Unscented Kalman Filtering for in-situ Bulk Identification of District Heating Meter Temperature Offsets and Service Pipe Insulation Level Detection

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Abstract. Unscented Kalman Filtering is applied to district heating meter data and GIS-data from a utility network to simultaneously identify temperature offsets in utility meters and service pipe insulation. Implementing estimation of the temperature in the main pipe allows for more accurate results, which also respect physical constraints. Unscented Transformations allow for easier implementation of the algorithm compared to existing solutions, as linearization is avoided. Correcting for potential offsets in the temperature measurement of the utility meter allows for a better estimation of the insulation level of the service pipe, improving the ability for the utilities to pinpoint their efforts in optimizing their renovation activities over several areas of interest.

1 Introduction

The European district heating network is distributed over more than 19,000 networks, with almost 200,000 km of distribution pipes. In 2022, it supplied a total of 608 TWh to more than 75 mio citizens. This corresponds to 13% of the total heating demand within the European Union. In some countries, like Denmark, more than two thirds of all residential buildings are heated by district heating [1].

The supply temperature in the district heating networks range from as high as 130 °C down to 60 °C or lower in certain 4th generation district heating networks [2]. As a district heating network has the goal of carbon neutrality, there is a movement towards even lower supply temperatures, as this allows for multiple, decentralized heating sources to be integrated into the network, such as accumulation tanks, heat pumps, surplus industrial heating, geothermal heating and similar sources. Many of these heating sources work best at temperatures below 60 °C [3], but to use such low temperatures in the district heating networks, it is a requirement that the insulation level is sufficiently good in all areas of the network. If not, the supply temperature will end up being so low at the consumer that domestic heating becomes troublesome, and the warm potable water ends up having a temperature which facilitates bacterial growth [4].

The European directive 2023/1791 [5] dictates that all utility meters must be remotely read by 2027.

While remotely read data from district heating utilities is often used by the utility to impose motivational tariffs [6,7] to the consumer, often by penalizing consumers who do not exploit the potential heat of the district heating water sufficiently and return water at a high temperature and reward the consumers who manage to return at a low temperature, it has also been used to calculate the insulation level of service pipes, allowing for more focused maintenance of the pipe network [8,9], monitoring installations [10,11], and leakage detection [12].

The meters, however, are mainly manufactured with a focus on measuring energy consumption by looking at temperature difference and volume flow. As such, the absolute temperature measured can deviate at levels defined by EN 1434-2022 [13].

Furthermore, when in service, a random sample of a given batch of utility meters from the same lot are spot-checked after 8 years to identify potential issues. If no issues are found during these checks of random meters, all meters in the batch are allowed to be in operation for an additional 8 years. During this time, no systematic monitoring of the potential drift of the sensors is conducted, potentially leading to false motivational tariffs to the consumers.

In this article, we propose a novel method, for identifying the utility meter temperature offset on top of the service pipe insulation level.

Added to the value found in previous works concerning insulation levels in service pipes, this method allows for a focused effort on changing faulty meters, thereby getting a better overview of the temperature in the network, allowing further reductions in supply temperatures without risking the public health, and for more fair motivational tariffs, as the temperatures used are corrected.

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The method proposed in this article exploits Unscented Kalman filters [14] for identifying the state of the district heating network. Using an Unscented Kalman filter over e.g. an Extended Kalman filter [15,16] has benefits, as shown in Wan and Merwe [17] . These benefits include better state estimation and more accurate co-variance matrices, especially for highly non-linear state functions. Furthermore, it is easier to implement, as it does not require linearization of the equations.

2 Method

The method described in this article uses an Unscented Kalman filter as described in Wan and Merwe [17].

This method enables the continuous evaluation of the state of the system, which in the case of district heating is the insulation level of the service pipes and the offset of the utility meters.

Existing methods for evaluating the insulation level of the service pipes already exist in literature [8,9] , but these have some issues in their implementation and/or their assumptions.

The method described in Kongsgaard [9], uses an Extended Kalman Filter for evaluating the insulation level of the service pipe. As part of the evaluation, a constant temperature along the entire main pipe is assumed at each time step. This assumption is questionable as the flow through the main pipe consists of the sum of the sub flows going to the consumers at the various pipe branching points. As such, the flow in a main pipe going down a residential street decreases according to the consumption of the individual houses. If the last house on the street only has a small consumption, the flow at the end of the street will be low, and cooling in that part of the main pipe will be significant.

For the method described in Fester et al [8] a recursive algorithm is used to estimate the parameters in the network. This can lead to significant computational times, which is far from ideal, looking at the potential number of service pipes in European district heating networks.

2.1 Assumptions/requirements for running the algorithm

The method described here takes full advantage of the remotely read temperature and flow data from district heating utility meters. The method requires meter readings at a high frequency (hourly measurements or better). Furthermore, the data used for optimizing the parameters need to be obtained at time points, at which the hot water consumption is stable. As such, the best data arrives in the winter period during the night, when it is relatively safe to assume that any consumption is due to heating demands.

The algorithm works by estimating the temperature in the main pipe, based on the readings from the individual utility meters. The temperature profile in the main pipe is fitted using least squares fit to a physical model of the temperature profile along the pipe, given the insulation level and the partial flows in the different segments.

Using the fitted temperature in the main pipe, the temperature is backpropagated to the utility meter, giving an offset between the utility meter reading and the expected temperature from the model. This offset is used in the Kalman filter for optimizing the meter's temperature offset and the insulation level of the service pipe to best fit the system.

Since many district heating networks use shunts at the end of cul-de-sacs to avoid still-standing water and ensure warm water for the consumers at the end of the roads, the algorithm allows for the identification of a flow through such a shunt.

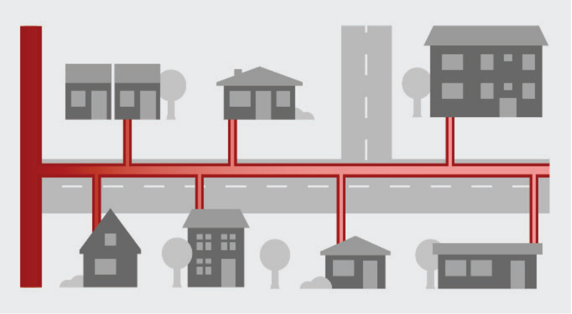

Figure 1: Sketch of district heating network. The main pipe, following the road, splits up into service pipes, each delivering district heating to individual houses. Insulation and flow levels at the different parts of the network determine the cooling of the water in each pipe segment.

2.2 Data quality requirements

2.3 Nomenclature

In the rest of the article, the following nomenclature is used:

T_{main}	Temperature at the main pipe
T_{supply}	Supply temperature at the utility meter
T_{ambient}	Ambient temperature
δT_{supply}	Offset of utility meter temperature measurement
P	Power loss through the pipe segment
Q	Flow
$c_{\text{H}_2\text{O}}$	Heat capacity of water
U	Thermal conductivity per length of pipe
L	Length of pipe segment

The energy loss in a pipe segment can, assuming steady state conditions, be found from two equations. The first way is to look at the temperature difference between the two ends of the pipe, and the second way is to look at the difference between the temperature of the water in the pipe and the ambient temperature:

$$P = \left(T_{\text{main}} - T_{\text{supply}}\right) \cdot Q \cdot c_{\text{H}_2\text{O}}$$
$$P = \left(\frac{T_{\text{main}} + T_{\text{supply}}}{2} - T_{\text{ambient}}\right) \cdot U \cdot L$$

Combining these two equations allows us to estimate T_{main} based on the measured temperature and flow at the consumer/utility meter and the ambient temperature. This gives

$$T_{\text{main}} = \frac{T_{\text{supply}} \cdot \left(c_{\text{H}_2\text{O}} \cdot Q + \frac{U \cdot L}{2}\right) - U \cdot L \cdot T_{\text{ambient}}}{c_{\text{H}_2\text{O}} \cdot Q - \frac{U \cdot L}{2}}$$

In this work, we assume that T_{ambient} equals the soil temperature, which is found through a meteorological source. The length of the service pipe is found through GIS-data, available from the utility network. To facilitate the analysis, T_{supply} is taken as the temperature indicated by the utility meter plus the meter offset, δT_{meter}, which we are interested in finding.

2.4 Unscented Kalman filtering for insulation level and offset estimation

Setting up the Unscented Kalman filter, three matrices/vectors need to be defined: The state vector, $\bar{x}$, containing the current expectation values for the temperature offsets and U-values, and the state covariance matrix, $\bar{\bar{R}}$, containing the covariance for the temperature offsets and U-values:

$$\bar{x} = \begin{bmatrix} \delta T_1 \\ U_1 \\ \delta T_2 \\ U_2 \\ \vdots \\ \delta T_n \\ U_n \end{bmatrix}$$

$$\bar{\bar{R}} = \begin{bmatrix} \sigma^2_{\delta T_1} & \sigma_{U_1,\delta T_1} & \sigma_{\delta T_2,\delta T_1} & \cdots & \sigma_{U_n,\delta T_1} \\ \sigma_{\delta T_1,U_1} & \sigma^2_{U_1} & \sigma_{\delta T_2,U_1} & \cdots & \sigma_{U_n,U_1} \\ \sigma_{\delta T_1,\delta T_2} & \sigma_{U_1,\delta T_2} & \sigma^2_{\delta T_2} & \cdots & \sigma_{U_n,\delta T_2} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{\delta T_1,U_n} & \sigma_{U_1,U_n} & \sigma_{\delta T_2,U_n} & \cdots & \sigma^2_{U_n} \end{bmatrix}$$

Finally, a matrix, containing the expected process uncertainty, $\bar{\bar{Q}}$, must be established. This matrix contains the expected noise in the system.

Initially we expect the temperature offset of the utility meters to be normally distributed: $\delta T = \mathcal{N}(0\ °\text{C}, 0.1\ °\text{C})$. The insulation of the service pipes is equally set to be normally distributed with $U = \mathcal{N}\left(0.10\ \frac{\text{W}}{\text{m}\cdot°\text{C}}, 0.01\ \frac{\text{W}}{\text{m}\cdot\text{K}}\right)$. Using the expected distributions of δT and U, both $\bar{x}$ and the diagonal elements of $\bar{\bar{R}}$ can be filled out.

Initially, all off-diagonal elements of $\bar{\bar{R}}$ are set to 0.

For the $\bar{\bar{Q}}$ matrix, the elements corresponding to process error for temperature are set to $\sigma_{\delta T,Q} = 0.01\ °\text{C}$

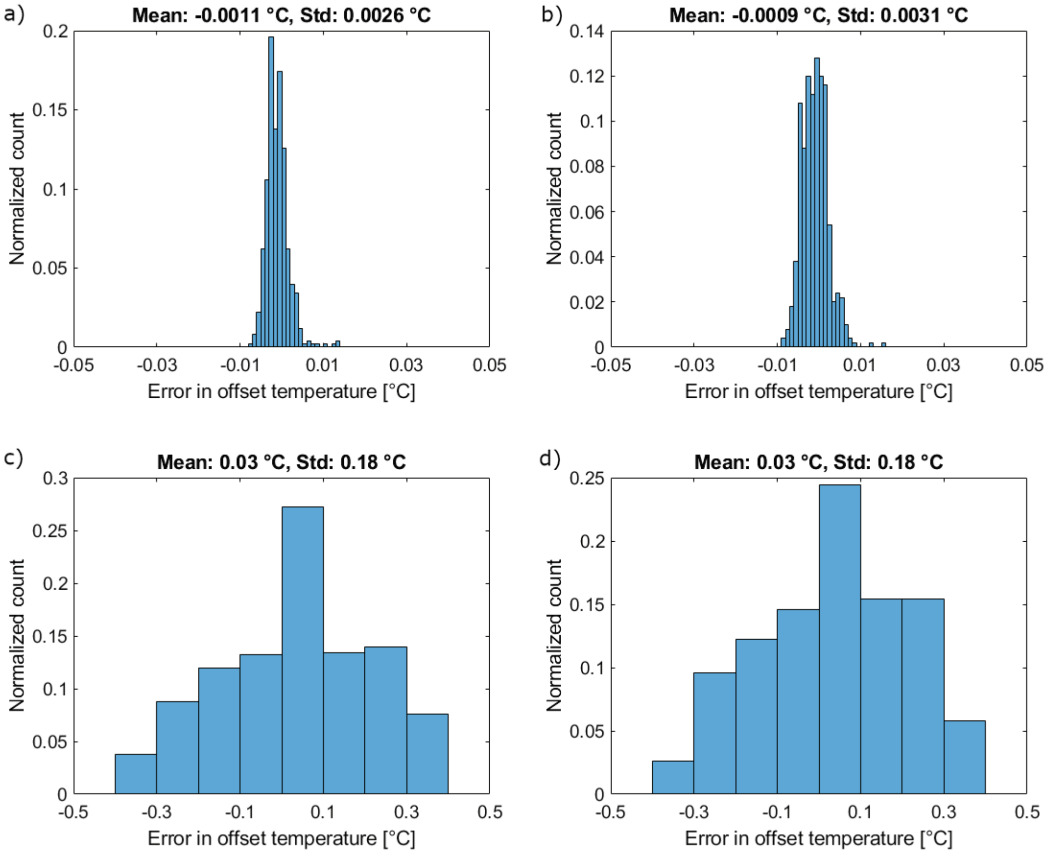

Figure 2: Deviations between utility errors and estimated errors found using the UKF. a) All data have high resolution and zero noise. Inlet temperature in main pipe is constant b) Data is rounded to same level as found in remotely read district heating meters. Inlet temperature to main pipe fluctuates. c) Individual, randomized service pipe insulation level and utility meter offset. d) Added uncertainty to location and length of service pipe.

and the process error for U to $\sigma_{U,Q} = 1 \times 10^{-5}\ \frac{\mathrm{W}}{\mathrm{m}\cdot{}^{\circ}\mathrm{C}}$. These values allow for the algorithm to converge towards stable solutions, without being too affected by noise in the measurements.

The diagonal elements of $\bar{\bar{Q}}$ are intentionally set lower than the diagonal elements of $\bar{\bar{R}}$ to obtain faster convergence.

3 Results

3.1 Synthetic data

To check the validity of the developed algorithm, the filter was run on 50 series of synthetic data [18]. Using synthetically generated data allows us to have a ground truth for the temperature offset and insulation level of the pipes.

The datasets are created in a way, which allows to add or remove noise for the different parameters. Using this feature, the Kalman Filter is first run on the synthetic data, where all information (meter readings, service pipe length, location of intersection between service pipe and main pipe) is known exactly, and the temperature at the beginning of the main pipe is constant. Using this data, the Kalman filter can identify the correct meter offsets with a standard deviation of 0.0026 °C.

In the second run, meter readings are rounded to a resolution of 0.01 °C and 0.01 $\mathrm{m^3/h}$, identical to many actual utility meters. Furthermore, the temperature at the beginning of the main pipe is fluctuated. With this data, the Kalman filter can identify all the meter offsets with a standard deviation of 0.0031 °C.

For these two cases, the identification of the offset must be considered ideal, as it is better than the resolution of the meter.

In the third case, each consumer is given an individual consumption, as well as individual meter offsets and insulation level of the service pipe. Here, the algorithm can identify the offsets with a standard deviation of 0.18 °C.

The same standard deviation is found in case four, where uncertainty to the location and length of the service pipes is added to the data. Results from the four cases are shown in Figure 2.

In case four, it was noticed, much of the standard deviation originates from a general offset in the expected δT, leading to an offset in the expected temperature of the main pipe. By adding information on the temperature in the main pipe, the standard deviation of the error in δT can be reduced to 0.065 °C, as seen in Figure 3. In practice, this information can come from a reference thermometer. Using a reference thermometer would also introduce direct traceability to the SI-system.

3.2 Actual data

The Kalman filter has also been used on historical data from a Danish utility network. For this data, the actual offsets of the utility meters are unknown, and thus, the standard deviation on the error of δT cannot be analyzed as in section 3.1.

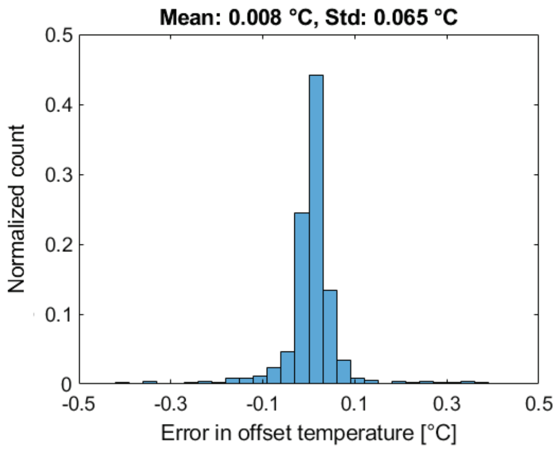

Figure 3: Deviation between error in temperature measurement and estimated error from the UKF.

For the utility data, data from a single road is analyzed. The dataset has data for one year. To avoid issues with non-stationary consumption, the filter only uses data from midnight to 5 a.m. and only, when the meters show a flow rate higher than 0.04 $\mathrm{m^3/h}$. This has the intended purpose of only analysing on the base load, used for heating.

Running the analysis shows, that for the road investigated, offsets are in the range [-0.4 °C; 0.4 °C] with uncertainties ($k = 1$) up to 0.08 °C. These δTs are within the expected range, as the ISO standard for energy meters allow δTs up to 0.5 °C.

Estimated errors in the temperature measurements of the meters from the test-area are seen in Figure 4.

For both synthetic and actual data, the insulation level of the service pipe is calculated simultaneously to the temperature offset. These results are similar to what has been found in previous studies [8,9] and will not be discussed here.

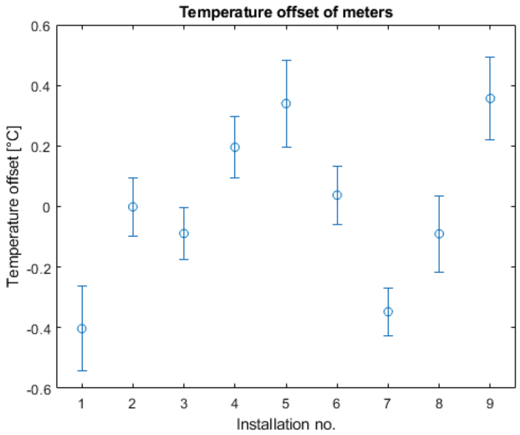

Figure 4: Estimated errors in temperature measurements on the test-area.

4 Potential pitfalls of Unscented Kalman Filtering for District Heating

In the above analysis of district heating data, both synthetic and actual data, the method appears to function

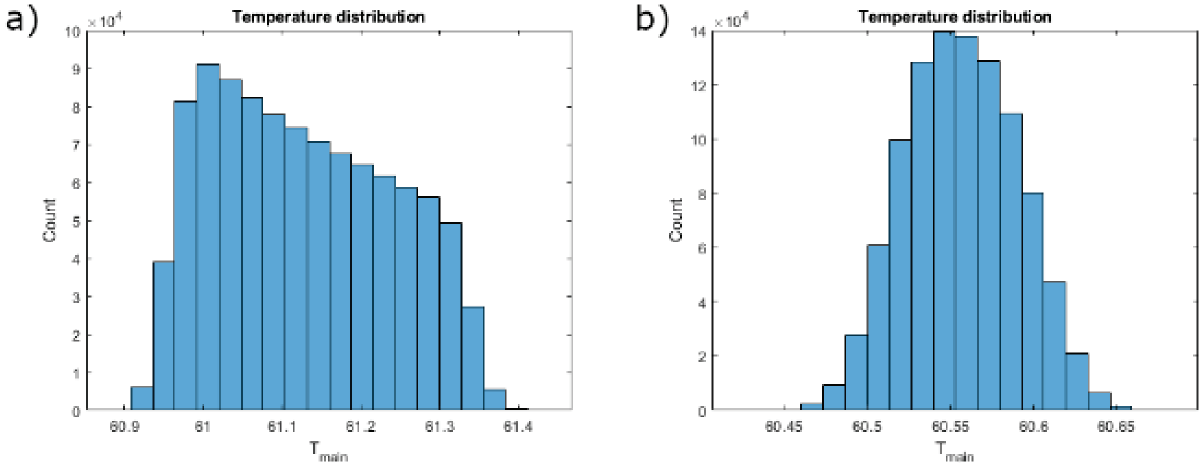

Figure 5 : Temperature probability distribution in the main pipe with a service pipe of 5 m. In both cases, the supply temperature is normally distributed N(60 °C, 0.02 °C). In a) the flow rate is uniformly distributed in the range [0.025 m3/h;0.035 m3/h], and in b), it is [0.055 m3/h;0.065 m3/h]

as expected. This is however not a guarantee that it will always work.

While unscented Kalman filtering does work significantly better on non-linear functions than regular Kalman filters and Extended Kalman filters, it still has some limitations when the transfer function is sufficiently non-linear. For district heating data this can be relevant when the flow in a pipe segment is low and the pipe segment is long. Here, the result of the transfer function can be shown to be skewed to a degree, as seen in Figure 5 a), which might cause issues. For such cases, it can be of interest to investigate other methods for parameter estimation, such as dual Unscented Kalman filters [19] or Particle Filters [20] (reference).

The temperature probability distribution in the main pipe, based on the temperature measurement at the utility meter can be seen in Figure 5 for a low flow ([0.025;0.035] m3/h) and a higher flow ([0.055;0.065] m3/h).

Another potential issue, which is generally true for all analyses of district heating data, is the frequency of the data gathering. Often, the flow rates in district heating networks are not stable or quazi-stable over the duration of one hour, as, e.g., taking a shower or cleaning dishes normally only takes a few minutes. Low duration events, if done at an unfortunate time, will lead to a meter reading showing a high flow, but low supply temperature (if the shower has just been started, and the warm water has not yet arrived at the house), or low flow and high temperature (if the shower has just ended, but the water at the utility meter is still warm).

5 Conclusion

We have found that it is possible to estimate critical parameters of a district heating network in the form of meter offsets, on top of the already characterized service pipe insulation levels using Unscented Kalman Filtering.

On synthetic data, the method can estimate the utility meter temperature offset for all meters on a road with a standard deviation on the error of less than 0.2 °C. If the temperature at the beginning of the road is known (e.g. by inserting a reference sensor here), the standard deviation of the utility meter temperature error is reduced to 0.065 °C, while also introducing direct traceability to the SI-system.

The method is used on real-world data, where offsets were estimated to be within the range [-0.4 °C – 0.4 °C], all within the tolerable limits as given by the relevant ISO-standard (Starndardization 2022).

The method described has potential issues with low flow rates, where the temperature probability density function in the main pipe becomes extremely non-Gaussian. These issues should be investigated, potentially using dual Unscented Kalman Filters or Particle Filters, capable of handling extremely non-linear transfer functions.

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