Short-term residential district load forecasting: impacts of district size and history length

Mickaël Tits, Benjamin Bernaud, Amel Achour, Maher Badri, Lotfi Guedria / CETIC, Charleroi, Belgium

Energy communities for collective self-consumption: frameworks, practices and tools
Session 8 - September 15, 2020
Consumers' role in the design and management of energy systems: from the individual to the collective

Overall context

PV + Network ≠ ❤️

corr(PV, inhabitant) ≈ 0 => Uncontrolled instable exportation => Network overload and harmonics :

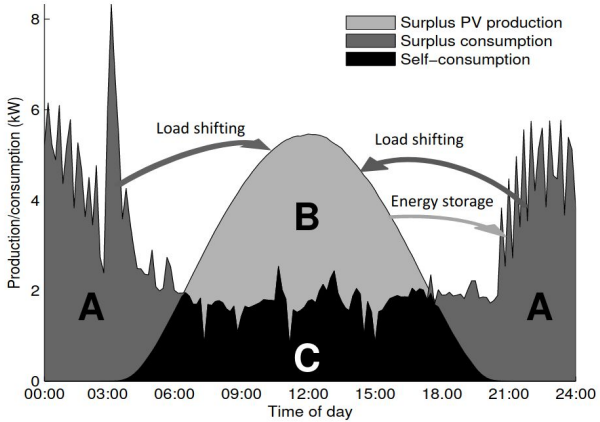
- direct energy loss (Joule effect % RI^2) € ↗️
- indirect loss (load shedding, value dropping) € ↗️
- infrastructure maintenance/reinforcement costs € ↗️
- (and taxes for prosumers in Belgium ...)

Proposed solution(s)

[1] : average individual self-consumption = 40%

- +2-15% with load shifting
- +13-24% with battery energy storage

⇒ **Collective load shifting ?**



[1]

[1] R. Luthander, J. Widén, D. Nilsson, and J. Palm, “Photo-voltaic self-consumption in buildings: A review,” Applied Energy, vol. 142, pp. 80 – 94, 2015.

How ?

(hypothesis : community ≈ big household

Minimize household/community energy exportation :

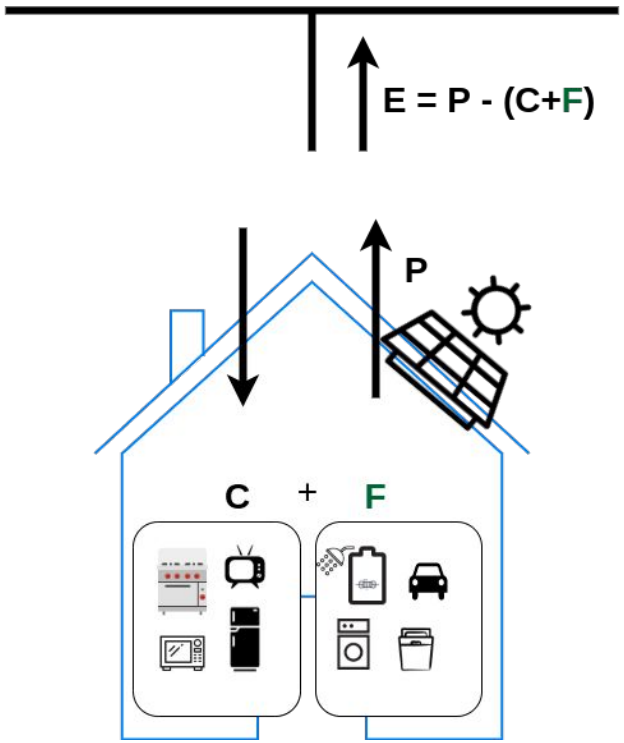
$$E = P - (C + F)$$

E: exportation

P: production (PV)?

C: non-flexible consumption?

F: flexible consumption (shiftable loads)?



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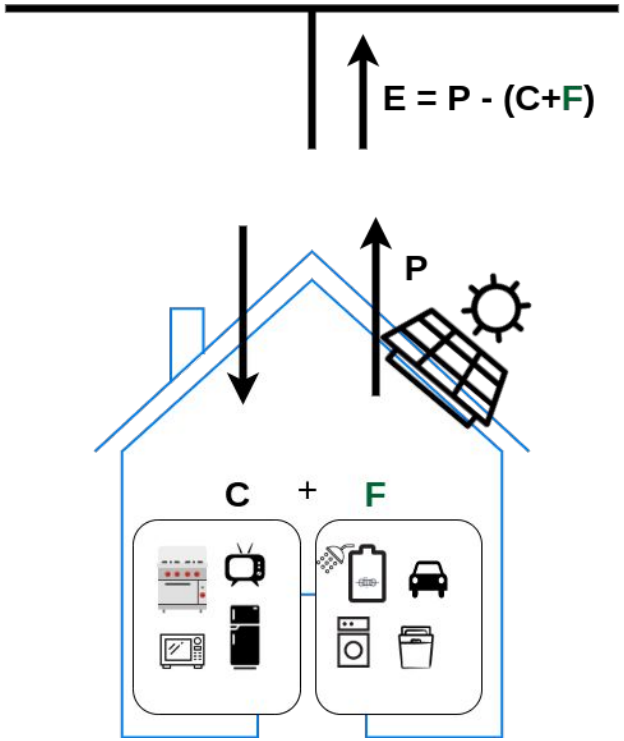

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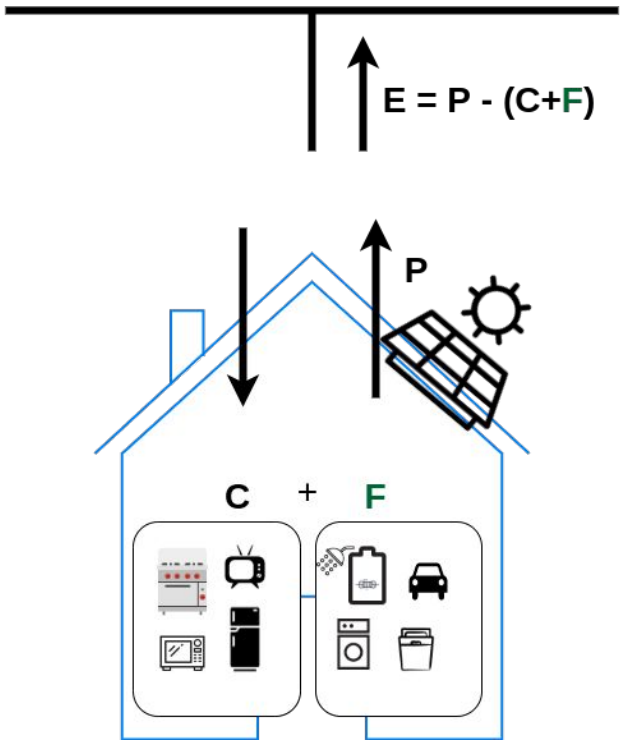

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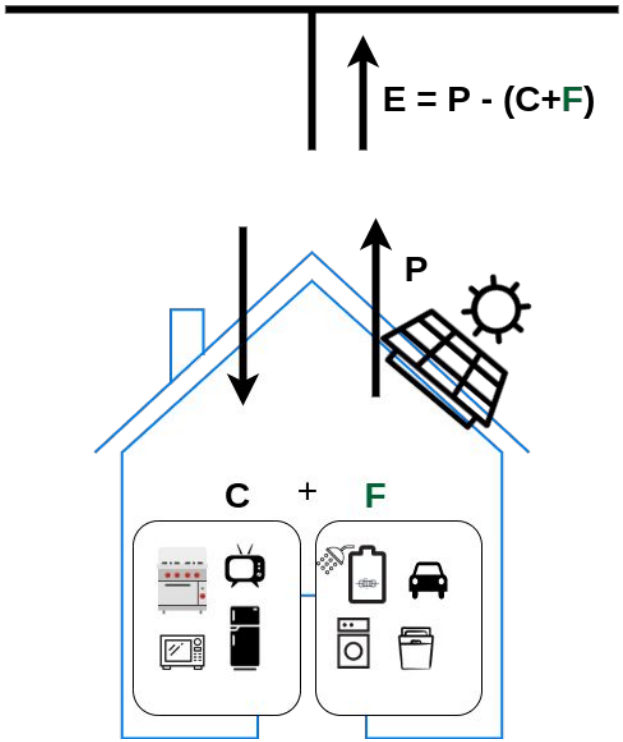
C: non-flexible consumption? ⇒ **forecasting model**!

F: flexible consumption (shiftable loads)? ⇒ load shifting (linear programming)



Energetic community load forecasting

Objective: forecast community load with a high accuracy!

Issue: depends on various community characteristics :

- **Community size**: noiseness ↘️ if size ↗️ (aggregation level)
- **History length**: model accuracy ↗️ if data ↗️
- **Resident behaviour**: more or less predictable patterns ?

Research question:

Impact of community characteristics on forecasting accuracy ?

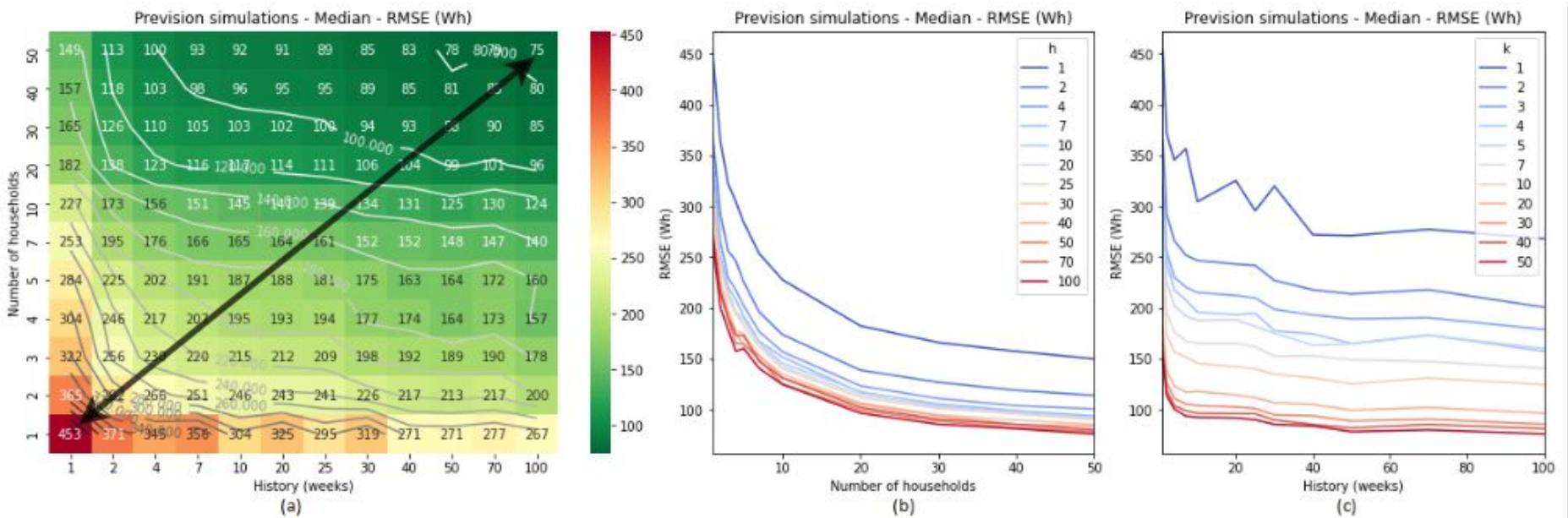
Methodology

1. Simulate load for virtual energetic communities (VEC)
    a. random sampling of **k households** from a dataset
    b. extract rolling windows of **h weeks** of data history

2. Train and test our model for each VEC simulated
    a. training set: h weeks of data
    b. test set: the next week of data
    c. train model and extract predictions for test set
    d. compute overall evaluation metrics (RMSE, compare with baseline models, …)

Results

- RMSE from 453Wh to 75Wh! (453Wh ≈ random forecast)



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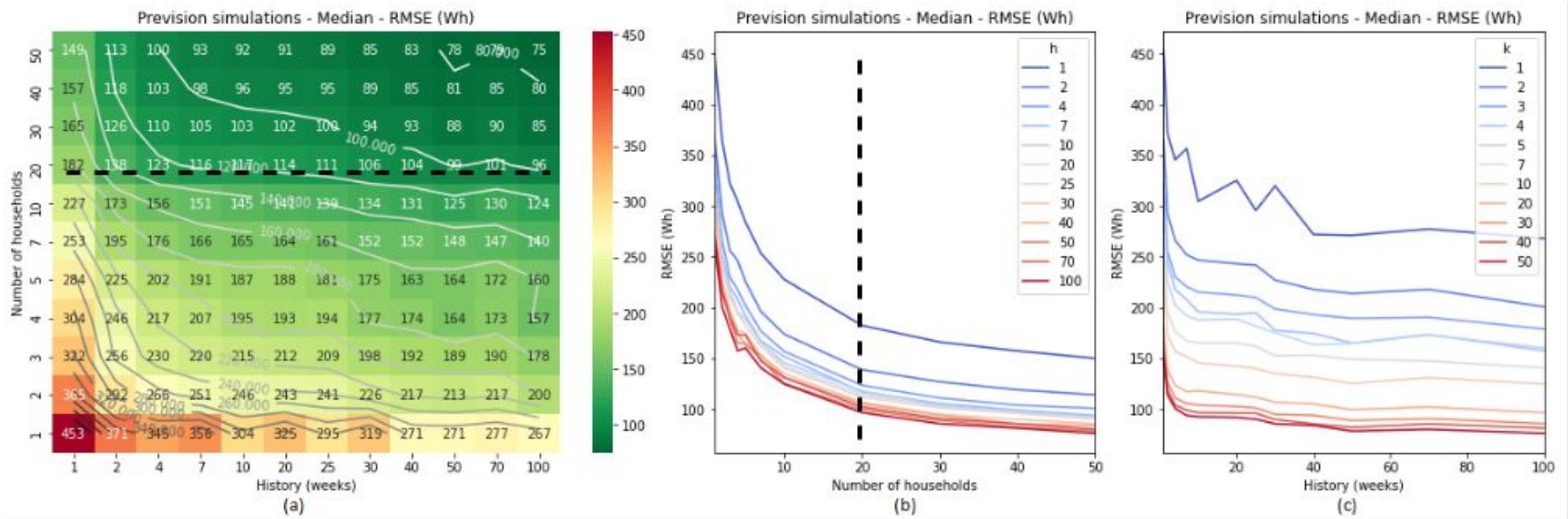

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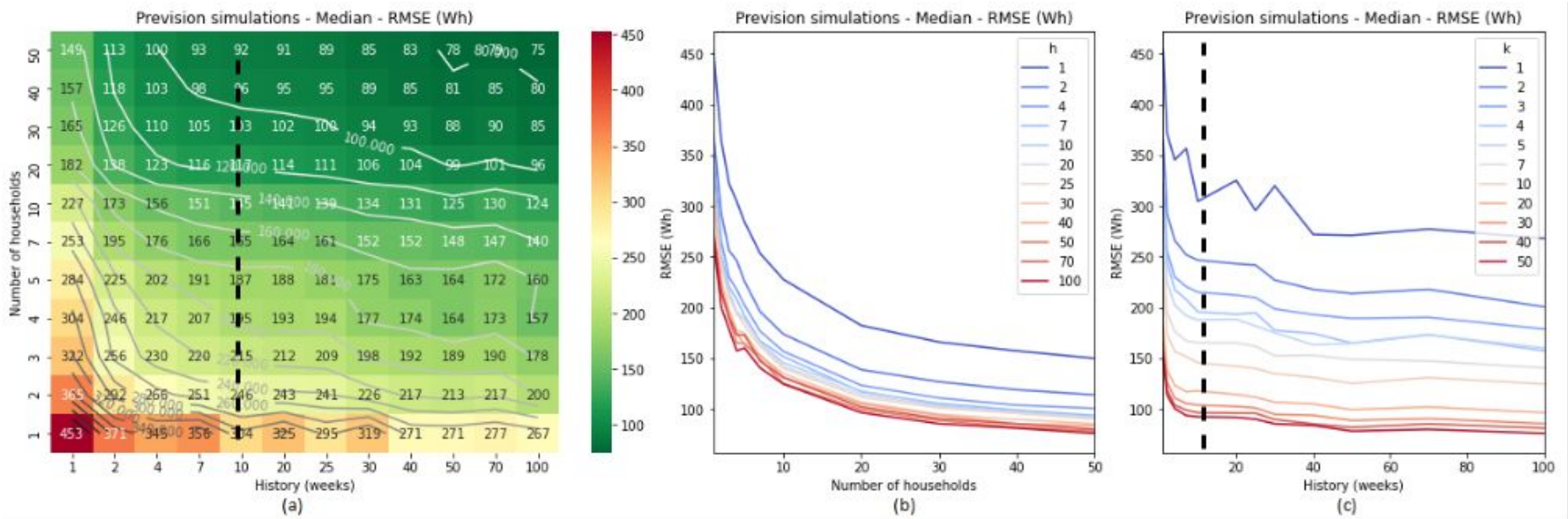
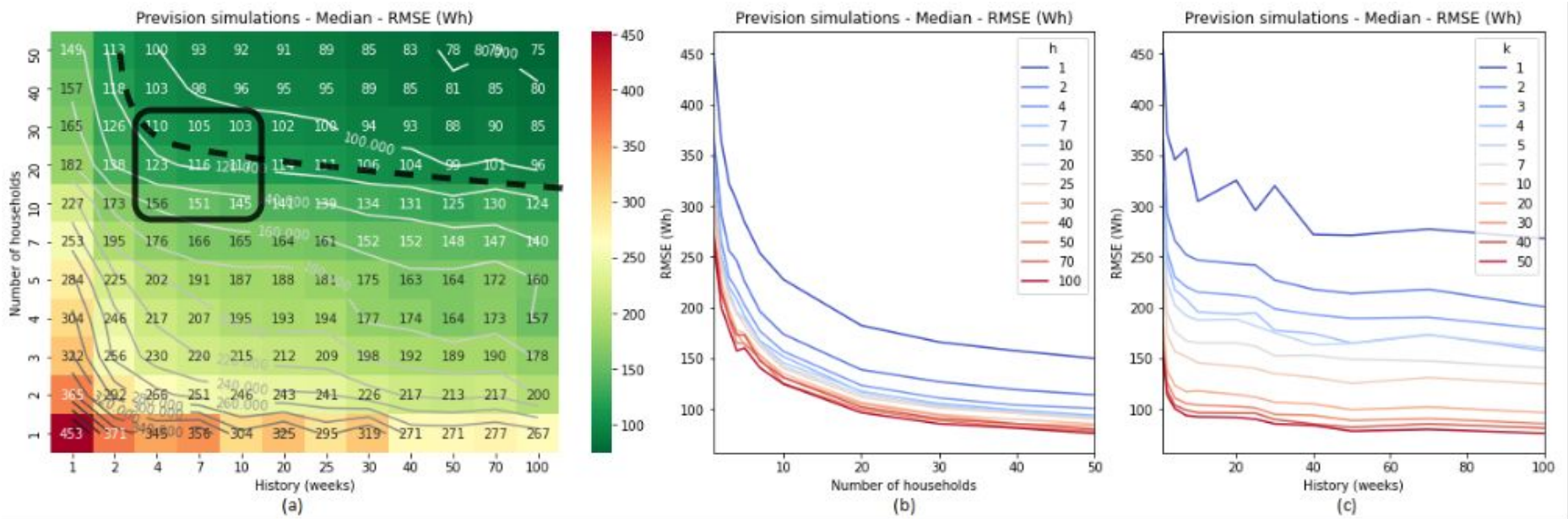


Results

- RMSE from 453Wh to 75Wh! (453Wh ≈ random forecast)
- High improv. until 20-30 households
- High improv. until 5-20 weeks
- Trade-off around 20 households/2 months

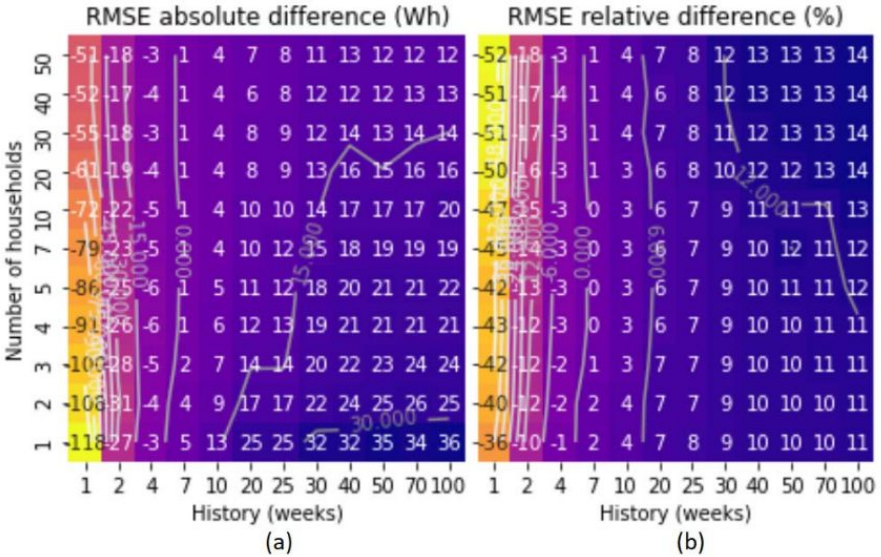


About model complexity ?

Baseline: 3-Week moving average
“Complex model”: Ridge autoregression

- Need more data (<2month ⇒ overfitting)
- Up to 14% RMSE improvement

⇒ Use a simpler model at the beginning! (or simply wait)



About community profile ?

- Larger communities (larger k) have more regularity ⇒ more predictable
- Older communities (larger h) are more predictable with ridge regression
- Communities with larger consumers (larger μ) seem more regular ⇒ (relatively) more predictable

Table I
SPEARMAN CORRELATIONS BETWEEN VEC PROFILE ATTRIBUTES AND EVALUATION METRICS.

R_{Sp}	μ	σ	ρ_{day}	ρ_{week}	k	h
μ	1.00	0.58	0.43	0.28	0.11	0.00*
σ	0.58	1.00	0.03	-0.12	-0.54	0.00*
ρ_{day}	0.43	0.03	1.00	0.94	0.62	0.00*
ρ_{week}	0.28	-0.12	0.94	1.00	0.68	0.00*
ϵ	0.39	0.86	-0.30	-0.44	-0.70	-0.28
δ	0.23	0.36	0.13	0.03	-0.15	0.75
Δ	0.18	0.16	0.27	0.19	0.05	0.82

* Not significant ($p > 0.1$). All others are significant ($p < 1E-13$).

Takeaway findings

1. Poor accuracy at starting, should increase over time for the first few months
2. Target more predictable communities: larger “regular” consumers, at least 10 households
3. Trade-off on “size” vs “age”. 20 houses/2months ≈ optimal efficiency
4. Limited interest of ML: up to 10-14% improvement (after 2-6 months)

Limitations/Takeaway questioning

1. Who are the larger and “more predictable” consumers ? (larger consumer = family? rich household with a heated pool?) ⇒ New data needed

2. Impact of load forecasting accuracy on planification accuracy ?? ⇒ Future work

3. We don’t care about load forecasting accuracy during the evening (nothing to self-consume)!
   ⇒ Future work: forecasting only needed during production hours (PV = day)

4. Consumer behaviour change (especially if participating in a energetic community) ⇒ forecasting model adaptativity ?

Thank you!

Mickaël Tits
mickael.tits@cetic.be

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Your Connection to ICT Research

Related paper: IEEE COMPSAC 2020 (ICT4SmartGrid workshop):
https://www.researchgate.net/publication/344097745_Impacts_of_size_and_history_length_on_energetic_community_load_forecasting_a_case_study