Evaluating forecasts of individual energy usage

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Introduction

The demands on future electricity networks are predicted to increase due to emergent economies, new technologies and a need to reduce carbon footprints.

- **Households used to be exclusively consumers, nowadays they may also supply energy through intermittent forms of generation (e.g. photo-voltaics).**
- **Electrical vehicles and heat pumps could cause peaks in demand at unusual times – overnight.**
- **Smart storage - batteries - can be placed in households or substations in order to optimise usage and mitigate possible shortages or for quality assurance.**
- **Smart meters enable better understanding (and potential influence) of user behaviour at a higher resolution.**

All this makes low voltage electricity networks more complex then before. Therefore, understanding and forecasting electrical energy demand on individual level will be important part of future networks.

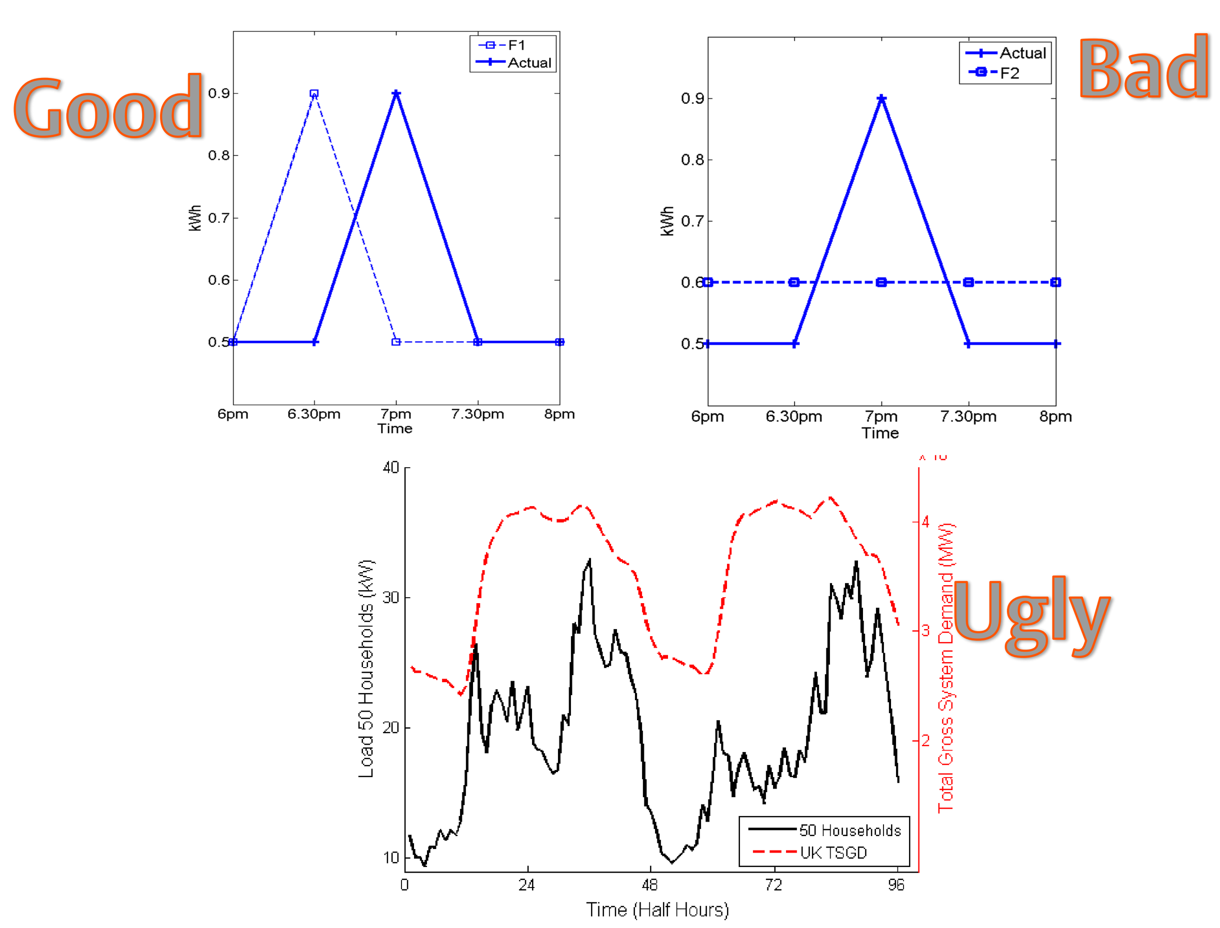
The Good, the Bad and the Ugly forecasts

Daily Individual load curves are normally:

-quite volatile, difficult to predict, lot of peaks

-aggregating 50 or 100 household is still non-smooth

-some regularities still exist - morning and evening peak, but they are not exactly the same time each day



Standard mean square error, p=2

Forecast / Actual

$$\|\mathbf{F}-\mathbf{A}\|_p = \left(\sum_{i=1}^{48}|f_i-a_i|^p\right)^{\frac{1}{p}}$$

Standard p-norm error actually favours the Bad forecast over the Good. Each slightly missed peak will be penalised twice.

Adjusted error

We propose the new measure, adjusted error, which allows limited time shifts of peaks.

$$E^w(x,f) := \min_{\pi\in P(w,n)} \left(\sum_{i=1}^{n}|f_{\pi(i)}-x_i|^p\right)^{\frac{1}{p}}$$

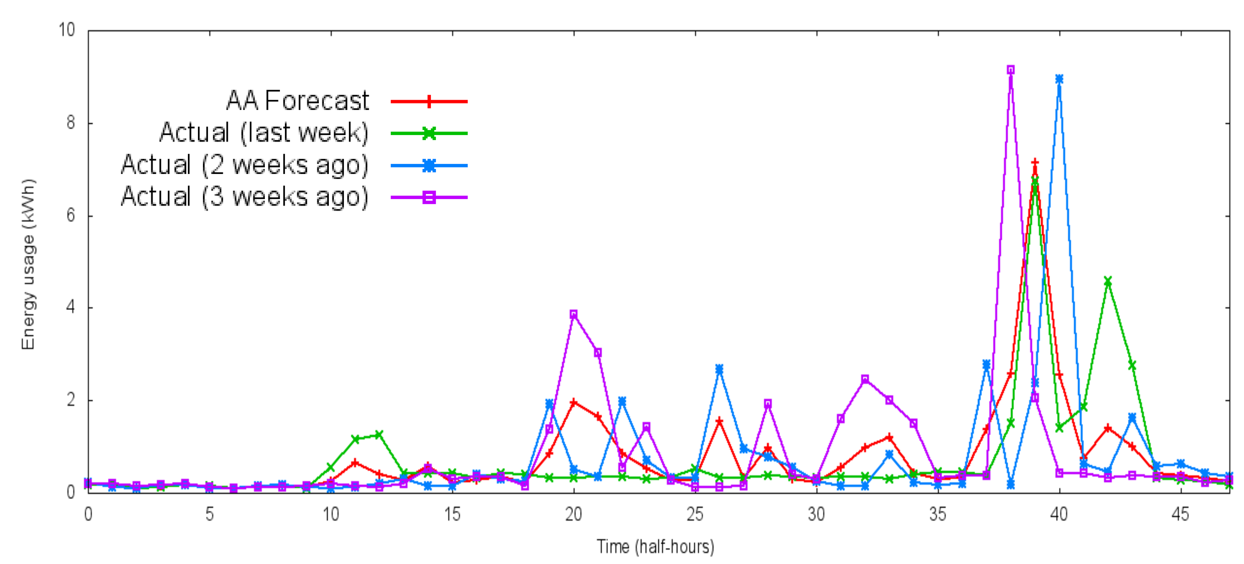
where $P(w,n)$ is a set of permutations that displace values by no more than w half-hours. We normally use $p=4$ in order to stress importance of getting amplitude right.

Hungarian algorithm

This minimisation problem is equal to finding minimum weight perfect matching in bipartite graph which can be solved in $O(n(m+n\log n))$ time using a version of Hungarian algorithm.

"Adjusted Average" forecast

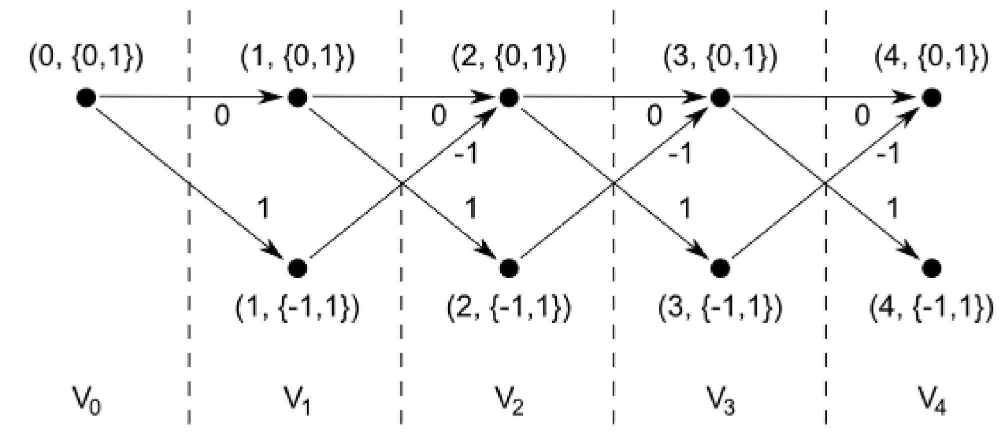
Allowing small time-shifts can be used in creating better forecasts based on historical "average". Here "average" is obtained by minimising adjusted distance for each new profile, and "better" means less reduction in regular peak compared to standard average. Note that more recent data will have more weight as we start with it.



Improving time

As window w is relatively small in our applications – it makes sense to move peak up to an hour or two but no more in each direction, we can actually do better than variants of Hungarian algorithm. We start by constructing

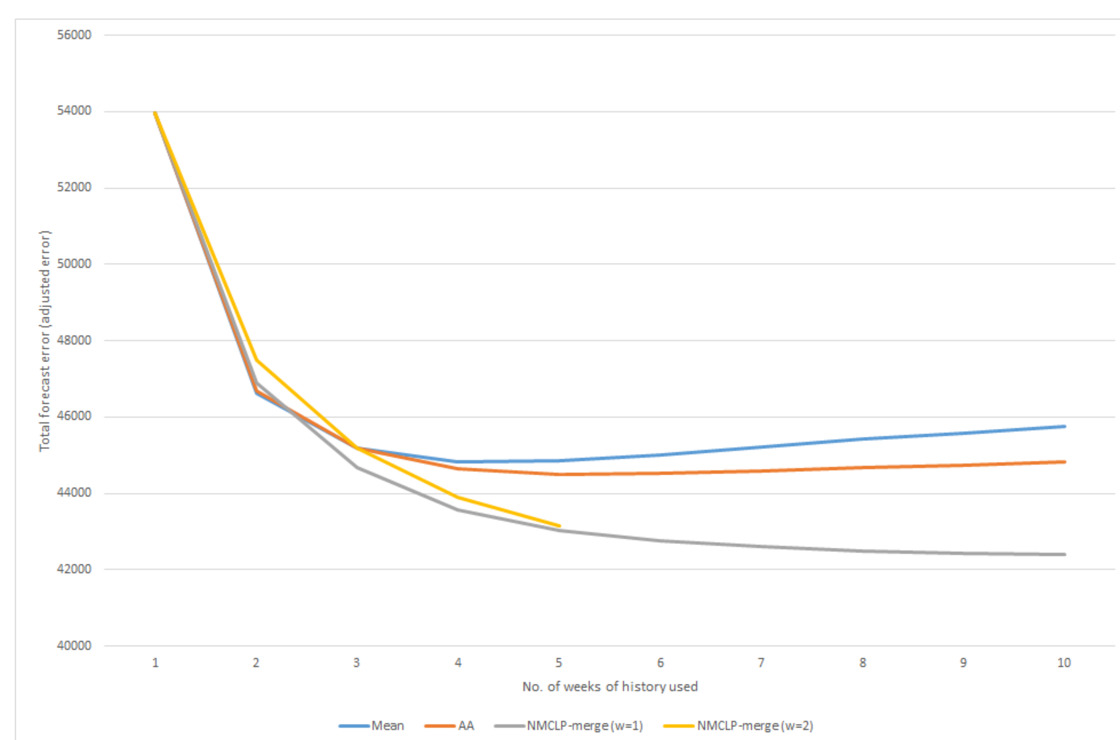
Window graphs



Now our minimisation problem can be turned into finding shortest path in such a graph which can be done in linear time.

New forecast

If we are given n historical profiles (e.g. individual daily usage, thus 48 points on n last Wednesdays) using n-layered window graph we can find a profile that is "in the middle" of this n profiles - which minimises adjusted distances between those n profiles. Here again limited time shifts are allowed. In that way we can create simple but effective forecast that works better than mean or median of n last Wednesdays.



Smart meter – big data?

Volume ☑ Velocity ☑ Variability ☐

Summary

- We were looking into half-hourly smart meter data and problems that arise by trying to predict individual or small-scale aggregated loads.
- Standard errors that work on aggregated data would prefer mean-usage flat forecasts to relatively good forecasts that slightly miss exact times of the peaks.
- For that reason we proposed an adjusted error measure which allows for limited time-shifts between forecast and actual
- Adjusted error can be solved in polynomial time by Hungarian algorithm
- We proposed faster algorithm that can be used for real-time error measures and forecasting.

Applications

- Smart storage solutions such as batteries could use adjusted error to create or to decide on roll-out predictions or to chose from ensemble
- The approach will work also when error is biased in time – if it is better to predict peak before then after the actual.

References

1. Haben et al. : "Mathematical solutions for electricity networks in a low carbon future." *CIRED, 22nd International Conference on Electricity Distribution , Stockholm, June 2013*
2. Haben et al. :"A New Error Measure for Forecasts of Household-level, High Resolution Electrical Energy Consumption", 2012 *University of Reading Preprint Series. Available at* http://www.reading.ac.uk/web/FILES/maths/preprint_12_14_Haben_6Sept.pdf
3. Charlton et al.: "Graph-based algorithms for prediction and comparison of household-level energy use profiles", 2013 *technical report*
4. Munkres, J. (1957). Algorithms for the assignment and transportation problems. *Journal of the Society for Industrial and Applied Mathematics, 5 ,32–38.*

Acknowledgements

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