Household Electricity Demand Forecasting: Benchmarking State-of-the-Art Methods

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The gist

The energy-efficient power networks of the future will require entirely new ways of forecasting demand on the scale of individual households. That won’t be easy. MIT Technology Review, April 11th, 2014

? How to forecast household power consumption in advance over timescales of minutes and hours?

! Sophisticated methods are no better than persistence forecasts and none produce forecasts with errors less than 30%.

⇒ A framework that adapts to individual household attributes.
Motivation

Increasing non-dispatchable energy production

Load balancing in smart grids with local generation

Affordable sensors and computing power
Our smart grid middleware vision

- **Smart Grid Applications**
  - Power system operator apps
  - Aggregator apps
  - End user apps

- **Smart Grid Middleware**
  - Distributed computation
  - Distributed storage

- **Physical Communication Network**
  - Wide area network
  - Local network access points

- **Power Grid**
  - Household Sensors
Challenges

- Experiments measure different features
- Households can have very different characteristics
- Real-time forecast requirements

*E.g., 15 min intra-day spot trading*
Device-level demand measurement data sets

1. Reference Energy Disaggregation Data Set (REDD)
   - 6 US households
   - Collected over period of 18 days
   - High variability in consumption

2. TUM home Experiment (TUM)
   - 1 household in Germany
   - Collected over period of 9 month
   - Low variability in consumption
For reproducibility, we only use forecasting methods provided by the R forecast package.

- Persistence as benchmark
- Autoregressive Integrated Moving Average (ARIMA)
- Neural networks with lagged inputs for forecasting univariate time series (NNAR)
- Exponential smoothing state space model (T/BATS)
Sampling strategies

1. **Sliding window**: data set is divided into smaller windows that slide through the data set.

2. **Day type**: join each day of the week into separate data sets.

3. **Hierarchical day type**: further separate data sets into channels for each appliance.
Parameters

- **Measurement granularity:** 15, 30, 60 minutes
- **Training window sizes:** 3, 5, 7 days
- **Forecasting horizons:** 15 minutes up to 24 hours
Exemplary illustration

Forecasting a 24 hour horizon with a neural network based on a 7 days training window and a measurement granularity of 15 min intervals.
Exemplary illustration

24 hour forecast
Exemplary illustration

Forecast from neural network
Exemplary illustration

Forecast from neural network
Exemplary illustration

MAPE = 79.7%  
→ large error
Results

1. Forecasting methods rarely beat corresponding persistence forecasts.

2. Results differ largely between the two data sets.

3. Increasing window sizes improve the results.
Results

4. Longer forecasting horizons lead to lower accuracy.

5. Lower granularities lead to better accuracy.

6. A division of the data into day type windows improves the forecast accuracy.
Results

7. Hierarchical strategy can improve accuracy.

To sum up:

If applied without tuning, the considered forecasting techniques beat persistence benchmark only in rare cases.

None of the forecasting methods performs particularly good.
Directions for future work

- Further features for multivariate forecasting
- Use consumption patterns from individual appliances
- Boosting with meta-algorithm based on user activity model
Thank you