt according to the needs of the building, and create its own heat curve that increases the thermal comfort and reduces the energy consumption up to 5%, depending on the initial setting of the heat curve. The system would require a room temperature sensor placed in a reference room. Until now, the temperature sensors were rarely installed in buildings, but the tendency is to have these sensors as a common feature in new buildings where intelligent control is applied. By having an adaptive curve the need of the installer to configure the heat curve each time when it does not meet the requirements is eliminated, in addition to a reduction in the maintenance costs. Also, if the dynamics of the buildings are changing throughout the time, this feature will ensure an optimal setting in time by self-tuning the curve.

At this stage, the adaptation of the heat curve could not eliminate the influence of wind and solar radiation. For this purpose further investigations are needed. In terms of usage, the adaptive heat curve could be enabled during the nights or the days when there is no solar radiation and operate without adaptation in the sunny days.

Because of its simplicity, this algorithm can be easily adjusted and implemented in any type of controller that is using the weather compensation approach.

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