Hierarchical Demand Forecasting Benchmark for the Distribution Grid

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Radial distribution grids present hierarchical measurements. Forecasts must be aggregate-consistent:

- Active distribution networks will require higher coupling between aggregation levels
- SOs will provide services to upper levels of the network controlling demand and curtailing production located in LV level
Related benchmarks

Compared with existing hierarchical demand forecasting benchmarks [1],[2]

- Top level: MV (vs State level)
- Lower sampling time: 10 mins vs 1-hour
- Weather forecasts: Meteoblue NWP [3]

<table>
<thead>
<tr>
<th>Datasets</th>
<th>NWP</th>
<th>Grid</th>
</tr>
</thead>
<tbody>
<tr>
<td>variables</td>
<td>$P, Q,</td>
<td>V</td>
</tr>
<tr>
<td>sampling time</td>
<td>10 min</td>
<td>1 h, 12 h updates</td>
</tr>
</tbody>
</table>

[3] content.meteoblue.com
Related benchmarks

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- Top level: MV (vs State level)
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The dataset can be downloaded here: [https://zenodo.org/record/3463137#Ximr9eEo-V6](https://zenodo.org/record/3463137#Ximr9eEo-V6)


[3] content.meteoblue.com
Distribution grid forecasting benchmark

Rolle, secondary substations and LV cabinets
Distribution grid forecasting benchmark

Rolle, secondary substations and LV cabinets

62 IEC 61000-4-30 Class A power quality meters manufactured by DEPsys (Puidoux, Switzerland)
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Different levels of smoothness and forecastability
Distribution grid forecasting benchmark

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Different levels of smoothness and forecastability

Data has been preprocessed, removing time series with long sequences of missing data. 24 series are selected
Evaluation strategy

One day ahead forecasts, 10-min sliding window

- ~ 52k day ahead tests

10-folds cross validation

- folds are composed by 7 days of training and 1 day of testing

Fig. 2. Cross validation segment. Green squares: training days. Red square: test day. During testing, due to the adopted 24 hours embedding, the algorithms only see data contained in the 8-th day, avoiding overlapping of training and testing datasets.
# Distribution grid forecasting benchmark

Compared regressors:

<table>
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<tr>
<th>Model</th>
<th>Quantile estimation</th>
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<tr>
<td>Persistent</td>
<td>$\varepsilon_{h,d}$ on training set</td>
</tr>
<tr>
<td>Bagged ARMAX</td>
<td>$\varepsilon_{h,d}$ on training set</td>
</tr>
<tr>
<td>Detrended HW</td>
<td>$\varepsilon_{h,d}$ on training set</td>
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<tr>
<td>kNN</td>
<td>quantiles of kNN</td>
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<td>LightGBM</td>
<td>quantile loss</td>
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![Graph showing distribution grid forecasting results](image)
Distribution grid forecasting benchmark

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NO HYPER-PARAMETER TUNING
NO FEATURE ENGINEERING
Top level results

We scored the forecasters with deterministic and probabilistic KPIs

MAPE for 4 forecasters w.r.t. the aggregated power, normalized with the persistent model MAPE, as a function of step ahead (x) and hour of the day (y)

Average quantile loss for 5 forecasters w.r.t. the aggregated power.

\[
\epsilon_\alpha = \hat{q}_\alpha - y \\
\bar{I}_\alpha = \sum_{t=1}^{T} \epsilon_\alpha (I_{\epsilon_\alpha \geq 0} - \alpha)
\]
Hierarchical levels

Time series have been fictitiously aggregated in a 4-level hierarchy. This create intermediate levels of smoothness

<table>
<thead>
<tr>
<th>Score</th>
<th>Forecasters</th>
<th>armax</th>
<th>hw</th>
<th>knn</th>
<th>lgb</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAPE</td>
<td>8.2 / 21.8</td>
<td>7.2 / 14.9</td>
<td>4.9 / 13.8</td>
<td><strong>3.0 / 9.8</strong></td>
<td></td>
</tr>
<tr>
<td>RMSE</td>
<td>67.1 / 6.1</td>
<td>60.4 / 4.7</td>
<td>46.2 / 4.4</td>
<td><strong>26.2 / 3.1</strong></td>
<td></td>
</tr>
</tbody>
</table>

Diagram:

- **Top**
  - **S1**
    - **S1,1**
    - **S1,2**
  - **S2**
    - **S2,1**
    - **S2,2**
Hierarchical reconciliation

We tested different hierarchical forecasting techniques on the dataset.

- minT: minimize the trace of the covariance matrix of the revised forecasts through GLS

- bayesian: use Bayes’ rule assuming a joint Gaussian covariance of bottom time series

Fig. 8. Boxplots of the RMSE reduction for the bottom time series, using different reconciliation techniques, as a function of step ahead. The values are normalized with the RMSE of the base forecasters, and aggregated using 4 hours bins. Positive values indicate an improvement.
Hierarchical reconciliation

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- minT: minimize the trace of the covariance matrix of the revised forecasts through GLS

- bayesian: use Bayes’ rule assuming a joint Gaussian covariance of bottom time series

Fig. 9. The same kind of plot of figure 8, referred to the aggregated time series.
Thank you for your time!

The dataset can be downloaded here:
https://zenodo.org/record/3393437#.Ximr9eEo-V6

Any questions? Write to me!
lorenzo.nespoli@supsi.ch