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From showers to heaters: Evaluating the different factors that play a role in buildings' energy signature

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Abstract:

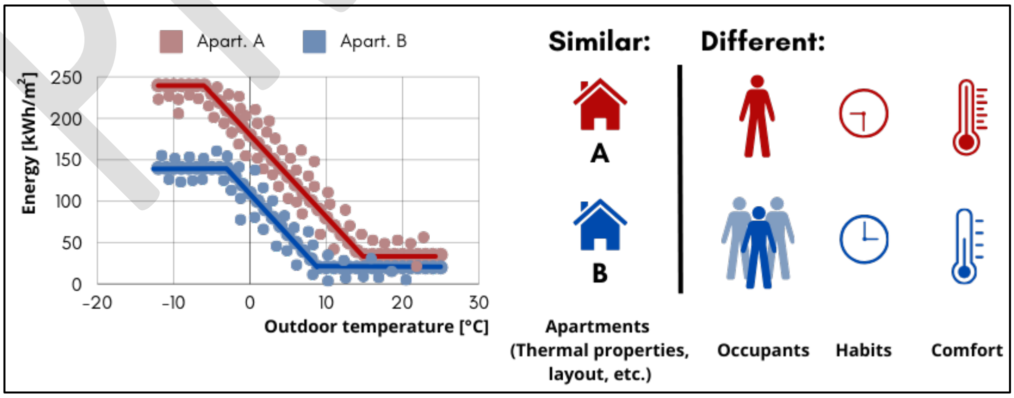
In the realm of energy sustainability, accurately evaluating the impact of domestic hot water (DHW) production on energy signature (ES) models is critical. Traditional approaches have often overlooked or simplified this aspect, potentially skewing efficiency assessments. This study aims to rectify this by dissecting the influence of DHW on ES models and exploring the occupancy heating habits that shape energy usage profiles. Employing a dataset from a small number of Danish apartments, this work delves into the differential energy impacts of DHW production and space heating (SH) operations on the ES model. The study investigates the ES model's applicability across similar apartments and examines whether SH operational patterns significantly alter the model's predictive accuracy. The findings reveal that the incorporation of DHW production into ES models is necessary but not as significant as someone might assume. Occupant behavior, particularly concerning SH habits, seems to be one of the most influential indicators in shaping the ES. Moreover, the study presents the sigmoid ES model as a robust alternative to the prevailing linear ES model, elucidating the reasons behind its distinct asymptote points. The research concludes that the sigmoid ES model displays an improvement in capturing the complexities of building energy dynamics. These insights pave the way for more refined energy assessments, with implications for policy-making and energy management in residential buildings.

Keywords: Linear and sigmoid energy signature, Domestic hot water, User-driven energy usage, Space heating efficiency, Indoor sensor integration.

Highlights:

- Analyzed DHW usage reveals stochastic patterns with consistent median levels.
- ES parameters vary significantly across similar buildings and spaces.
- Occupant behavior impacts heat performance more than thermal characteristics.
- Window opening behavior seems to affect the upper asymptote in the ES model.
- Integrating sensor data provides deeper insights into energy usage patterns.

Graphical abstract:



Introduction

The impact of climate change is being felt across the globe, with rising temperatures, extreme weather events, and the loss of biodiversity. To mitigate these effects and ensure a sustainable future for generations to come, the reduction of carbon emissions and energy usage is crucial. In the European Union, the energy share in buildings accounts for 40% [1]. Due to this large share and knowing that people spend most of their time in their homes [2], a deeper knowledge of the building's energy usage is required. On the Danish side, energy efficiency has been under much focus, and it has been one of the main drivers of building regulations [3]. Energy-efficient buildings have lower energy usage and operating costs and are designed to secure the health and comfort of occupants. However, to attain these benefits, accurate and reliable methods for energy analysis are necessary. This analysis allows building owners and designers to understand how energy is used within a building, identify areas of inefficiency, and develop strategies to improve the building's energy performance. When considering the analysis frameworks in civil engineering, models with different accuracy and complexity are needed for different applications: e.g., early-design parameter optimization, model-predictive control, energy demand baselining, urban-scale modeling, and energy performance assessment, to name a few. Nevertheless, the selection of an appropriate method depends on several factors, e.g., the building's characteristics, energy use patterns, or other specific project objectives. Therefore, the correct choice of suitable, accurate, and reliable methods is essential to ensure that energy-saving measures are effective and provide tangible benefits.

One of these methods is the Energy Signature (ES) model, which is based on the analysis of the correlation between energy usage in buildings and outdoor temperature. This model due to its simplicity and integrability in different analysis frameworks is one of the most applied in the academic and industrial context. Moreover, since the early 1900s, this method has been used [4], and further applied in academic articles, and improvements have been discussed and proposed on how to use this model accurately [5]. However, due to the increasing availability of smart energy meter data, this methodology has been applied much more for the operational energy assessments, and it has been combined with other computational simulations, and also compared with more complex methodologies [6–8]. This study examines the application of the ES model, paying particular attention to certain characteristics that in the authors' opinion, have not been thoroughly explored or have been simplified in previous research

Background

The ES model, also known as the change-point model, expresses the buildings' energy demand as a function of the outside temperature, according to the ASHRAE guideline 14 [9]. In the guideline, it is explained that this model is steady-state and can have from one to several representative parameters, depending on the HVAC systems present in the assessed building. According to the guidelines, it is a useful tool for understanding how a building's energy use changes with the weather, and for identifying opportunities for energy savings. The ES can use different types of energy outputs (e.g., electricity, cooling, heating, etc) and it can also show the operation of different systems working simultaneously or a singular system operating with different operation settings. In this study, we focus on the ES model applied to residential buildings with water-based heating and without cooling systems. The representative parameters that define the ES for only heating systems are seen in Table 1 and represented in Figure 1.

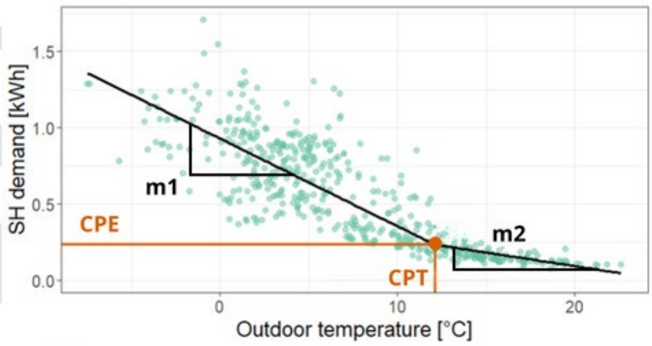


Figure 1: Representation of the ES model for heating purposes.

Table 1: Main characteristics and definitions of the ES model.

ES parameters	**Definition**
Heating season slope (m_1)	Slope of the ES model concerning the heating season.
No heating season slope (m_2)	Slope of the ES model concerning the no heating season.
Change-point temperature (CPT)	Outdoor temperature limit when the seasons change.
Change-point energy (CPE)	Energy demand limit when the seasons change.

Using the parameters presented in Table 1, the model is defined by a set of two equations corresponding to a continuous piecewise linear function over two distinct ranges, E_h and E_{nh} refer to the heating and no heating seasons, respectively:

$$\begin{cases} E_h = CPE + m_1(CPT - T_{out}), & when\ T_{out} \leq CPT \\ E_{nh} = CPE + m_2(CPT - T_{out}), & when\ T_{out} > CPT \end{cases} \quad (1)$$

In Denmark, a larger portion of residential heating systems are based on a substation connected to the district heating network that fulfills the combined demand of space heating (SH) and domestic hot water (DHW) production. The SH is the energy needed to heat the building's interior and is mainly driven by the dynamic heat balance between the building's thermal inertia, heating and ventilation output systems, miscellaneous heat gains (e.g., solar, people, equipment, etc.), and heat losses (e.g., transmission and ventilation). The DHW is the energy used to heat water for bathing, washing, and other domestic purposes. The DHW demand throughout the day is quite stochastic and can increase significantly during peak usage times, such as in the morning and evening. Due to this, when plotting the ES relation, it is always assumed that the main reason for outliers is the randomness and different intensities inherent in DHW production due to the direct influence of the occupants on tapping usage [10]. However, literature also shows that when taking the ES model, often the DHW is accounted as constant [11]. Thus, this opens the question, of whether the DHW is as constant or irregular as some theorize when applied to the ES. Therefore, this is the first topic that this manuscript attempts to address.

Regarding the ES overall methodology, several research articles in the literature have applied this model to investigate the following topics:

- SH and DHW estimation [11,12].
- The impact of the outdoor temperature on the building's energy use, by analyzing the slope of the linear trend [13-17].
- The potential for energy savings through refurbishment initiatives applied in buildings [18-20].
- Fault detection applications of heating systems [21-23].
- Application of the ES to large urban areas to investigate the building stock [24-26].

Regarding the last topic, some studies have focused on characterizing buildings' thermal characteristics based on the ES model values described in Table 1. However, this opens another question – are these ES properties similar in alike buildings and spaces? This question is also addressed in this study, by analyzing the ES performance for four similar residential apartments with the same construction and thermal characteristics.

Lastly, other research contributions have focused on the specificities of this model itself, where a few works investigated the following key ideas:

- Pros and cons of the ES model [5]
- Improvement of the robustness of the ES model [27-31]
- Proposing another type of ES model based on a sigmoid function [8,32,33]

Regarding the last listed point, these articles proposed that the ES model should be a sigmoid function instead of a linear change-point model. In [33], it is discussed that the sigmoid behavior is observed, and it is theorized to be due to significant changes in venting/ventilation routines by the users or by the supply temperature limitations when reaching extremely low outdoor temperatures. Therefore, another question is raised, regarding the reasons behind the horizontal asymptotes for data points in the sigmoid model. As known, the lower asymptote point is due to a change of heating/no heating seasons, analogous to the CPT in the linear ES model. However, the reason for the upper asymptote point (at low outdoor temperatures) is still unclear. Therefore, this study also attempts to shed some light on the reasons behind the upper limit point when the outdoor temperatures are low using other sensor data retrieved from the measurement campaign [34]. The sigmoid function is represented and discussed further in the Methodology section.

Contributions and novelty of the current study

Due to this combination of different heating demands (SH+DHW) that coexist in the ES representation, this manuscript focuses on the analysis and effect of the DHW production on the ES methodology. As theorized, the DHW energy usage must have an impact on the overall ES model. Until now, this impact was neglected or set constant when applying this methodology. However, for the research's sake, this influence must be tested, which can only be done, if a separate measurement of DHW and SH is available. Also, this work attempts to address the different user heating habits and their influence on the ES model. Lastly, the sigmoid ES model is proposed, analyzed, and compared with the current linear ES model while addressing its properties.

Therefore, the contributions of this paper are the following:

1. The application of the proposed methodology in a small dataset of Danish apartments to evaluate the impact of including/excluding the DHW energy use on the ES model results.
2. To evaluate the applicability of the ES model for the assessment of overall building/apartment heating efficiency and fault detection potential.
3. To investigate and discuss the suitability of the sigmoid ES model in building energy assessment.

Outline

Following the *Introduction*, the *Methodology* section describes the dataset utilized in this work and the assessment methodology developed to answer all questions raised above. The results from the assessment are examined in the section *Results and Discussion*. The manuscript closes with *Conclusions* and *Suggestions for Further Work*.

Methodology

Building case description

The measurements dataset comes from the Danish demo case of the European project E-DYCE situated in Frederikshavn, Denmark [35]. The overall building was built in 1972 and was renovated in 2011, and encompasses a total of 28 apartments, covering a heated space of 3,120 m^2. It is divided into three different addresses (staircases). Each staircase spans four or six floors, housing two apartments per floor. The present study investigates four apartments on the same staircase where two of them are positioned on the first floor, one on the second floor, and one on the ground floor. In 2021, an energy performance certificate was issued for the building, assigning it an energy label of B. This classification indicates that the building's total energy usage for all appliances is expected to be below 71 kWh/m² per year.

Regarding the apartment's heating systems, the SH operates through a central mixing loop powered by district heating, located in the basement's technical room. While all apartments receive the same temperature from this loop, however variations in the actual temperature may occur due to pipe distribution losses. Additionally, each stairwell has mechanical ventilation equipped with heat recovery and a heating coil, also drawing from the main mixing loop. The centralized hot-water production is implemented through a heat exchanger that feeds a circulating loop connected to all apartments. Every apartment is equipped with a water flow meter that measures water consumption. Both the central SH and DHW mechanisms are managed by a Danfoss ECL 310 controller. The building has a control system, called PreHeat [36], which is a self-learning forecasting algorithm implemented in the building's system to save energy. It does this by accumulating knowledge about the home's thermal properties, such as the degree of insulation, the influence of solar radiation, wind, and outside temperature, as well as the household's user behavior. By combining this information with the weather forecast, the control system predicts the apartments' heating demand.

Measurements dataset

The measurements campaign consists of a set of hourly measurements at the apartment level and the room level. Concerning the apartment level, two submeters were installed, one for SH and another for DHW usage. The SH meter measures the hourly flow, supply, and return fluid temperatures. The DHW meter measures hourly flow and supply temperature.

At the room level, it is installed sensors to measure the indoor climate conditions (e.g., indoor temperature, relative humidity, CO_2 concentrations, and window opening rate). Additionally, all radiators were attached with contact temperature sensors to monitor the radiator's heat output throughout the campaign (supply, return, middle of radiator). The measurement period is from the 23rd of September 2021 to the 18th of June 2023. In Figure 2, one can see two of the apartment's layouts with the location of the different sensors combined with a table that shows the different units of the measurements. In Figure 3, one can see two types of sensors installed in one of the apartments.

Level	Shape (color)	Parameter	Units
Apartment	Pentagon (green)	SH flow	m^3/h
		SH supply/return temperature	ºC
		DHW flow	m^3/h
		DHW supply temperature	ºC
Room	Circle (purple or yellow)	Indoor temperature	ºC
		Relative humidity	%
	Circle (purple)	CO2 concentration	ppm
	Triangle (pink)	Window opening rate	%
	Square (red)	Surface pipe supply temperature	ºC
		Radiator surface temperature (middle)	ºC
		Surface pipe return temperature	ºC

Figure 2: Measurement campaign – description (the sensor location is not representative).

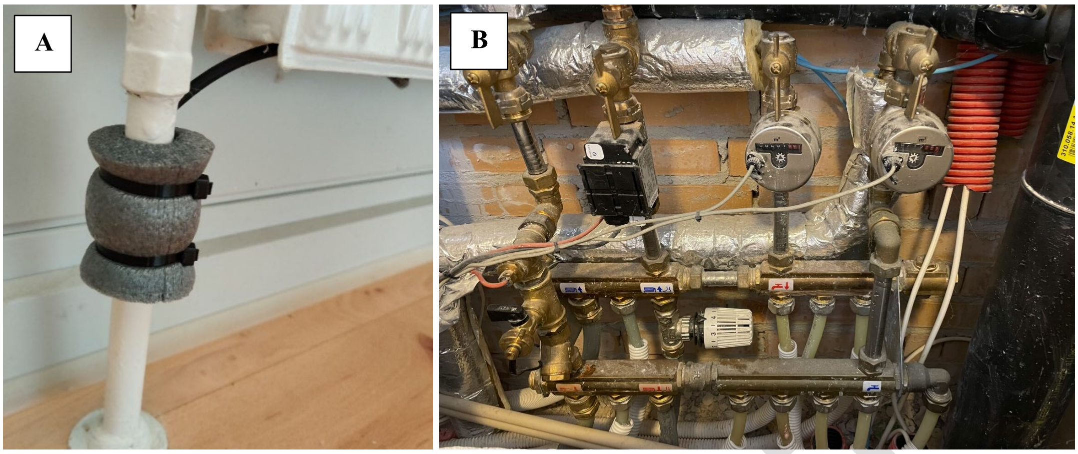


Figure 3: A) Contact sensor mounted on a radiator pipe in the apartment. B) SH and DHW apartment submeters installed in a shaft.

Users' heating habits

To better understand the data retrieved from the sensors' measurements, it was decided to collect additional insight about the occupants' habits. To retrieve this information, a phone survey was conducted with the apartments' occupants. In Table 2, a summary of the different user interactions with their apartment systems is presented. More details regarding these interviews can be found in [34].

Table 2: Occupancy heating habits in each apartment.

	Apt. A	Apt. B (B.1)	Apt. C	Apt. D
OCCUPANTS				
Nr. of adults	1	3	2	1
Nr. of children	0	2	0	0
Weekly occupancy	Not at home from 9-12h and Thursdays from 12-15h	Adults are always at home. Children at school from 8-15h	Always at home	Out of apartments in the afternoons
AIR QUALITY				
Which rooms are vented?	All rooms	All rooms	Bedroom and bathroom	Bedroom (every day) and living room (summer only)
How long and when do you vent the apartment?	Each day bedroom, bathroom, and living room 2-3 times a week. Long venting in summer (every day) and short in winter (10 minutes)	Summer: All day Winter: 1-2 h in the morning	Summer: All day Winter: 1-2 h per day	Summer: All day Winter: 3-4 h in the morning
THERMAL COMFORT				
What is the setting on the radiators' thermostats?	Bedroom is set to be cold (setting 1). Bathroom set on 2.	Different settings in the rooms.	Only the radiator in the living room is open (setting 4-5). Underfloor heating in bathroom (operating).	All radiators are set on 3. Radiator not used in the bedroom. Bathroom underfloor heating is always in use.
Is the temperature in the apartment uniform?	-	Yes, except for one bedroom (where no heating is used)	-	-
ENERGY SAVING MOTIVATION				
Do you pay too much for energy?	Yes	Yes	No	No

Regarding the collection of the data, one should note that there was a change of dwellers during the measurement campaign in apartment B. Therefore, throughout the results and discussion, this apartment is analyzed concerning the different dwellers' periods. Where the first occupants are denoted as B.1 and the occupants that moved after are denoted as B.2. The period when the apartment was vacant, is removed from the analysis. In Table 2, the survey responses for apartment B are associated with the family that resided there prior to moving out (B.1).

Data pre-processing

Regarding the dataset pre-processing, it was ensured that the raw data was transformed and cleaned into a format suitable for further analysis. In this stage, the different sensor hourly measurements were combined into two different datasets. All the data concerning the apartment level (SH and DHW energy submeters) are combined in a single dataset. While all data from indoor sensors installed in the different apartments' rooms (room level) are merged into a second dataset. The next step of the data treatment process is handling missing measurements. The submeters data are cumulative values, therefore the imputation technique applied was a linear interpolation. While "point-in-time" (instantaneous) measurements (e.g., indoor sensors) are imputed using a linear moving average. Lastly, the hourly measurements were aggregated into daily values. The daily values were the ones used throughout this analysis.

Energy signature and its dependence on DHW usage and occupancy SH habits

In the context of analyzing the linear energy signature model concerning DHW usage, the application of a segmented regression approach was used in this article instead of the combination of two linear regressions. This approach, by applying the segmented regression from [37,38] enables the model to account for multiple variables and breakpoints, which in this case, have two linear segments and one breakpoint. This is particularly relevant for DHW usage, where the rate of energy use could vary at different temperature intervals. Such breakpoints signify where the relationship between total energy usage and external temperature shifts, indicating a larger share of DHW usage in the warm periods (e.g., summer) versus a lower share in the cold periods (e.g., winter) due to the simultaneous operation of DHW systems with SH emitters.

Concerning the linear ES model, the impact of the SH systems' interaction with the users was also analyzed. To achieve this, the contact temperature sensors' measurements attached to the radiators in each room of the apartments were investigated. These sensors provided valuable insights that offered an overview of the heat distribution within each apartment. By visualizing this data, it was possible to discern the heat allocation, which in turn enables to understand the similarities or differences in the ES of each apartment.

Sigmoid energy signature

The concept of the sigmoid ES offers a different approach than the linear model to evaluate energy usage in buildings. This method hinges on the sigmoid function, a mathematical S-shape curve that is represented by two asymptotes and a linear trend in between. In the context of building energy assessment, the sigmoid ES function is expected to behave more robustly and, therefore not influenced by outliers and different heating behavior by the dwelling's occupants. Also, it might provide a nuanced way to understand how energy usage patterns change over time in extreme weather conditions (i.e., colder and warmer outdoor temperatures). The mathematical expression that defines the sigmoid ES is given by:

$$E(T_o) = ae^{-e^{cT_o - b}} + d \tag{2}$$

Where the parameters a, b, c, and d affect the function as follows:

- "T_o": Measured outdoor temperature.
- "a": This parameter scales the maximum value of the sigmoid function. It determines the upper asymptote of the curve. If "a" increases, the height of the S-curve increases accordingly. In the context of building physics, it represents the maximum energy demand for heating as the outdoor temperature decreases. As the value of "a" increases, the potential maximum heat loads the building might require in extremely cold conditions also increases.
- "b": This parameter shifts the curve along the outdoor temperature (T_o) axis. If "b" is increased, the S-curve asymptote x-point (CPT) moves to the right (higher T_o-value).
- "c": This parameter controls the steepness or slope of the curve. A higher value of "c" makes the transition from the lower to the upper asymptote steeper, meaning that the change occurs more rapidly. If "c" is smaller, the transition is more gradual. The parameter is related to the building's insulation properties; poor insulation would result in a steeper increase in heat load with a decrease in outdoor temperature.
- "d": This parameter shifts the curve vertically. Increasing "d" will move the entire curve upwards without changing its shape. This affects the lower asymptote of the curve, setting the minimum value that the energy baseline can take, reflecting the base load that is constant regardless of outdoor temperature. Moreover, "d" represents the DHW daily baseload during warmer days, i.e., summer.

An example of the sigmoid of the curve can be seen in Figure 4, with the representation of the different parameters and how they impact the S-shape function. More details of this function can be consulted in [8].

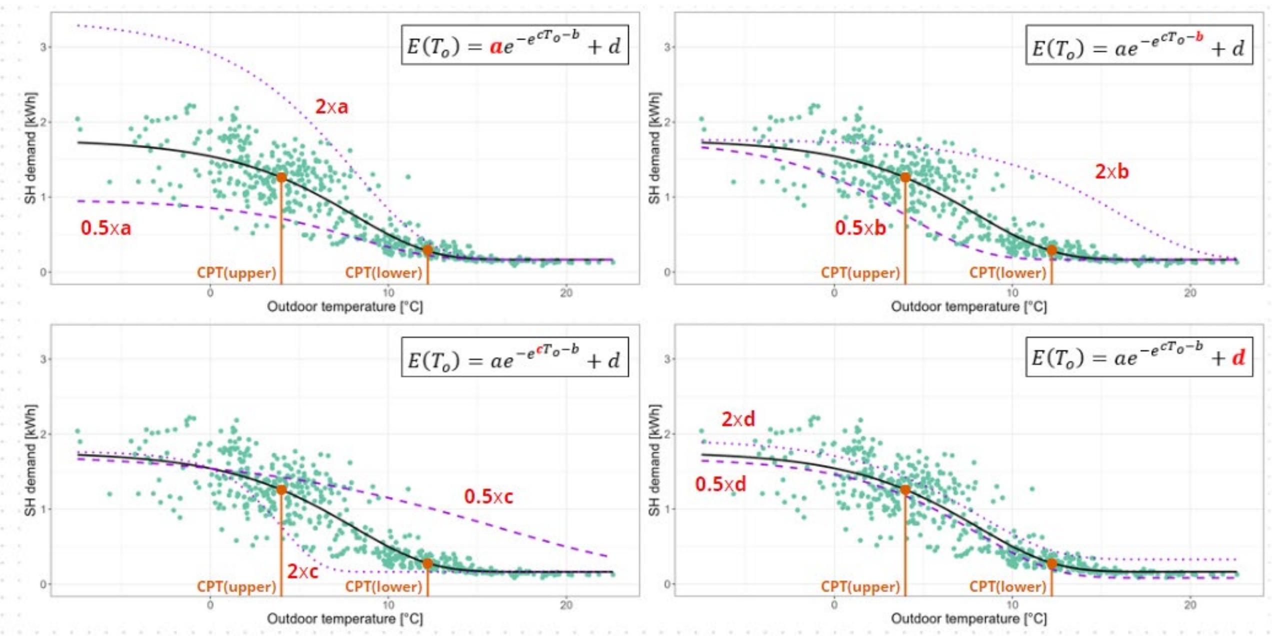


Figure 4: Sigmoid ES model - Representation of its parameters.

Similarly, with the linear energy signature, this function also has change points that can be obtained through equation (3), as shown in the appendix of this manuscript.

$$\begin{cases} CPT_{upper} = \dfrac{1}{c}\ln\left[\dfrac{1}{2}e^{b}(3-\sqrt{5})\right] \\ CPT_{lower} = \dfrac{1}{c}\ln\left[\dfrac{1}{2}e^{b}(3+\sqrt{5})\right] \end{cases} \tag{3}$$

From the equation above, it is observed that the CPT values are only dependent on the parameters “c” and “b”, from equation (2).

Results and Discussion

In the ensuing analysis, we delve into the empirical findings obtained from our assessment of energy demand within the studied apartments. The results underscore the complex interplay between SH and DHW usage, revealing distinct temporal patterns and consumption behaviors. This section aims to break down these findings, drawing on the sigmoid ES model to elucidate the underlying trends and anomalies in the data.

Linear energy signature

The first part of this work is the comparison of the ES model when using the total energy demand (SH+DHW) and the SH energy measurements. However, before, it is necessary to visualize the daily time series of both SH and DHW energy usage for the full extent of the measurement campaign to have a full grasp of ITS values (see Figure 5).

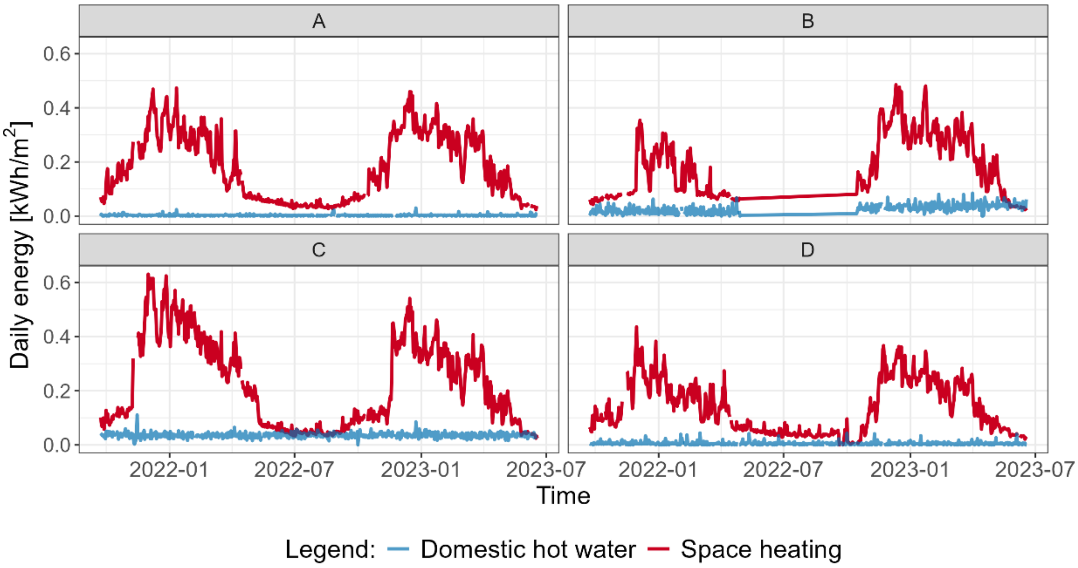


Figure 5: Time-series data from SH and DHW energy measurements.

From Figure 5, one can see that the SH produces a certain seasonality throughout the months, due to a variation of the heating needs due to outdoor temperature changes, while the DHW presents a more stochastic behavior, however, the observed DHW oscillations seem to fluctuate around a consistent average. To better visualize this constant trend of DHW usage, it is plotted in Figure 6, the distribution of the daily DHW volume consumption for each month as a boxplot. The dark dots in the plot are the daily measurements that deviate significantly from the measurements interquartile (outliers).

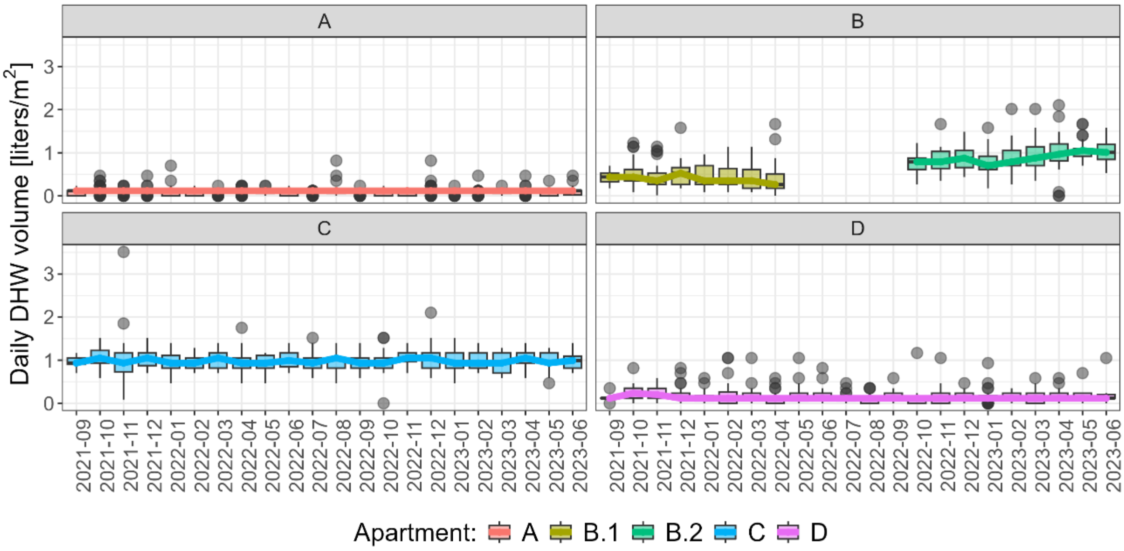


Figure 6: Daily DHW volume consumption per square meter per month.

By visualizing the monthly trend in Figure 6, it becomes clearer that all the apartments exhibit a constant monthly median DHW usage pattern when aggregating the measurements in a lower time resolution. In apartment B, however, there was a change of dwellers during the measurement campaign. After September, a new family moved in with larger DHW demands than the previous one. Another conclusion that can be drawn from this plot is that the magnitude and variation of this trend seem to be based on the number of dwellers in each apartment. As observed, the baseline for both apartments A and D, which have a single dweller each, is much lower than that of the other apartments. Therefore, it can be concluded that the DHW patterns are greatly influenced by the number of occupants and their routines. Nevertheless, apartment C, with two dwellers, shows similar high energy usage for DHW production as apartment B.1 did when it housed five people. This example demonstrates that in some cases, a larger number of occupants in a building does not directly indicate higher DHW consumption.

Focusing on the energy signatures generated from the SH demand alone, one can see in Figure 7, that apartments A, C, and D show distinctly the two seasons due to the change in heating demand. While apartment B has two noticeably different heating season trends, where the smallest heat usage (B.1) regards the family with five dwellers. When applied the same change-point model to the total energy usage (SH + DHW), the final result is plotted in Figure 8.

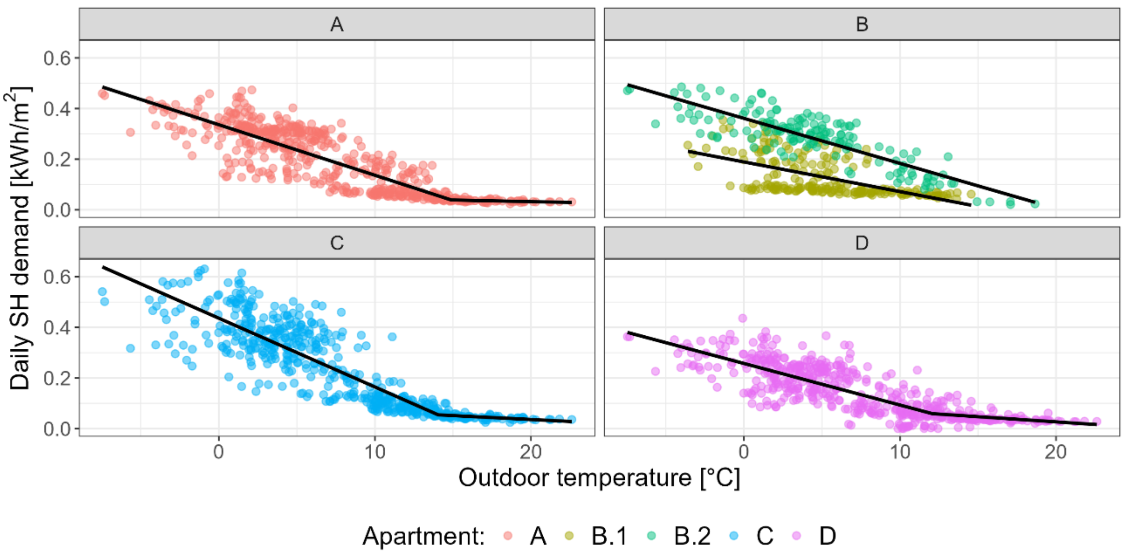


Figure 7: SH energy signature for each apartment.

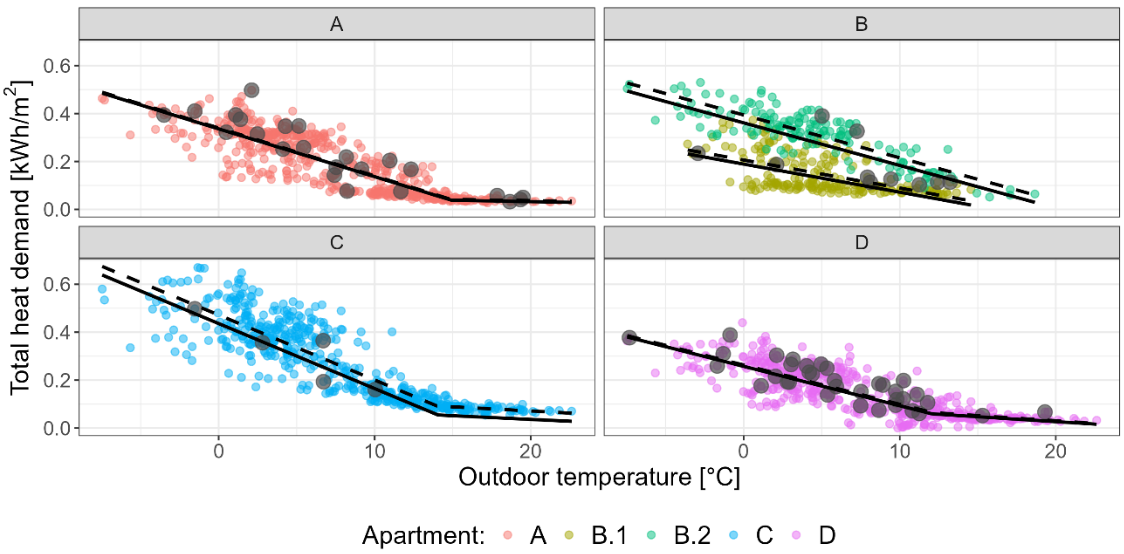


Figure 8: SH (solid line) and Total (dashed line) energy signatures for each apartment. Dark grey highlighted points are measurements assigned as outliers due to the DHW demand (see Figure 6).

In Figure 8, one can observe the SH (solid line) and Total (dashed line) energy signatures for each apartment. While all data points are the total heat measurements. The grey highlighted points indicate measurements identified as outliers due to the spikes in DHW demand as identified in Figure 6. Such outliers, as it seems do not represent the outliers in the total heating measurements. As one can see in Figure 7 and Figure 8, the four analyzed apartments display different linear ES models from each other. This result does not follow the usual hypothesis that similar buildings/spaces should display alike thermal characteristics and thus similar ES. Therefore, these plots show that the building ES properties (e.g., slope, CPT, and CPE) can be different for similar buildings (alike thermal characteristics). The reason for such differences can only be due to occupancy behavior (i.e., different heat setpoints and occupancy presence) or the presence of faults in SH systems inside the household (i.e., unbalanced radiators, broken thermostatic valves, etc.). To understand, how much is the variation of the ES parameters for the different cases, the plot in Figure 9 was generated.

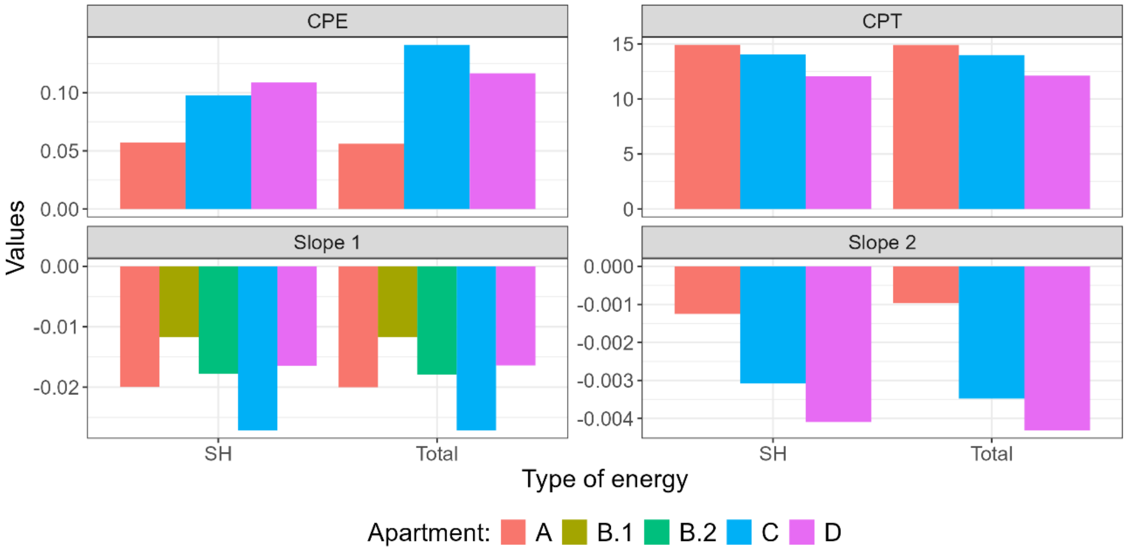


Figure 9: Linear ES parameters of SH and total heat (SH+DHW) demand per each apartment.

Figure 9 shows the ES parameters for different apartments, highlighting the individual energy usage patterns in terms of SH and total energy. The grouped bar charts compare the CPE, the CPT, and two slopes that measure the rate of change in energy demand concerning heat demand seasons (heating and no heating needs). The CPE bars illustrate notable differences among the apartments, a metric that reflects the energy levels at which the heating demand shifts, signaling the apartment's heat baseline. Variations in CPE suggest that each apartment's heating system might engage differently at the DHW production level and minor SH systems (underfloor heating in the bathroom) during summer. The slopes, labeled slope 1 (heating season – m_1) and slope 2 (no heating season – m_2), quantify how energy demand escalates or declines as temperatures rise or fall. A steeper slope would imply a more sensitive change in energy demand with temperature shifts, potentially influenced by the thermal losses (transmission and ventilation) of each apartment. Slope 1 shows a small change between the SH and total per apartment, however, there are significant changes when comparing the same energy demand type between apartments. Slope 2 has similar flagrant differences for the same reasons behind the slope 1 values.

As one can see, the plot shows that in some cases the linear parameters do not change significantly when assessing the dwelling energy demand if using SH or the total demand, where the best case to see this is slope 1. However, when comparing the same energy type for each apartment, these values differ much more. This result is counterintuitive because the most common hypothesis is that similar buildings must thermally behave alike. Because these apartments have similar thermal characteristics (e.g., U-values), architecture, and heating systems, and still display such significant results, one can conclude that other factors are affecting the overall heat performance of the apartments. To better investigate the possible factors noted above, it was investigated the SH and DHW efficiency and profiles with distinct heat meters and interviews with the dwellers of each apartment.

Human-building interaction with the heating systems

Despite the initial hypothesis that apartments with similar physical structures and heating systems would exhibit similar thermal behavior, the observed discrepancies in the energy demand data compel us to look into the heating practices of each apartment's dwellers.

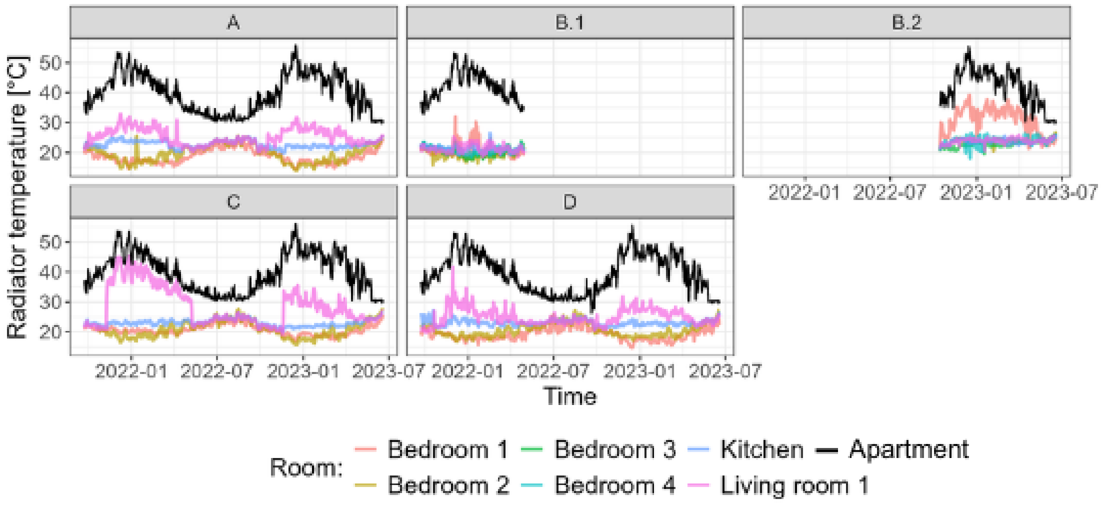


Figure 10: Radiators' temperature per room (colored) compared with the apartment SH supply temperature (black).

Figure 10 presents a comparative analysis of radiator temperatures across different rooms within various apartments, measured over time from January 2022 to just before July 2023. The data shows a seasonal fluctuation in temperatures with peaks suggesting increased usage during the colder months for SH purposes. It is evident that the hot fluid supply temperature of each apartment, marked in black, is set higher than the radiators' temperature in individual rooms. Each colored line represents a different room, with some, like bedroom 1 and the living room, showing consistently higher temperatures, which could point to higher heating setpoints due to the preference for warmer temperatures in these spaces. For instance, bedroom 2's lower temperature readings, as compared to bedroom 1 (in some of the dwellings), reflect less frequent use. The subplots labeled A, B.1, B.2, C, and D represent different apartments where the measurements were taken, showing that the heating profiles vary not only within an apartment but also across different apartments showing that varying occupant interaction with their heating systems are most likely the cause of variations in their ES. Periods of potential overconsumption are suggested in the winter months, where the radiator temperatures are significantly similar to the SH supply temperature (as seen in apartments C and B.2), hinting at inefficiencies in heating distribution or control. This highlights the need for potentially adjusting the heating system to better match the actual demand in each room and apartment to optimize energy efficiency and comfort.

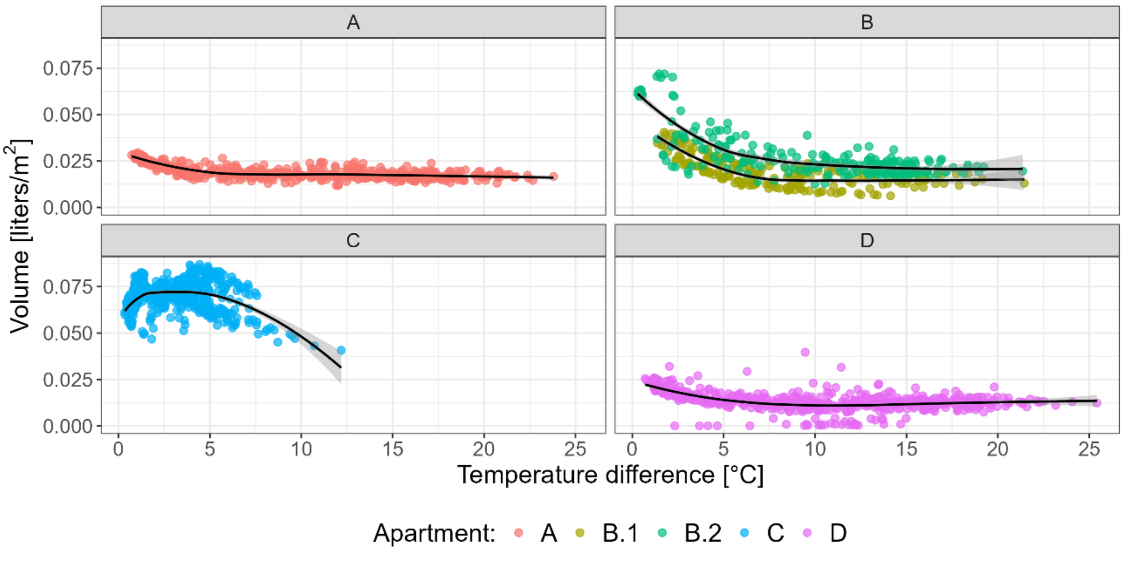


Figure 11: Performance of the overall SH systems per apartment.

In Figure 11, one can see, the performance of SH systems in four different apartments. The performance is assessed by plotting the volume of hot water against the temperature difference (ΔT) between the supply and return temperatures of the hot water provided by the DH grid. Apartment A shows a relatively constant volume of hot water use across the range of temperature differences, suggesting a stable and possibly efficient SH system performance, as also seen in apartment

D. Apartment B shows a decrease in the volume used as the temperature difference increases, which could indicate that the system is responding to the need for less water flow as the difference between supply and return temperatures grows. In apartment C, there is a constant large volume with a lower temperature difference compared with the other apartments. This indicates that apartment C has a much larger overflow with a lower ΔT.

By comparing these measurements with inputs from the surveys in Table 2, it is inferred the reasons behind the patterns in Figure 10 and Figure 11. Apartments A and D have the most similar heat performance of all the apartments. The reasons behind it are that these apartments have the same number of dwellers. However, apartment D has more outliers regarding the volume and ΔT, which are probably related to the fact this resident stays longer in its house, therefore it might change the setpoints more often. This hypothesis is corroborated, as one can see in Figure 10, where the living room (the space that probably is more occupied during the day) radiator has a larger emitted temperature, due to the increasing thermostat setpoint by the user. With a larger intensity but also an alike pattern, it is apartment B, where B.1 occupants have less SH demand than B.2. And it is also seen that B.2 has a higher SH usage due to a larger setpoint in Bedroom 1. Apartment C has the most different pattern from all the dwellings, and according to Figure 11, the worst heat efficiency because of its high overflow and lowest ΔT. The primary cause of this inefficiency is due to the living room radiator being set to the highest thermostat setting while all others are turned off, essentially making it the sole emitter attempting to heat the entire apartment. This also shows that the SH efficiency is not fully dependent on the number of occupants, as B.1 has more people than apartment C.

Sigmoid energy signature

The initial segment of this article investigation focuses on examining the linear ES model, while in this section, the focus shifts toward the proposal of the sigmoid ES model to explain the energy usage in a building. This analysis is critical for understanding the energy demand and the underlying factors influencing its variability in extreme outdoor temperatures. Before delving into the detailed analysis, it is essential to depict the sigmoid ES through graphical representation, which will elucidate the gradual increase and saturation points of energy use over time per apartment (see Figure 12). Apartment B was not investigated in this section, due to the lack of occupants during the no heating season.

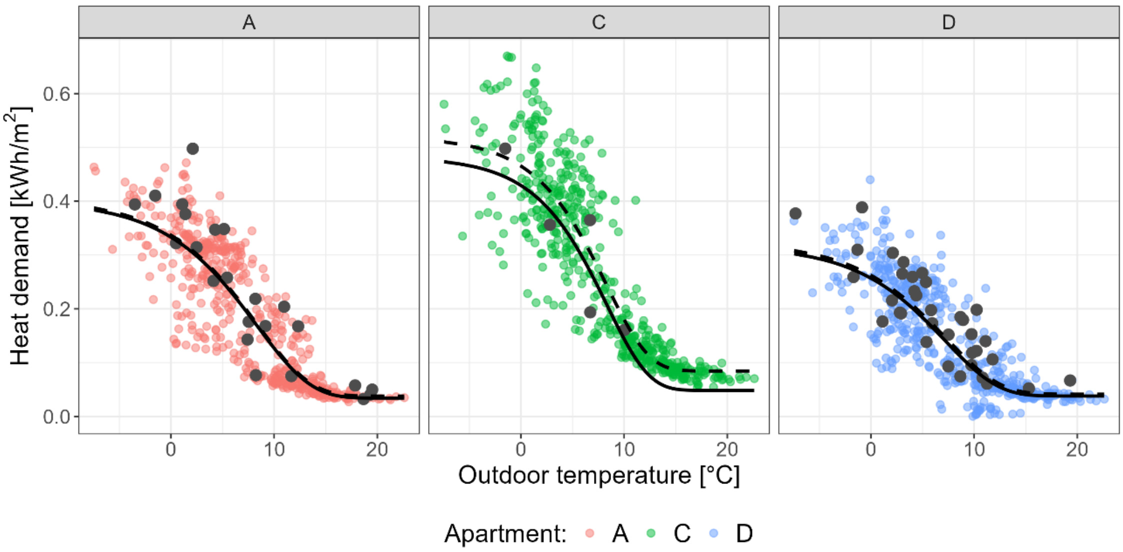


Figure 12: SH (solid line) and Total (dashed line) sigmoid ES for each apartment. Colored data points are the total heat demand recordings. Dark grey highlighted points are measurements assigned as outliers due to the DHW demand (see Figure 6).

The plot shows the sigmoid relationship between outdoor temperature and energy demand for heating across different apartments, with SH shown by a solid line and total heat demand by a dashed line. The energy demand increases as the outdoor temperature decreases, indicating more heating is needed. However, the demand plateaus in extreme outdoor temperature conditions. The grey highlighted points indicate measurements associated with outlier DHW demand however they do not impact the overall energy measurements. To quantify the extent of variation in the sigmoid ES parameters across the different apartments, the subsequent figure was produced (Figure 13).

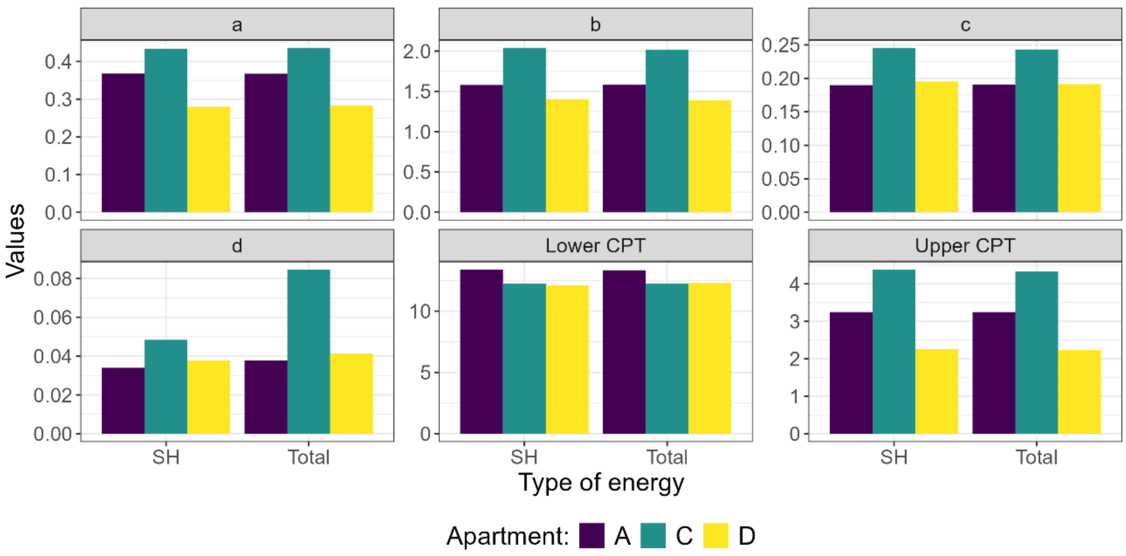


Figure 13: Sigmoid energy signature parameters of SH and total heat (SH+DHW) demand per apartment.

Similarly to the parameters of the linear ES model in Figure 9, sigmoid ES displays a similar display. As one can see in Figure 13, sigmoid parameters have small variations for both SH and the total demand. However, when comparing the same type of energy usage for each apartment, these values differ much more, as explained for the linear ES, it is due to the occupancy interaction with their heating systems.

To compare both models, the root mean squared error (RMSE), R2, and Akaike Information Criterion (AIC) were calculated for the SH measurements. RMSE measures the average magnitude of the errors between predicted and observed values, indicating the model's prediction accuracy. R2 (known as coefficient of determination), indicates the proportion of variance in the dependent variable that is predictable from the independent variables, reflecting the model's goodness of fit. While the AIC evaluates the model's quality by considering both the goodness of fit and the number of parameters used, penalizing more complex models to prevent overfitting. For both RMSE and AIC, the lower these values the better, while R2 the closest this value to 1, the better the model. In Table 3, it is seen the metrics for each model.

Table 3: RMSE, R2, and AIC of both linear and sigmoid ES models for the SH measurements.

	Linear ES			Sigmoid ES		
	Apart. A	**Apart. C**	**Apart. D**	**Apart. A**	**Apart. C**	**Apart. D**
RMSE	5.346	6.683	4.596	5.233	6.401	4.548
R2	0.754	0.776	0.703	0.764	0.795	0.709
AIC	3222.8	3461.3	3066.1	3200.8	3416.4	3055.2

The sigmoid ES model outperforms the linear ES model across all apartments, as evidenced by lower RMSE and AIC values, and slightly higher R^2 values. However, the difference between these metrics is quite small. To better corroborate the sigmoid model, 5-fold cross-validation was also performed using the RMSE (see Table 4).

Table 4: Results of the 5-fold cross-validation using RMSE.

		RMSE					
		Fold 1	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**	**Mean**
Apart. A	**Linear ES**	5.176	5.714	5.829	5.237	4.850	**5.361**
	Sigmoid ES	4.999	5.531	5.817	5.200	4.680	**5.246**
Apart. C	**Linear ES**	6.673	6.198	7.488	6.602	6.445	**6.681**
	Sigmoid ES	6.343	5.544	7.633	6.457	5.819	**6.359**
Apart. D	**Linear ES**	4.273	4.891	4.996	4.631	4.320	**4.622**
	Sigmoid ES	4.185	4.777	5.181	4.512	4.328	**4.596**

From the cross-validation, its results confirm that the sigmoid ES model performs better than the linear ES model. The sigmoid model consistently shows lower mean RMSE values across all apartments (A, C, D), indicating better predictive accuracy, but also better robustness when being trained and tested with the different folds. This reinforces the initial findings that the sigmoid ES model is the preferable choice, even though with slightly better metrics.

Besides these metrics, the primary feature of the sigmoid model is its distinctive dual energy plateaus. The plateau corresponding to the higher outdoor temperatures is already accounted for in the conventional linear ES model, reflecting a decrease in the building's SH demand. However, the plateau occurring at lower outdoor temperatures represents a significant innovation of this model. As noted in references [32,33], the possible explanations for this phenomenon include a) a reduced venting rate due to fewer window openings by occupants, thereby diminishing ventilation losses, or b) reaching the maximum power output by the building's SH systems.

Further analysis is conducted using data from sensors installed during the measurement campaign to elucidate the causes of this plateau. The other sensors measure the following: CO2 concentration, the apartments' SH supply temperature, and the window opening.

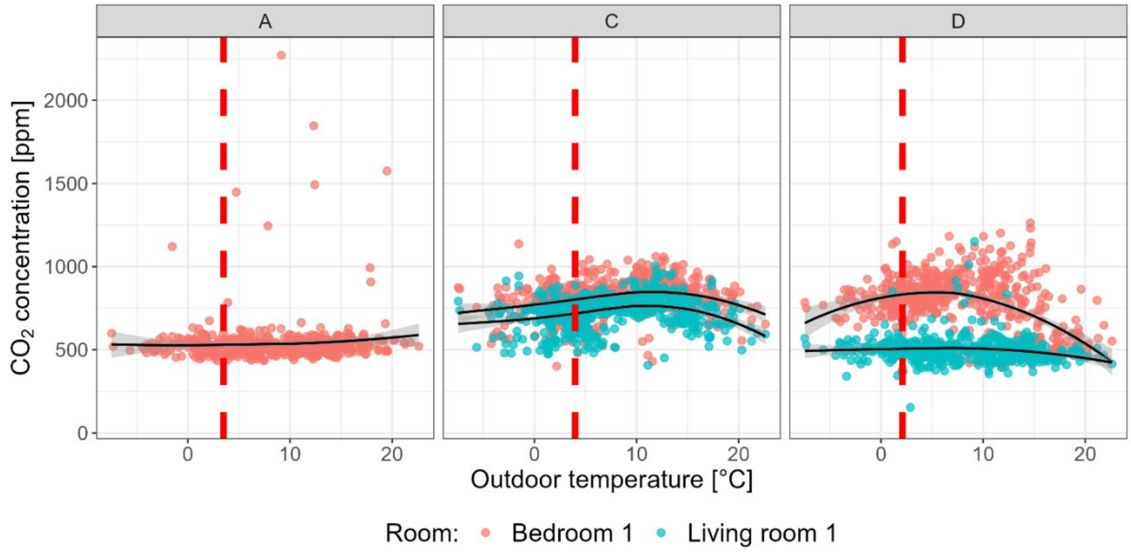


Figure 14: Daily CO_2 concentration for each apartment over the outdoor temperature. The dashed red line represents the upper CPT from the sigmoid ES.

These scatterplots in Figure 14 provide an insightful view into the daily CO2 concentration variations across different rooms within apartments A, C, and D, against the outdoor temperatures. The data, delineated by room type does suggest an almost constant relationship between CO2 concentration and external temperatures. The upper CPT is denoted by a dashed red line across the plots providing the reference point that indicates the colder outdoor temperature plateau from the sigmoid ES of each apartment. It was expected to see in these measurements an increase in CO2 concentration during the colder days due to a decrease in the window opening, however, this was not observed. The main reason is possibly the existing mechanical ventilation system that prevents the CO2 levels from reaching higher values.

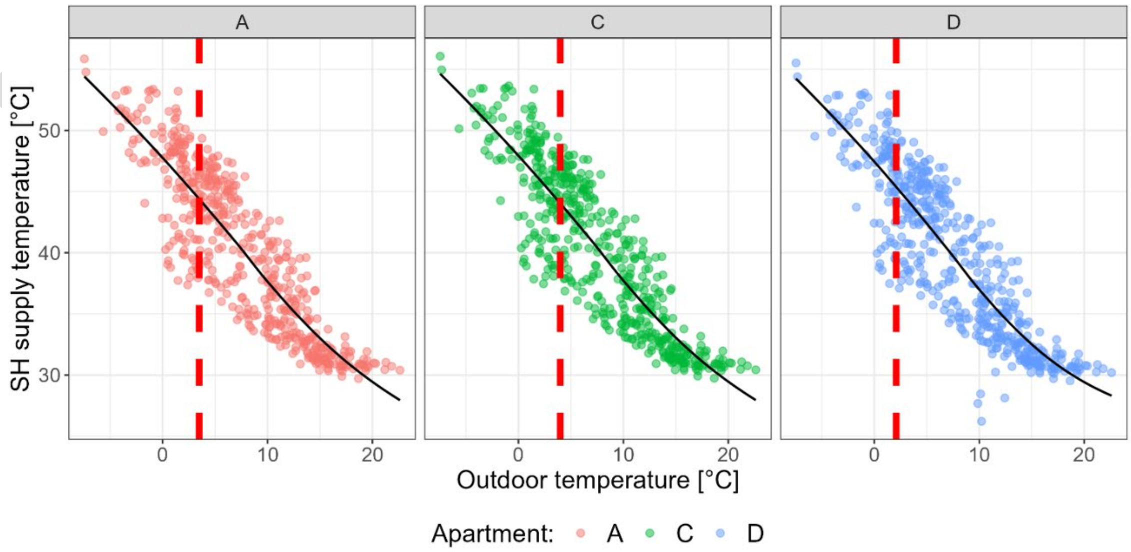


Figure 15: Daily supply temperature of the SH system for each apartment over the outdoor temperature. The dashed red line represents the upper CPT from the sigmoid ES.

While examining the SH supply temperature per apartment, Figure 15 distinctly illustrates an inverse relationship between the daily SH system supply temperature and the outdoor temperature for apartments A, C, and D. As the outdoor temperature increases, the SH system's supply temperature decreases consistently across these apartments, indicating a system that dynamically adjusts its output in response to external temperatures [36]. However, similarly with the CO2 concentration measurements, there is no discernible pattern in the region where the outdoor temperature is below the upper CPT that could explain the sigmoid model's plateau. Consequently, the plateau cannot be attributed to the maximum heating output of the SH system. This leads to the conclusion that the causes of the energy plateau lie elsewhere, necessitating further investigation.

Unfortunately, the window-opening sensors installed in the measurement campaign (see Figure 2) encountered numerous issues, rendering some of the gathered data unusable. Despite these setbacks, the sensors in apartment A yielded the results, as depicted in Figure 16.

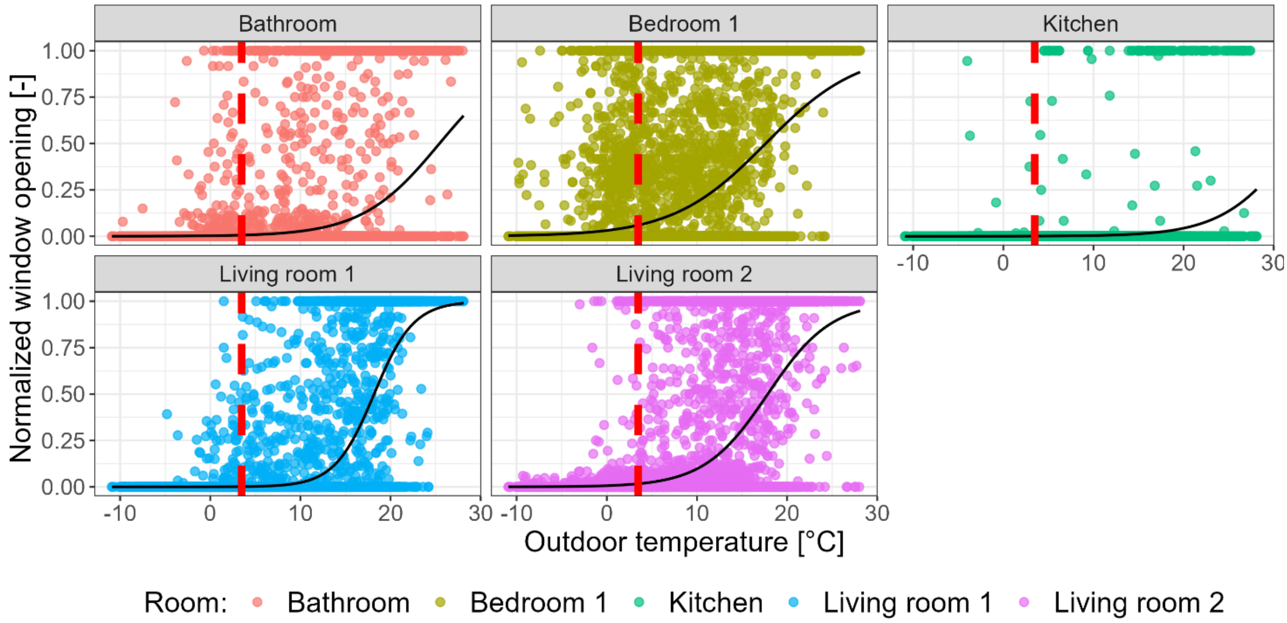


Figure 16: Hourly normalized window opening fraction for apartment A over the outdoor temperature. The dashed red line represents the upper CPT from the sigmoid ES for the SH measurements.

One can see in Figure 16, the hourly normalized window opening fraction for different rooms within apartment A, plotted against the outdoor temperature. The normalization of the window opening fraction allows for a comparison of window usage patterns relative to temperature changes. The data reveals a clear pattern: in both the bathroom and the living rooms, there's a positive correlation between window-opening behavior and outdoor temperature, with window openings becoming more frequent as the temperature outside rises. This trend is especially marked in the living room, where the frequency of window openings significantly increases with higher temperatures. In contrast, the bedroom shows a less pronounced dependency on outdoor temperature, as evidenced by the relatively flat trend lines, indicating that factors other than temperature, such as the need to ventilate the room after waking up, may influence window-opening behavior in these spaces.

This observation suggests a potential explanation for the sigmoid low external temperature plateau observed in the model. As hypothesized in other research articles [32,33], the venting rate appears to be a primary factor behind this plateau. This correlation might have been more evident in the CO2 concentration measurements if the apartments lacked mechanical ventilation, hinting at a direct link between air quality and window-opening habits. Furthermore, these findings underscore the importance of accounting for user behavior, particularly window-opening routines, in building energy models, as they significantly impact energy usage and efficiency.

Conclusion

In the introduction of this article, it was raised three questions that we attempted to answer based on the integration of smart heat meters' data with other indoor sensors data and surveys to have more insights into the occupants. As a product of this analysis, it was concluded the following:

- Is the DHW energy usage constant or irregular when applied to the ES model?

Visual analysis of daily time series data showed that while SH displayed a seasonal pattern, DHW usage was more stochastic but generally fluctuated around a consistent average. Monthly trends further confirmed a constant median

DHW usage pattern, with variations primarily influenced by their different routines and not the number of occupants. Consequently, all DHW outliers, a product of its stochasticity, did not seem to influence the ES model significantly besides increasing slightly its CPE-value (see Figure 9).

- Are the ES characteristics similar in alike buildings and spaces?

Contrary to the initial hypothesis, the ES parameters were not consistent across similar buildings and spaces. Analysis of energy signatures for SH and total energy demand showed significant differences among the apartments, suggesting that factors other than thermal characteristics, such as occupancy behavior and potential faults in SH systems, significantly affect the overall heat performance. This finding was reinforced by examining the heating profiles and efficiency variables, such as water volume and ΔT, from the radiator heat allocators which indicated that occupant interaction with heating systems plays a crucial role in the observed variations.

- What are the reasons behind the upper asymptote point in the sigmoid ES model at low outdoor temperatures?

The reasons behind the upper asymptote point in the sigmoid ES model at low outdoor temperatures were explored using additional sensor data. The upper asymptote, representing a plateau in energy demand at low temperatures, could not be explained by supply temperature limitations of the heating systems or CO_2 concentration variations. However, data from window opening sensors suggested that reduced venting due to less window opening at lower temperatures is likely a primary factor, nevertheless, more data is required to confirm this assumption. This behavior, influenced by occupant routines, underscores the importance of accounting for user behavior in building energy models to better understand and predict energy usage patterns.

Suggestions for Further Work

Based on the findings of this study, several paths for further research are proposed. A primary focus should be on enhancing fault detection and diagnosis (FDD) in buildings' heating systems and district heating substations. Given the significant influence of occupant behavior towards their systems on the ES model, future research should integrate advanced FDD methods that leverage the variability in energy usage patterns to identify anomalies and inefficiencies in heating systems. This could involve the development of machine learning algorithms trained on extensive datasets from smart heat meters and indoor sensors, aiming to detect subtle signs of system malfunctions or suboptimal performance before they escalate into more significant issues.

Additionally, exploring the integration of real-time monitoring systems with user-friendly interfaces could empower occupants to better understand and manage their energy usage, potentially reducing the occurrence of faults due to user error. Research should also investigate the impact of various occupant behaviors on the efficiency of heating systems, using detailed surveys to refine predictive models.

Another promising direction involves the application of the sigmoid ES model to a broader range of buildings and climates to validate its robustness and versatility. This includes assessing the model's performance in commercial and industrial buildings, where energy usage patterns and HVAC systems differ from residential settings. Moreover, expanding the dataset to include more diverse building types and regions would provide a comprehensive understanding of this ES model's applicability and limitations. Further investigation into the reasons behind the upper asymptote in the sigmoid ES is also needed. More extensive data collection, particularly focusing on window opening behavior and its correlation with indoor air quality metrics, could help confirm the initial findings and provide deeper insights into occupant-driven energy dynamics.

Credit author statement

Daniel Leiria: Conceptualization; Methodology; Software; Validation; Formal analysis; Investigation; Data curation; Writing - original draft; Writing - review & editing; Visualization. **Hicham Johra:** Conceptualization; Methodology; Resources; Writing - review & editing; Supervision. **Yue Hu:** Data curation; Resources; Writing - review & editing. **Olena Kalyanova Larsen:** Conceptualization; Methodology; Writing - review & editing. **Anna Marszal-Pomianowska:** Conceptualization; Resources; Writing - review & editing; Supervision. **Martin Frandsen:** Resources**;** Writing - review & editing. **Michal Zbigniew Pomianowski:** Conceptualization; Resources; Writing - review & editing; Supervision; Project administration; Funding acquisition.

All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Determination of the changepoint temperatures (CPT) of the sigmoid energy signature model

The sigmoid energy signature is an inverted-s curve function, and it is defined mathematically as:

$$y = ae^{-e^{cx-b}} + d \tag{A.1}$$

This function has two x-points where the graph's asymptote "starts". In mathematical terms, it can be represented where the third derivative of the function is zero (as one can see in A.2).

$$y'''(x) = \frac{d^3y}{dx^3} = 0 \tag{A.2}$$

The first derivative of function y is defined as:

$$y' = -ac \cdot e^{-e^{cx-b}+cx-b} \tag{A.3}$$

By derivating A.3, it is reached the second derivative of y (y''):

$$y'' = ac^2 \cdot e^{-e^{cx-b}+cx-2b}(e^{cx} - e^{b}) \tag{A.4}$$

By derivating A.4, it is reached the third derivative of y (y'''):

$$y''' = -ac^3 \cdot e^{-e^{cx-b}+cx-3b}(-3e^{cx+b} + e^{2cx} + e^{2b}) \tag{A.5}$$

Using A.5, it is necessary to find the x values that fulfill the condition A.2:

$$-ac^3 \cdot e^{-e^{cx-b}+cx-3b}(-3e^{cx+b} + e^{2cx} + e^{2b}) = 0 \tag{A.6}$$

In the expression A.6, the coefficients a and c must not be equal to 0. Therefore, to find x-values that fulfill the condition, only the expression inside the parenthesis must be equal to zero:

$$-3e^{cx+b} + e^{2cx} + e^{2b} = 0 \tag{A.7}$$

Converting the following:

$$\begin{cases} \beta = e^{cx} \\ \gamma = e^{b} \end{cases} \tag{A.8}$$

Therefore, substituting in equation A.7 by the variables in A.8.

$$-3\beta\gamma + \beta^2 + \gamma^2 = 0 \tag{A.9}$$

Solving the first condition above for β:

$$\beta = \frac{3\gamma \pm \sqrt{9\gamma^2 - 4\gamma^2}}{2} = \frac{3}{2}\gamma \pm \frac{1}{2}\gamma\sqrt{5} \tag{A.10}$$

Substituting in A.10 with the values in A.8:

$$e^{cx} = \frac{1}{2}e^{b}\left(3 \pm \sqrt{5}\right) \tag{A.11}$$

Finally obtaining:

$$\begin{cases} x_1 = \frac{1}{c}\ln\left[\frac{1}{2}e^{b}(3-\sqrt{5})\right] = CPT_{upper} \\ x_2 = \frac{1}{c}\ln\left[\frac{1}{2}e^{b}(3+\sqrt{5})\right] = CPT_{lower} \end{cases} \tag{A.12}$$

These two x-values are the points that represent the two outdoor temperature values where the sigmoid energy signature becomes constant.