Forecasting electricity demand in the short-term and prospective extension at seasonal scale

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Introduction

• Predicting the electrical load is essential for daily operation and planning activities of power network operators (grid stability, energy market etc.)
• The electrical load strongly depends on the weather conditions (e.g., high demand for cooling in summer)
• Weather forecasts can be used to link relevant weather variables with the electrical load using statistical post-processing methods
• A short-term probabilistic forecast system for electricity demand is developed to generate day-ahead probabilistic load forecasts
• Long-term degree-days projections are elaborated to provide information useful in planning electro/energetic system
• Prospective extension of short-term application at seasonal scale
Electricity demand in Italy

• 2015: +2% over 2014 (hot summer)
• 2014, 2016 lowest since 2002
• 2017 = ~ 320 TWh (again +2%)
• January – September 2018: 242 TWh (+0.6%)

A2A, 2017
Data and geographical reference area

- Hourly Actual Load (AL) data, i.e., the production units’ injections of power into the grid, including grid losses. Imports are not included.
- Period: 2015-2017
- Weather forecasts: WRF-ARW 3.9, 4 km horizontal resolution, 12 UTC, +84 h
- Weather variables averaged by municipality and then aggregated at national level
Electricity demand and relationship with meteorology
Post-processing algorithms

• Support Vector Regression (SVR)
  Machine-learning tool that uses a kernel function (e.g., RBF) to transform the data into a feature space where a non-linear problem can be solved linearly.

• Analog Ensemble (AnEn)
  After finding the n strongest analogs, each of the n AnEn members is taken as the verifying observation from each analog.

Delle Monache et al., 2013
Hourly Electrical Load Prediction with MEteorology

**Inputs:**
- GHI
- Heat index
- Load
- Id day
- Load d-1
- Load d-7
- Hourly weight

**Outputs:**
- SVR (deterministic AL forecast)
- AnEn weight optimization
- AnEn (probabilistic AL forecast)

**Training + weight optimization (2015 - 2016)**
**Test (2017)**

(10-member distribution)
Forecast verification: deterministic metrics

- **MAPE**: $\text{MAPE} = 100 \cdot \left( \frac{\text{obs} - \text{forecast}}{\text{obs}} \right)$

- **BIAS**: $BIAS = \langle \text{forec} \rangle - \langle \text{obs} \rangle$

**Quantile Regression (QR, Bremnes, 2004)**
**Hourly Electrical Load Forecasting (HELFo, Apadula et al., 2018)**
Forecast verification: probabilistic metrics

\[ CRPS = \frac{1}{N} \sum_{i=1}^{N} \int_{-\infty}^{\infty} (F_i^f(x) - F_i^a(x))^2 \, dx \]

Compared to a full probabilistic distribution with the observations, when both are expressed as CDF

\sim MAE
Extension to longer time scales

• Beyond a few days, the chaotic nature of the atmosphere limits the possibility to predict precise changes at local scales; long-range forecasts of atmospheric conditions have large uncertainties.

• Long term predictions rely on aspects of Earth system variability which have long time scales (months to years) and are, to a certain extent, predictable (e.g., El Nino Southern Oscillation cycle).

• Like the medium and extended ranges, long range forecasts are produced by the IFS coupled ocean-atmosphere model.

• E.g., the ocean temperatures typically vary on timescales of weeks/months, with an impact on the overlaying atmosphere. This can modify both local and remote atmospheric conditions.

C3S, Copernicus Climate Change Service
Seasonal forecasts

C3S multi-system seasonal forecast service

• Include data and graphical products, updated every month
• Time period: 6 months, horizontal resolution: 1° x 1°
• Forecasts created in real-time (since 2017) and retrospective forecasts (hindcasts) initialized at equivalent intervals during the period 1993-2016
• E.g., for application related to electricity demand:
  ✓ 2m temperature (6h instantaneous)
  ✓ Surface solar radiation downwards (24h aggregation)
Climate applications

Estimating energy demand for heating and cooling buildings to assess impacts of climate change on the urban environment.

**Degree-Days** - JRC/MARS-EUROSTAT (J)

\[
\begin{align*}
\text{hdd} &= \max(\, T^* - T_m, \, 0) \quad T^* = 18°C \text{ if } T_m < 15°C \\
\text{cdd} &= \max(\, T_m - T^{**}, \, 0) \quad T^{**} = 21°C \text{ if } T_m > 24°C
\end{align*}
\]

- [E-OBS](http://eca.knmi.nl/dailydata)
- [MESAN](https://ecds.se/dataset)
- [ENSEMBLES](http://ensembles-eu.metoffice.com/data.htm)

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**Heating Degree Days**

![Heating Degree Days graph](image)

**Cooling Degree Days**

![Cooling Degree Days graph](image)
Conclusions

- Predicting the electrical load necessarily requires weather forecasts.
- Different forecasting systems have been compared on a 730-day long training period and 365-day long verification period over Italy.
- The HELPME forecast system can outperform a weighted persistence method and QR.
- Prospective extension at seasonal scale: test with C3S seasonal forecasts and electricity demand data (Terna).
Bibliografia

- A2A, Italian Energy Market Overview, March 2017