

Uncertainty in Hourly Readings from District Heat Billing Meters

Lukas Lundström^{1,2} Erik Dahlquist¹

¹ Mälardalens University, Västerås, Sweden

² Eskilstuna Kommunfastighet, Eskilstuna, Sweden

lukas.lundstrom@mdh.se, erik.dahlquist@mdh.se

Abstract

Hourly energy readings from heat billing meters are valuable data source for the energy performance assessment of district heating substations and the buildings they serve. The quality of such analyses is bounded by the accuracy of the hourly readings. Thus, assessing the accuracy of the hourly heat meter readings is a necessary (but often overlooked) first step to ensure qualitative subsequent analyses.

Due to often limited bandwidth capacity hourly readings are quantized before transmission, which can cause severe information loss. In this paper we study 266 Swedish heat meters and assess the quantization effect by information entropy ranking. Further, a detailed comparison is conducted with three heat meters with typically occurring quantization errors. Uncertainty due to the quantization effect is compared with the uncertainty due to typical accuracy of the meter instrumentation. A method to conflate information from both energy readings and energy calculated from flow and temperature readings is developed.

The developed conflation method is shown to be able to decrease uncertainty for heat meters with severely quantized energy readings. However, it is concluded that a preferable approach is to work with the heat meter infrastructure to ensure the future recorded readings holds high enough quality to be useful for energy performance assessments with hourly or subhourly readings.

Keywords: heat meters, uncertainty, district heating, information entropy, EN 1434

Nonmenclature

<i>Symbols</i>	
Q	Energy/heat [kWh/h]
V	Volumetric flow rate [m ³ /h]
θ	Temperature [°C]
$\Delta\theta$	Temperature difference [°C]
H	Information entropy [bits/sample]
c	Heat capacity [MJ/(K·m ³)]
Δ	Quantization step size
L	Number of quantization levels

σ	Standard deviation
<i>Subscripts</i>	
$0,1,2$	Conflated, energy reading, calculated from flow and temperature readings
p	Permanent/nominal approved flow
i	Inferior/minimum approved flow
qe	Quantization error
met	Meter instrumentation error
f	Flow meter
t	Temperature sensor pair

1 Introduction

Many district heating operators gather hourly values to centralized databases from their heat billing meters (Gadd and Werner, 2015; Sandin et al., 2013). These hourly readings are a valuable information source for fault detection and energy performance assessment of the district heating substations and the buildings they serve (Gadd and Werner, 2015; Mansson et al., 2019; Sandin et al., 2013). In Sweden, district heating operators are required to share daily meter readings to their customers (EIFS 2014:2), while hourly values only must be provided if these are used for billing. Readings typically available in heat meter data management systems are hourly averages of energy and flow and hourly instantaneous samples of the primary side supply and return temperatures (Sandin et al., 2013). Because of bandwidth constraints, only a finite number of bits are available and recorded values are therefore quantized before transmission. Quantization can cause increased uncertainty, especially when the recorded value needs to be able to represent a large value range (e.g. cumulative values). Therefore, hourly values transmitted from the heat meters can have quantization error that is much larger than the accuracy of the measurement equipment. Such large quantization errors can severely deteriorate the quality of subsequent analyses.

In this paper we study 266 Swedish heat meters and assess the quantization effect by information entropy ranking (Section 2.1). Further, a detailed comparison is conducted with three heat meters. Uncertainty due to the quantization effect is compared with the uncertainty

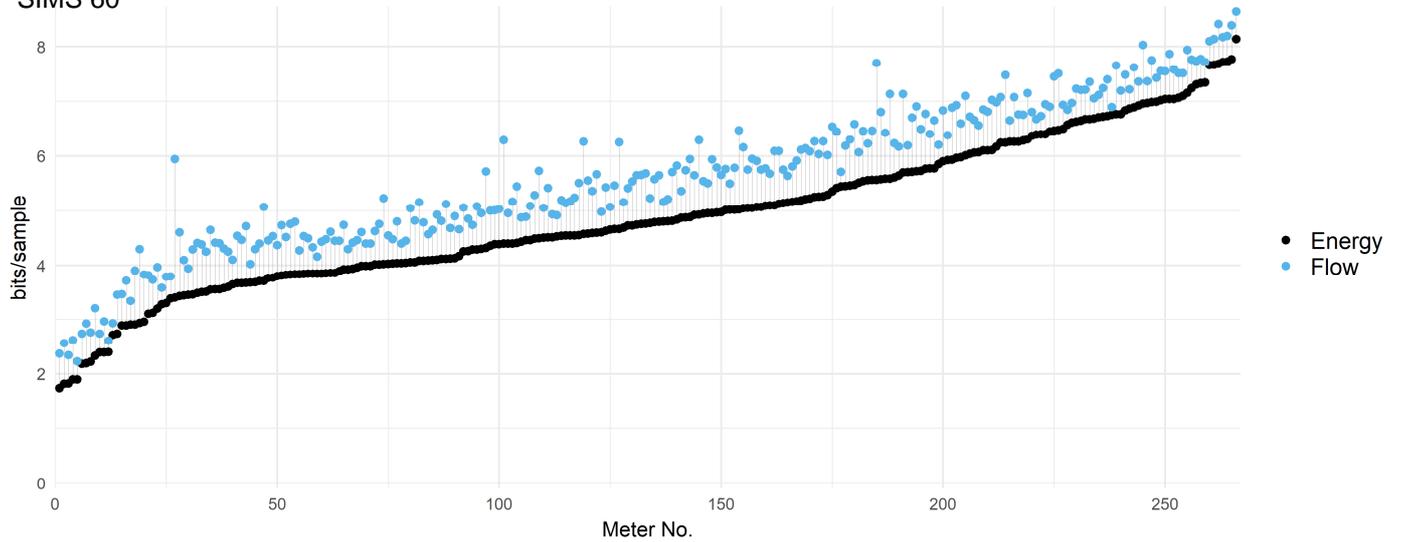


Figure 1. Entropy ranking of hourly energy and flow readings from 266 heat meters.

due to typical accuracy of the meter instrumentation (Section 2.2). A method to conflate information from both energy readings and energy calculated from flow and temperature readings is developed (Section 2.3-2.4).

2 Material and methods

Material consist of data from 266 district heating billing meters, serving multifamily buildings located in Eskilstuna, Sweden. Most of the heat meters are Kamstrup Multical 601 / 602 calculators equipped with Kamstrup Ultraflow 54 / 34 ultra sonic flow meters.

2.1 Information entropy

Sandin et al. (2013) suggested using information entropy ranking as a way of identifying heat meter readings with large quantization errors. Information entropy is defined as the sum of the negative binary logarithm $\log_2(\cdot)$ of the probabilities $p(\cdot)$ for each value in the time series of length n :

$$H = - \sum_{k=1}^n p(x_k) \cdot \log_2(p(x_k)) \quad (1)$$

Two to the power of the entropy indicates the number of quantization levels (L) available in the meter readings: $\propto 2^H$ (provided that the observation period holds rich enough operation conditions). For example, $H = 8$ would indicate 256 levels and $H = 4$ would indicate 16 levels. However, information entropy depends on the actual operation conditions such as weather and the probability of an observation to occur (i.e. meters repeating same observation quantities, due design or even weather conditions, will get a lower information entropy value). Therefore, the 2 estimate, will generally result in fewer levels than what is available due to the meter configuration. Figure 1 shows the 266 heat meters ranked by their calculated entropy for energy readings and flow readings.

2.2 Uncertainty of the energy readings of the heat meter

The energy reading at time index k is denoted as $Q_{1;k}$. The time-varying uncertainty of the energy readings is estimated as

$$\sigma_{1;k} = \sqrt{\sigma_{met;k}^2 + \frac{\Delta_Q^2}{12}} \quad (2)$$

where $\sigma_{met;k}$ is the standard deviation (SD) at time index k due to uncertainty of the meter equipment and Δ_Q denotes the quantization step size of the energy readings (i.e. the largest unit of measure, typically 1, 10 or 100 kWh). The $\Delta_Q^2/12$ is a commonly used approximation of the variance for the quantization effect used for noise modelling (Marco and Neuhoﬀ, 2005).

The uncertainty calculations of the meter equipment is adopted from the European Standard EN 1434-1:2015:

$$\sigma_{met;k} = \sqrt{\sigma_{f;k}^2 + \sigma_{t;k}^2} \quad (3)$$

where $\sigma_{f;k}$ is the standard deviations of the flow meter at time index k and $\sigma_{t;k}$ is the standard deviation of the temperature sensor pair and the calculator (where the temperature sensor pair is the dominating error source). Typical accuracy of Multical heat meters equipped with Ultraflow flow sensors (Kamstrup A/S, 2018) is used

$$\sigma_{f;k} = \begin{cases} Q_{1;k}(1 + 0.01V_p/V_k)/100, & \text{if } V_k > V_i \\ \Delta\theta_{1;k}V_i c(1 + 0.01V_p/V_i)/100, & \text{if } V_k \leq V_i \end{cases} \quad (4)$$

$$\sigma_{t;k} = \begin{cases} Q_{1;k}(0.6 + 6/\Delta\theta_{1;k})/100, & \text{if } \Delta\theta_{1;k} > 2 \\ 2V_k c(0.6 + 6/2)/100, & \text{if } \Delta\theta_{1;k} \leq 2 \end{cases} \quad (5)$$

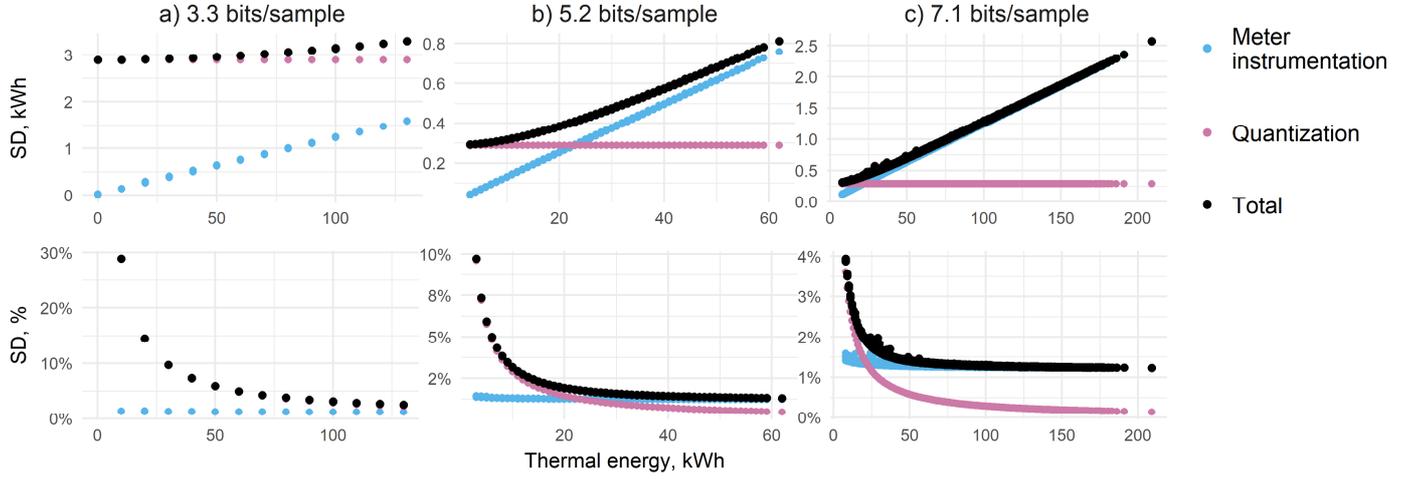


Figure 2. Uncertainty of hourly energy readings due to meter instrumentation accuracy and quantization effects for three example substations. Information entropy of the hourly energy readings are given in the subtitles.

where $Q_{1;k}$ [kWh] is the energy reading at time step k (accumulated heat use between $k-1$ to k), V_k [m^3/h] is the flow rate reading at time step k (flow rate between $k-1$ to k), V_p is the permanent nominal flow rate, V_i is the inferior flow rate (where the meter shall function without exceeding the allowed accuracy), c is the heat capacity of the fluids (assumed as a constant of $4.12 \text{ MJ}/(\text{K}\cdot\text{m}^3)$ (OIML R 75-1, 2002)), and $\Delta\theta_{1;k}$ is the average temperature difference between fluids calculated as

$$\Delta\theta_{1;k} = Q_{1;k}/(V_k c) \quad (6)$$

2.3 Energy calculated from flow and temperature readings

The quantization error of flow readings is generally lower than for the energy readings, especially during operation conditions when the temperature difference is low (see visualization in Figure 3). Therefore, in case of large quantization errors, it can be more accurate to estimated energy use from flow and temperature readings:

$$Q_{2;k} = c \cdot \Delta\theta_{2;k} V_k \quad (7)$$

$$Q_{2;k} = \max(Q_{1;k} - \Delta_Q, \min(Q_{1;k} + \Delta_Q, Q_{2;k})) \quad (8)$$

where $\Delta\theta_{2;k}$ denotes the temperature difference estimated from the temperature readings. Due to the instantaneous nature of the temperature readings, the $\Delta\theta_{2;k}$ approximation can deviate much from the true average temperature difference. While, Eq. (6) can be assumed to calculate the true average $\Delta\theta$ when the quantization error is negligible.

Following equations are suggested to estimate the time-varying standard deviation for the energy use Q_2 :

$$\sigma_{2;k} = \sqrt{(\sigma_{2;t;k})^2 + (\sigma_{2;qe;k})^2 + (\sigma_{met;k})^2} \quad (9)$$

where $\sigma_{2;t;k}$ denotes the uncertainty due to instantaneous nature of the temperature readings and $\sigma_{2;qe;k}$ denotes the quantization error due to low resolution in the flow readings (see Eq (11)).

$$\sigma_{2;t;k} = Q_p/200 + 0.02 \cdot Q_{2;k} \quad (10)$$

$$\sigma_{2;qe;k} = \frac{\Delta\theta_{2;k} \Delta_V c}{\sqrt{12}} \quad (11)$$

where Q_p denotes the energy at nominal flow and Δ_V is the width of the quantization step size of the flow readings.

2.4 Conflation

The two energy variables Q_1 and Q_2 are not fully independent as they are derived from the same metering equipment. Therefore, the two quantities are weighted as two dependent normal variables (Winkler, 1981)

$$Q_0 = \frac{(\sigma_2^2 - \rho\sigma_1\sigma_2)Q_1 + (\sigma_1^2 - \rho\sigma_1\sigma_2)Q_2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} \quad (12)$$

$$\sigma_0^2 = \frac{(1 - \rho^2)\sigma_1^2\sigma_2^2}{\sigma_1^2 + \sigma_2^2 - 2\rho\sigma_1\sigma_2} \quad (13)$$

where ρ denotes the correlation, which is assumed as $\rho = 0.5 \cdot \min(\sigma_1, \sigma_2)/\max(\sigma_1, \sigma_2)$. The practical impact of assuming a dependency between the variables is a more conservative conflated estimate (both on mean and uncertainty interval) than if the variables would be assumed fully independent.

3 Results

Figure 2 shows the estimated uncertainty of hourly energy readings due to meter instrumentation accuracy and quantization effects. For the heat meter (a) the quantization error is a much larger uncertainty source than the meter instrumentation accuracy – the quantization causes severe information loss. For heat

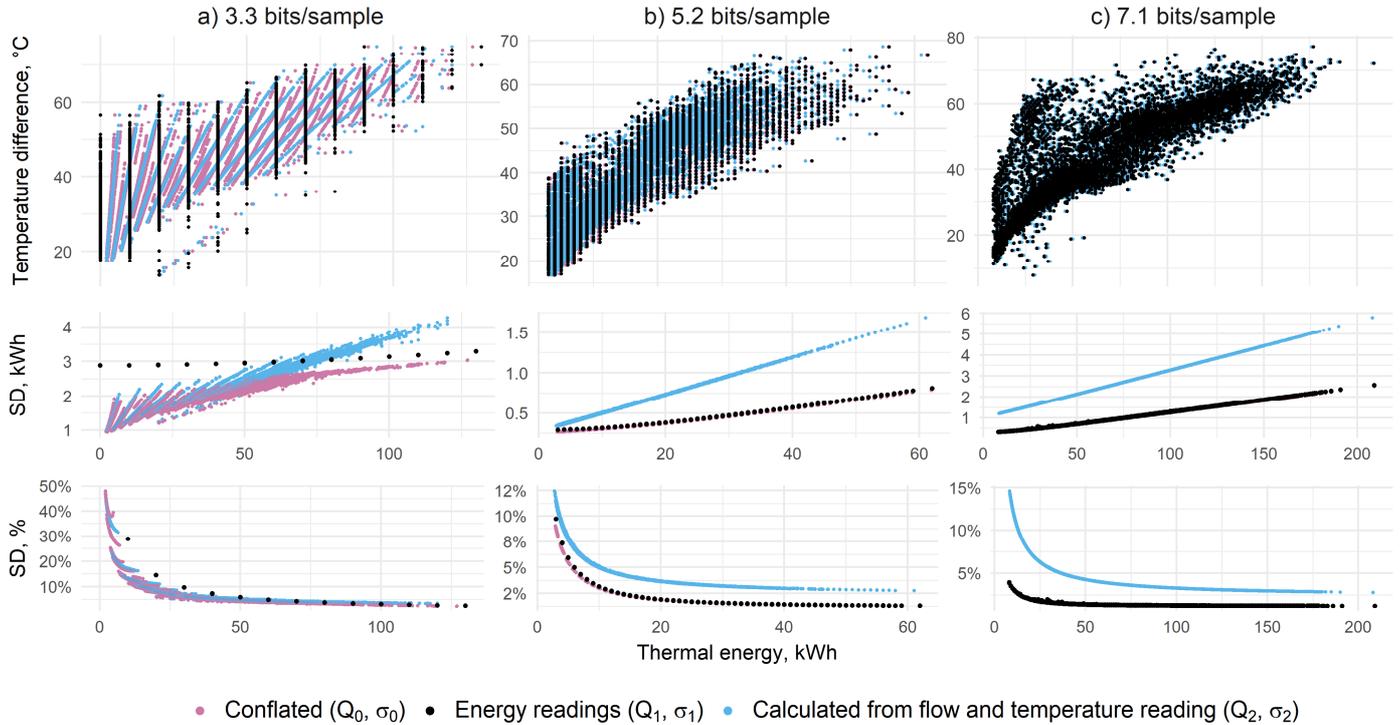


Figure 3. Three example heat meters (columns a, b and c) visualizing the impact of typically occurring quantization errors. Entropy of the hourly energy readings are given in the subtitles. Upper row: energy vs temperature difference between supply and return flows. Bottom row: energy vs standard deviation.

meter (b), the quantization does contribute to increased uncertainty, especially during low energy use conditions. For heat meter (c), the quantization only has effect during very low energy use conditions.

Figure 3 shows hourly energy readings with standard deviation for three example substations. As can be seen in the figure, the uncertainty of the calculated energy quantity (blue dots) dominates under most conditions (due to the high uncertainty in that the instantaneous temperature readings represent the average temperature difference for the whole integration step). However, when the quantization error is large, as in substation (a), the calculated energy quantity is a better estimate than the energy readings (black dots), especially during low energy use conditions. The conflated variable (purple dots) is a weighted estimate that weights the two variables according to their empirically estimated time-varying uncertainties.

4 Discussion

The information entropy ranking method, suggested by Sandin et al. (2013), is suitable for identifying meters with large quantization errors. The method is straightforward to conduct as the only required input are the readings themselves. However, it is dependent on the actual operation conditions, which makes it less suitable to compare meter readings from different time periods or different district heat operators.

There is no explicit regulation regarding the accuracy of the recorded energy readings. Flow meters have a

maximum allowed error (1.96σ) of 5 % at $0.1 \cdot 3_4$ (SWEDAC, 2007) and district heat operators are required to provide their customer with daily energy readings (EIFS 2014:2). Using a 5 % error limit also for the quantization effect on daily energy readings would mean that hourly energy readings still could have entropy values as low as approximately 2.8-3.0 bits/sample.

The next generation of heat meters and data acquisition infrastructure (Kamstrup A/S, 2018) can provide data with higher resolution. However, it will take many years before all current infrastructure is upgraded. Therefore, the suggested conflation method can play a role in improving hourly readings for many years to come.

The proposed conflation method assumes normal distributions. The quantization error is however uniform and can also be biased (Marco and Neuhoff, 2005). The used additive noise approximation ($\Delta/12$) is only valid if Δ is small compared to the quantization levels. Therefore, the proposed method is likely to have some discrepancies and can still be improved. The empirical uncertainty models, equations (4), (5) and (10), are however likely to be a larger error sources than the conflation method or the additive noise approximation. Notwithstanding, the proposed conflated energy quantity Q_C can be anticipated to be closer to the true mean values and have a tighter distribution than and would by themselves.

5 Conclusions

District heat operators should aim at information entropy at minimum of 5 bits/sample (approximately 32 observable quantization levels in a typical year) to ensure qualitative hourly readings.

To ensure high quality readings for the whole metering range and enable sub-hourly sampling, at least 7 bits per hourly sample information entropy is required.

For energy readings with entropy less than approximately 5 bits/sample, the suggested conflation method can counteract part of the quantization error by merging information from the flow and the instantaneous temperature readings, especially during low energy use conditions.

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