Disaggregation of Heating and Cooling Energy Consumption via Maximum a Posteriori Estimation

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OUR
IDENTITY

Key figures

2009
Creation date

+ 3 000
Companies and local authorities sensitized to the energy transition

+ 3 200
Companies accompanied in reducing transport and logistics GHG emissions

ecoCO2

Mission

Helping businesses and communities gain in **performance** and **sustainability**

Expertise

CSR consulting firm

Domains

CSR & **Climate**

Strong expertise in decarbonization in transport and mobility

Introduction and Motivation

- Smart meters now provide continuous energy consumption data; however, their low temporal resolution complicates the identification of individual energy uses. [1]

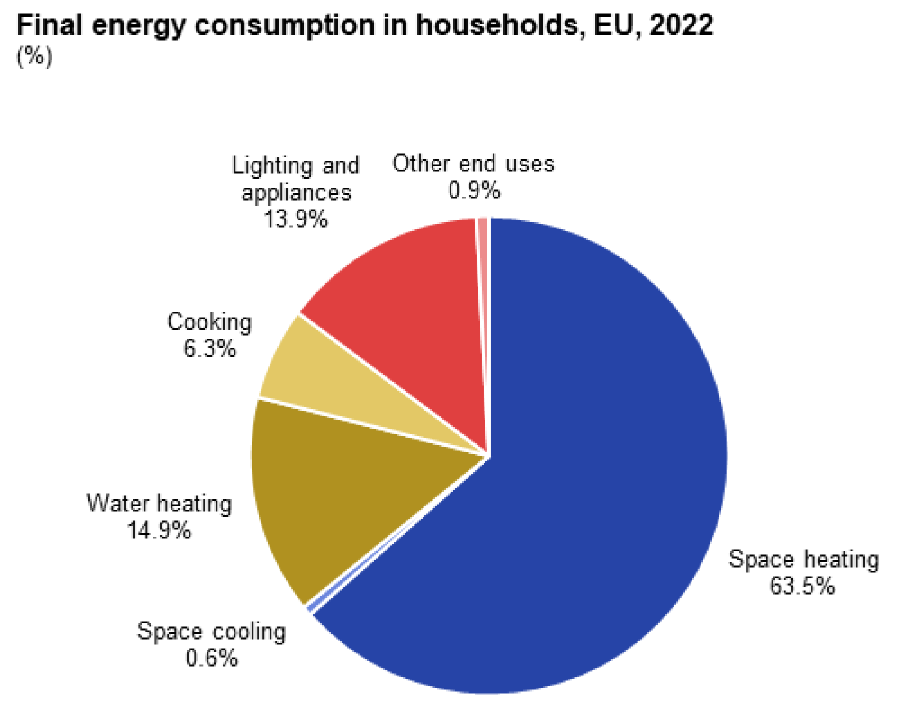
- Accurate estimation of heating and cooling consumption is essential for optimizing building performance and reducing operational costs.

- Disaggregating aggregated energy data has several advantages:
  - it enables targeted energy efficiency measures
  - it improves overall energy management strategies.

[1] A. Petralia, P. Charpentier, P. Boniol, and T. Palpanas, “Appliance Detection Using Very Low-Frequency Smart Meter Time Series,” en, in Proceedings of the 14th ACM International Conference on Future Energy Systems, arXiv:2305.10352 [cs, eess], Jun. 2023, pp. 214–225. DOI: 10 . 1145 / 3575813 . 3595198.

HVAC Energy Consumption & Smart Meters

- HVAC systems represent a significant proportion of building energy consumption, ranging from 38% to 60% in many regions.
- Smart meters typically record aggregated energy consumption at low frequencies, which limits the direct detection of individual appliances or systems.
- Conventional disaggregation methods often disregard influential explanatory variables such as weather conditions and occupancy patterns.
- Incorporating environmental variables is crucial for developing robust models that accurately reflect the dynamics of energy consumption.



Final energy consumption in households EU, 2022 (%)
Source: Eurostat (nrg_d_hhq)

Objectives

- The total building energy consumption comprises heating, cooling, and other non-temperature-dependent uses. When electricity is the only energy source, and without sub-meters, all usages are aggregated.

- The primary objective is to decompose aggregated energy data into its constituent components using advanced statistical techniques to improve current approaches.

- The study employs Degree-Days (DD) metrics and Maximum a Posteriori (MAP) estimation to enhance the accuracy of disaggregated energy estimates.

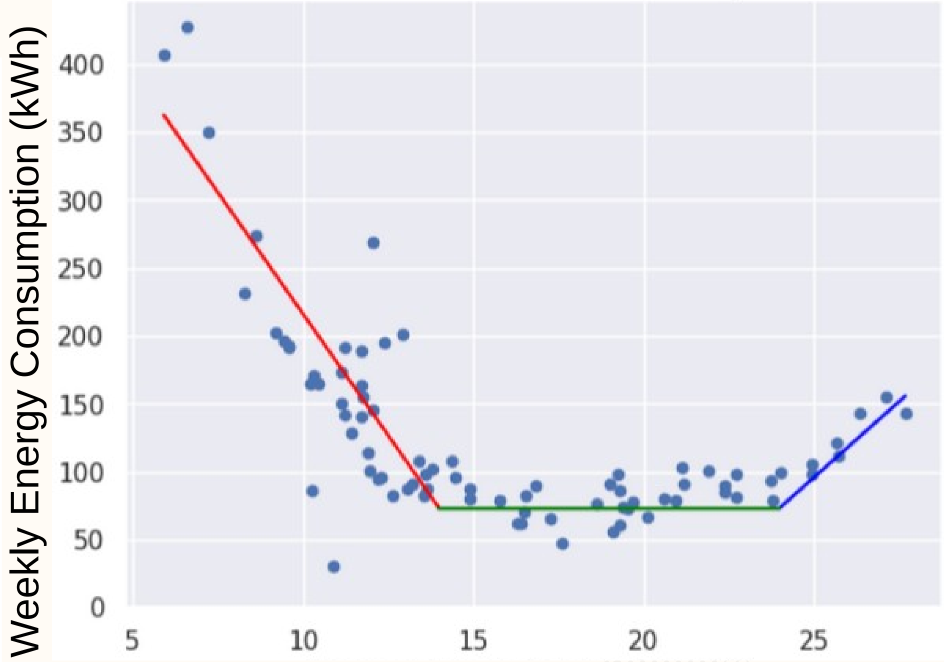
- This method ensures that the sum of estimated components is equivalent to the total measured energy, adhering to the principle of energy conservation.

[1]

Thermosensitivity Consumption Model

- The model decomposes total energy consumption into heating, cooling, and other energy uses. The other uses do not depend on the weather, and are usually referred as the baseline consumption.
- Degree-Days (DD) quantify energy demand based on deviations from defined baseline temperatures. HDD stand for Heating DD and CDD stand for Cooling DD. [1]
- Linear relationships between Degree-Days and energy consumption are established, with additional random variables accounting for unobserved deviations noted ϵ

Illustration of the Thermosensitivity Model



Mean weekly temperature (°C)

$$E = E_{\text{baseline}} + \epsilon_{\text{o}} + \begin{cases} \alpha_{\text{c}} \cdot CDD + \epsilon_{\text{c}} & \text{if } CDD > 0 \\ \alpha_{\text{h}} \cdot HDD + \epsilon_{\text{h}} & \text{if } HDD > 0 \end{cases}$$

[1] J. A. Azevedo, L. Chapman, and C. L. Muller, “Critique and suggested modifications of the degree days methodology to enable long-term electricity consumption assessments: A case study in Birmingham, UK,” en, Meteorological Applications, vol. 22, no. 4, pp. 789–796, 2015, ISSN: 1469-8080. DOI: 10.1002/met.1525.

MAP Estimation Methodology

- The objective of the estimation is to affect the deviation from the linear thermosensitivity model to the components.

- MAP estimation integrates prior information with observed data to refine the disaggregation of energy components.

- The method allocates the residual deviation between the linear model and the measured energy consumption into heating (or cooling) and non-HVAC uses.

- This approach formulates the estimation problem as an optimization that maximizes the joint probability of the observed residuals.

- Compared to conventional methods, MAP estimation reduces the standard error and ensures that the sum of component estimates equals the total energy measured.

[1]

Illustration of the MAP estimation

- Let’s try to guess the values of two dices. With no more information, with uniform probabilities, both dice can have a value from 1 to 6. This is the **a Priori estimation.**

- Now if we are told the value of the sum of the dice, let’s say 8. Only the following combinations can be expected: {2,6}, {3,5}, and {4,4}. We reduced the possibility space by six! Hence improving the accuracy of the estimation. This is the **a Posteriori estimation.**

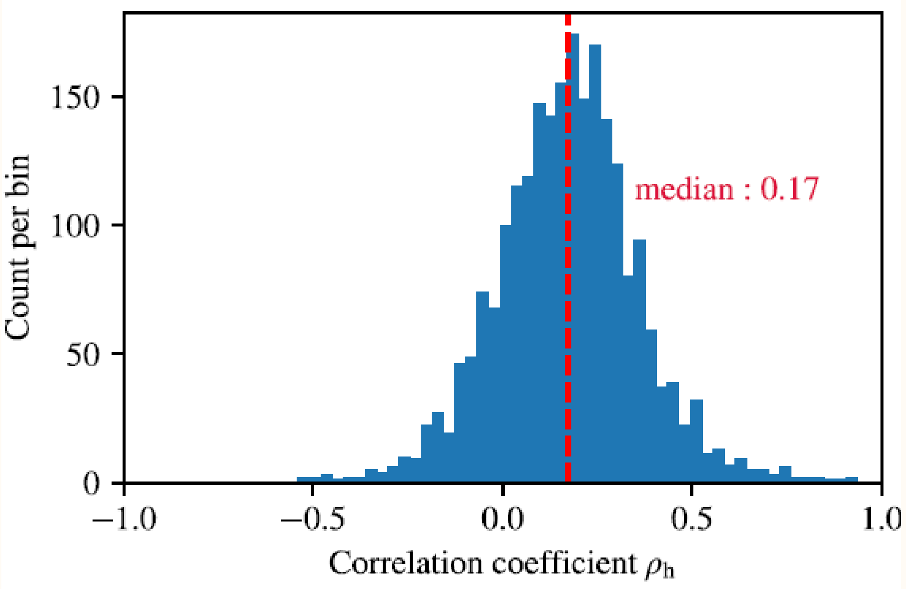
- MAP estimation uses the joint distribution and the Bayes law to improve the estimation’s accuracy

Dice values	1	2	3	4	5	6
1	2	3	4	5	6	7
2	3	4	5	6	7	**8**
3	4	5	6	7	**8**	9
4	5	6	7	**8**	9	10
5	6	7	**8**	9	10	11
6	7	**8**	9	10	11	12

Table of all possible combinations for the sum of two dices

Estimation of Residuals Correlation

- The model introduces random deviations (ϵ_h, ϵ_c, ϵ_o) to capture variability not explained by the linear relationships with Degree-Days.



- An analysis of the EDRP dataset[2], comprising over 8,000 households, was conducted to estimate the correlation coefficient (ρ_h) between heating and other energy deviations.

- The statistical analysis yielded a median correlation value of approximately 0.17, indicating a weak positive association.

- Precise estimation of ρ_h is critical to the MAP framework, as it directly influences the accuracy of the disaggregation process.

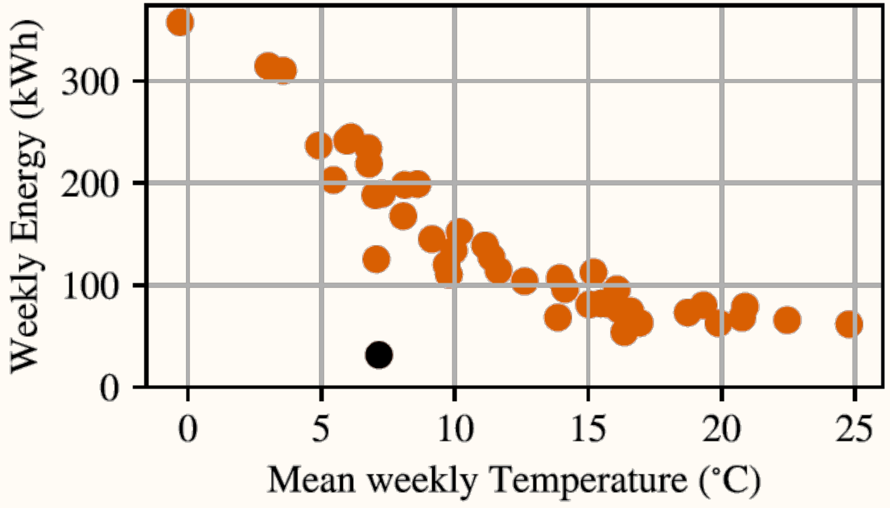
[2] AECOM Building Engineering, Energy Demand Research Project: Early Smart Meter Trials, 2007-2010. [data collection]. UK Data Service. SN: 7591, 2014. DOI: http://doi.org/10.5255/UKDA-SN-7591-1

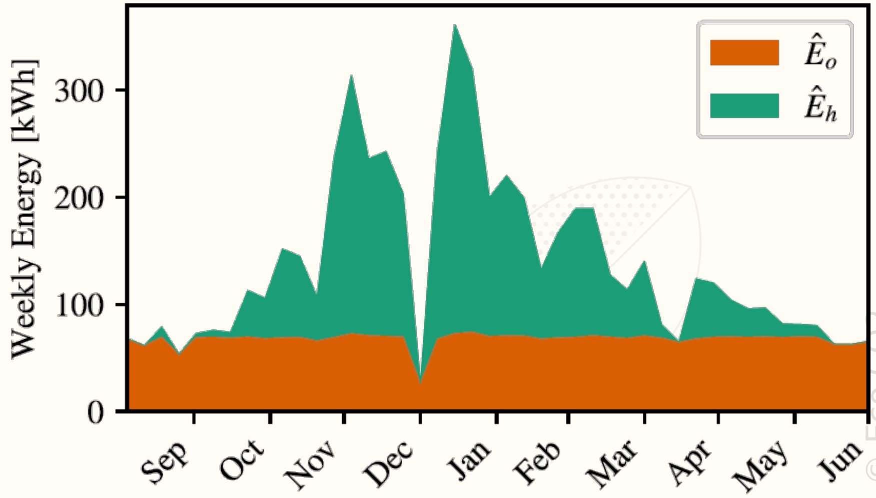
Case Study: Application on a Real Building

- A case study was performed on a residential building near Lyon, France, using data collected from a Linky smart meter and outdoor temperature records via the OpenWeatherMap API.

- Key parameter estimates obtained include an $E_{baseline}$ of 69 kWh, σ_o of 8.9 kWh, α_h of 1.8 kWh/°C·week, and σ_h of 73 kWh.

- The MAP estimation reveals as expected that the estimated heating energy ($\hat{E}_h$) increases during winter months, while the non-HVAC energy ($\hat{E}_o$) remains relatively stable throughout the year.

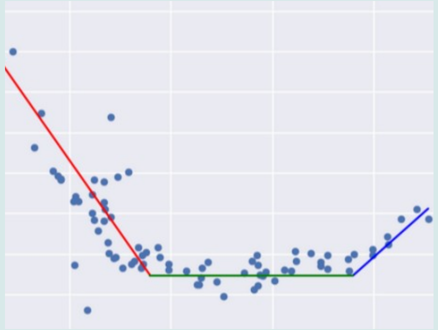




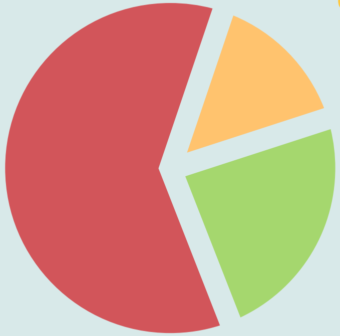
Discussion of Method & Comparisons

- The MAP estimation method offers improved standard error estimates relative to traditional Maximum Likelihood Estimation (MLE) methods.
- This approach conserves the total energy balance by ensuring that the sum of the disaggregated heating, cooling, and other components equals the measured total energy.
- Limitations include the sensitivity to the estimated correlation coefficients (ρ_h and ρ_c) and the omission of additional explanatory variables such as occupancy and electricity pricing.
- The model requires further validation with comprehensive, labeled datasets to assess its performance across varied building types and conditions.

Conclusions and future work

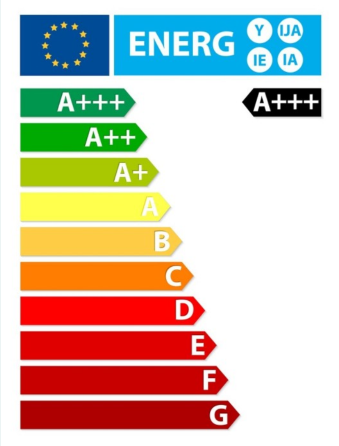


👉This study presents a novel disaggregation method that integrates Degree-Days metrics with MAP estimation to accurately partition HVAC energy consumption from total energy usage.



👉The proposed model successfully decomposes energy data into heating, cooling, and non-temperature-dependent components, enhancing the precision of building energy management.

👉Future work will focus on validating the model using labeled datasets, incorporating additional factors (e.g., occupancy and dynamic pricing), and extending the methodology to improve cooling energy disaggregation.



👉The findings contribute to the advancement of energy efficiency practices and support the development of sustainable energy management solutions.

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