Adaptive Time Series Forecasting of Energy Consumption using Optimized Cluster Analysis

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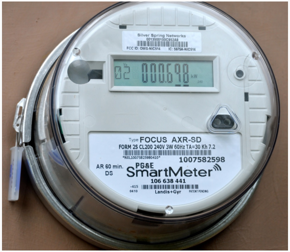
Motivation

More accurate forecast of electricity consumption is needed due to:

- Optimization of electricity consumption.
- Production of electricity. Overvoltage in grid.
- Distribution (utility) companies. Deregulation of the market. Purchase and sale of electricity.

Smart grids:

- Intelligent networks.
- Smart meters (every consumer has them).
- Usually 48 measurements per day.
- Advanced methods of forecast.



Forecast methods

Factors influencing electricity load:

- Seasonality (daily, weekly, ...)
- Weather (temperature, humidity, ...)
- Holidays
- Random effects

Methods:

- Time series analysis
- Regression
    - Linear model
    - AI methods
- Time series data mining + clustering

Clustering and forecast of load

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Target:

- Compare and find most suitable forecast methods that are suitable for the combination with clustering.

Data from smart meters

Available data come from smart meters from Ireland.

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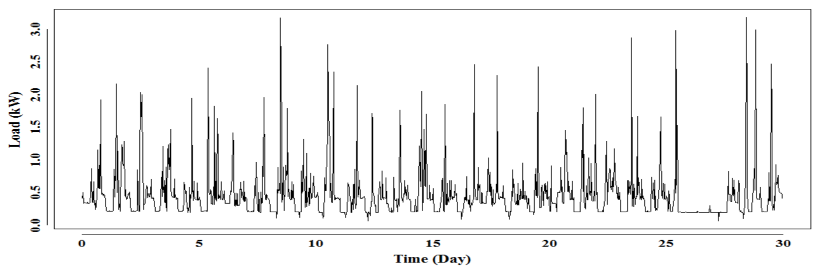
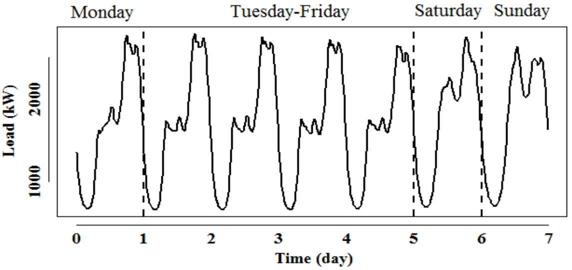
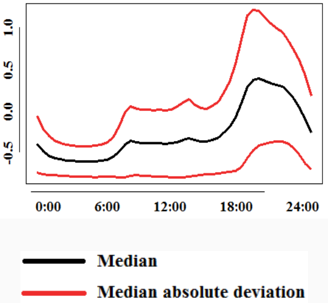


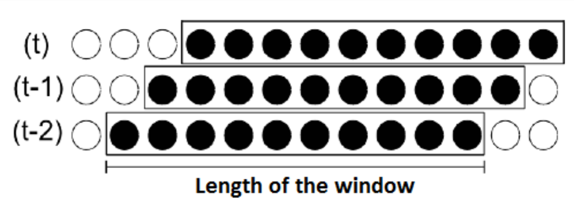
Median weekly and daily profile





What we want to do

Data come every day: batch processing (sliding window approach).



Batch of the length of two weeks (enough, fast).

Adaptability:

- Automatic selection of the number of clusters.

Proposed approach

Aggregation with clustering

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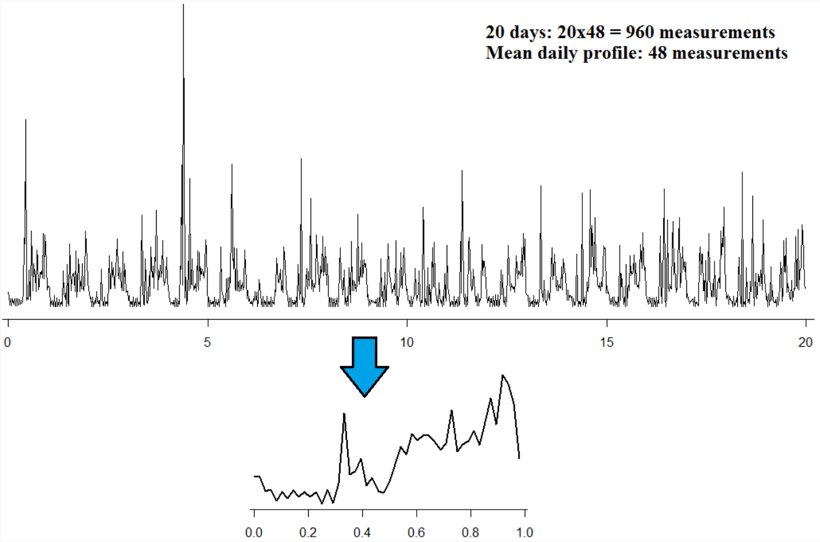
9. Remove first day and add new one to the training window (sliding window approach), go to step 1

Representations of time series



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Model based representations:

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Model based representations:

- Suitable for seasonal time series

Model based methods

- Representations based on statistical model.
- Extraction of regression coefficients $\Rightarrow$ creation of daily profiles.
- Creation of representation which is long as frequency of time series (48).

$$x_i = \beta_1 u_{i1} + \beta_2 u_{i2} + \cdots + \beta_{seas} u_{iseas} + \varepsilon_i, \; where \;\; i = 1, \ldots, n$$

New representation: $\hat{\boldsymbol{\beta}} = (\hat{\beta}_1, \ldots, \hat{\beta}_{seas})$.

Applied methods:
Robust Linear Model. Generalized Additive Model (smoothing function).

- Triple Holt-Winters Exponential Smoothing. Last seasonal coefficients as representation.

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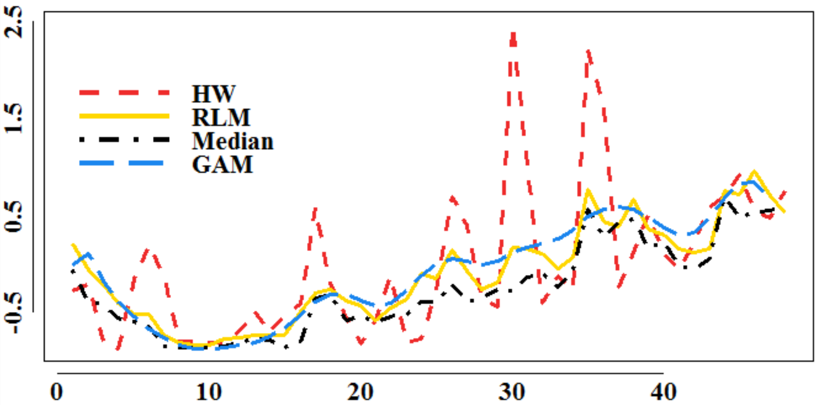
- Median daily profile.

Comparison of model based representations



HW - Holt-Winters, RLM - Robust Linear Model, Median - Median daily profile, GAM - Generalized Additive Model.

Forecast methods

Ten methods:

- Double Seasonal Holt-Winters Exponential Smoothing
- STL decomposition + Exponential Smoothing
- STL decomposition + ARIMA
- Support Vector Regression (SVR)
- Random Forest
- Extreme Gradient Boosting (xgboost)
- Extremely Randomized Trees
- Bagging
- Multilayer Perceptron
- Deep Learning

Evaluation of forecast

The accuracy of the forecast of electricity consumption was measured by MAPE (Mean Absolute Percentage Error).

$$\mathrm{MAPE} = 100 \times \frac{1}{n} \sum_{t=1}^{n} \frac{|x_t - \bar{x}_t|}{x_t},$$

where x_t is a real consumption, $\bar{x}_t$ is a forecasted load and n is a length of the time series.

Experiments

Setup:

- Sliding window of 14 days.
- Number of clusters from 8 to 18.
- One day ahead forecast.
- One model for all days during the week and separate models for workdays and weekdays.
- Various lengths of training windows for forecast methods.
- Various features (inputs) to forecast models. Dummy time variables (SVR), time of the day and day of the week, sinus and cosinus form of time, lagged load (denoised).

- Mean values of MAPEs $\rightarrow$

Results

	Sum		Median		GAM	
Method Name	MAPE	window	MAPE	window	MAPE	window
DSHW	4.577	14	**4.304**	14	**4.279**	14
STL + ARIMA	7.310	9	**7.008**	8	**6.968**	8
STL + ETS	11.014	4	**7.767**	8	**7.672**	8
SVR	4.206	14	**4.046**	14	**4.114**	14
RF	4.26	9	**4.193**	9	**4.19**	9
XGB	4.015	14	4.004	14	4.007	14
ExRT	3.758	14	**3.754**	14	**3.754**	14
Bagg	3.960	14	**3.818**	14	**3.795**	14
MLPnet	5.776	14	**5.227**	9	**5.229**	9
DLnet	4.473	14	4.395	14	4.433	14
Mean	5.054		4.869		4.879	

Results - with separation of days

	Sum		Median		GAM	
Method Name	MAPE	window	MAPE	window	MAPE	window
STL + ARIMA	4.317	4	**3.982**	6	**4.001**	6
STL + ETS	6.024	4	**4.813**	4	**4.804**	3
SVR	3.828	10	3.886	10	3.819	10
RF	3.855	5	**3.817**	5	**3.805**	5
XGB	4.081	10	**4.023**	10	**4.030**	10
ExRT	3.800	10	**3.796**	10	3.797	10
Bagg	3.822	10	**3.685**	10	3.680	10
Mean	4.003		3.924		3.913	

Conclusion

- Clustering of consumers can improve forecast accuracy.
- Significant improvement: DSHW, STL + ARIMA, STL + ETS, RandomForest, Bagging and MLPnet.
- Same results as simple aggregation most of times: SVR, ExtraTrees, xgboost and DLnet.
- We have shown that the best representations are RLM, Median and GAM.
- Average forecast error of forecasting methods with separated workdays and weekend models was lowered by 0.852% in comparison with methods without model separation.