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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



A2A, 2017



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

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





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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



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Forecast verification: deterministic metrics



 $BIAS = \langle forec \rangle - \langle obs \rangle$



Quantile Regression (QR, Bremnes, 2004)

Hourly Electrical Load Forecasting (HELFo, Apadula et al., 2018)

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 $MAPE = 100 \cdot$

|obs - forecast|

Forecast verification: probabilistic metrics





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

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



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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 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

Degree-Days- JRC/MARS-EUROSTAT (J) $hdd = max (T^* - Tm, 0)$ $T^* = 18^{\circ}C$ if $Tm < 15^{\circ}C$ $cdd = max (Tm - T^{**}, 0)$ $T^{**} = 21^{\circ}C$ if $Tm > 24^{\circ}C$

E-OBS <u>http://eca.knmi.nl/dailydata</u> *MESAN* <u>https://ecds.se/dataset</u> *ENSEMBLES* <u>http://ensembles-eu.metoffice.com/data.htm</u>

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







Conclusions



- Predicting the electrical load necessarily requires weather forecasts
- Different forecasting system 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
- HELPME short-term forecasts at national level soon available on SUNRISE: <u>http://sunrise.rse-web.it</u>
- Prospective extension at seasonal scale: test with C3S seasonal forecasts and electricity demand data (Terna)

Thanks! simone.sperati@rse-web.it



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