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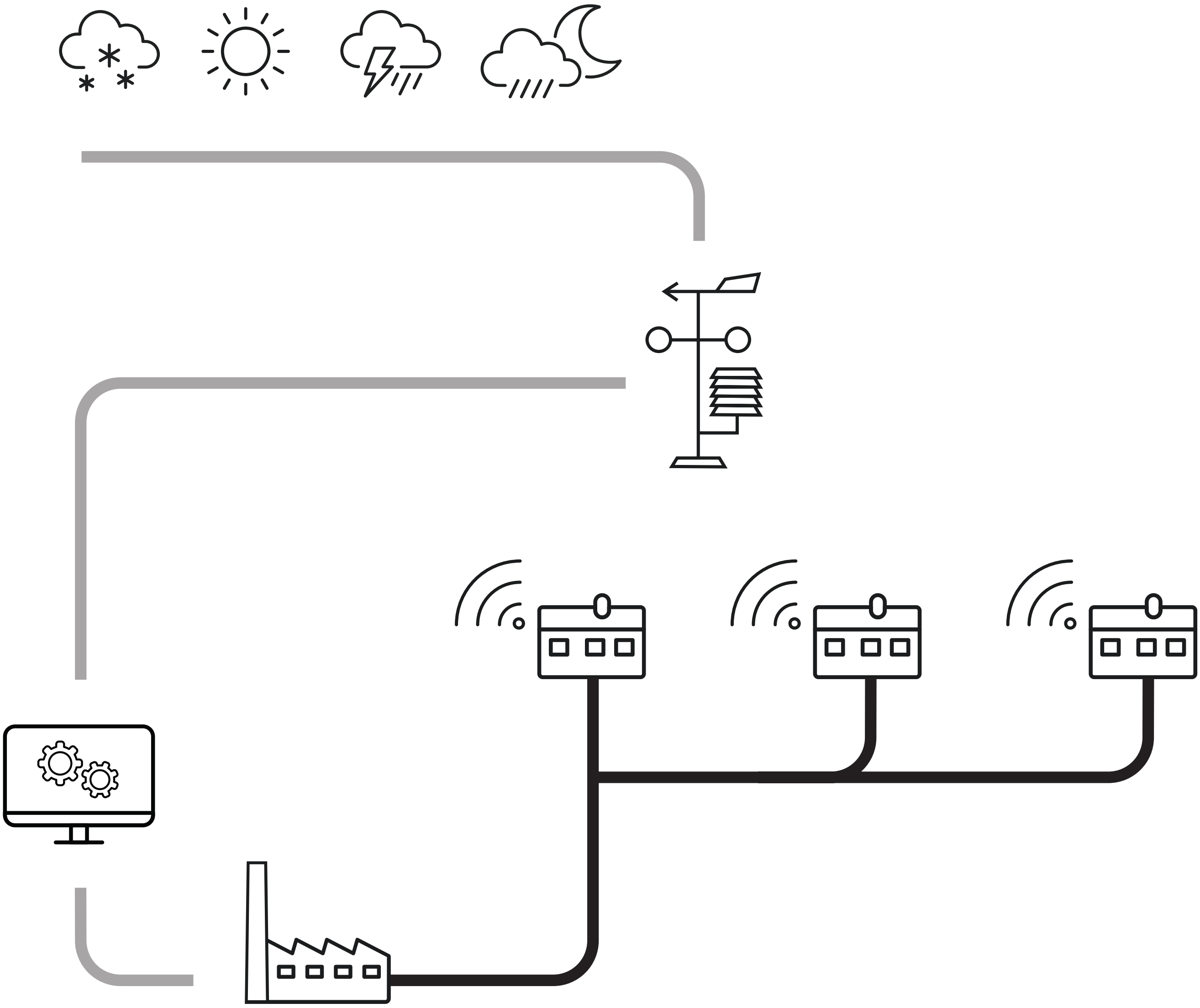

Digitalization of District Heating

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Experience of using Data-Driven Methods in District Heating: Digitalized Operation in Tingbjerg, Copenhagen

June, 2021

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Summary

Operating district heating network using additional data with the traditional data extracted from the SCADA system at the production is discussed. The benefits of including new data in daily operation for the utility is demonstrated. For the past decade, more and more data is becoming available for district heating utilities with the smart meters being installed in every home connected to the district heating network. More local climate stations inside the city are also being installed, and made accessible for everyone. In this report, data from smart meters are presented and how they can be used to operate the network more efficiently. Also, weather forecast in cities is discussed and how they can be improved by localizing them to the local climate using climate stations.

The case study in this report is a on-line operation of temperature control in Tingbjerg which is a small area that is operated by HOFOR. HOFOR is a utility company in Copenhagen which handles for example the district heating, and waste water. They also produce energy for the Copenhagen area. The case study demonstrate how to localize heat demand forecast and operate closed-loop temperature control for a small area. The result for the operation is compared to the previous operation where it was done using open-loop temperature control, i.e. no feedback of the system. The report emphasizes how current state-of-the-art methods can be improved by using newly available data (e.g. smart meters as feedback of the network) and thereby enhancing the efficiency of the operation.

The present report is followed by two other deliverables: the report "Energy data: mapping, barriers and value creation" and the report in Danish, entitled "Digitalisering af fjernvarmen - erfaringer der luner" ("Digitalization of district heating").

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Special thanks to Torben S. Nielsen at ENFOR for providing us detailed information about the district heating system and insights on how data-driven methods can be applied. Furthermore, we would like to acknowledge ENFOR for allowing us to use their state-of-the-art software to demonstrate how digitalization can improve state-of-the-art methods.

Contents

Chapter 1

Introduction

The IDASC, *Intelligent Data-Anvendelse i Smart Cities* (Intelligent Data Use in Smart Cities) project's goal is to investigate potentials from several different data sources that are now available because of digitalization in district heating systems and generally in cities. The overall purpose is to consider and combine all relevant data from meteorological services, city weather data, production data, SCADA data, and end-user smart meter data to enhance the operation of a network. We will evaluate the advantages of combining different data sources and analyze the improvements compared to the typical situation today using only data from the SCADA system. Data from the SCADA system are usually measurements measured at the production site, e.g. supply temperature, return temperature, flow, and ambient air temperature. The focus is to demonstrate the potential of how the new data sources can improve the operating district heating network, i.e. delivering heat from production to consumers in a more optimal setting. In this study, we do not directly consider how digitalization can lead to more optimal production of the heat; however, operating the network efficiently will obviously also have a positive influence on the possibilities for optimized production planning, hopefully lowering the production cost. Therefore, in this report, we only consider heat demand forecast and temperature optimization to increase the operation of the district heating network. The additional data used in this report are the smart meters at consumers in the area where the heat is delivered and a local climate station that is located close to the area. In theory, using this additional data will enhance the operation as it gives more detailed information on the response characteristics of the network and the local climate in the area. We will demonstrate this by using state-of-the-art and off the shelves algorithms for forecast and control provided by ENFOR, an energy forecasting company. ENFOR is a spin-off company from DTU where the initial ideas of these algorithms were established. We will show how to include the proposed additional data in the algorithms and demonstrate the improvements in the operation of the district heating network. In the case study, we will apply these digitalized methods in an on-line operation trial to analyze the gain of using smart meters when used as feedback to obtain a closed-loop temperature control of the network, and the importance of binding numerical weather prediction to a local climate using a local weather station. The trial was conducted in Tingbjerg (Copenhagen), an area which is operated by the district heating utility, HOFOR.

1.1 District Heating (DH) Operation

During the past decades, the district heating sector has been transformed from using primarily traditional fossil fuels to using renewable heat sources and biomass. During the same period, the DH systems have become more digitalized, e.g. with sensors in the district heating network and smart meters at the consumers. At the same time, district heating is becoming a crucial part of the overall integrated energy system because of its flexibility potential, e.g. by storing excess energy as thermal energy [1, 2]. Hence, optimal operation of district heating is crucial.

The inherent flexibility of the DH system is highly valuable for the future integrated and low-carbon energy system. An important aspect is a fact that DH systems can store energy when there is

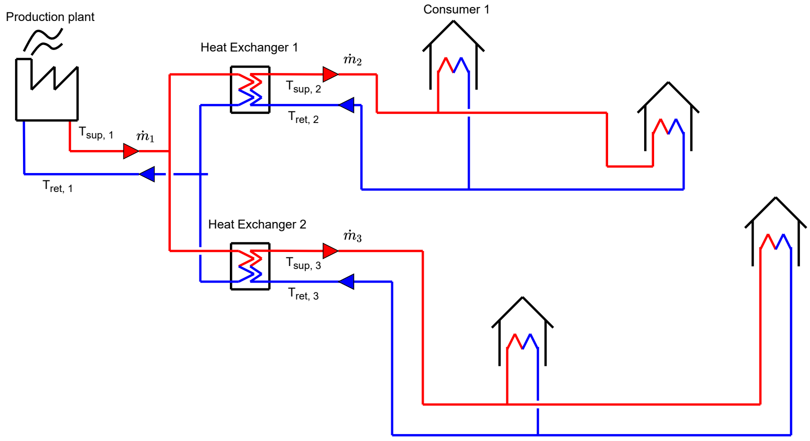

Figure 1.1: Simple schematic view of district heating; The heat production, the transmission lines to heat exchangers then distribution lines that deliver the hot water to the consumer substations.

a surplus of energy from intermittent renewable energy sources (e.g. wind and solar). However, to maximize the flexibility potential of district heating, they would need to operate efficiently by optimizing the production and the temperatures of the network. This report will focus on how to improve the efficiency of operating an existing district heating network by applying data-driven methods using additional data.

District heating consists of heat production, a network of pipes (transmission and distribution) where the hot water is either delivered to substations (heat exchangers) at the consumers and returned to the production facility, and the final component is the consumers. This is illustrated in Figure 1.1. The supply temperature is generated at the production by heating the water, for example, at a Combined Heat and Power (CHP) plant where the temperature is increased by cooling the steam after it has generated electricity in the turbine. The mass flow in the pipes is then controlled using pumps at the production plant. Frequently, additional pumps are required in the network to maintain the desired pressure in the system. First of all, an optimal operation of DH systems implies that the supply temperature and the network temperature should be kept as low as possible without violating any requirements, e.g. supply temperature at a given outdoor temperature. Lowering the supply temperature will reduce the heat loss in the network, and improve the efficiency of the electricity production at CHP plants [3, 4]. Furthermore, a lower temperature implies also more optimal use of, for instance, heat pumps.

Delivering the heat demand is controlled by varying the supply temperature [5]. Controlling the operation of a district heating network rely on either an open-loop or a closed-loop controller to estimate how the heat should be delivered, by regulating the supply temperature where the flow is indirectly varied to meet the demand of the consumers. The open-loop controllers use either a white-box simulation of the system to operate the supply temperature in the network or a simple algorithm based on the knowledge of the system to regulate the temperature. Hence, the open-loop operation does not have any feedback from sensors and data in the network and therefore such controllers can not adapt to any disturbance in the system or changes to the network characteristics. Thereby, they do not use the information from the network to adapt to achieve more optimal operation.

There have been proposed control schemes that operate the supply temperature in a closed-loop [5, 6]. Such a system typically uses a few measurement points located in the network. These points are usually located in the network where the operator believes that the lowest (critical) temperature is, i.e. where the largest temperature loss occurs. Therefore, the supply temperature at the production site is controlled to satisfy the requirements at these critical points. The controllers also control the flow in the system to match the heat demand of the system, and therefore the optimal operation is implemented with a sequence of controllers trying to deliver the heat while keeping the supply temperature at a minimum.

The approach for temperature control in this report is found by lowering the supply temperature while keeping the flow close to the operation limit of the system; see [7]. At the same time, a lower supply temperature will enhance the efficiency of power generation at the CHP plant. Heat demand forecasts are needed for production optimization, and these forecasts are also used for finding the optimal supply temperature [8]. The heat demand is highly correlated with ambient air temperature and therefore usually the forecast model uses numerical weather prediction (NWP) of the ambient air temperature as input. Accurate NWP will be beneficial to the district heating operation as they improve the heat demand forecast accuracy. In addition, both smart meter and local climate station data can help to improve the closed-loop control of the system. The models used are self-calibrating, and consequently, the models automatically adapt to network characteristics as well as local climate conditions.

1.2 Structure of this Report

In Section 1.3, we will describe the case study used in this report. In Section 2, we will discuss how to use data from smart meters and how it can lead to additional cost savings related to district heating operations. Section 3 describes how Numerical Weather Predictions (NWPs) and local climate data can be beneficial for the district heating operations. Heat demand forecasting is characterised in Section 4, while control of district heating network temperatures is described in Section 5. The report finally concludes in Section 6.

1.3 Case study: Tingbjerg district heating area

The case study used in this report is the district heating network located in Tingbjerg, which is a small area with large apartment buildings located in the northwestern part of Copenhagen. The area is supplied by heat from a heat exchanger that connects the central Copenhagen transmission system operated by CTR to the distribution network in Tingbjerg operated by HOFOR. The transmission system operated by CTR supplies heat to approximately 250.000 buildings in central Copenhagen. HOFOR is the distribution network operator, and consequently, HOFOR is the district heating supplier to buildings in central Copenhagen. There are 45 buildings connected to the network inside the Tingbjerg area and 39 of them are equipped with a smart meter. Figure 1.2 shows the layout of the network in Tingbjerg.

Previously, HOFOR has operated Tingbjerg as an open-loop system using the TERMIS tool to simulate and adjust the supply temperature and flow from the heat exchanger. Thus, they had no knowledge of what temperature consumers were receiving, i.e. how the system was working except when consumers complained because of too low temperatures. However, each apartment building in Tingbjerg has a smart meter that is connected to the district heating side. These smart meters can provide the forward temperature, return temperature, flow, and energy consumption for each building. HOFOR also needs a heat demand forecast to regulate the temperature for the heat exchanger, which they get by scaling demand forecasts for a larger area that contains Tingbjerg heating demand. The scaling factor is the ratio between the larger area's historical demand and the historical demand from Tingbjerg.

Therefore, Tingbjerg is an ideal case for demonstrating how the operation of an existing network can be improved with data-driven methods and digitalization. In this study, the smart meters will be used to provide feedback for closed-loop control using the data from the smart meters to increase the efficiency of the network operations and to show potential savings by lowering the supply temperature at the heat exchanger while satisfying all requirements. Heat demand forecast

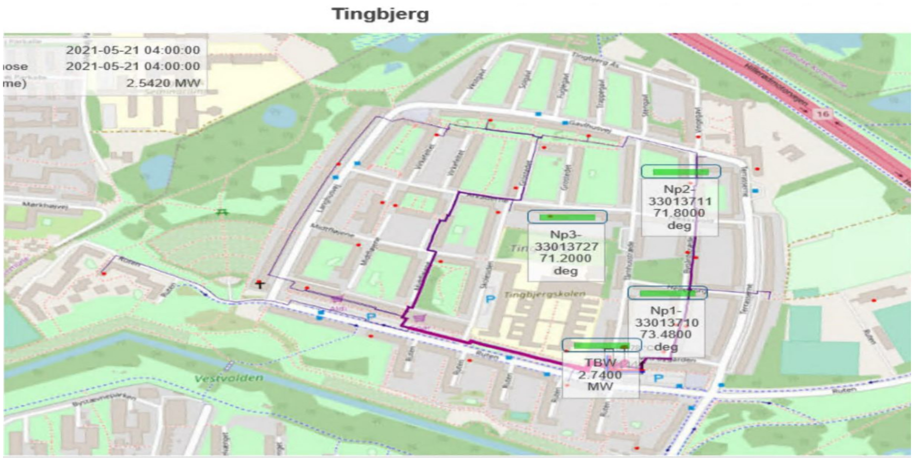

Figure 1.2: Layout view of the district heating network in Tingbjerg. The heat exchanger is located where the box with the TBW text is located. The other three shows the status of the smart meters used to give feedback.

for the Tingbjerg area will be created based on the historical demand and NWPs that will be localized to the area by using a local climate station that is close by. We will then demonstrate the benefits of using automated feedback techniques from an on-line operation use of our setup. The period from the start of the on-line operation trial from 1st of November 2020 until 1st of April 2021 will be used to compare the new data-driven approaches with the methods used previously.

Chapter 2

Smart Meters in DH systems

This chapter introduces smart meters in district heating and their role in transforming district heating systems into the digital age. We will also discuss how smart meters can give value for both consumers, where they are installed, as well as for the district heating utility by enhancing the network performance. This report will focus on using smart meter data as feedback to the production and use the response of the network to improve the performance, as the objective of this report is to increase operational savings for the utility using additional data.

Smart meters are and have been installed at district heating consumers in Europe for the past decade because of requirements from the European Union. The requirement is that consumers that are connected to district heating networks have to be equipped with smart meter devices where feasible [9]. This enables the consumer to be more aware of their current energy consumption and allows linking the consumption to the billing from the utility. They can now see their consumption on higher resolution and even in some cases, they have it available on-line. This has prompted a different payment schema from the district heating operator. For example, consumers are penalized with a fine if their daily average return temperature in a period is higher than a certain limit because it is costly to the system. District heating utilities attempt to recover these costs by penalizing consumers that have a bad cooling effect in their buildings and hence a higher return temperature. A higher return temperature implies extra heat loss in the return pipes, higher pumping costs, and less efficient production at the plant [10, 5]. Hence, the large amount of data that is now available due to the smart meters, that can be used to identify the energy performance of buildings and the network. This can be used to give valuable insights into the network performance and building energy efficiency, i.e. leakage in the system or insufficient cooling of the water from inlet to outlet in some buildings.

Current studies that use smart meter data often only have the building's energy performance improvements as the center of attention. Kristensen and Petersen [10] use smart meter data to derive three heating efficiency indicators of buildings and give an overview of the smart meters system at the district heating utility in Aalborg in Denmark. The three heating efficiency indicators are annual heating energy use intensity, daily heat load variation, and cooling efficiency. Thilker et al. [11] demonstrate that it is possible to lower the operation cost by 10% by a date-driven control of the heating system of a Danish school building, and they use model predictive control to estimate future set-points of the thermostats of the radiators to lower the return temperature of the district heating to the school. Bacher et al. [12] suggest a method to separating the heat load used to hot tap water from the load needed for space heating. Most of the research is focused on individual building energy performance. Improving the aggregated performance of a larger network using smart meters is usually not investigated except for identifying bad coolers in the network, i.e. high return temperature from substations. Lowering the return temperature from substations in the building is immensely important for district heating, especially networks that have combined heat and power production (CHP). As also stated in Arvastson [4] a higher return temperature

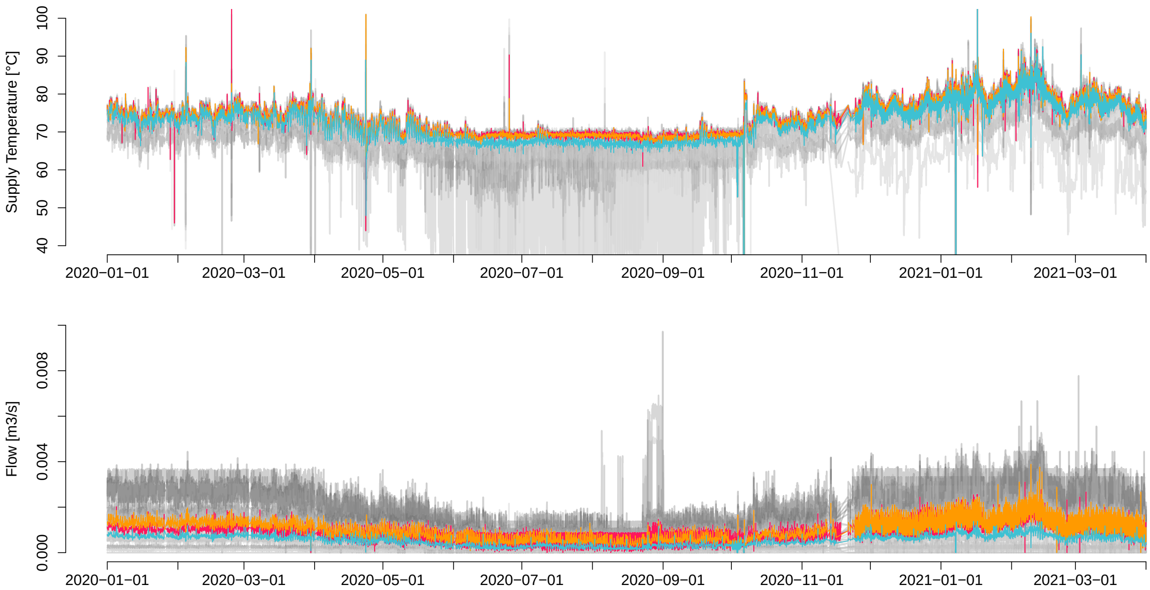

Figure 2.1: Supply temperature and flow from smart meters at Tingbjerg visualized. The coloured lines are the meters that were selected to be used as feedback for the temperature optimization.

from the network to the condenser will decrease the efficiency of the operation of the CHP plant. Lower return temperature will also lower the heat loss in the return pipes. It also implies a lower necessary flow rate or supply temperature for the given energy.

Data from smart meters have not previously been used to enhance the operation of the network, i.e. used as feedback of the temperature of the network to the temperature optimization at production. Until now, for closed-loop temperature control, only data from a few measurement points in wells have been used. These measurement points are called critical points and selected where the operators believe to have the highest temperature loss. The temperature control uses the feedback of the system as input to estimate the model parameters and time delay of the system to control the supply temperature and flow with the objective of keeping the temperature as low as possible [5]. Hence, smart meters can be used as a feedback signal to the controller either by estimating the supply temperature in the street pipe using groups of smart meters or by using a single smart meter from a large apartment building where the heat loss in the service pipe to the building is negligible because of the high flow [13].

The smart meter data used in this report will be introduced in Section 2.1 and a more detailed description of using the smart meter as feedback to the control will be given in Section 2.2.

2.1 Smart meter data

The smart meter data comes from the case study area, Tingbjerg where HOFOR provided access to on-line smart meter data from 39 meters located in large apartment buildings from January 2020. In the beginning, the data was sent only at 09:00 each morning where the data had an hourly resolution. These readings contained data from each smart meter for the past 24 hours. However, by the end of November 2020, the resolution was updated to 15 minutes and the data was sent each hour containing the past four data readings. Table 2.1 shows the variables that are logged by the smart meter. Usually, the utility companies use this information to bill the consumers based on their energy consumption. Moreover, if the return temperature is too high then there could be a penalty payment scheme in place as discussed before. Otherwise, the data is often not analyzed further.

Variables	Units
Time	Date, Time
Cumulative Energy	MWh
Cumulative Volume	m^3
Supply Temperature	°C
Return Temperature	°C

Table 2.1: Variables from the smart meters.

Figure 2.1 shows the supply temperature and flow from the smart meters in Tingbjerg. The flow rate is computed from the cumulative volume by taking the difference between the volume at each time-step and divide with the corresponding time in seconds between, resulting in a flow rate in cubic meters per second. Notice, the difference between the readings in the summer and winter periods. The winter period consists of stable temperatures, it has a quite constant variation and does not drift off towards zero. In the summer period, the temperature is noisier and fluctuates more. For some of the meters, the temperature seems to drift off towards zero. The reason for this is the low heat demand during the summer when there is almost no need for space heating in Denmark because the ambient air temperature is around 20 °C. Only domestic hot water usage is needed during warm periods. This seasonal variation of the heating demand can be seen in the flow plot as the flow decreases over the summer periods. Therefore, when there is no heating consumption, the water in the service pipe to the building becomes still and the temperature starts to drop because of the heat loss to the surroundings [13]. Thus, the readings from smart meters over the summer period are more unreliable compared to the winter periods as they do not give an accurate representation of the temperature of the hot water in the distribution pipes. When selecting smart meters to be used as feedback to the controller, this needs to be considered. The selected smart meters need to have a very stable and constant flow during the summer period, or create an algorithm that addresses the temperature drop.

During a short period at the end of November 2020, readings from the smart meters are missing. This is happening when HOFOR increased the resolution of the readings from hourly to 15 minutes and updated the frequency of the readings. Therefore, the period from 2020-11-15 to 2020-11-22 has almost no information. We also see frequent spikes in the data for both high and low temperatures. These can be faulty readings in the meters as the figures present the raw data (instantaneous values), i.e. no quality check of the values has been conducted. There is also a significant peak period in the flow, just before September 1st, 2020. The peak could be a consequence of the fact that the ambient temperature dropped rather quickly and the heating demand therefore increased while the supply temperature at the production has not increased. Notice also that after the increase in resolution the data seems to be more volatile compared to the hourly resolution period. Higher resolution leads to an increased risk of outliers and also that we are able to see more dynamics in the heating demand than before.

2.2 Smart meter data used in the feedback loop

The main objective of this report is to demonstrate the value of smart meter data for operating the district heating network. More specifically, we will use smart meter data as feedback to temperature optimization. The feedback will be used to give the controller signal on how the network is reacting to changes in the supply temperature, and hence creating a closed-loop controller. Previous closed-loop controllers used measurement wells in the network as feedback. This replacement of a well measurement with the use of meter data constitutes a digital transformation of the closed-loop control as demonstrated in Figure 2.2. This digital transformation reduces the need for measurement wells in the network and reduces the maintenance effort. We think that this gives significant savings potential for the district heating operator as it reduces the cost of having feedback control for operators without the need of installing measurement wells in the system.

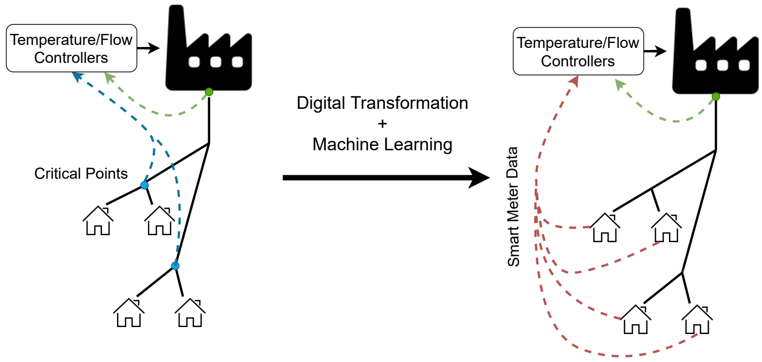

Figure 2.2: A sketch of DH network demonstrating that the production site uses feedback from smart meters for the temperature control, instead of the measurement wells (critical points).

In Tingbjerg, the operation in the past did not allow for a closed-loop installation as the area does not have any measurement wells in the network to send feedback. In this study, Tingbjerg will be operated using a closed-loop controller and demonstrate the benefits of having a closed-loop by comparing the result to the open-loop operation. The controller will use feedback from the network using data from smart meters at large apartment buildings. The methodology behind the temperature control is described in more detail in Section 5. However, in short, district heating systems are complex non-stationary and time-varying systems therefore methods for tracking the time-varying parameters are needed as a part of the modeling process. In practice, the parameters are updated based on different input data, and here the feedback from the network data is essential due to how the system reacts to different flows, e.g. how the time delay varies. Thus, we have to select smart meters that send reliable signals to guarantee suitable feedback for real-time estimation of the parameters of the model. As mentioned before, three smart meters were selected as feedback. More meters could have been used however the Tingbjerg district heating network is rather small and three feedback or critical points are considered to be sufficient.

Finding suitable meters to be used as feedback is critical. An obvious first task is to identify a set of meters that we consider ideal for representing the entire district heating area. Ideal meters are meters that during the summer period, they have a stable supply temperature which implies that the flow is usually high during longer periods. From this group of ideal meters, three meters were selected based on a few numbers of missing values and seemed ideal to be used as feedback as historically they have sent reliable data and usually constant flow, i.e. heating of the house was not stopped by closing the flow of the water. Figure 2.1 shows data from all of the meters and the three meters are highlighted with bolder colored lines. Other meters from the ideal group could also have been used. In the future, other meters can replace the current feedback meters if deemed necessary for being able to include the lowest temperature in the network at all points in time. The three selected meters are shown in color in Figure 2.1 to visualize their reliable signal. The meters were selected without knowing their exact location in Tingbjerg. Knowing the location of the meters gives additional useful information, as selecting meters that are placed the furthest away from the production could be ideal for the feedback loop. Usually, the consumers with the highest transportation time have also the largest temperature loss in the system however it could be that some part of a network is older and the efficiency of the pipes insulation has been reduced. Therefore, having larger temperature loss even though they are closer than other areas. By satisfying the requirements of the consumers with the highest temperature loss (which are the critical points in the network), the other consumers' requirements are also therefore fulfilled. An exception is if other buildings have faulty service pipes into the houses or leakages, but these issues can be quickly discovered and fixed when investigating the smart meter data.

Chapter 3

Weather Forecasting for Cities

District heating is mostly applied in urban areas therefore in this section, we will introduce the climatic characteristics inside cities and highlight the effects of climate variables on heat consumption. Numerical Weather Predictions (NWPs) are also introduced as they are critical for district heating operations. They are needed to forecast the future, concerning demands, temperatures, and production planning, or in short; everything that district heating operates needs weather forecast as input in order to operate the systems efficiently. We will discuss the advantages of localizing NWPs to cities, and more specifically, we will look into enhancing short-term heat demand forecast in cities. The heat demand forecast accuracy is improved by correcting the short-term weather forecast using real-time measurements of the climate from a local station. Hence, increasing the accuracy of the short-term forecast is highly desirable for temperature control.

3.1 Urban Heat Island effects

Temperature optimization in the district heating network depends on obtaining reliable and relevant monitored outdoor air temperature data. The more accurate the air temperature around the district heating network and the more frequent the temperature measurements, the more accurate the temperature optimization model can be. Research has shown that the outdoor air temperature can vary across a large district heating network and it is therefore also important to obtain temperature data across the network - if possible Steeneveld et al. [14]. Outdoor temperature data are historically monitored in rural areas at sites where measuring the correct temperature has been easiest. Airports have been a good choice because they are in a rural setting, where the only impact is from the natural environment including lack of woody vegetation and directly exposed to natural rain, sun, and wind. Historically, temperature data from airports are often used as input for the temperature optimization in operating the district heating network, simply because they are available from the meteorological institutes. Recently data from other sources are becoming available, e.g. Danish Meteorological Institute recently started to give the public access to their climate station that are located everywhere in Denmark. However, it is important to notice that the air temperature measured in the airports may deviate from the temperature insides cities, where the air temperature is exposed to human activities and the built environment.

Research shows that the outdoor air temperature typically is higher in urban areas than in rural areas Steeneveld et al. [14]. The effect is termed urban heat island (UHI). An urban heat island (UHI) is an urban area that is warmer than its surrounding rural areas due to human activities or build human infrastructures. Research related to UHI has recently got more attention because of the concern that climate change with an average temperature increase of 2 to 3 K will cause more heat waves, becoming more severe in the future, causing significant stress to the urban population. That problem is however only relevant for hotter climates where there is no district heating or at least it happens outside of the heating season. It is though still relevant for the energy sector as a whole with significant cooling demand during a heat wave. Unfortunately, there is not the same interest in studying temperature differences between urban and rural areas during winter which would be relevant for the district heating sector.

The variation of outdoor air temperature data is both spatial and temporal. A number of studies point towards a typical difference in urban and rural temperatures of 2-3 K. In a study in Barcelona the city centre was 2.9 K warmer than the airport during nighttime, but during the day the centre is slightly cooler than the periphery. Annually and overall, Barcelona centre is 1.4 K warmer than the airport. With regard to the average differences between the minimum at the two places, all are over 2.5 K, reaching 3 K in November and March [15]. Solecki et al. [16] examined the UHI mitigation potential of two highly urbanized places in the state of New Jersey, areas in and around the cities of Newark and Camden. Each city and surrounding suburbs included a set of neighborhoods with widely varying characters. The UHI effect in Newark is estimated to be on average about 3.0 K and for Camden between 1.0 and 1.5 K. Steeneveld et al. [14] has in a comprehensive study collected data from both private weather enthusiasts and weather stations to determine UHI in the Netherlands. They report a temperature difference of 2.5K. However, the paper focuses on UHI and its effects during warm seasons. There is no seasonal evaluation of the differences. It is therefore not certain that the same temperature difference occurs during the heating season. A review of research studies and data found that in the United States, the heat island effect results in daytime temperatures in urban areas about 1–7°F higher than temperatures in outlying areas and at nighttime temperatures are about 2–5°F higher. Humid regions (primarily in the eastern United States) and cities with larger and denser populations experience the greatest temperature differences [17].

For most cities, the difference in temperature between the urban and surrounding rural areas is largest at night. Throughout the daytime, particularly when the skies are cloudless, urban surfaces are warmed by the absorption of solar radiation. Surfaces in the urban areas tend to warm faster than those of the surrounding rural areas. By virtue of their high heat capacities, urban surfaces act as a giant reservoir of heat energy. As a result, the large daytime surface temperature within the UHI is easily seen via thermal remote sensing [18]. The typical temperature difference is several degrees between the center of the city and surrounding fields. The annual mean air temperature of a city with 1 million people or more can be 1.0–3.0 K warmer than its surroundings. In the evening, the difference can be as high as 12 K. [17]. This is also shown in the Barcelona study [15]. At night, the situation reverses. The absence of solar heating leads to the decrease of atmospheric convection and the stabilization of the urban boundary layer which traps urban air near the surface, and keeping surface air warm from the still-warm urban surfaces, resulting in warmer nighttime air temperatures within the UHI. Furthermore, the heat retention properties of urban areas, the nighttime maximum in urban canyons could also be due to the blocking of "sky view" during cooling: surfaces lose heat at night principally by radiation to the comparatively cool sky, and this is blocked by the buildings in an urban area. Radiative cooling is more dominant when wind speed is low and the sky is cloudless, and indeed the UHI is found to be largest at night in these conditions [19]. The outdoor air temperature changes from hour to hour, minute to minute, and even second to second. A change in wind and clouds can change the air temperature very rapidly.

During the last 100 years, cities have not been built with the UHI impact in mind. The main cause of the urban heat island effect is from the modification of land surfaces, which traps heat during the day. Waste heat is produced by energy usage as a secondary contributor. Dark surfaces such as roads and buildings absorb significantly more solar radiation, which causes increased heat absorption in cities more than suburban and rural areas during the day [16]. Materials commonly used in urban areas for pavement and roofs, such as concrete and asphalt, have significantly different thermal bulk properties (including heat capacity and thermal conductivity) and surface radiative properties (albedo and emissivity) than the surrounding rural areas. This causes a change in the energy budget of the urban area, often leading to higher temperatures than surrounding rural areas [20]. It is therefore also clear that mitigating strategies can be applied in city planning to reduce the UHI. Using lighter, more reflective materials in the built environment will reduce the UHI effect as well as planting trees will reduce the UHI effect [19].

The Barcelona study [15] also illustrated that the higher outdoor air temperature occurred at the city center. The further out the less dense the city is and the more trees are part of the build

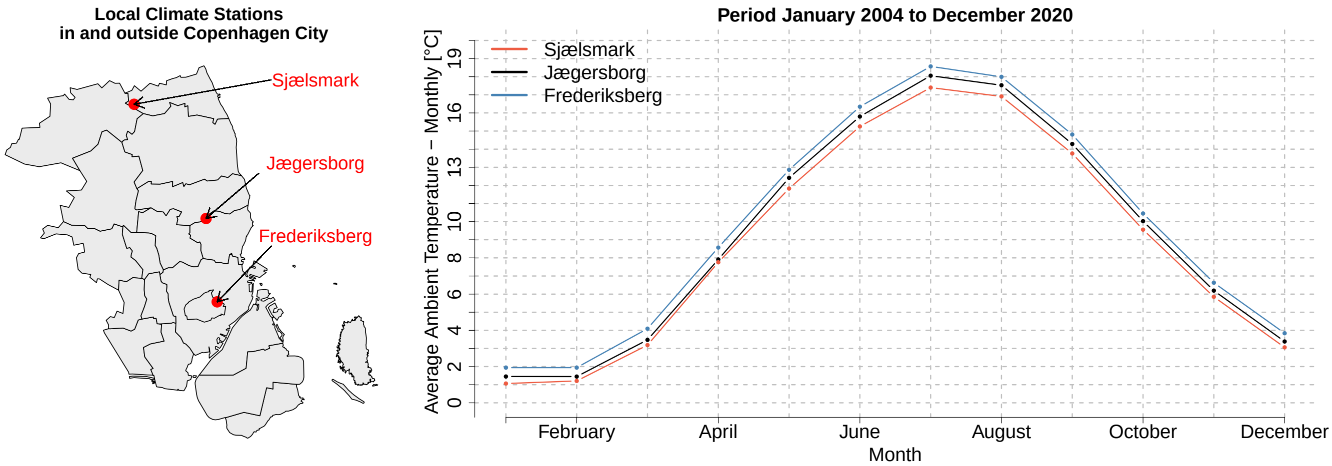

Figure 3.1: Urban Heat Island: Copenhagen demonstrated using three climate stations located with different proximity to the center of Copenhagen; The center (Frederiksberg), in the outskirts (Jægersborg), and in a rural area (Sjælsmark) as shown in the map and the plot showing the difference in the average monthly temperature for the three stations.

environment. In cities where the UHI effect is taken into account in the city planning, it is likely that the impact of the UHI is lower in the newer build districts.

Although as a rule of thumb the temperature is higher in urban areas than in rural areas where the outdoor temperature data is measured - it is also likely that the temperature difference between urban and rural is not so high in the outer districts of the city. It is therefore reasonable to have a number of temperature measurement stations implemented across the city.

3.2 Urban Heat Island: Copenhagen

As discussed, researchers have shown that there is a temperature difference within cities and between urban and rural areas. We would like to confirm this phenomenon in Copenhagen and investigate the magnitude of the difference. Our goal is also to discuss the impact on district heating operations due to different climates within the city. This will be done using three local climate stations. The data was extracted from the Open Meteorological Data provided by the Danish Meteorological Institute (DMI) [21]. Figure 3.1 shows a map of Copenhagen and the locations of the climate stations as red points, also the average monthly temperature from the stations is visualized in a plot. One climate station, Frederiksberg, is located very close to the city center, a densely populated area. The Jægersborg climate station is located in the outskirt of Copenhagen, while Sjælsmark is located in a rural place north of Copenhagen. The past hourly mean temperature was extracted from January 2004 to December 2020 from each climate station. The monthly average ambient temperature was then computed over the period. The temperature plot in Figure 3.1 demonstrates the UHI effect in Copenhagen. The temperature difference between the stations illustrates a significantly higher average temperature in stations that are located closer to the city, with more population and building mass. The difference is close to 1 K during the heating season and 1.5 K during summer periods. The difference between the season could be due to the solar radiation which heats up the buildings, streets while in the rural area, the terrain does not absorb as much solar gain, thus the temperature average increases over summer. The difference during heating seasons could be because of the heat from the buildings, transportation, and people as mentioned in Section 3.1.

Figure 3.2 shows hourly temperature average for four different months computed using same period. We can see that the climate has a time-varying process, both a diurnal variation and yearly. For example, comparing the result from July shows that the average temperatures in the mornings are very similar. However, as time progress, it differs, with higher temperature difference in the city and during the night it gets colder at the rural side, Sjælsmark. Thus, the city does not lose heat

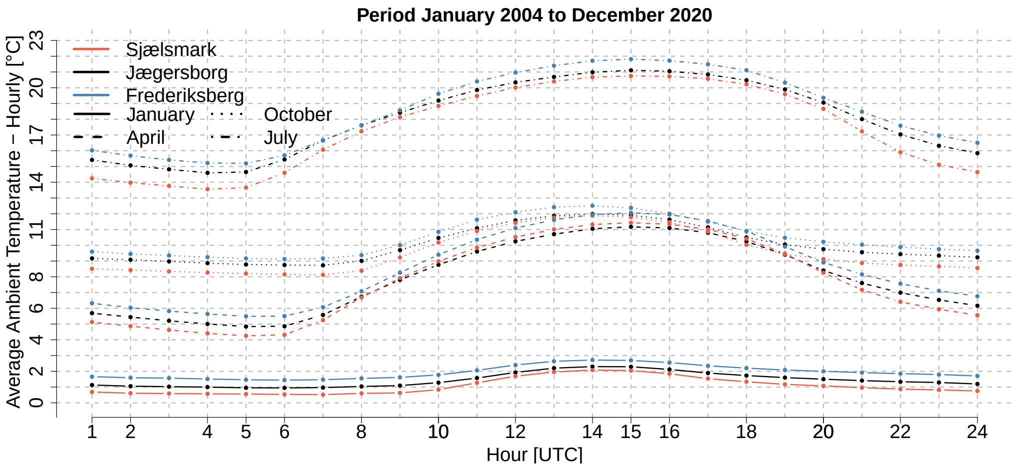

Figure 3.2: Urban Heat Island: Copenhagen, where four months are used to demonstrate time-varying climate for each station and between them. The plot shows the average temperature per hour for four months computed from the period, January 2004 to December 2020.

as fast as the rural part. January has quite a constant offset between the stations, except during the day when the temperature at Sjælmark is almost the same as at Jægersborg.

3.3 Numerical Weather Prediction in Cities

We have exemplified that the UHI phenomenon is relevant in Copenhagen where the temperature inside the city is different compared to the rural areas because of dense population and different environments (e.g. buildings, roads, etc) which entraps heat in cities. Three climate stations located in different areas in Copenhagen were used to demonstrate the phenomenon that exhibits higher temperatures closer to the city. Thus, the climate differs between locations. In Section 5, we will discuss that the temperature operation of district heating is heavily dependent on the most recent climate variables, where the ambient temperature is the most important. The climate where the district heating system is located needs to be analyzed to operate the network in an optimal setting. District heating is an efficient way to provide heat to buildings in densely populated areas. It therefore means that it is highly important to have localized climate data that can be used to analyze the heating demand dependency. For example, see Figure 4.2, to see heating demand vary over time. The variation can be explained both from the climate variation over time, e.g. high sea temperature in October contributes to higher ambient temperature during the night, see Figure 4.3. Hence, we have seen that ambient temperature differs depending on the location, building mass, sea temperature, i.e. there are many factors that contribute to the temperature. This holds also for other climate variables like wind and solar radiation. Climate variables are an important factor for analyzing heating consumption. In Nielsen and Madsen [22] and Madsen et al. [23] suggest that the climate variables: ambient temperature, solar radiation, and wind speed (including direction) have the most effect on the heating demand. They are also arranged in decrease importance. Nielsen and Madsen [22] give a detail description on how these climate variables interact with the heating consumption based on physical consideration, i.e. stationary relations. Here is a short summary of the findings;

- *Ambient Temperature:* The ambient temperature affects the indoor climate through heat conduction in the outer walls and windows, also through ventilation. It has been shown that the outdoor temperature affects the indoor temperature with a low-pass filter, a transfer function to model the variations in the outdoor temperature to variations in the indoor temperature.
- *Solar Radiation:* The solar radiation affects the indoor climate based on the angle of beams hitting the building, where the orientation of the beams through the windows and the window

area are most important. Basis functions are used to translate the non-linear dynamics of the solar radiation to its contribution to heating consumption.

- *Wind Speed:* The wind speed and the direction of the wind affect the indoor climate as natural ventilation, the effect is depending on the quality of the insulation. The wind speed also affects the convection heat coefficient on the outside of the buildings. It is therefore modeled as a low-pass filter as the contribution to the consumption.

Hence, to use these climate variables to describe the heating demand to estimate future supply temperatures then a forecast of them is needed. NWP is computed as a physical model of the atmosphere and ocean to predict climate variables. They are computed over a grid of the earth and are then interpolated together to a specific location where weather predictions are needed. However, NWPs have problems adjusting to the local climate in cities due to the local climate phenomenon. Thus, the models seem to have trouble adjusting to local heat contributions, e.g. solar heat in the street, heat from buildings, etc. District heating relies heavily on NWP to operate their system efficiently therefore it is important to correct them before using them as input. Especially, for temperature control of the system as it is done on a short-term horizon (between hourly and 24 hours) and is heavily dependent on the current local climate. Using local climate station to localize the NWP, corrects the short term NWP forecast by adapting them to the climate using real-time climate measurement [22]. Hence, this yields an optimal weather forecast for a certain area that can be used to operate the temperature control in the most optimal setting. This is discussed in more detailed in Section 4 where local climate station improved heat demand forecast and in Section 5 to improve the temperature control.

3.4 Localize Numerical Weather Prediction

We have discussed that it is important to localize numerical weather prediction to enhance the operation of district heating systems. Combining weather forecast to a local climate have been studied for many decades as it can be highly desired to have an accurate forecast to yield optimal operation. Incorporating certain local climate features into the forecasts is done to adjust the systematic errors from the NWP model. Glahn and Lowry [24] propose Model Output Statistics (MOS) to bind NWP to local climate stations observations, e.g. localize the forecasts. The MOS is a simple technique that uses linear regression where the observed climate variable is the response variable and predictors are the NWP variables which therefore bind the NWP to the local climate. It is a simple and frequently used method that will reduce systematic bias in the NWP if there is any. Crochet [25] propose using an adaptive method to reduce the systematic bias and lowering the RMSE of the NWP. A Kalman filter is used to localize NWP to the local area. It was demonstrated that the proposed methods decreased the systematic bias and reduced the error in areas where systematic bias is high. If there was no systematic bias then the Kalman filter does not significantly improve the forecast. The Kalman filter also gives useful information about the uncertainty of the local predictions when localizing the NWP to climate stations. The uncertainty from the weather forecast can be useful information for both temperature control of the network and production planning of the plant.

Chapter 4

Heat Demand Forecasts

Operating a district heating production facility and controlling the network efficiently is a difficult process. Both tasks need to consider multiple inputs to deliver a feasible production plan and accurate controller. One of these inputs is the heating demand of the consumers. Satisfying the consumers' heating consumption need is the most important requirement for the district heating utility. To meet these demands, the production planning needs to know the heating demand up to months ahead, e.g. scheduling biomass purchases to be able to deliver the required demand (long-term) [26]. While the temperature control of the network tries to meet these demands by regulating the supply temperature, $T_{s,t}$ and the mass flow of the water is indirectly varied to satisfy the demand, $\dot{m}_t$ as the heat energy is computed as the temperature difference times the mass flow and the specific heat constant,

$$Q_t = \dot{m}_t c_w (T_{s,t} - T_{r,t}), \quad c_w = 4.186\text{J kg}^{-1}{}^{\circ}\text{C}^{-1} \tag{4.1}$$

to satisfy the heating demand, Q_t where the objective is to increase savings and reduce heat loss in the system. Thus, the controller needs to know the future demand between one hour ahead to the control horizon of the system which is usually the longest transportation time of the system. For large networks, the transportation time can be up to 24 hours. As the future demand is not known, a prediction of it needs to be available for the operators. The accuracy of the predictions is of high importance because the uncertainty of the forecast heating demand needs also be considered in the production and network operations. Along with the requirement of satisfying the heating demand of the consumers, the production of heat has become more complicated than firing up boilers using oil or natural gas. The shift from fossil fuels to renewable energy sources needs to be taken into account as these energy sources are not always available due to their weather dependency. Therefore, to utilize renewable energy sources, energy sector coupling is needed between the power and district heating market, i.e. smart energy system [27]. This makes accurate heat demand forecast highly valuable for the energy sector. Especially, as district heating plants usually also produce electricity with their CHP plants, and therefore need to plan their power production for the next market day. District heating utilities can also store energy as hot water in large thermal storage tanks when an excess of electricity is available.

Consequently, heat demand forecast is the first aspect that utilities need to have for operating the system efficiently. However, heating demand is an inherently non-linear and non-stationary process. The consumption has a non-linear relationship with the ambient air temperature because of the thermal mass of buildings [22, 5, 11]. The non-stationarity comes from the seasonal variation of the ambient temperature and social behavior of the consumers, i.e. time-varying demand. Other weather components than temperature also demonstrate some effect on the heating demand, it is however not as significant as the temperature and social behavior. Dotzauer [28] suggest a simple forecasting model that has a future insight into the heating demand for two different systems. Modeling the ambient air temperature dependency as a piecewise linear relationship to the heating demand is discussed. The social component was modeled by estimating a daily profile using the residual after having removed the dependency of the temperature from the heating demand.

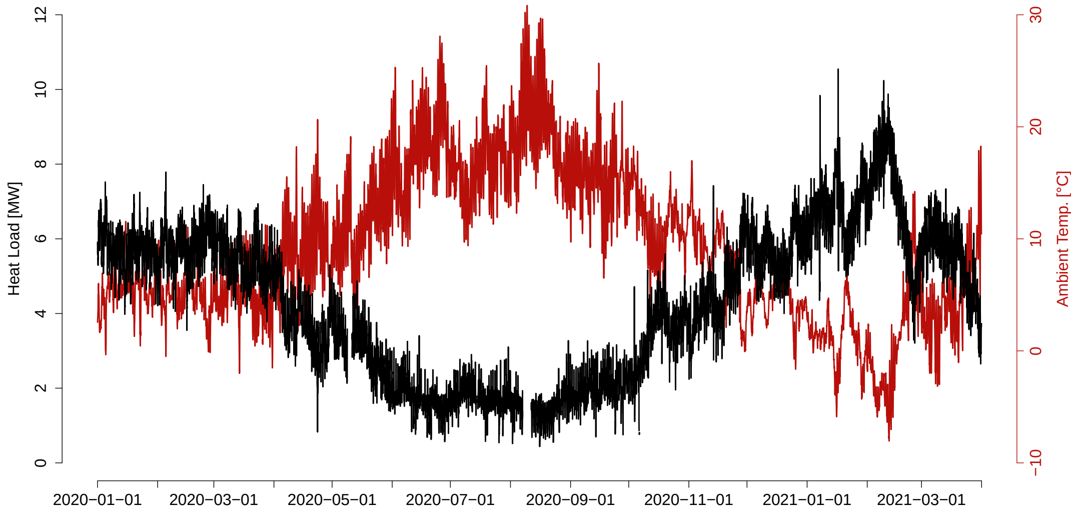

Figure 4.1: Heat load observation from Tingbjerg and ambient air temperature measured from a local climate station in Copenhagen, Station 06186 [21].

The model demonstrates adequate results however temperature measurements are used instead of the numerical weather forecast as input to the model. Also, the model does not handle the time-varying process as the parameters do not change over time as needed for heating demand systems. Nielsen and Madsen [22] suggest using adaptive methods to change parameters during the transition periods, i.e. from cold to warm season. They also propose to use on-line numerical weather predictions as inputs to the model and how to handle the nonlinear dependencies to be used in linear regression models. Their proposal of using grey-box modeling to describe the known physical relationship between heating demand and weather has high accuracy and has proven quite successful. Trying to use new sophisticated models to identify known physical relationships is time- and computer-demanding and is therefore undesirable.

In this project, ENFOR delivered the heat load forecast to be used for the temperature control in Tingbjerg. In the following, we shall describe the climate variables that influence the heat consumption, the consumption in Tingbjerg and compare the localized heat demand forecast from ENFOR to the scaled forecast that HOFOR used previously.

4.1 Data Exploration

Figure 4.1 shows the observed heat demand from Tingbjerg and the measured ambient air temperature at the local climate station in Copenhagen. The data from the climate station was extracted from DMI Open Data [21]. As we mentioned before, heat demand is a non-stationary process due to the time-varying demand following the climate and social behavior. The figures show that the heating demand follows the ambient temperature closely. During the heating season, the ambient temperature has a slow influence on the heating demand, and this influence is usually modeled using a low-pass filter [22]. As the temperature decreases or increases, the heating demand follows with a negative correlation as the plot demonstrates. In the summer season, when the temperature is above 17°C, there is no need for space heating. In these periods, district heating only needs to fulfill the need for domestic hot water usage, e.g. showering. One of the most difficult periods to predict the heat demand is during the transition periods from winter to summer and vice versa. The transition periods are when the temperature starts to increase or decrease, and at the same point in time, the solar gain starts to change.

In the spring, the solar radiation starts to warm up the buildings and therefore contributing to heating to maintain a comfortable indoor climate [29]. However, it has a complex relationship because the penetrating radiation onto the windows is related to the time-varying orientation of solar radiation. The orientation changes during the day as the earth rotates around its axis and has yearly dependency as the earth rotates around the sun. The solar gain does not contribute as much to the heat consumption during the summer as the ambient temperature is the main driving contribution and is quite high during warm periods. However, during the fall similar effect appears as the angle changes and the ambient temperature has decreased. Thus, the climate variable, solar radiation influences heating consumption. The wind speed and the direction of the wind also contribute to the heating consumptions during the transition periods with natural ventilation. The weather is also known occasionally to change rather quickly during these periods.

The time-varying relationship between heat demand and ambient temperature is visualized in Figure 4.2 where the plots show the heat demand plotted against the temperature for each month. A reference curve is also plotted in each plot to highlight the difference between months, especially in the transition months. The piecewise linear reference curve was estimated by tuning the knots to fit the overall period in the top plot. When investigating the transition months from cold to warm (the months' March, April, and May) we can see that the demand tends to be more scattered below the reference curve between 0 and 10 degrees. In this period, solar radiation could have started to influence consumption even though the ambient temperature is still quite low. Comparing the spring transition period to fall, the demand in the fall is more constant, i.e. it has less spread around the curve. This could be due to the fact that Copenhagen is a coastal city. The sea temperature is higher in the fall period as it has been warmed up during the summer and it gives a quite constant heat to the city. Figure 4.3 shows the monthly average sea temperature in Copenhagen over 20 years. The plot shows that the fall periods have a higher temperature than spring. The data was extracted from the DMI Open Data platform [30]. The social behavior could also vary over time and that could drive the difference between the transition periods. People probably have a different perspective on ambient temperature when comparing the periods. Also, sea temperature could play a big part in keeping the climate milder in the fall.

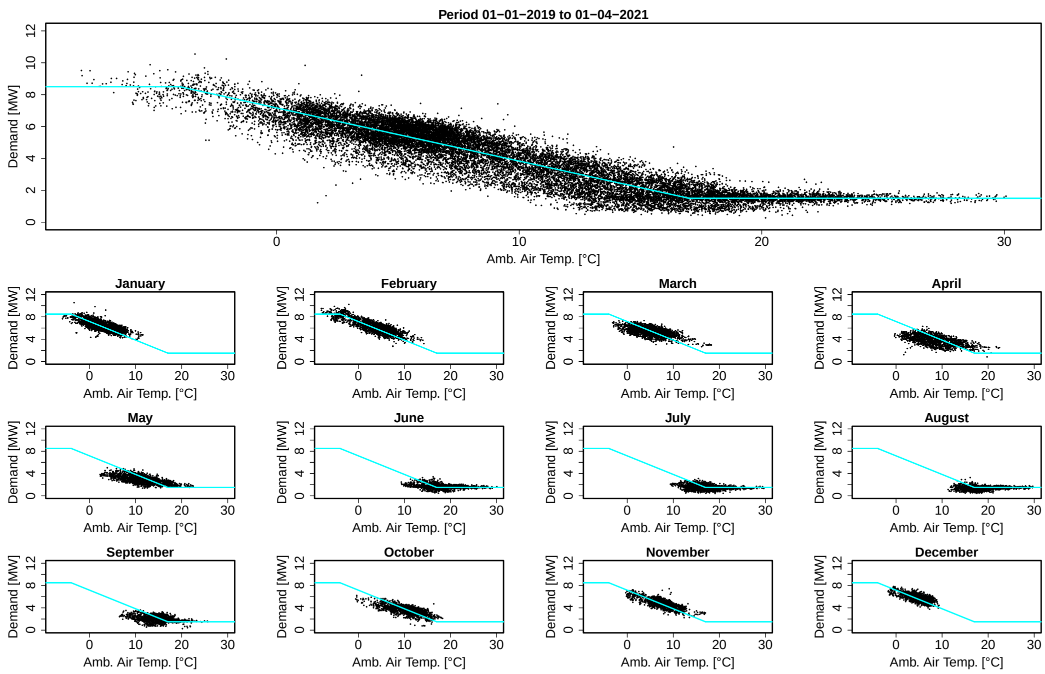

Figure 4.2: Time-varying relationship between heat demand and ambient air temperature demonstrated over different months.

As discussed, solar radiation is an interesting aspect regarding the heating demand during the transition periods. Figure 4.4 shows the mean solar radiation per month, the mean ambient air temperature per month, and the mean heating demand vs the mean solar radiation per month.

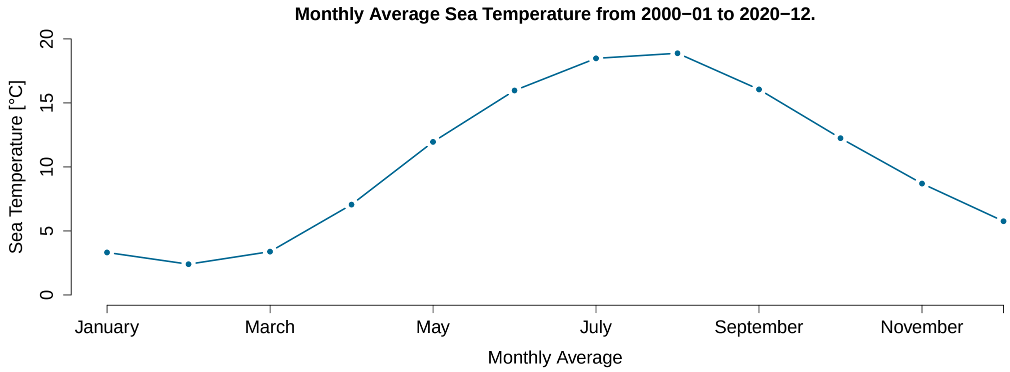

Figure 4.3: Monthly average sea temperature in Copenhagen from January 2000 to December 2020. Station 30336 from DMI Open Data [30]

The data was extracted from the DMI Open Data platform [21]. Investigating these plots together starting with the lowest plot, you would assume for the transition months that the solar radiation has less effect in spring. The spring months have similar solar radiation as the fall months but they require more heat. However, considering the mean ambient temperature it becomes evident that it is quite warm during the fall months than spring in Denmark. This could be explained by the fact that during spring and summer the ground and sea temperature have increased and have slow time variation, i.e. they react to changes slowly. Therefore, in the spring they have yet to be warmed up and during the fall they give away heat to the air temperature as we see in Figure 4.3.

We do not analyze the wind speed effect on the heating demand in-depth. However, it has an effect on the consumption, and largely when it is high and the ambient temperature is low [31, 32].

Considering these climate variables and how they influence heating consumption emphasizes the importance of having an accurate forecast of the heating demand to operate district heating systems. It shows that accurate numerical weather predictions of these variables and a time-varying model, that can react to these changes, is needed. Both the rapid changes in how the climate variables related to the consumption changes over the day and the slow variation in the heating demand can be explained by, for example, the change in social behavior, renovation of houses, new house connected to the network, so on and so forth.

4.2 Localized heat load forecast

In the previous subsection, we demonstrate that heat demand is a non-linear and non-stationary process due to dependencies on climate data and social components. We also learned in Section 3 that NWPs need correction to forecast the climate in specific areas to enhance the accuracy, especially for the short-term forecast. Therefore, we need to localize the NWP to a specific area using climate stations to handle the influence of the buildings, humans, cars, pollution that contribute to the climate. This was done for the heat demand forecast in Tingbjerg. A local climate station in Copenhagen that is located close to Tingbjerg was used to correct the NWPs. After the correction, the NWP was used as input to the heat demand forecast model. The model was therefore both localized to the heating demand in Tingbjerg by estimating the parameters of the model using historical demand from Tingbjerg and the climate as the NWPs are used as input.

In the previous operation in Tingbjerg, the heat demand forecast from a bigger area, Brønshøj, was scaled to match the demand in Tingbjerg. We will demonstrate the accuracy difference in heat demand forecasting by scaling the heating demand versus creating a localized heat demand forecast for Tingbjerg that uses numerical weather predictions that have been corrected to the climate in Tingbjerg. The scaled forecast is scaled by dividing the forecast for the large area by the percentage of Tingbjerg heating demand to the total demand. HOFORs estimation of the fraction

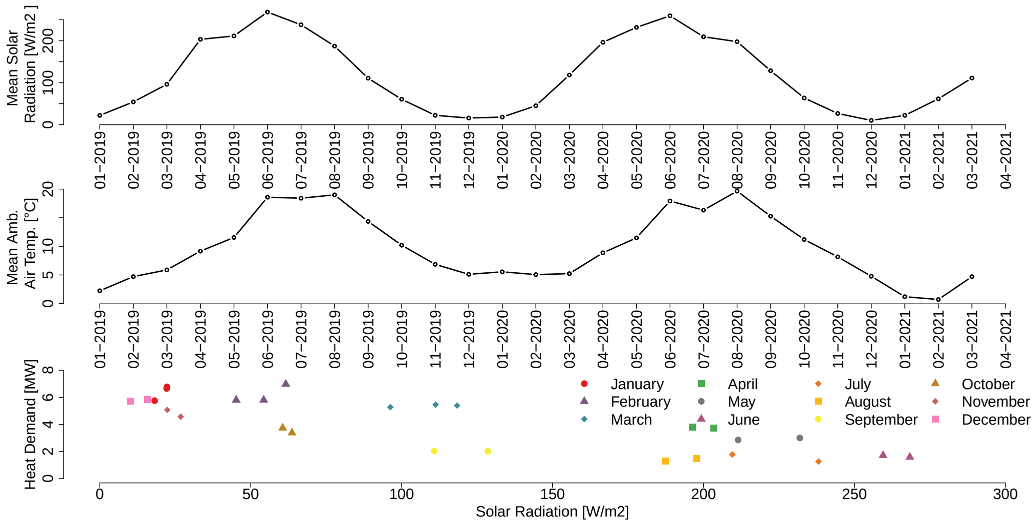

Figure 4.4: Climate data from the climate station in Copenhagen demonstrate the heating demand dependency on temperature and solar radiation. It shows the monthly average of these two climate variables.

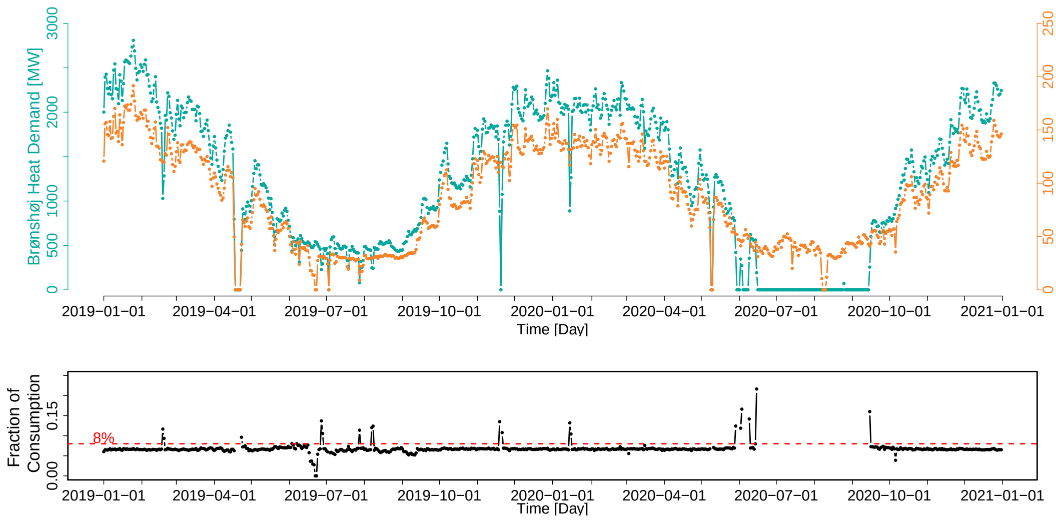

Figure 4.5: Daily heat demand from Brønshøj and Tingbjerg which is a small area inside of Brønshøj. Fraction of Tingbjerg daily consumption compared to Brønshøj consumption is illustrated in the bottom plot.

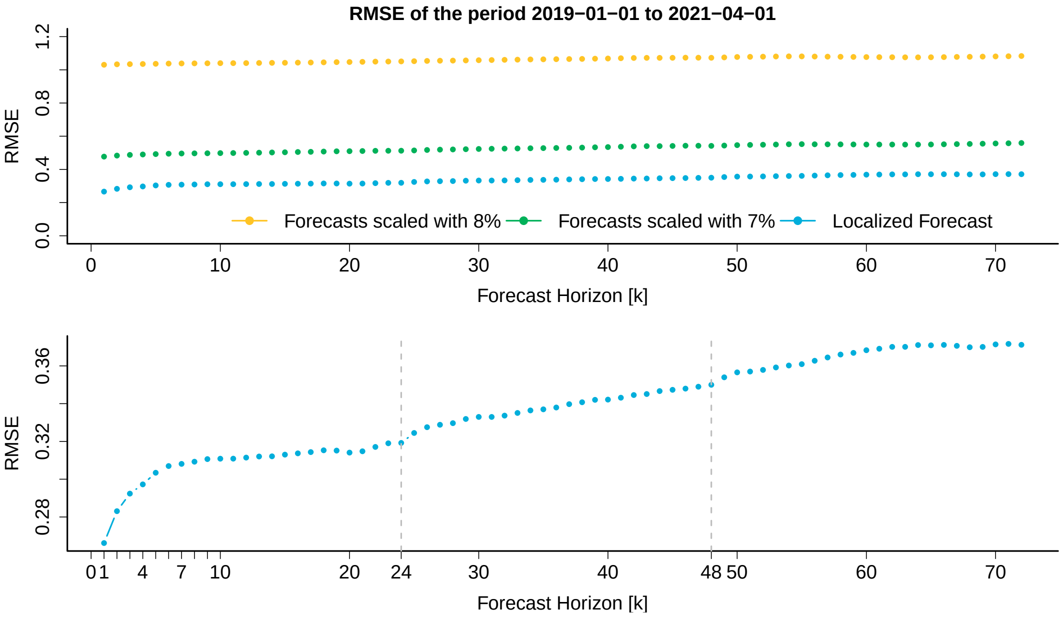

Figure 4.6: Performance of forecasts compared using RMSE for one to 72 steps ahead. The top plot visualize the results and bottom plot shows the localized forecast to demonstrate the affect of having local climate station to improve the short term forecasts, i.e. the forecast horizon between 1 and 8 hours.

of Tingjerg consumption was to be 8% of the total consumption in Brønshøj. Figure 4.5 shows the daily heat demand from Brønshøj and Tingbjerg in the top plot while the bottom plot shows the fraction of the Tingbjerg to the Brønshøj. Based on these data, the 8% that previously used, estimated from older historical data is off by 1% as for the years 2019 and 2020 the fraction of the consumption is around 7%. Notice, that the heat demand in Brønshøj during summer 2020 is zero. This could be the result of HOFOR supplying heat to Brønshøj from other heat sources than usually therefore the measurements are zero in this data-set.

The comparison between the forecasts is demonstrated in Figure 4.6. They are compared using the Root Mean Square Error (RMSE) metric,

$$\text{RMSE}_k = \sqrt{\sum_{t=1}^{T} \frac{y_{t+k} - \hat{y}_{t+k|t}}{T}} \tag{4.2}$$

where the metric is computed for each prediction horizon, k. The heating demand observations are y and predictions are $\hat{y}$. This is computed over the whole period. We have also added the heat demand forecast scaled with the newer update on the fraction between Brønshøj and Tingbjerg demand than was estimated before. The upper plot demonstrates the RMSE over the first 72 steps horizon for all three forecasts, where the localized forecast significantly outperforms the scaled forecasts. This is not surprising as the model has both tuned the parameters to the area and the NWPs have been adjusted to the climate. Notice, the effect of localizing the weather forecast to the climate when comparing the localized forecast to the 7% scaled forecast in the first seven steps ahead. We see that there is a curvature for the localized which is the result of the corrections to the climate and the dynamic process of the forecast model. This is demonstrated in more detail in the lower plot in Figure 4.6 where the curvature is seen more easily. Usually, the RMSE over the horizon demonstrates a straight line with a slope over the horizon however by using the climate information in the area it is possible to enhance the short-term forecasts as demonstrated and using historical heat demand observation for the dynamical process of the model.

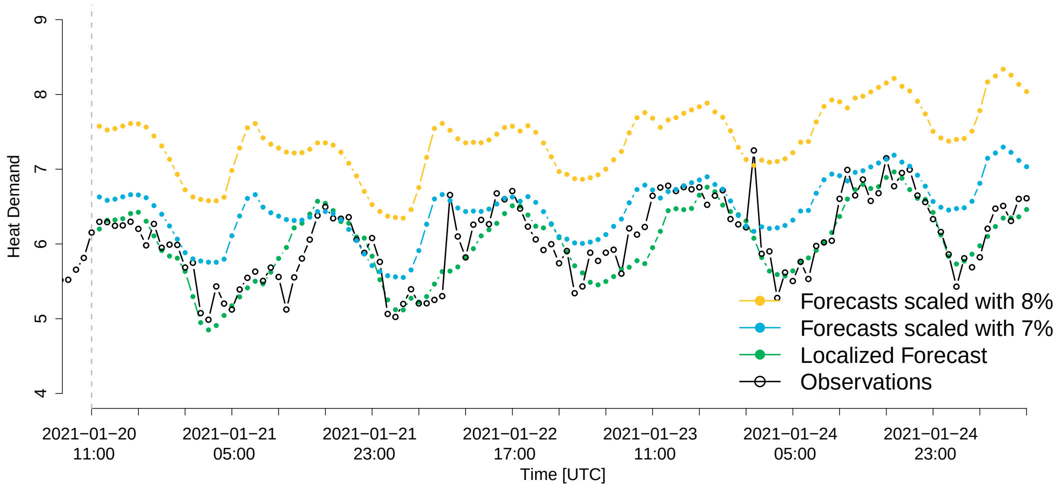

Figure 4.7: Figure demonstrate the performance of the three forecasting models. It shows the 72h steps ahead when generate at 2021-01-20 11:00.

Figure 4.7 shows the three forecasts created at 11:00 on the 2021-01-20 for the next 72 hours. We see that the localized forecast follows the observation significantly better than the other forecasts. Notice, that the scaled forecast does not resemble the diurnal variation in the Tingbjerg observation.

Chapter 5

Temperature Optimization and Control

We have demonstrated that district heating has a difficult task on forecasting the demand because of the local climate and social components of the consumers. An even more difficult task is to provide heat to the consumer without wasting heat and minimizing the cost. The process is a complex procedure as it needs to be delivered through the piping system to the consumer and more specifically it needs to arrive at the correct time to satisfy consumers demand. Hence, temperature control is an essential tool for the efficient operation of district heating. The production of heat has become more challenging as we move away from fossil fuels towards renewable energies. The goal of temperature control is to reduce heating production costs and heat losses in the network and at the same time, fulfill the requirements of the network and consumers. Nielsen [8] describes that the optimal operation of the district heating system is to be achieved by minimizing the production cost without violating these restrictions;

- A maximum allowable flow rate in the system
- A minimum guaranteed inlet temperature at the consumers
- A maximum allowable supply temperature
- Limited short term variation in the supply temperature
- Maximum allowable diurnal variations of the supply temperature

These restrictions are required to be satisfied by the temperature control and the controller also needs to reduce the operational costs without violating them. Therefore, it also needs to consider the heat loss in the pipe, the pumping costs, and maintenance costs of the system. As for all operational aspects of district heating, temperature control needs to know the future heating demand in order to minimize the operation costs for the given planning horizon. Thus, depending on the type of the plant, production will need to have 1) heat demand forecast, 2) supply temperature forecast, 3) future optimal scheduling of the productions, e.g. for a CHP plant needs future sales price for power, also heat and power production costs, 4) restriction in the system, e.g. hydraulics, minimum or maximum time-varying heat production 5) flexibility of the system. These factors need to be considered in advance to optimally achieve minimizing the operation costs. In this part of the report, we will only focus on finding the optimal future supply temperature to give the operators of the network, however in Nielsen [8] and Arvastson [4] further readings on how operating district heating in an optimal setting are given while considering the whole district heating system.

Benonysson et al. [3] formulate a mathematical model of a district heating system for estimating the optimal supply temperature. The model includes the production, the network, and the consumers where the objective is to minimize the operational cost while satisfying all requirements of the system. They describe a number of items that need to be considered when modeling the dynamics of a district heating network. We have summarized them here below:

- *Time Delay:* The transportation time of the DH water from the production plant to the consumer. The transportation time varies for the individual consumer according to the distance from the plant and the flow velocity in the pipes. The heat capacity of the DH pipes also affects the time delays.
- *Heat loss:* The heat loss is approximately proportional to the difference between the temperature of the DH water and the surrounding temperature. Ground temperature varies over time, following the ambient air temperature with a slow change in undisturbed ground, i.e. not heated by the DH pipes.
- *Friction loss:* When the pumping energy transforms to heat energy due to the friction loss in the pipes. Most often negligible but when the flow velocity of the water is relatively high (extreme cases), the produced amount of heat can be of the same size as the heat loss to the surrounding ground.
- *Pressure:* The flow in the system changes spread in DH networks around 1000 times faster than temperature changes. This leads to to the fact that the dynamics of the flow in the network are of minor importance compared with the dynamics of the temperature changes, from an operational optimization point of view.

The dynamics of the network are therefore highly important to understand to be able to utilize these physical facts to enhance the operation of the network. They give the opportunity of keeping the supply temperature as low as possible when modeling them adequately along with accurate modeling of the consumers' dynamics, i.e. accurate heat demand predictions.

Initial controllers to operate the temperature optimally had a reference curve, i.e. a control schema that changes the set-point of the supply temperature for a given outside temperature. This is a good restriction on the supply temperature, it is however a naive control strategy. Firstly, it does not consider the time for the heat to reach the consumer, the transportation time. Secondly, the flow is usually kept at a low rate, thus the potential of keeping the flow close to the maximum hydraulic constraint is dismissed, i.e. higher flow results in lower supply temperature. Therefore, when the heat finally reaches the consumer, the outside temperature could have changed and the supply temperature is then either too high or too low than required. Also, as the reference curve only considers the ambient temperature as the meteorological factor that influences heat consumption, it must necessarily take into account the worst possible condition with respect to other meteorological factors [33]. This schema also frequently does not consider the social behavior of the consumer, the diurnal variation. Madsen et al. [5] propose a control schema that utilizes the relationship of supply temperature and flow in Eq. 4.1 and consider the dynamics of the network and social behavior of the consumer to increase savings potential. They predict the heating demand using historical heating demand, and the response of the network to change the supply temperature and keep the flow high to have the supply temperature as low as possible without violating any of the restrictions mentioned before. The response of the network is usually done by having measurements wells within the network, located where the lowest temperature is believed to be, a critical point. Thus, this critical point is used to give feedback on how the network is responding to changes at the production, makes it possible to estimate the time delay and heat loss in the network for given supply temperature and flow.

Madsen et al. [5] suggest controllers for the district heating to have an overall controller, supply temperature sub-controller, and a flow sub-controller to estimate the future supply temperature at the production. For each critical point, a sub-controller is developed to compute the lowest supply temperature from the plant satisfying the reference curve. Flow controller considers the variation of the heat demand, by varying either the mass flow or supply temperature. It utilizes the possibility of keeping the flow high as possible as the objective is to maintain as low a supply temperature as possible without violating the maximum flow constraint due to the hydraulic properties of the pipe network. However, as the flow approaches the limit, the flow controller will start to increase its supply temperature predictions to meet the forecast heating demand. These controllers regulate the supply temperature and flow without violating any restriction with a certain probability, e.g. the supply temperature at the consumers needs to be above the reference curve 99% of the time. The overall controller at the productions then uses the set-points from the sub-controllers to select the highest supply temperature to generate the heat for the consumer.

In this report, a temperature controller from ENFOR was used, `HeatTO`™[1]. It is based on the methodology mentioned previously in this section, i.e. based on the articles and projects that have been discussed [8, 5]. Furthermore, in this project, `HeatTO`™ was extended to receive feedback from smart meters in large apartment buildings, instead of the normal measurements wells in the network. In Section 2.1 the smart-meter data and how they were selected to be used as feedback are described. Feedback from smart meters makes temperature control more desirable to use, especially for district heating networks that don't have measurement wells or are poorly calibrated. They can instead use feedback from smart meters to control the supply temperature at the production. Another advantage of using smart meters is the ability to change the location of critical points. District heating network dynamics changes over time due to many reasons, e.g. new areas are built that are further out in the system, old pipes are replaced with new, and old pipes getting older, i.e. the characteristics of the network vary over time. As the network dynamics vary, the critical point changes also, and therefore the critical feedback needs to be moved to give accurate feedback of the system to satisfy the requirements of the consumers. This is solved by selecting different smart meters to give feedback on the network. Bergsteinsson et al. [13] suggest how to use a group of single-family house smart-meters to establish an estimate of the temperature in the street temperature to be used as feedback. However, in this project, the area used has many large apartment buildings and it was demonstrated in Section 2.1 that some of the smart meters can be used to give feedback. Three meters were chosen to be used as feedback for the trial.

5.1 Trial at Tingbjerg

The demonstration of using additional data for the temperature control trial started on 1 November 2020 and lasted until 1 April 2021. The main task of the trial is to demonstrate that smart meters can be used as feedback of the network for temperature control. The trial was done in the Tingbjerg area using the HOFOR district heating system where the production unit is a heat exchanger that supplies the area with heat. Here the focus was on how district heating utilities can create value from digitalization and use it for control of the network. Three smart meters were selected to be used as feedback in Tingbjerg to control the distribution supply temperature at the heat exchanger.

Prior to the trial in Tingbjerg, an open-loop control was used to vary the supply temperature. It was operated by a hydraulic simulation of the system and using a reference curve at the consumers to estimate the optimal set-points for supply temperature. However, as there was no feedback of the network on how it reacted to changes or if the consumers were receiving what they are promised, i.e. the control was open-loop. It also used scaled heat demand forecast as was shown in Section 4 as input. The new controller in the trial is a feedback controller using data from the three smart meters, a reference curve at the location of each smart meter, localized heat demand forecast, and a flow controller to achieve the optimal future supply temperature to reduce the operational cost of the system by lowering the temperature.

Figure 5.1 illustrates the performance at the three smart meters, referenced as netpoints, for the old and new controller. The supply temperature for both operations is plotted versus the rolling average of the outside temperature for the past 24 hours. This is to stabilize the time series, smoothing out any small outliers. The grey solid lines show the reference curve that was used for the new controller and how it was believed to be for the old controller at the netpoints as it did not have feedback of the network before. All three plots demonstrate that the supply temperature from the new controller has less spread and rarely violates the desire reference curve at the netpoints thus the

[1] https://enfor.dk/services/heatto/

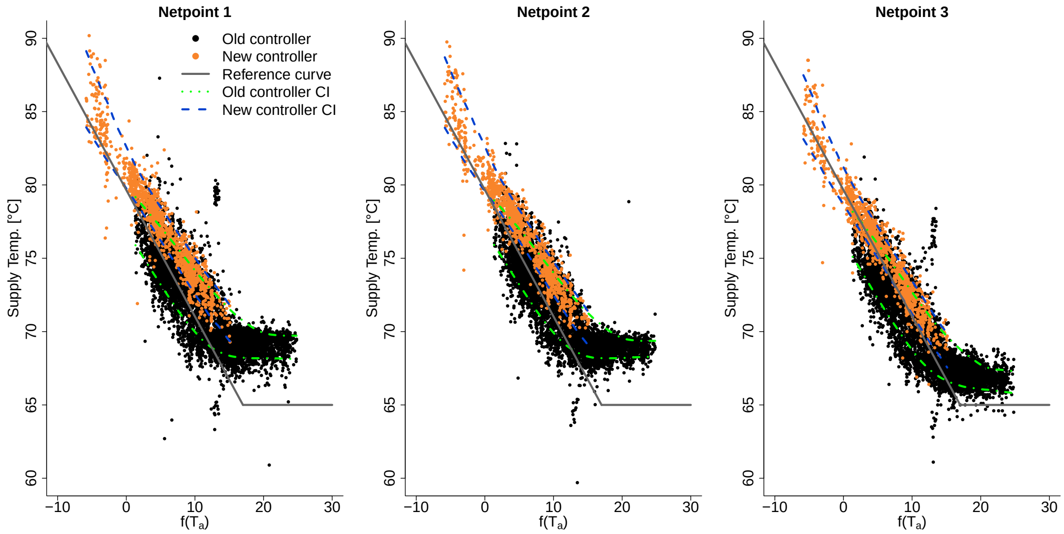

Figure 5.1: Figure compares the two controller performance at the netpoints. It also demonstrates the reference curve used and the estimated confidence interval of the supply temperature for both controllers

system was controlled with more precision. Hence, the new controller gives a better level of security than what was possible with the previous controller as the previous operation violates it rather frequently. This is visualized in more detail by comparing the confidence intervals (CI) between the two operations in the plots. The intervals were estimated using nonparametric quantile regression and using the 10th and 90th quantiles as the upper and lower bounds. These results indicate that the new controller can not compete with the old control of lowering the supply temperature as it can not violate the requirements as frequently as in the previous operation. This suggests that the reference curve for the new controller could have been lower, resulting therefore in a lower and more stable supply temperature. We notice that the reference curve can be adjusted 5°C lower when comparing supply temperature close to the reference curve for the new controller to the low group points at 10°C for the outside temperature. This suggests that the reference curve can be adjusted without breaking any requirements when comparing to the previous operation. The supply temperature will also be adjusted to investigate "what if" scenario when a more reasonable reference curve had been used. The suggested reference curve to be used with the new controller is demonstrated in Figure 5.2. The supply temperature for the trial has also been adjusted with the 5°C. By having more suitable reference curve for the new operation, it could have resulted in lower supply temperature without violating any constraints and thereby lowering the operational cost.

Figure 5.3 compares the old and the new controller operation at the heat exchanger. They were not in operation at the same time therefore the months the new controller was varying the temperature were also selected for the old controller, just one year earlier. The left plots are demonstrating the stability of the controllers, i.e. the variation in time of the supply temperature. This is important for the network, as large and frequent fluctuations in the supply temperature should be avoided as it increases the maintenance costs compared to more stable operation [34]. Comparing the old and new controller, it is noticeable for the period of the new controller, that the outside temperature is changing more dramatically. It is has a long period of very cold temperature and quite warm also. However, for the old controller, the outside temperature is more stable, there are never significant changes between warm or cold periods. Investigating the supply temperature in these two different periods it is evident that the new controller gives a more stable operation, i.e. fewer large fluctuating supply temperatures. This is exhibited in the bottom left plot where the difference series (subtracting past value with current value) of the supply temperatures are shown. The new controller difference series is more stable and the plot also show the variance of the differences where the old controller has around $\sigma^2_{old} = 0.633$ and new, $\sigma^2_{new} = 0.345$. Hence, with the new controller, there is less strain to the pipe system due to the slow variation in the supply temperature.

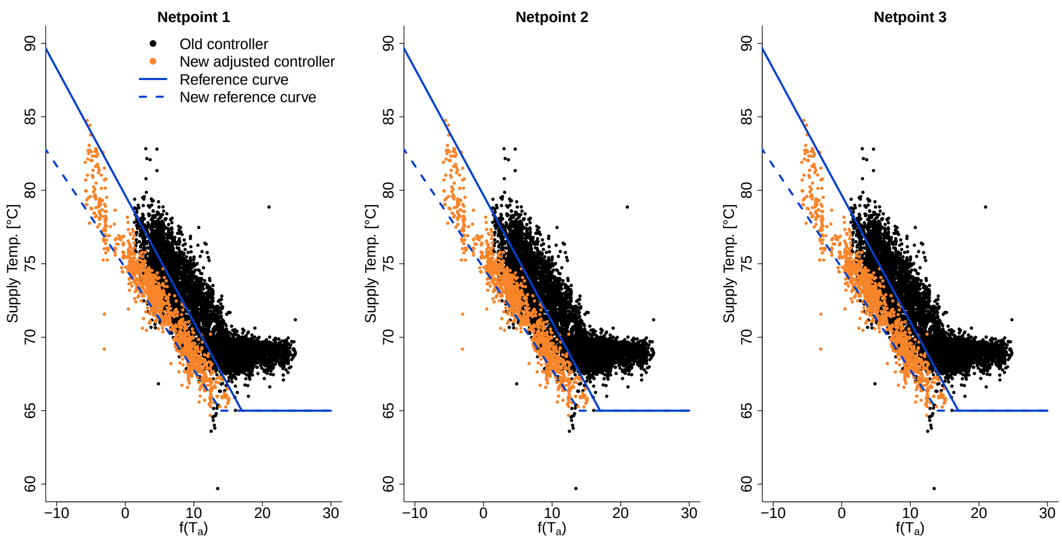

Figure 5.2: Figures shows the new adjusted reference curve and the supply temperature from the new controller periods using the 5°C adjustment.

The plots to the right in Figure 5.3 compare the performance of the controllers versus the degree days. Degree days are used to compare supply temperature between heating seasons when comparing different operations. The degree days, T^{dd} are computed by estimating the difference between the average ambient temperature, $\bar{T}_a$ an over one day, and using 17°C as the cut-off of heating demand from buildings,

$$T^{dd} = \max(0, 17 - \bar{T}_a) \tag{5.1}$$

The average supply and return temperature for each day is then computed and plotted against its corresponding degree day as shown in the top and bottom right plots. The top plots demonstrate the supply temperature performance of the controllers, and the adjusted supply temperature for the new controller as suggested before. We see that the new controller has quite a stable but higher supply temperature than the previous operation as expected because of the high reference curve as shown in Figure 5.1. Consequently, the new controller results in higher supply temperature at the production and thereby higher operation cost. However, it is not significantly higher than the previous operation even though it was penalized by higher restrictions. We see notably improved operation when the adjusted supply temperature is investigated, where the supply temperature is lower.

To compare these operations, a regression model using Ordinary Least Squares to estimate the parameters of a model with an intercept and slope have been fitted to each operation as shown in Figure 5.3 and rewritten here below,

$$\text{New controller: } T_{supply} = 68.48 + 0.71T^{dd} \tag{5.2}$$

$$\text{Old controller: } T_{supply} = 62.61 + 0.97T^{dd} \tag{5.3}$$

$$\text{New adjusted controller: } T_{supply} = 63.48 + 0.71T^{dd} \tag{5.4}$$

Hence, that the new controller has a lower slope, which indicates that it does not increase the supply temperature as fast when the outside temperature decreases compared to the previous operation. However, the intercept is quite higher, which translates to that the overall expectation of supply temperature is higher for the given degree day. The adjusted regression lines have a lower intercept as we have adjusted the data by 5°C however it still has a higher intercept than the previous operation.

Decreasing the supply temperature for operation leads to an increase in savings for the utility. Madsen et al. [33] suggest a rule of thumb for savings resulting from lowering the supply temperature

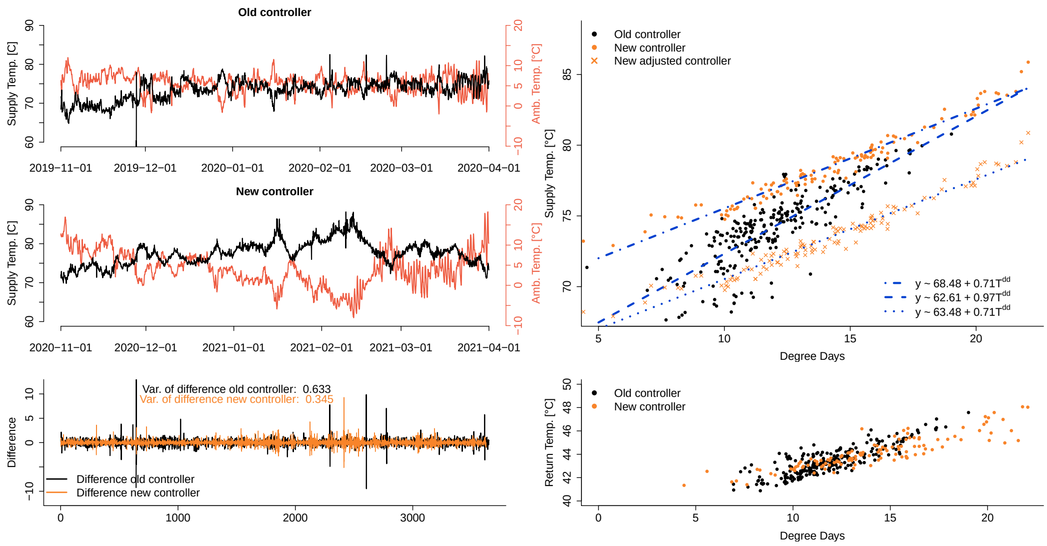

Figure 5.3: Comparing old and new controller at Tingbjerg. The left plots demonstrate the stability of the supply temperatures while the right plots compare the supply temperatures against degree days.

in CHP plant; For each degree lowered, the savings for the heat loss in the network is 0.5 % and at the production for more efficient production is 1 %, thus the savings can be compute as

$$\text{Savings} \; = (\text{Cost}_{\text{before}} * x \; [°C] * 0.5\%) + \text{Shares}_{Production}(\text{Cost}_{\text{before}} * x \; [°C] * 1\% \qquad (5.5)$$

where x is the lowered supply temperature for the system. Thus, estimating from Figure 5.3 with the new adjusted controller, the supply temperature would be 3°C. The savings would be around 4.5% for the operation of the district heating network in Tingbjerg. The rule of thumb and how to compute the savings are heavily dependent on the system and how the heat is produced. Lowering the supply temperature for a CHP plant gives the highest savings for district heating. Decreasing the supply temperature results in an increase in the ratio of the power to heat output for CHP plant, and as electricity is more valuable than heat, a more profitable operation is achieved [5]. Thus, the equations are just a rule of thumb to demonstrate potential savings when sufficient production data is not available.

Concluding this section, we have demonstrated that having feedback of the network improves the stability of the system, i.e. few and smaller fluctuations in the supply temperature. We saw that the restrictions of the new operation were probably too high compared to the previous as it was allowed to violate the restrictions while the new controller tries to satisfy them within a certain probability. However, adjusting the result with the new controller, we could demonstrate a potential of 4.5% in savings.

Chapter 6

Conclusion

In this report, we have demonstrated how digitalization in district heating can improve the operation of the utility. Smart meters in the network can act as feedback of the system for temperature control to give response characteristics of the network. Accurate modeling of how the system will respond to changes at the production will increase the performance of temperature control and lowering the operation cost. The climate in cities was discussed and the climate in Copenhagen was used to visualize the temperature differences, i.e. different climates within the city. Therefore, a local climate station was used to bind weather forecasts to the area's climate, resulting in more accurate NWPs for the climate area. The NWPs improvements will result in a more accurate heat demand forecast, especially for the short-term forecast. An accurate short-term heat demand forecast is beneficial for the temperature control to deliver the desired consumer consumption and lowering the operational cost by intelligent control in the next hour.

A trial was conducted to demonstrate these benefits. The focus was to improve the heat demand forecast and temperature control of the area using additional data than typically is used. We illustrated the accuracy improvements of localizing heat demand forecast by using the area's historical demand and binding the NWP to the area using a local climate station. The local heat demand forecast was compared to the previous heat demand forecast in Tingbjerg where it was scaled from a forecast from a large area that contains the Tingbjerg area. This highlighted how crucial it is to localize heat demand forecast to an area where the temperature control is operating. The heat demand forecast is used for all operations of the utility, hence the desire of increasing the accuracy of the forecast that will improve the efficiency of the operations. Temperature control was in operation on-line during the trial to demonstrate that smart meters can be used as feedback for closed-loop control. The previous operation in the area was done with open-loop control using current ambient air temperature and hydraulic simulation of the system to operate the network. Unfortunately, the reference curve was placed quite conservatively in order to avoid complaints during the trial. Therefore, the trial operation demonstrated a higher supply temperature than the previous operation. However, we showed that the closed-loop control usually satisfied the reference control requirement at the consumer while the open-loop violated it frequently. The closed-loop operation also demonstrates that it results in higher precision of the supply temperature, e.g. it does not vary as much for the given ambient temperature compared to the open-loop operation. To summarize, the proposed data-driven methods lead to higher precision and that it has the potential of lowering the supply temperature by 5°C, i.e. savings potential of more optimal operation of the network.

In the report, all of these findings are demonstrated and highlighted, the importance of an accurate understanding of the area where heat is delivered. Three things are needed to be considered for efficient operation: 1) The local climate 2) The local social consumption behavior 3) The local response characteristics of the network. Accurate representation of the heating in the area and the local climate can be achieved by using data that has become available through the digitalization in district heating. We therefore conclude that digitalization in district heating will highly benefit the operation of district heating.

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Appendix A

Temperature Optimization and Control at Svebølle Viskinge Fjernvarmeselskab

For the past couple of years, the district heating utility Svebølle Viskinge Fjernvarmeselskab has been improving its network operation by installing temperature sensors in the network (the critical points) to have feedback of the network. The previous operation of the supply temperature had been selected based on an open-loop system. Thus, without considering how the network response to changes and what supply temperature is received by the consumers. Along with getting feedback, they have also been using the temperature optimization software from ENFOR, the `HeatTO`™. The same software was installed and used in the Tingbjerg network.

The result of the changes made in the network operation can be seen in Figure A.1. In the figure, heating season is defined as the months; November, December, January, February, and March. The savings gain of using closed-loop temperature optimization can be seen when comparing the previous and new controller in the top plot where the average daily supply temperature against the degree days. The old controller was in operation during the heating season 2018/2019 and the new controller using the feedback and the `HeatTO`™ software during the heating seasons 2019/2020 and 2020/2021. The old controller was also kept running during the 2020/2021 heating season when the new controller was in operation as shown in the figure. It was only used in computing an alternative setpoints of the supply temperatures, while the new controller was operating the supply temperature in the network. The flow at the production from the previous and current operation is shown in the bottom plot. The plot shows that the new controller has a higher flow. Thus, it increases the flow until it reaches the physical flow maximum of the system before increasing the supply temperature.

Comparing the new operation to the heating season 2018/2019, it can be condluded that the supply temperature has been on average lowered by 8°C therefore the savings can be estimated using Eq. 5.5 to be 12%. However, comparing the new controller to the old controller during the same heat season (2020/2021), the temperature was decrease by 10°C, and the savings are 15%. Hence, investing in data-driven methods can increase the savings of the network.

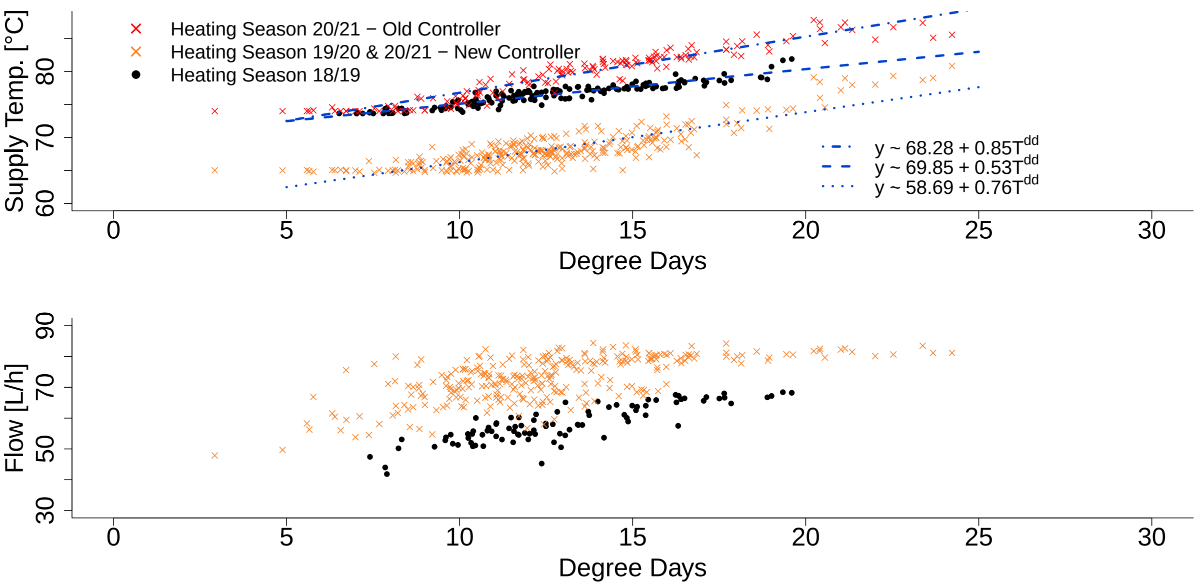

Figure A.1: Temperature optimization at Svebølle Viskinge for three heating seasons; 2018/2019, 2019/2020, and 2020/2021. The heating season months are November, December, January, February, and March. Average daily supply temperature and flow are plotted against the degree days in the top and bottom plots.

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