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Analytical modelling and prediction formulas for domestic hot water consumption

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ELSEVIER

Analytical modelling and prediction formulas for domestic hot water consumption in residential Finnish apartments

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- DHW heating is the **second largest source of energy use** after space heating in the building sector: 20% of the total domestic consumption in the UK, 13% in Germany.

- Knowledge of the true consumption patterns is **crucial to avoid** improper sizing of DHW heating systems (=> **high costs**), e.g. as a tool for dedicated **simulation programs**.

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- Previous studies: stochastic bottom-up models, probabilistic models, seasonal and social probability, end user questionnaires, daily usage of appliances... **many variables needed**!
- **Not always successful** (sometimes consumption overestimation up to 70%)

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- **1)** derive the **correlations** between occupant groups and different seasons => **MAIN TREND OF CONSUMPTION**
- **2)** generate a **PREDICTIVE FORMULA** for the DHW consumption of **unknown occupant groups**.

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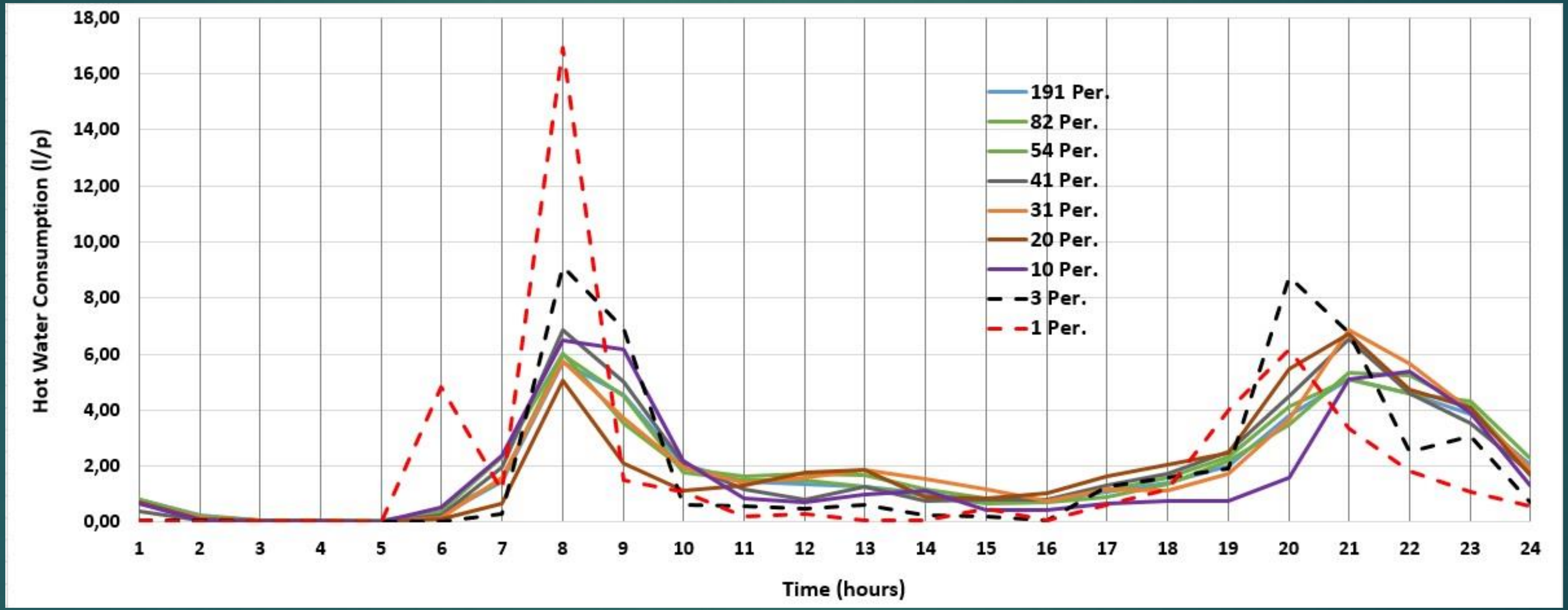
METHOD, PRELIMINARIES: FIT THE DATA

- DHW consumption data for November, Weekdays (WD) **[1]**:

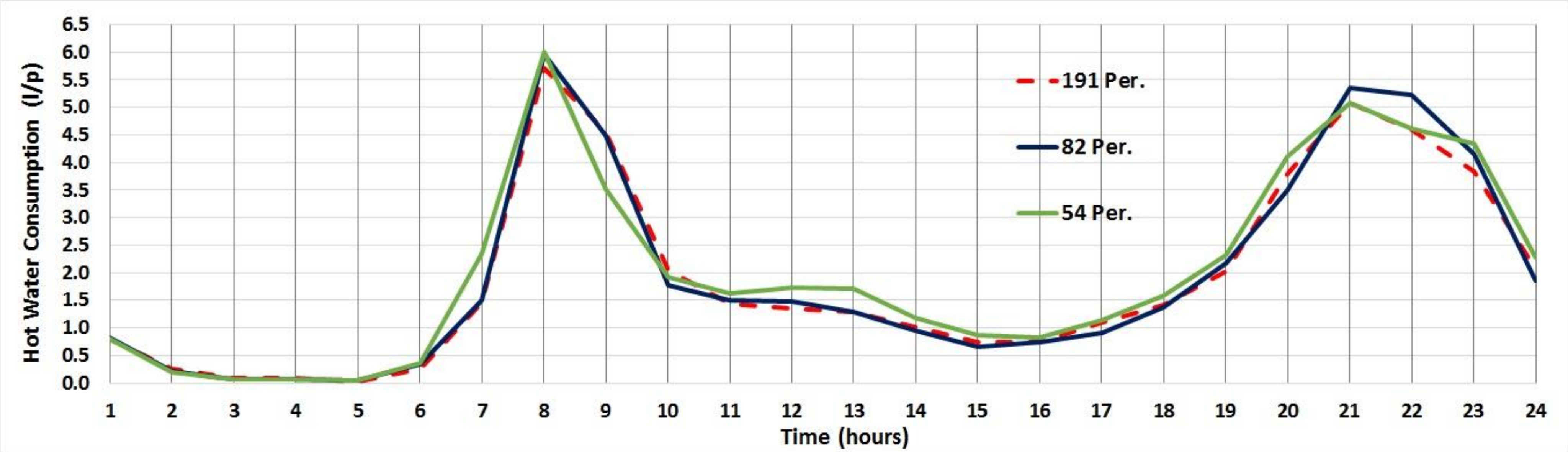


- **Fig.1**

[1] K. Ahmed, P. Pylsy, J. Kurnitski. Hourly consumption profiles of domestic hot water for different occupant groups in dwellings, Sol. Energy 137(2016) 516-530

METHOD, PRELIMINARIES: IDENTIFY TRENDS

- **Common pattern**: for >50 occupants **only one curve** is needed! No qualitative difference, and the Total consumption is very similar.



- **Fig.2**

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- The corresponding dataset will be called **structural dataset**.

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- Interpolate the data for 82 persons in November, WD **[2]**: use a **constrained least square method** (i.e. with a consumption constraint to minimize the difference between observed and fitted values)

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- Let us then choose **82p as the structural dataset**.
- Interpolate the data for 82 persons in November, WD **[2]**: use a **constrained least square method** (i.e. with a consumption constraint to minimize the difference between observed and fitted values)
- **Energy (or consumption) difference**:
  E82=45.055 l/p vs E82fit = 45.065 l/p => **%(ΔE)=0.22‰**

  (without the consumption constraint, %(ΔE)=3.7%)

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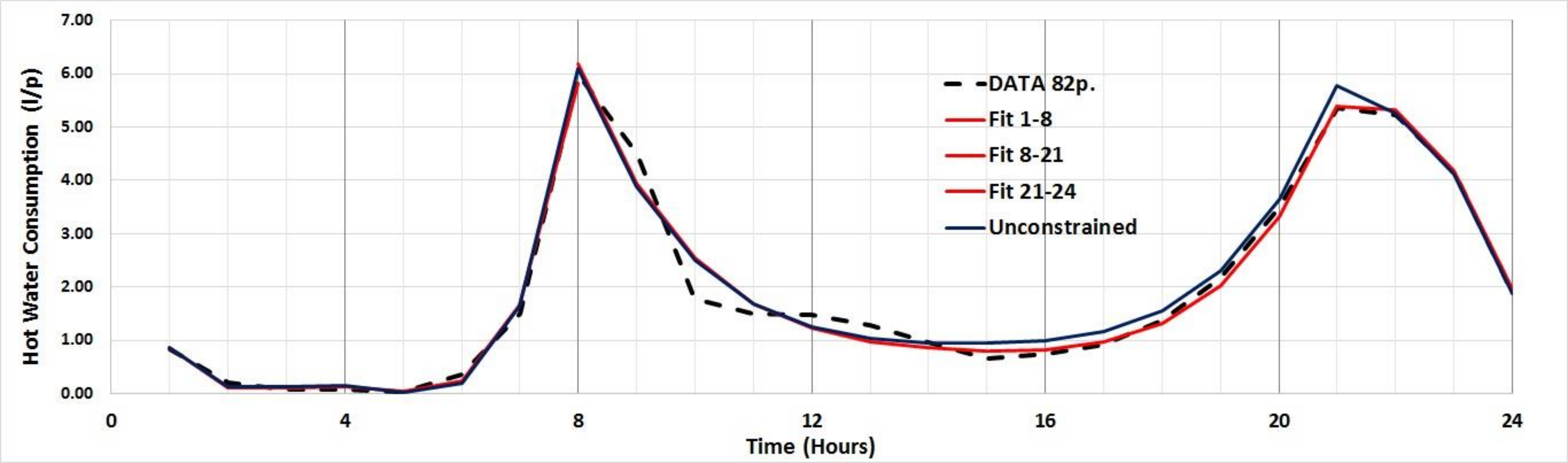

To avoid a large propagation of errors, it is critical to obtain **<u>the most precise fit</u>** (structural curve) we can!

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- Compute **correlations between each and every dataset** with the *structural dataset* 82p.

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- Compute **correlations between each and every dataset** with the *structural dataset* 82p.
- Each fit curve **for *n* occupants** can be thus written in function of the structural curve E82(t) as

$$E_n(t) = f_n[E_{82}(t)] = A(n) + B(n)E_{82}(t)$$

Let us call the above the **structural formula**.

METHOD, PT.3: THE STRUCTURAL COEFFICIENTS

- ***1)*** *Compute* ***A(n)*** and ***B(n)***, the ***structural coefficients*** in the **structural formula** ***En(t)=A(n)+B(n)E82(t)***:

$$E_{10}(t) = 0.02158 + 1.10392 E_{82}(t),$$

$$E_{31}(t) = -0.04761 + 0.97903 E_{82}(t) \ldots t[h] \in [1, 8)$$

$$E_{10}(t) = -0.5662 + 1.1279 E_{82}(t),$$

$$E_{31}(t) = 0.16737 + 0.99834 E_{82}(t) \ldots t[h] \in [8, 21)$$

$$E_{10}(t) = -0.82974 + 1.146 E_{82}(t),$$

$$E_{31}(t) = -0.6951 + 1.2794 E_{82}(t) \ldots t[h] \in [21, 24).$$

METHOD, PT.3: THE STRUCTURAL COEFFICIENTS

- ***2)*** Then interpolate ***A(n)*** and ***B(n)*** as ***f(n)*** **[2]:**

November WD	
1–8	$A(n) = 0.2336 - 0.02984n + 8.43 \times 10^{-4}n^2 - 6.268 \times 10^{-6}n^3$
	$B(n) = 1.358 - 0.03694n + 9.171 \times 10^{-4}n^2 - 6.346 \times 10^{-6}n^3$
8–21	$A(n) = -1.471 + 0.1243n - 2.494 \times 10^{-3}n^2 + 1.462 \times 10^{-5}n^3$
	$B(n) = 1.276 - 0.02183n + 3.954 \times 10^{-4}n^2 - 2.081 \times 10^{-6}n^3$
21–24	$A(n) = 0.1427 - 0.1341n + 4.909 \times 10^{-3}n^2 - 4.016 \times 10^{-5}n^3$
	$B(n) = 0.66 + 0.06384n - 1.944 \times 10^{-3}n^2 + 1.482 \times 10^{-5}n^3$

[2] R core team. R: A Language and Environment for Statistical Computing. R Foundation, Vienna, Austria.

METHOD, PT.3: THE STRUCTURAL COEFFICIENTS

- **3)** Finally, substitute *A(n)* and *B(n)* in the **structural formula** ***En(t)=A(n)+B(n)E82(t)*** for any **unknown** ***n***.

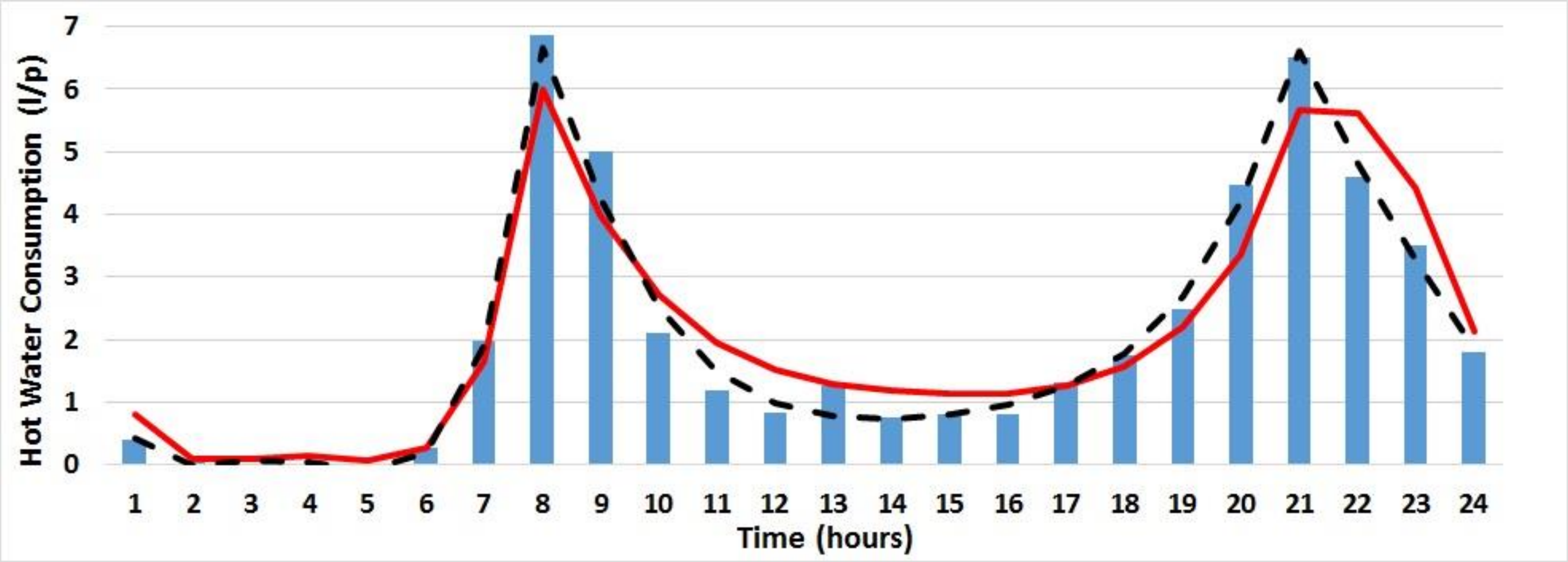
METHOD, PT.3: THE STRUCTURAL COEFFICIENTS

- **3)** Finally, substitute *A(n)* and *B(n)* in the **structural formula** ***En(t)=A(n)+B(n)E82(t)*** for any **unknown** ***n***.

*For **n=41**, an unknown dataset, **E41(t)=A(41)+B(41)E82(t)=***

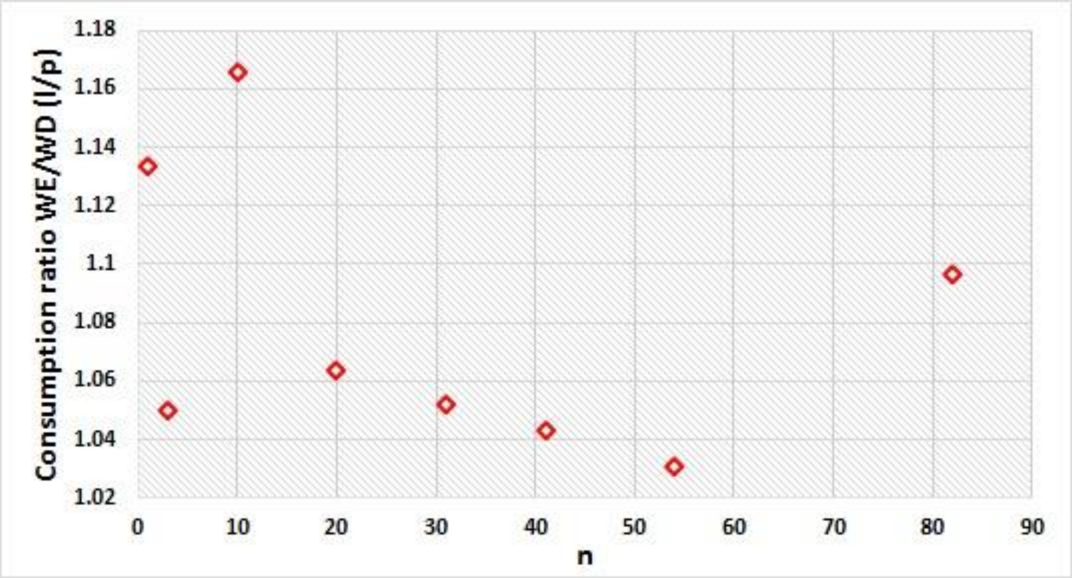
$$E_{41}(t) = \begin{cases} -0.004753828 + 0.947732E_{82}(t), & 1 \leq t[h] < 8 \\ 0.440511 + 0.902213E_{82}(t), & 8 \leq t[h] < 21 \\ 0.128762 + 1.030985E_{82}(t). & 21 \leq t[h] < 24 \end{cases}$$

VALIDATION: UNKNOWN DATASET

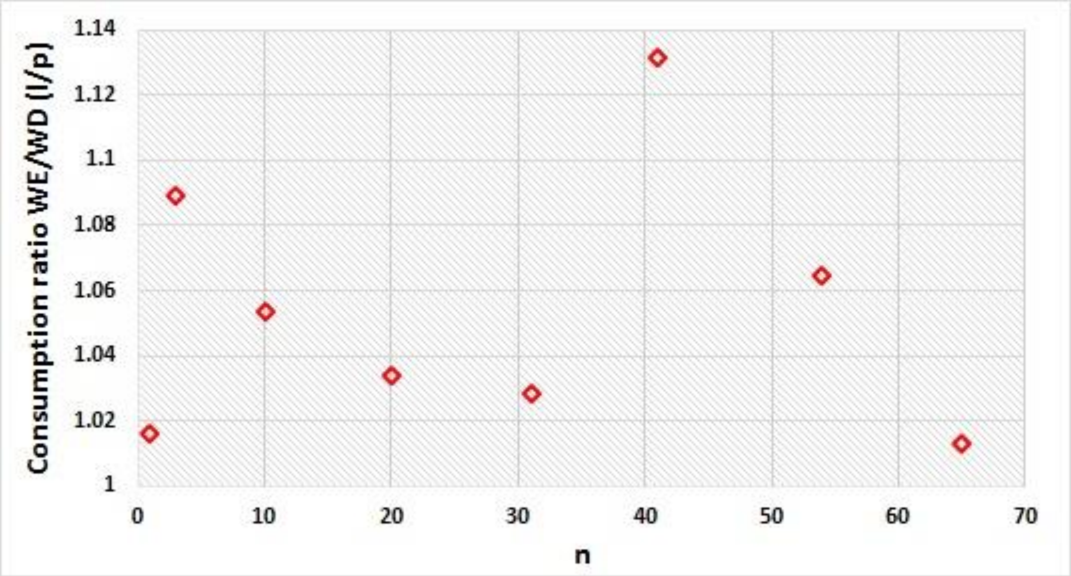


- ***n=41**, data=columns, fit=dashed, **model prediction=solid**.*
- ***Energy difference Data vs Prediction~2.3%***

EXTRA: CORRELATION WD VS WE



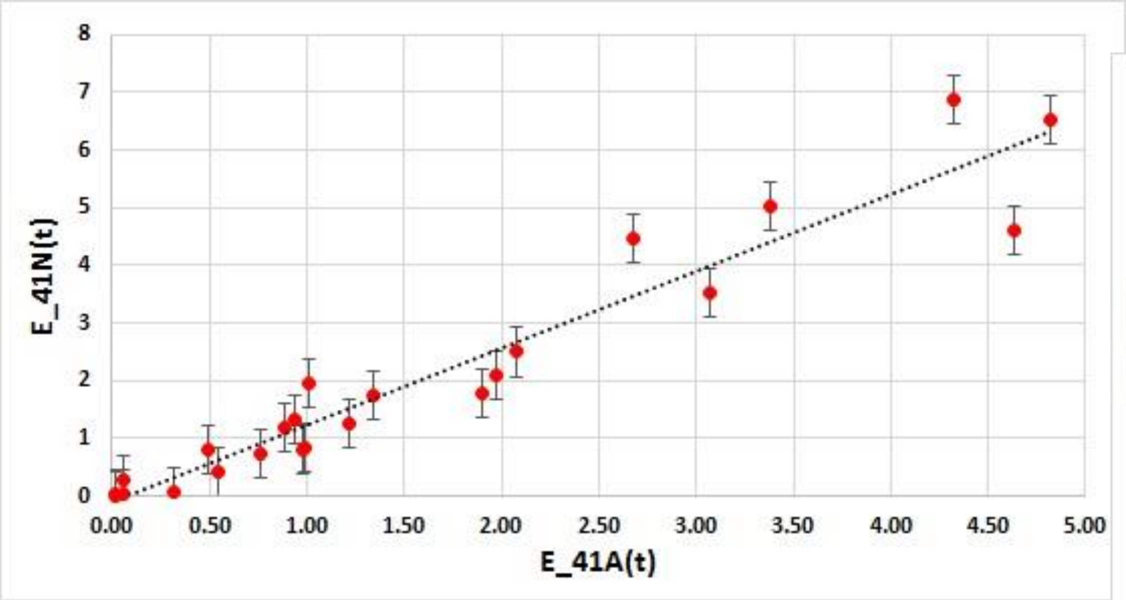
November

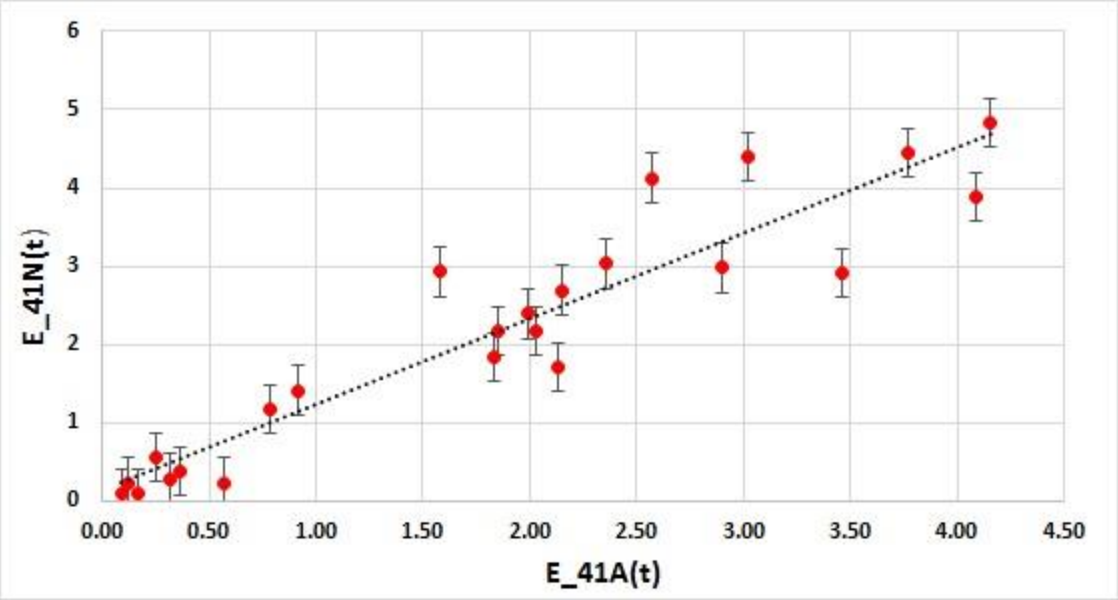


August

- ***No evident correlation** between weekday and weekend*

CORRELATION NOVEMBER VS AUGUST





- **n=41**, Weekdays (left) and Weekends (right)
- **Linear correlation**! Standard errors 0.4196 & 0.313

CORRELATION NOVEMBER VS AUGUST

$$E_{41N}(t) = -0.09454 + 1.33133 E_{41A}(t), \quad \text{WD}$$

$$E_{41N}(t) = 0.1447 + 1.0929 E_{41A}(t), \quad \text{WE}$$

- Hourly consumption for **41p**, N=November, A=August
- Possible to **correlate different seasons** with a simple formula!

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- **2) compute** *linear* correlations between the fit for the SD and those for the other datasets => ***structural coefficients***
- **3) interpolate** the structural coefficients to **predict** the hourly consumption for **unknown** datasets.

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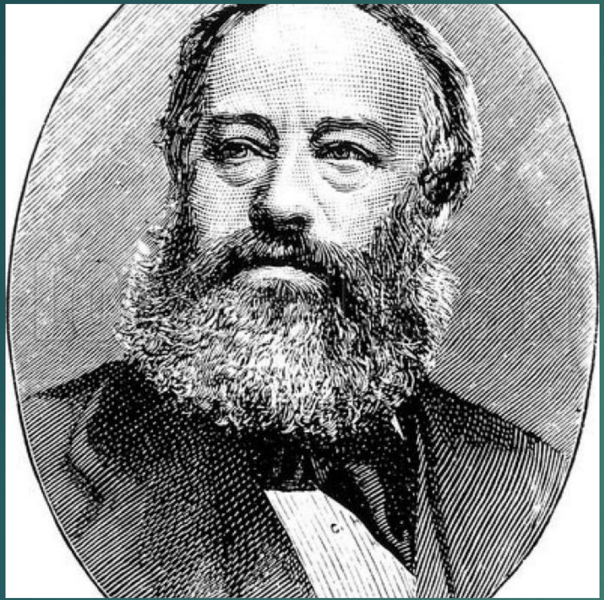
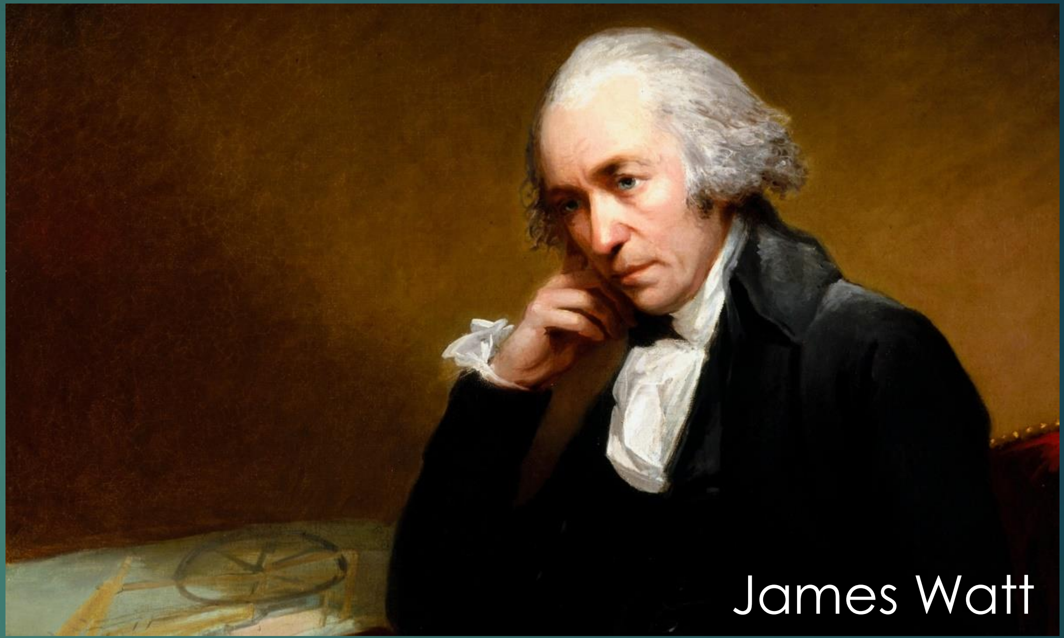
- Immediate implementation **into simulation tools** for energy investigations and heating sizing in Finland
- Straightforward **application to other countries**
- Possible **generalization to other engineering contexts**: this method is all about **identifying underlying patterns!**

THANK YOU FOR YOUR ATTENTION!



James P. Joule



James Watt

- A. Ferrantelli, K. Ahmed, P. Pylsy, J. Kurnitski. *Analytical modelling and prediction formulas for domestic hot water consumption in residential Finnish apartments*. **Energy and Buildings 143, 53-60**

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Appendix: MEASUREMENTS AND PROFILES

- **<u>Data</u>**: DHW consumption datasets for 86 Finnish apartments located in a single building in Tampere, during one year. Total of 191 occupants, with supply water temperature 55C [1].
- <u>Hourly profile for each apartment in a day</u>: average consumption of the apartment *a* at the hour *t*

$$v_{t,a} = \frac{\sum_1^n v_{t,a,n}}{N} \quad [\mathrm{L}]$$

with *n* number of days and *N* total number of days in a month. The hourly average consumption for a single user is

$$v_{t,a,o} = \frac{v_{t,a}}{O_a} \quad [\mathrm{L/p}]$$

[1] K. Ahmed, P. Pylsy, J. Kurnitski, Hourly consumption profiles of domestic hot water for different occupant groups in dwellings, Sol. Energy 137(2016) 516-530