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1 **Estimation of Temperature Setpoints and Heat Transfer Coefficients Among Residential Buildings in**
2 **Denmark Based on Smart Meter Data**

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9
10 **Abstract**

11 Thermal comfort preferences of occupants and their interactions with building systems are top influential factors
12 of residential space heating demand. Consequently, housing stock models are sensitive to assumptions made on
13 heating temperatures. This study proposes a heat balance approach, inspired by the classical degree-day method,
14 applied to an extensive urban dataset. The goal of this analysis is to determine heterogeneous characteristics,
15 such as temperature setpoints of heating systems and thermal envelope characteristics from an overall population
16 of residential buildings. Measured energy data are utilized for the purpose of the study from the city of Aarhus,
17 Denmark, where the energy usage for heating of circa 14,000 households was monitored over time via smart
18 meters. These data are combined with actual weather data as well as data extracted by a national building
19 database. Using linear regression and heat balance models, temperature setpoints for the whole dataset are
20 determined with a median and average of 19°C and 19.1°C, respectively. Furthermore, building related
21 characteristics such as thermal and ventilation losses per building and overall heat transfer coefficients are
22 extracted at urban scale. The reliability of the method over its complexity is discussed with regards to the big
23 sample that has been applied to. In general, the overall performance of the approach is satisfactory achieving a
24 coefficient of determination with an average of 0.8, and is found to be in line with previous findings, considering

25 also the high uncertainty associated with building-related input parameters. The extracted setpoint distribution
26 should be transferrable across Scandinavia.

27 **Keywords:** smart meter data, temperature setpoints, housing stock model, thermal comfort preferences, U-values,
28 urban scale

29 **1 Introduction**

30 A number of modeling methodologies have been developed to obtain information on physical resource flows
31 through the building stock [1]. These are mainly used to characterize and predict energy demand of residential
32 building stocks and to estimate energy savings after energy retrofiting strategies. Housing stock models can thus
33 play an important role in supporting energy policy-making. In order to be useful, they should be reliable, efficient
34 and interpretable [2]. Housing stock models can be broadly classified into two categories: top-down and bottom-
35 up approaches. Top-down models rely on historical energy data and cannot model in detail individual end-uses
36 [3]. Bottom-up models consist of engineering-based and statistical models. Statistical methods usually include
37 macroeconomic and socio-economic effects, enable the determination of end-use energy consumption and are
38 easy to develop and be used [4]. However, they cannot model the impact of specific technologies implemented
39 and are less flexible. Engineering-based housing stock models use actual building physics and overcome some
40 of the limitations induced by statistical models [2]. However, the majority of them are developed at national scale
41 to support policy making and disregard heterogeneity within a country. They are also usually time intensive and
42 are fully dependent on input data, hence inducing a high degree of uncertainty. Therefore, there is a need to focus
43 on regional housing stock models that handle heterogeneity.

44 According to the International Energy Agency in the Energy Buildings and Communities Program (IEA EBC) Annex
45 53: Total Energy Use in Buildings, the six driving factors of energy use in building stock are : i) climate, ii) building
46 envelope, iii) building energy and services systems, iv) indoor design criteria, v) building operation and
47 maintenance, and vi) occupant behavior. Even though significant progress has been made in quantifying these
48 primary drivers, more emphasis on energy related occupant behavior in buildings is needed to develop reliable
49 and standardized methods [5, 6]. Neglecting this aspect can lead to severe miscalculations and inaccurate

50 conclusions about the energy performance of the building stock [7]. Occupants' interaction with building systems
51 affects significantly the total energy use of buildings. The occupants' gratification with their thermal environment
52 defines thermal comfort [8]. Therefore, the occupants' perception of comfort or satisfaction in the built environment
53 drives them to perform various controls (e.g. on HVAC systems and window operations) [9]. The adjustment of
54 thermostat setpoints and indoor thermal environment are the most influential factors of heating loads along with
55 heated areas [10]. Some studies have even classified occupants as active, medium and passive users based on
56 their heating setpoint preferences which impact the indoor thermal environment and energy consumption [11, 12].
57 Therefore, thermostat setpoints are crucial input parameters to building energy models due to their big influence
58 on residential energy use [9]. Currently, the understanding of occupant behavior is still insufficient both in building
59 design, operation and retrofit, leading to incorrect simplifications in modeling and analysis [5]. In the past,
60 information about occupants' interactions with systems was based on sporadic visits to households and rough
61 estimates of thermal preferences of occupants.

62 The increasing deployment of intelligent metering systems in buildings and district systems creates a vast amount
63 of building energy use and occupant-related information. Following the Third Energy Package in the Electricity [13]
64 and Gas Directive [14] issued by European Commission in 2006, European countries plan to convert part of their
65 legacy meter stock to smart by 2020 with a focus on electricity. According to the projections, by 2020, it is expected
66 that almost 72% of European consumers will have a smart meter for electricity and about 40% will have one for
67 gas [15]. The enormous amount of information and data opens up endless opportunities for researchers and
68 engineers to study building dynamics and performance at a large scale. In combination with weather data and
69 cross-sectional data, they can be utilized to develop more accurate prediction models and detailed analyses on
70 the drivers of building energy consumption [16]. Smart meter data can also help developing and applying control
71 strategies to improve building energy performance and efficiency [17]. Therefore, they can be utilized to decrease
72 uncertainty related to building energy performance and occupant behavior and provide detailed information on
73 energy monitoring.

74 National building databases and registers can support housing stock energy analysis, by providing information
75 about building typologies and construction characteristics. These databases are usually created with regards to

76 building regulations and schemes. In some cases, information from building owners via questionnaires has also
77 been collected. Building information can be updated by local authorities and by citizens. However, occupants'
78 interventions on the building fabric (i.e. energy renovation measures) are not regularly reported to building
79 databases. Therefore, there is a significant gap between the data that has been registered and the real energy
80 performance of the building.

81 This study aims at utilizing a big urban dataset, consisting of smart meter data from more than 14,000 households
82 in a Danish city, to estimate temperature setpoints and thermal transmittances on building level. In addition, actual
83 weather data, as well as data collected from a national building register and a geographic information system (GIS)
84 have been utilized. A heat balance approach is implemented to the measured energy data of one year applying
85 linear regression analysis to extract parameters that represent the whole heating season and the total building
86 envelope. This approach has been inspired by the degree-day theory and aims at providing a new useful tool for
87 utilities and researchers to extract building and thermal comfort-related characteristics at urban scale based on
88 smart meter data. The data used allows us to capture the full range of heterogeneous behavior among people,
89 through their temperature preferences. The estimation of people's variation enables the development of
90 customized solutions and messages for them. The estimated thermal transmittance of the building envelope
91 indicates the refurbishment state of the building and thus, provides more accurate insights into the building stock.
92 The generated results -in the form of distributions- can be used to improve urban building energy models for the
93 Scandinavian housing stock.

94 The rest of the article is organized as follows. In section 2, related works and methods to predict room temperature
95 setpoints are summarized. In Section 3, we present and apply the heat balance model to the smart meter dataset.
96 In Section 4, the dataset is presented and basic information about the examined housing stock is described. In
97 Section 5, the results are compared and validated with previous findings and relevant literature. The applicability
98 of the methods with regards to the considerations made and the data used is discussed in Section 6. Section 7
99 summarizes the research findings.

100 **2 Background**

101 To evaluate the potential impact of different energy retrofitting scenarios in urban areas, bottom-up urban building
102 energy models (UBEM) have been introduced over the past years. UBEMs have the potential to become key
103 planning tools for utilities, municipalities and urban planners [18]. A key input of UBEM models are building
104 characteristics of a given building stock from thermal envelope properties to usage patterns including the number
105 of occupants, equipment loads and schedules as well as thermostat settings. Some of those information may be
106 derived from census data. However, there is generally a surprising lack of data available related to the thermal
107 performance of buildings. A useful source of information can be derived from individual building energy audits [19].
108 In [19], the authors used the Monte Carlo method and created a physics-based housing stock model for energy
109 performance prediction, where inputs were probability distributions based on an Energy Performance Certification
110 national database. Another source are nationwide building databases which include information such as floor
111 areas, construction materials, age of construction, etc. Nevertheless, these databases may have flaws or may not
112 be updated frequently enough. Therefore, there is high uncertainty related to input parameters of UBEMs.

113 Several studies have been conducted on district or urban scale making use of statistical models and data mining
114 techniques in order to extract hidden useful knowledge from building-related data, as well as to forecast energy
115 consumption. The authors of [20] presented a data-driven approach to modeling end user consumption based on
116 data from 6,500 buildings in Cambridge, Massachusetts, using linear regression analysis and Gaussian process
117 regression. In [21], electric energy data of thousands of buildings were investigated to extract specific features
118 based on socio-economic information. In [17], a data mining method was proposed to analyze building-related
119 data in order to establish building energy demand predictive models and examine the influence of occupant
120 behavior on energy consumption. Older studies had also made use of regression analysis based on billing data to
121 determine household energy. A study by [22] used monthly energy billing data to decompose energy use to
122 weather and non-weather dependent elements, as well as explain anomalies in energy use of some households.

123 Determining the internal temperatures or temperature setpoints has been of particular interest, especially in
124 residential buildings in mostly heating dominated climate since the main source of building energy demand is
125 driven by heating which in term directly depends on the temperature difference between inside and outside.

126 Temperature setpoints and heating duration may differentiate across dwellings based on their preferred thermal
127 comfort range, which affect the resulting internal temperatures. Nevertheless, many top-down urban scale models
128 assume the same constant temperature setpoints for the whole building stock, while the rest calculate internal
129 temperatures as a function of building envelope, occupancy and systems [23].

130 Most of the existing literature puts emphasis on predicting internal temperatures or measuring household room
131 temperatures at district scale based on temperature recordings [24]. For example, the authors in [25] collected
132 temperature and humidity data from 1,604 study dwellings in order to determine the effect of dwelling and
133 household characteristics on indoor temperature variation. The median standardized daytime living room
134 temperature was calculated to be 19.1°C, while the night time bedroom temperature was found to be 17.1°C.
135 Temperatures were affected by the building envelope characteristics, thermal efficiency, number and age of
136 occupants. The socio-economic status was not strongly related to them. In [26], temperature recordings from 821
137 English dwellings were collected and analyzed, which were monitored in different zones within the dwellings. The
138 standardized internal temperatures were estimated by regressing the mean hourly indoor temperatures on outdoor
139 temperature. The results showed that more efficient buildings have higher indoor temperatures at all outdoor
140 conditions, as well as that households with children were the warmest. In another study [23], internal temperatures
141 were predicted at high temporal resolution using panel methods based on data from 280 households. Temperature
142 recordings were taken every 45 minutes for 6 months, while the model was generated using mean daily
143 temperature data. It was concluded that thermostat settings play an important role in reducing total energy
144 consumption. Moreover, centrally heated dwellings and detached homes had lower internal temperatures, while
145 for each additional person living in a household the mean internal temperature increased by ~0.25°C. In another
146 study [27], internal temperature recordings were gathered by 54 households in China, which were found to be on
147 average 13.5°C for living rooms and 12.7°C for bedrooms. These are far outside the ASHRAE steady state thermal
148 comfort zone, highlighting the differences among climates in terms of construction and cultural behavior.
149 Furthermore, the effect of the climate is pronounced on these findings, as this study referred to the 'hot summer-
150 cold winter' climatic zone of China being characterized by relatively low ambient temperatures during winter
151 season -which is quite limited- and very high temperatures during the rest of the year. However, these winter
152 climate conditions are comparable to the ones in UK. The very low internal temperatures noticed in this study are

153 a result of the fact that domestic heating is operated part-time-part-space in that region of China, meaning that
154 only specific rooms are heated up instead of the whole house and only for a shorter time than a usual heating
155 season duration.

156 Apart from the measurement of internal temperatures, some studies have tried to predict them. Most of them refer
157 to smaller cases and make use of simple heat balance models. The authors in [28] used the Domestic Energy and
158 Carbon Model [DECM] to estimate among others the annual internal temperatures in different types of English
159 dwellings, which were on average 18.4°C. The mean internal temperature was also found to be highly correlated
160 with the CO₂ emissions of each dwelling and outweighed the effect of climate and building fabric construction. The
161 authors of [29] proposed a method to explore future transformations in the UK housing stock based on the English
162 House Condition Survey data. Besides energy demand prediction, they used the heat-balance method to infer the
163 appropriate modeling temperatures for a base year in UK. In particular, the profiles for the internal temperatures
164 varied from 14.1 to 18.7°C for one of the two modeled zones, while these temperatures were 3°C lower for the
165 other zone. The study by [30] modeled 37 dwellings employing the BREDEM algorithms [31] and predicted the
166 annual internal temperatures and the heating demand temperatures which equals the temperature setpoint in most
167 cases. It should be noted that most of the afore-mentioned studies refer to the UK housing stock, while there is a
168 lack of similar literature for Scandinavian or Danish building stock.

169 In cases where internal temperatures are not available, degree-days have been used as a tool to assess and
170 analyze weather related energy consumption in buildings for over seven decades. The concept originates from
171 agricultural research, where variation in outdoor air temperature is also important which is also the case for building
172 energy use [32]. Degree-days can be defined as the summation of differences between the outdoor temperature
173 and a building reference temperature (base) over a specified time period for both heating and cooling systems.
174 The simplicity of the concept of heating degree-days (HDD) has led to a plethora of studies in the area of building
175 energy use analysis. The influence of HDD and heating degree hour (HDH) on hourly electricity consumption of
176 hundreds of Norwegian households was investigated and concluded that HDD achieve a slightly higher goodness
177 of fit compared to HDH [33]. The authors in [34] proposed a city-scale degree-day method, according to which
178 they extracted the average building heat loss rate and a city-scale base temperature for the area of Strasbourg in

179 order to estimate the aggregate heating energy demand, while accounting for the urban heat island effect. In
180 addition, residential heating energy requirements and fuel consumption for the city of Istanbul were estimated
181 making use of HDD method and air temperature records, while studying different construction types [35]. A study
182 by [36] utilized energy data to estimate the base temperature of a single building along with the heat loss coefficient
183 and subsequently heating degree-days using Bayesian inference. The performance line method and energy
184 signature method were presented in [37] to estimate the building's base temperature based on daily energy data
185 and outdoor temperatures and to extract degree-days.

186 **3 Method**

187 The method applied in the current experiment takes an existing heat balance approach a step further. The
188 temperature setpoints and total heat loss coefficients are estimated from smart meter data for thousands of
189 buildings. The granularity of energy data is hourly and the sample of buildings covers a large share of a Danish
190 urban building stock, as opposed to previous studies that have been found in literature and cover much smaller
191 building samples. This allows to draw conclusions about the applicability and accuracy of the method applied.

192 **3.1 Main considerations**

193 To treat this urban-scale sample of buildings, the following considerations were made. Firstly, only the coldest
194 days of the year were considered. In particular, only the data that correspond to days when average daily ambient
195 temperature was lower than 15°C were taken into account. In this way, a normal operation of the heating system
196 would be ensured. Moreover, solar gains are reduced in Denmark especially during winter time. This results in
197 transient phenomena being less dominating. Thus, steady-state conditions would be applicable. The investigated
198 buildings are small enough that uniform air mixing was assumed. All households were treated as single-zone
199 models in order to reduce complexity and computation times. In addition, the investigated housing stock is
200 homogeneous with regards to building type (consisting only of single-family houses), allowing a somewhat
201 accurate estimate of occupant density and construction standard. As no information about specified occupancy
202 schedules was available either, internal heat gains were defined according to the Danish Building Research
203 Institute guidelines [38] as 5 W/m² (corresponding to external floor areas), which is a sum for people loads and
204 equipment loads for a residential building. This value was used as an average for all different spaces in households

205 (kitchen, living room, bedrooms etc.), so that it is in line with the single-zone model approach. Furthermore, the
206 'equivalent' temperature setpoint, which represents the volume-weighted mean temperature across all conditioned
207 and unconditioned spaces in every household, was assumed to be constant throughout the heating season that
208 we investigated.

209 **3.2 Calculation of equivalent thermostat heating temperatures and U-values**

210 Inspired by the classical degree-day method and based on the steady-state heat balance for a room, the following
211 formula (equation 1) can be derived. According to that, total energy loads for building space heating over a
212 specified period are directly proportional to the building heat losses that vary with the change in the current indoor-
213 outdoor air temperature gradient (i.e. natural ventilation and air infiltration, wall heat conduction). Similar equations
214 to the following heat balance model, solved for Q_H , have been traditionally used to calculate the heat output of well
215 controlled heating systems [37].

$$T_o = T_i - \frac{Q_H + Q_{SG} + Q_{IG}}{UA + c_p \rho n} \quad (1)$$

216 where T_i is the equivalent internal temperature in °C, T_o is the ambient temperature in °C, Q_H is the heating demand
217 in W, Q_{SG} stands for solar gains in W, Q_{IG} represents the internal heat gains from occupants and equipment in
218 W/m², U is the overall heat transfer coefficient across the building envelope in W/m²K, A is the total envelope area
219 in m², n is the ventilation or infiltration rate in m³/s, c_p is the specific heat capacity for air under constant pressure
220 which equals to 1000 J/kg K and ρ is the density of air which equals to 1.2 kg/m³. The heat loss factor due to the
221 air change can be also simplified to equal $0.33 N V$, where N is the ventilation rate in air changes per hour (ACH)
222 and V is the volume of the building in m³.

223 Due to the extensive data quantity both in terms of number of monitored buildings and data granularity, complicated
224 approaches would be less suitable. So, the methodology applied in this case was simple linear regression analysis.
225 The ordinary least squares (OLS) method was used and run for each household's data. According to [39], the OLS
226 method is the most efficient for urban scale models having the lowest deviation from measured data.

227 The four main statistical assumptions regarding OLS method were tested to prove whether they were satisfied on
228 building level: the regression is linear in parameters, the sampling of observations is random, the conditional mean
229 is zero and there is no multi-collinearity.

230 Thus, in the current model, the ambient temperature T_o was modeled as an affine function of the total energy load,
231 so that $T_o = T_i - \frac{load}{losses}$, where $load = Q_H + Q_{IG} + Q_{SG}$ and $losses = UA + 0.33 N V$. The internal temperature or
232 temperature setpoint and the losses are expressed by the intercept and the slope of the linear model, respectively.
233 The losses represent the envelope and ventilation losses. The energy load quantity will always be positive. Q_H
234 represents the space heating consumption of the households which was given on hourly resolution. However, in
235 order to account for latent thermal mass effects in the buildings, it was decided to aggregate the hourly energy
236 data on daily basis and report the aggregate value of energy consumption (heating). Thus, internal temperatures
237 in equation 1 refer to the mean of internal temperatures recorded, representing the relative heating profile of a
238 dwelling. The internal gains were also aggregated on a daily resolution based on the indicated hourly values.

239 In the afore-described model, the heat losses are mainly attributed to conduction through the building envelope
240 and to ventilation losses. For that reason, we are focusing only on the winter time or heating season when the
241 ambient temperatures are low; furthermore, the solar gains are significantly lower. Thus, as mentioned before,
242 the regression model was restricted to periods when the mean ambient temperature was less than 15°C.
243 Information concerning building characteristics and occupancy were retrieved by the national building database
244 and by national building regulations, where no detailed information was available. Actual weather data on hourly
245 resolution were acquired for the area of Aarhus covering the examined period (2014-2015) and included ambient
246 temperature, solar radiation and relative humidity.

247 The calculation of solar gains was based on the actual weather data available for the area consisting of direct and
248 diffuse radiation. An exemplary building was made in DIVA software [40], which is a daylighting and energy
249 modeling plug-in for Rhinoceros, according to a Radiance calculation, where time-integrated solar irradiance on
250 each surface was calculated as presented in [41, 42]. Radiance is a backward raytracer that was originally
251 developed at Lawrence Berkeley National Laboratory [43]. An average value of integrated solar irradiance for all

252 four surfaces of an exemplary building was taken, which was then inserted into the model. According to the
253 following equation (2), the solar gains are calculated as the product of overall solar heat gain coefficient (*SHGC*),
254 projected area of fenestration A_f in m^2 and incident total irradiance E_t in W/m^2 .

$$Q_{SG} = SHGC_t A_f E_t \quad (2)$$

255 To estimate the equivalent overall heat transfer coefficient of the building envelope for each household, the losses
256 factor in equation 1 had to be determined. The geometry of the houses (i.e. envelope areas) was available through
257 an additional dataset consisting of GIS data at city scale. Therefore, the ventilation and infiltration rate had to be
258 determined taking into account the type of mechanical systems installed in each house, possible insulation state
259 of building envelope and air leakages.

260 **4 Data**

261 **4.1 Typical dwelling characteristics in Denmark**

262 Approximately 45% of Danish dwellings are detached houses [44], although their share is significantly less in
263 larger cities (e.g. Copenhagen or Aarhus). A large share of heating (namely 63%) in private Danish houses is
264 provided by district heating, which covers both space heating and domestic hot water demand [45]. Hydronic
265 systems are the most common heat emission systems found in residential buildings. Mechanical cooling and
266 ventilation is mostly available in commercial buildings. The national average energy consumption for Danish
267 single-family houses constructed in the period before 1980 is 151 kWh/m^2 per year and 102 kWh/m^2 per year for
268 houses constructed between 1980 and 2000 [46]. That gives an indication of the energy efficiency of the
269 investigated building stock. Moreover, according to the Danish building regulations, there should be a sufficient
270 amount of thermal mass and insulation layer in newer buildings, which results in more airtight building envelopes.
271 More information and typical building construction examples of Danish single-family houses can be found in [47].

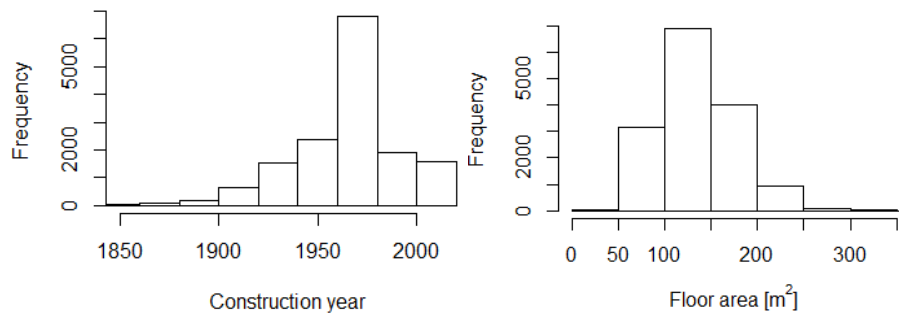
272 **4.2 Description of smart meter data**

273 Our approach is evaluated on basis of smart meter data collected initially from 15,063 households in Aarhus,
274 Denmark at a 60-minute granularity of one full year. The data is provided by Aarhus AffaldVarme (AVA), which
275 supplies district heating to the inhabitants of Aarhus. The data ranges from August 2014 to August 2015. The data

276 contains the heating consumption of residential AVA customers. The households are all single-family houses
277 (SFH). The periods that the data cover range depending on when each of the smart meters was installed. There
278 is a slightly smaller number of smart meters that have recordings for the whole investigated period. Thus, energy
279 data from 14,182 households are utilized in the experiment, which correspond to the whole examined period. The
280 data has been cleansed and aggregated at a daily time scale and the results of this analysis are presented in the
281 results' section.

282 4.3 Building characterization

283 The dataset covers a big spectrum of single family houses in Aarhus, ranging from buildings constructed in 1800
284 to 2015. The floor areas range from 25m² to 504m², with a mean of 134m². The number of floors varies between
285 1 and 3, with the majority of the buildings being single-floor houses. These information are presented in Figure 1.



286
Figure 1. Building information of dataset

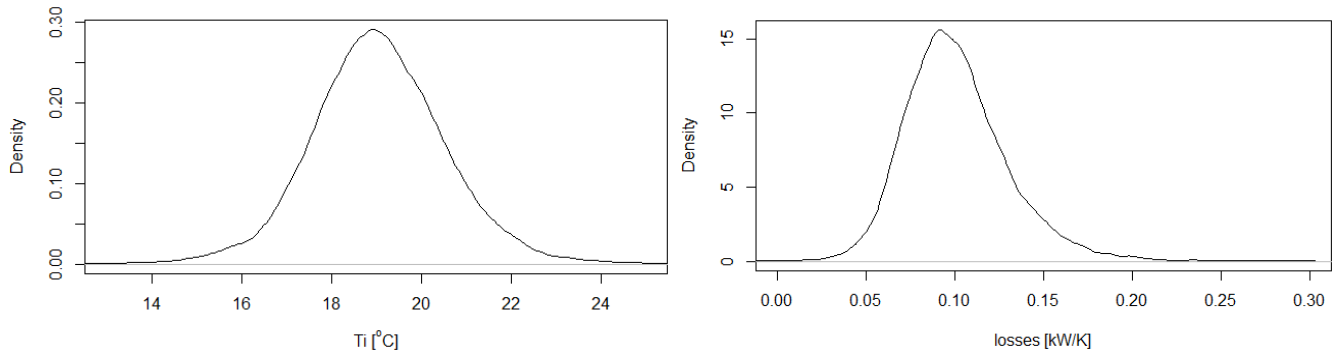
287 5 Results

288 The afore-mentioned method was applied to smart meter data of 14,182 households over one full year and the
289 results are presented hereafter.

290 5.1 Variables' distributions

291 Figure 2 presents the main results of this study, which are the temperature setpoint distribution and the distribution
292 of the total envelope and ventilation loss factor for all examined households, as estimated according to equation
293 1. As it can be seen, the mean equivalent temperature setpoint that was calculated for the whole sample of
294 buildings was 19.1°C, while the median value was 19°C. The standard deviation was 1.54°C. This temperature is

295 a bit lower than the expected indoor temperature value, which would be close to 20°C according to estimations of
296 the Danish Building Research Institute [48] included in Danish Standards [49]. It can be attributed to two reasons.
297 First, every household is modelled as a single-zone, which means that any unconditioned spaces are also included
298 and represented with this specific equivalent parameter. Second, this figure refers to equivalent temperature
299 setpoint, which is inferred over a whole season. So, unoccupied periods and hours with night-setback are also
300 included in this estimation. The internal heat gains that were assumed in the model proved to have a decisive
301 impact on the temperature results, so higher internal gains than the ones defined in the standard would lead to
302 higher temperatures. Nevertheless, the uncertainty associated with the internal and solar gains did not result in
303 high inaccuracy of the model. Daily internal heat gains ranged from 5 kWh to 110 kWh among the different
304 households. The temperature setpoint distribution seems to approach normality, while the building envelope and
305 ventilation losses graph approximates a log-normal distribution curve. The mean building envelope and ventilation
306 losses were calculated to be 0.1 kW/K with a standard deviation of 0.03 kW/K. Additional conclusions can be
307 drawn on how close to expectation the current used model has performed and the goodness of the accuracy that
308 can be achieved at such a large scale. Despite the steady-state heat balance model that was applied on the
309 building sample and the considerations that were made about input parameters, the results indicate a reasonable
310 range of temperature setpoints and loss factor across the dwellings. In order to interpret the thermal environment
311 and thermal comfort that occupants perceive based on the estimated equivalent internal temperature, the
312 Predicted Mean Vote (PMV) and Predicted Percentage Dissatisfied (PPD) indices proposed by Fanger [50] were
313 used. The average PMV was calculated to be -0.6, which corresponds to PPD equal to 12.9%. Based on these
314 estimations, the thermal environment falls into Category C out of the three desired thermal environment categories
315 as described in [51].



316

317

Figure 2. Distribution of temperature setpoint (left) and total building envelope and ventilation losses (right)

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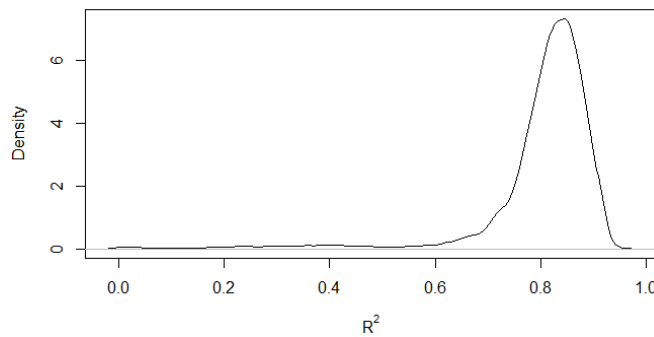
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To assess the goodness of the fit for the simple linear regression models, the coefficient of determination (R^2) was utilized to estimate the variance of the predictable variable from the independent variable. The results are presented in Figure 3. It has to be noted that a relatively high R^2 is achieved with respect to the nature of the experiment, which regards end users energy use. The mean and median value of the coefficient of determination were found to be 0.8 and 0.83, respectively, with a standard deviation of 0.11. That confirms the good fit of the linear regression models to the smart meter data, as well as a quite consistent model, considering the large amount of data that has been used.



325

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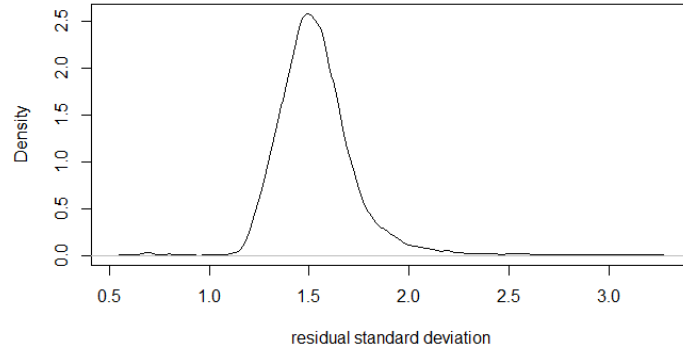
Figure 3. Distribution and boxplot for R^2 for all houses' fits

327

328

In Figure 4, the residual standard deviation distribution is illustrated, which can indicate the variability of predictions in the regression. This shows the deviation of the errors and not the errors of the regression themselves. It can be

329 observed that the deviation of the residuals has a mean of 1.53, which is satisfactory considering also the big
330 building sample.

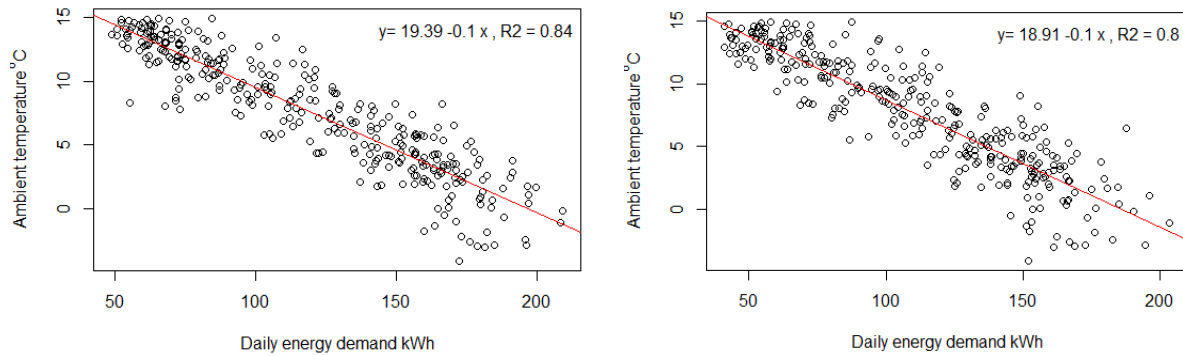


331

332 *Figure 4. Residual standard deviation distribution for all houses*

333 5.2 Exemplary households

334 The regression models for two randomly selected households are presented hereafter. The intercept of the models
335 represents the estimated temperature setpoint, while the slope stands for the coefficient of envelope and
336 ventilation losses. The coefficient of determination for these two cases were $R^2=0.84$ and $R^2=0.8$, respectively.
337 The estimated temperature setpoints for these two models were 19.39°C and 18.91°C, respectively. Both models
338 are quite similar, with the household presented to the right having a bit more scattered energy use data and higher
339 number of outliers.



340

341 *Figure 5. Regression fit for two random households*

342 **5.3 Regression diagnostics**

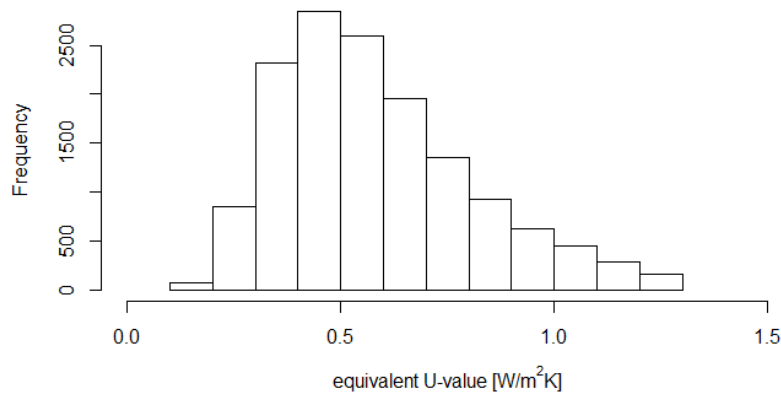
343 The main assumptions of OLS were tested for numerous randomly selected models and the following conclusions
344 were drawn. First, normality was tested by checking the probability plot of the standardized residuals against the
345 values expected under normality, concluding that the normality assumption is satisfied. Second, the residuals did
346 not have non-linear patterns, confirming the linearity condition. Third, the constant variance assumption was met,
347 since the residuals were spread equally and randomly along the ranges of predictors. The errors of the regression
348 models had zero mean as required by the Gauss-Markov theorem. The independence assumption was also
349 satisfied. Lastly, the outliers that were influential to the regression results were determined. That means that these
350 may be influential to the regression analysis and the results will change if we exclude these cases.

351 **5.4 Estimation of equivalent total U-value of building envelope**

352 After the total loss factor for each household was calculated, the equivalent overall heat transfer coefficient, U-
353 value, for the building envelope was calculated. This would provide additional valuable information for the
354 insulation state of the buildings and indicate any possible energy refurbishments. Thus, the ventilation and
355 infiltration rate on building level had to be determined. According to [52], the infiltration rates for Danish single-
356 family houses vary between 0.1 and 1 ACH. These were estimated for each household in accordance with
357 available information about the age of the building and construction characteristics extracted from the national
358 building register. Specifically, an algorithm was used according to which the infiltration rate took values in $[0.1, 1]$
359 based on the construction year of the building and a binary variable that indicated if the house had undergone any
360 energy renovation that has been registered in the national building database. These two factors would collectively
361 indicate any thermal bridges on the building envelope affecting the infiltration rate. The estimated infiltration rate
362 for each household was assumed to be constant throughout the course of the day. The mean value of natural
363 ventilation rate for the investigated building stock was estimated to be 0.5 ACH. Rough information for the
364 geometry of the houses and the envelope areas on building level was available through the Danish Building
365 Register (BBR) [53]. BBR is a nationwide register including data for the majority of Danish buildings and
366 households. Nowadays, it contains information about 1.6 million properties, 3.8 million buildings and 2.7 million
367 dwellings and commercial units [54]. It was originally set up in 1977 by collecting information from building owners

368 via questionnaires. Since then, it has been updated by local authorities and by citizens [55]. Data contained in
369 BBR -provided for every registered house- are categorized into areas, building constructions and installations.
370 Information about areas can be summarized to the following: total building/residential/commercial area, built-up
371 area, number of storeys, attic and total basement area. The information extracted for the current analysis was the
372 building footprint area and the number of floors for each building. This information was then coupled and validated
373 with an open-source GIS dataset for the city of Aarhus [56]. Thus, the total envelope area for each building was
374 extracted, as well as the total building volume.

375 The results of this analysis are presented in Figure 6. The distribution approximates a log-normal curve. The mean
376 value of the equivalent U-values for the examined residential building stock is calculated to be $0.58 \text{ W/m}^2\text{K}$ with a
377 standard deviation of $0.22 \text{ W/m}^2\text{K}$. The median value is $0.54 \text{ W/m}^2\text{K}$. This finding gives insight into the state of the
378 building envelopes across Danish SFH, as well as their current energy refurbishment state. According to the
379 Danish Building Research Institute [57], the average area-weighted U-values of Danish single family houses -as
380 calculated with regards to the national building regulations- mainly vary from 0.3 to $0.65 \text{ W/m}^2\text{K}$ depending on the
381 construction age of the building. It should be noted that the majority of the investigated single-family houses were
382 constructed in the 1960's, which have an average area-weighted U-value of $0.52 \text{ W/m}^2\text{K}$ according to [57]. The
383 overall heat transfer coefficients of the buildings do not always comply with the ones defined in the national building
384 databases or introduced by the building regulations. Therefore, the calculated U-values can determine the level of
385 energy refurbishment that might have been implemented to the buildings. Such updated information, although very
386 important for energy calculations, is missing from the majority of the Danish building register [58]. The results from
387 this study can also validate existing values in building databases. In addition, since this equivalent U-value
388 summarizes the heat transfer coefficient for the whole building structure, no specific conclusions can be drawn for
389 the particular building components. However, they can be assessed in combination with the rest of building
390 characteristics and reveal valuable information about the building energy performance of the stock.



391

392

Figure 6. Distribution of equivalent U-values for the building stock

393

6 Discussion

394

The proposed method aims at investigating the applicability of a simplified heat balance approach on smart meter data to derive temperature setpoints and thermal transmittances at urban scale. Our analysis focused on fitting the overall heating energy distribution across the investigated building stock. The lack of information about the share of heated and unheated space resulted in the use of an equivalent temperature setpoint, which represented the volumetric mean temperature indoors. That means that there may be rooms that are warmer (i.e. occupied spaces) and rooms that are cooler in a building. However, the scope of our analysis was to treat the whole building as an entity. In Danish building regulations and directives, a dimensioning internal temperature of 20°C is commonly used for the majority of Danish houses. However, it is also mentioned that in older poorly insulated houses, the room temperature can be even lower than 20°C or some rooms are unheated to reduce the heating costs [48]. The thermal environment evaluation was conducted assuming that the living spaces (i.e. whole house) were heated. However, if unheated spaces were to be evaluated, the desired thermal environment follows a different classification. According to steady-state conditions of the model, changes in temperature setpoints were not taken into account. The use of a steady-state model resulted in extreme conditions and transient states not being taken into account. If a transient model was to be used instead, the temperature setpoint would no longer be represented by a single value for the whole heating season but replaced possibly with daily or even hourly

408

409 ones. Moreover, the assumptions on constant infiltration rates throughout the day and over the heating season
410 and constant internal gains throughout the day and among the different households would have to be adjusted. In
411 particular, varying heat flow rates from occupants and appliances could be used based on hourly schedules and
412 differentiating between weekdays and weekends. Nevertheless, the current study aimed at producing results that
413 could be utilized subsequently by urban building energy models or housing stock models, which in their majority
414 require a single heating temperature setpoint per building or zone. Thus, it would be outside the scope of this work
415 to calculate dynamic temperature setpoints. In addition, this would increase the computational complexity
416 enormously and subsequently the computation time for urban-scale or district-scale building stocks.

417 The biggest uncertainty on the total energy load factor comes from the internal gains and solar gains factor. Internal
418 gains were assumed to differentiate according to floor area based on Danish standards. As a result, the residents
419 of the investigated area were assumed to have the same occupancy patterns. Internal gains depend on occupancy
420 behavior and schedules, as well as cultural patterns that can be estimated but not be predicted accurately at a
421 large scale. Thus, a certain amount of assumptions based on recommendations by standards had to be taken,
422 which resulted in a higher uncertainty in the housing stock model predictions. Solar gains had comparatively
423 smaller impact on the energy load and the assumption about an average orientation did not seem to affect
424 significantly the results. This should be considered in combination with the local climate, which in this case is
425 characterized by relatively low solar radiation during the heating season and low ambient temperatures.

426 Despite the considerations that were made regarding the envelope properties, the performance of the proposed
427 approach was satisfactory compared to existing knowledge and statistical values included in literature. The
428 analysis was run on a private scientific cloud (SciCloud) using a web-based interface to interact with the data [59].
429 SciCloud consists of 18 physical servers with 80 cores and 564 GB of memory, as well as 4.2 TB of node storage,
430 plus 1.2 TB of network storage. The environment used for the data analysis was *R*. The computation time for the
431 whole housing stock analysis did not exceed two hours, due to the low complexity of the heat balance models and
432 the OLS method. Therefore, the proposed model is expected to balance predictive accuracy and parsimony. If
433 more complicated heat transfer phenomena were to be included in the model, the computation time would increase
434 significantly. The big amount of historical measured energy data led to statistically significant results and

435 strengthened our methodology. On the other hand, such large-scale energy data are mostly available to utilities
436 and less to the research community due to privacy issues. Anonymization techniques can be applied and facilitate
437 significantly the data acquisition and publishing process.

438 Measurements of internal temperatures for a smaller sample of the examined building stock would validate this
439 methodology. The installation of smart sensors in newly constructed buildings measuring internal temperatures in
440 rooms would allow this. However, the share of newly constructed buildings remains quite low in the city of Aarhus
441 and the employment of smart sensors in the existing building stock would be a relatively long and costly procedure.
442 Moreover, the application of the proposed method on a much smaller sample, which more detailed building and
443 occupant-related information (i.e. infiltration rates, occupancy schedules) would be available for, would be a next
444 step to continue this study. In this direction, occupant data could be used to approximate internal heat gains more
445 accurately. The current sample is a relatively homogeneous building stock, including only single-family houses in
446 the same urban area. Their thermal envelope characteristics varied a lot, though, in terms of building envelope
447 insulation, construction materials and geometry. Thus, a wide range of building construction types was covered.
448 Our method proved to work reliably on the examined stock with regards to the number of assumptions that were
449 made. This resulted in the estimated parameters including high second-order uncertainty. To cope with this
450 uncertainty, probabilistic methods would be required which would be less attractive for this case of thousands of
451 buildings. Despite the uncertainty included in the input variables and estimated parameters, heterogeneous
452 preferences of occupants regarding thermal comfort were determined successfully. Nevertheless, further work
453 needs to be carried out to investigate how it can be expanded upon more diverse building stocks. Finally, the
454 Danish climate is characterized by decreased solar gains and cold winters, which make the transient phenomena
455 being less dominating. If this work was to be reproduced to different climates with increased solar gains, the quasi-
456 steady-state conditions would be less valid. Also, equation (1) would have to be adjusted accordingly so that a
457 utilization factor for solar heat gains (e.g. function of time constant) is included that accounts for the dynamic heat
458 flows within the building.

459 **7 Conclusion**

460 This study has utilized an urban dataset of more than 14,000 households in Aarhus, Denmark to derive
461 temperature setpoints and overall heat transfer coefficients at house level. This dataset comprised of measured
462 daily heating energy data, actual weather data, basic building typological data and geometry information extracted
463 from a building register and GIS data. A heat balance model –inspired by the degree-day theory- was proposed
464 and applied in combination with linear regression analysis. The results showed that a good fit was achieved overall
465 in the majority of the examined households. The results provided distributions of i) equivalent temperature
466 setpoints, ii) a factor for building envelope and ventilation losses, as well as iii) equivalent U-values for the building
467 envelopes. The average equivalent temperature setpoint was calculated to be 19.1°C across the investigated
468 Danish dwellings, considering both heated and unheated spaces in the buildings. This value represented the mean
469 volumetric temperature indoors. The mean overall heat transfer coefficient for the total building envelope of all
470 houses was estimated to be 0.58 W/m²K. The mean value of the coefficient of determination (R²) was 0.8,
471 indicating a good fit of the linear regression models. It was found that Danish homes differed in heating setpoint
472 temperatures and envelope insulation state. The energy data was proven to be highly correlated with the weather
473 data (consisting of ambient temperature and solar radiation), as expected. Statistically significant results have
474 been reported due to the big sample size and the consistent and granular energy measurements. Therefore, the
475 proposed steady-state approach is applicable and recommended for urban-scale building samples when a uniform
476 setpoint temperature is adequate to be extracted for the whole heating season. Furthermore, overall heat transfer
477 coefficients for the whole building envelope can be used to determine any possible energy retrofit measures that
478 have been applied to the envelope. Moreover, this method enabled the capturing of the full range of heterogeneous
479 behavior among people, as reflected on their temperature preferences. These findings are important to
480 characterize the thermal comfort preferences of occupants and their interactions with the building systems, which
481 are top influential factors of residential heating energy loads.

482 The interest of using this method goes beyond the results that are presented here. The study provided insights
483 that will help direct future research in identifying ways to estimate temperature setpoints, assess indoor thermal
484 comfort and consequently improve urban building energy models. Thus, customized messages and solutions for

485 occupants can be developed. Furthermore, it provided better understanding of the Danish building stock and its
486 occupants, which is crucial in building energy demand calculations. Thus, the given methodology can be applied
487 to large scale smart meter datasets to acquire building-related and thermal comfort-related characteristics. In
488 addition, it can provide valuable information to utilities to further optimize their network and apply advanced
489 technologies (i.e. virtual storage on district heating network) based on the temperature setpoint distribution of the
490 district. The proposed simplified approach opens up new possibilities of building performance analysis at urban
491 scale. Next step would be to couple this energy dataset with internal temperature recordings, which would enable
492 the validation of the estimated variables at urban scale. In that way, the current findings could be utilized to
493 challenge assumptions used in Scandinavian housing stock models regarding heating patterns and mostly,
494 temperature setpoints throughout the heating period.

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