



Forecasting of heat demand in district heating systems and their integration into smart grid controllers – Fractals, ensembles and expert advisers

COPENHAGEN, 13 SEPTEMBER 2017
Davy Geysen – Gowri Suryanarayana



Overview



Part I The context: STORM

Part II Machine learning

Part III Expert Advice

Part IV Results

Part V Conclusions

Self-organising Thermal Operational Resource Management



- **4th generation DHC**
- **Generic intelligent DHC network controller**
 - Thermal load forecasting
- **Karlshamn DHS**
 - **100 buildings**

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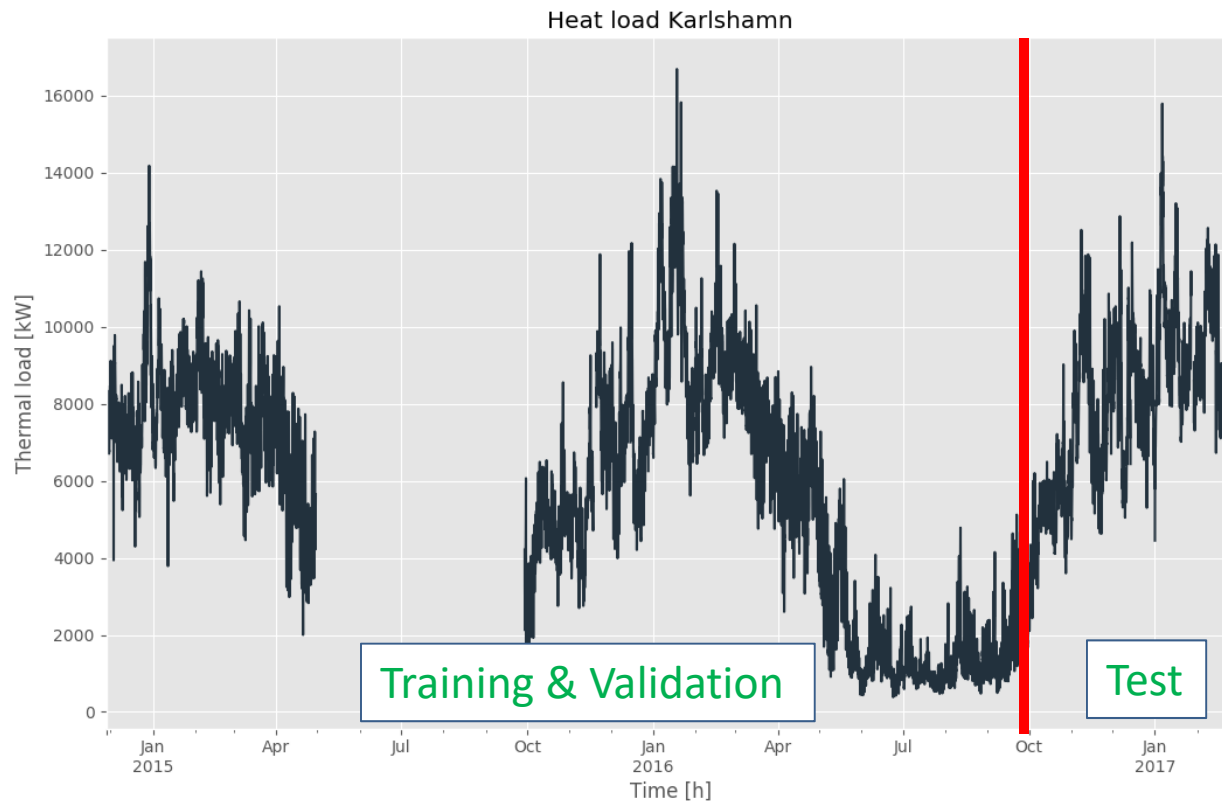
Part IV Results

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Machine learning



- **Building a model from sample inputs**



Supervised Machine learning



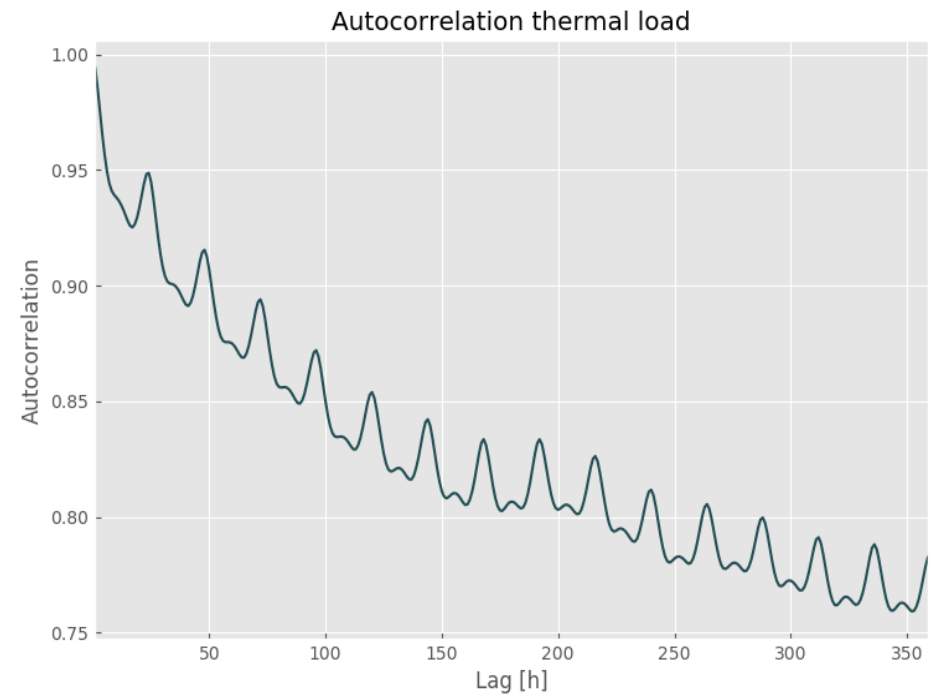
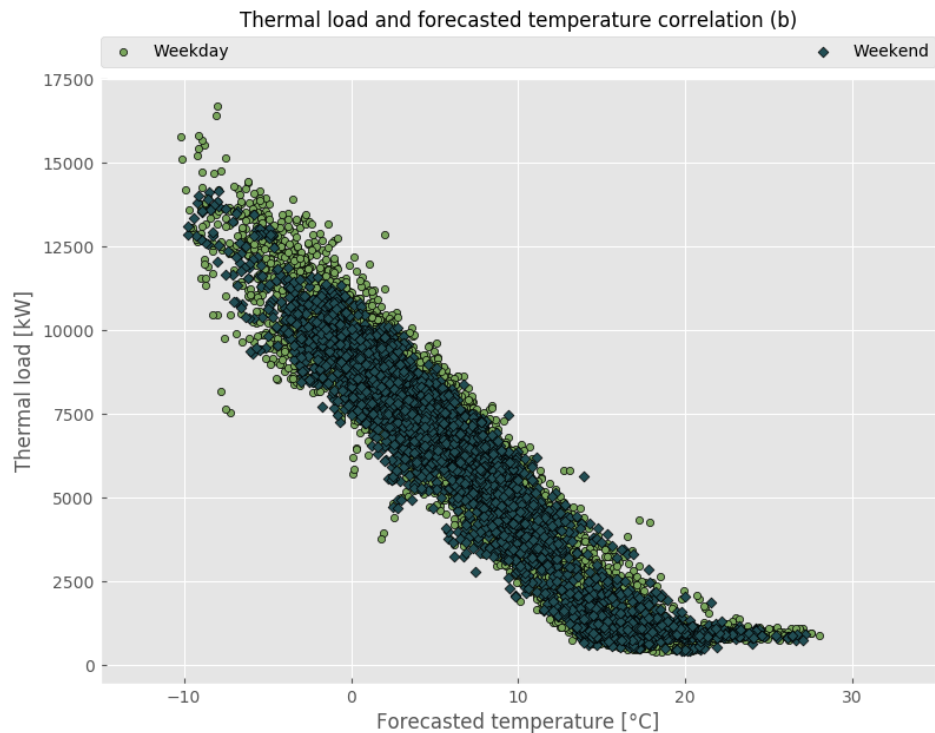
- **Input vector (features) to output value (target)**
 - **Multiple linear regression (LR)**
 - **Decision Tree Learning¹**
 - **Extremely-Randomized Trees (ETR)**
 - **Artificial Neural Network (ANN)**

2: Pierre Geurts, Damien Ernst, and Louis Wehenkel. 2006. Extremely randomized trees. *Mach. Learn.* 63, 1 (April 2006), 3-42. DOI=<http://dx.doi.org/10.1007/s10994-006-6226-1>

Feature selection

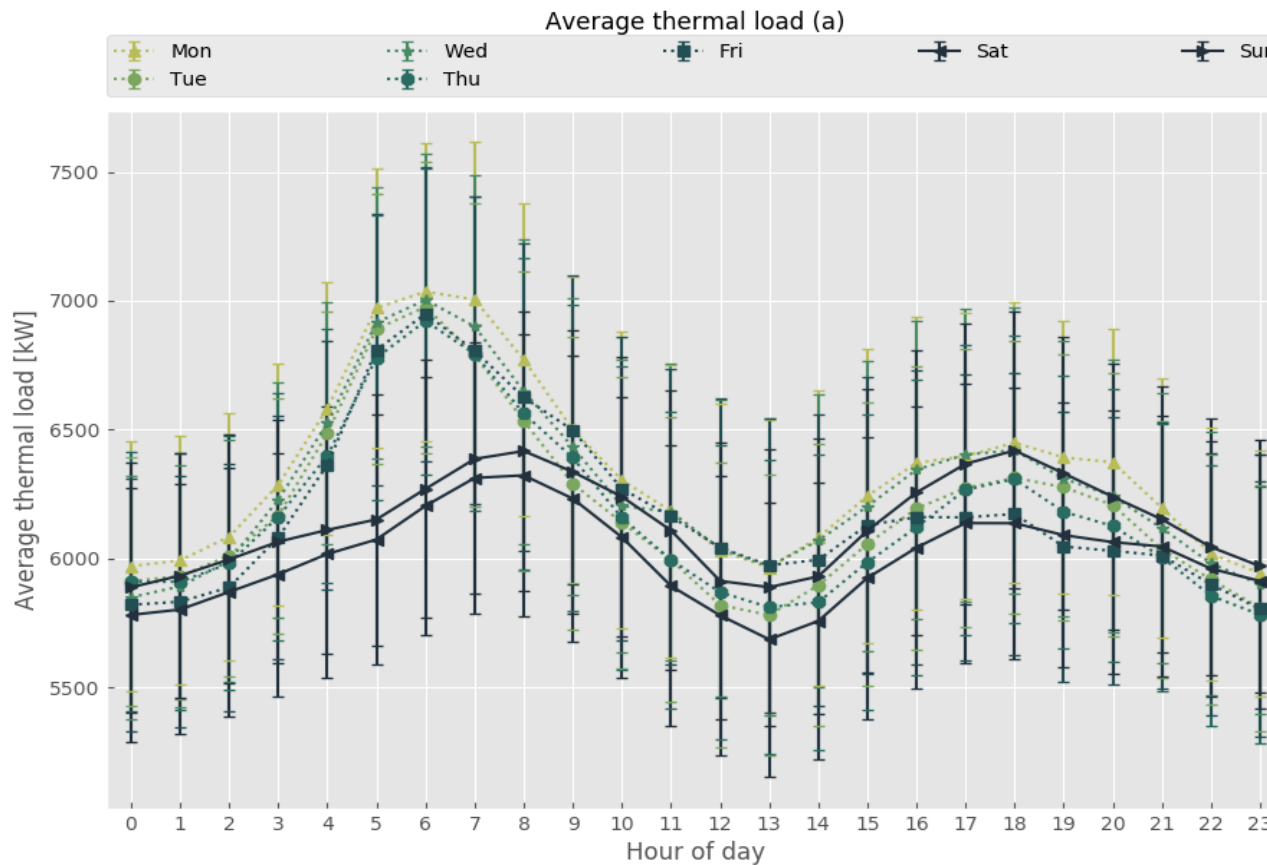


- **Temperature forecast and historic thermal load** 



Feature selection

- **Timing information**



Feature selection



- **Temperature forecast + lags**
 - Quadratic and cubic dependence on the above temp features
- **Thermal load + lags**
 - Quadratic and cubic dependence on the above thermal load features
- **Timing information**
 - Day of the year, day of the week, hour of the day

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Expert advice



- **Combine N thermal load forecasting experts**
 - Multiple linear regression, ExtRa Trees regressor, Artificial Neural Network
- **Track the best expert**
 - Losses and regret
 - Minimize $R_k = \hat{L}_k - \min_{1 \leq i \leq N} L_{i,k}$
- **Fixed-share forecaster (FS)²**

2: P. Gaillard, Y. Goude, Forecasting electricity consumption by aggregating experts; how to design a good set of experts, in: A. Antoniadis, X. Brossat, J.-M. Poggi (Eds.), Modeling and Stochastic Learning for Forecasting in High Dimensions, Vol. 217 of Lecture Notes in Statistics, Springer, 2015, pp. 95{115. doi:10.1007/978-3-319-18732-7.

Expert advice



Algorithm 1 Prediction of thermal load with expert advice

- 1: Parameters: decision space $\mathbb{R}_{\geq 0}$, outcome space $\mathbb{R}_{\geq 0}$, loss function ℓ , set ε of expert indices
 - 2: **for** $k = 1, 2, \dots$ **do**
 - 3: prediction of experts $\{F_{E,k} : E \in \varepsilon\}$, expert advice;
 - 4: reveal expert advice to forecaster;
 - 5: prediction of forecaster based on expert advice \hat{P}_k
 - 6: calculate forecaster's loss $\ell(\hat{P}_k, Y_k)$ and the expert losses $\ell(F_{E,k}, Y_k)$
-

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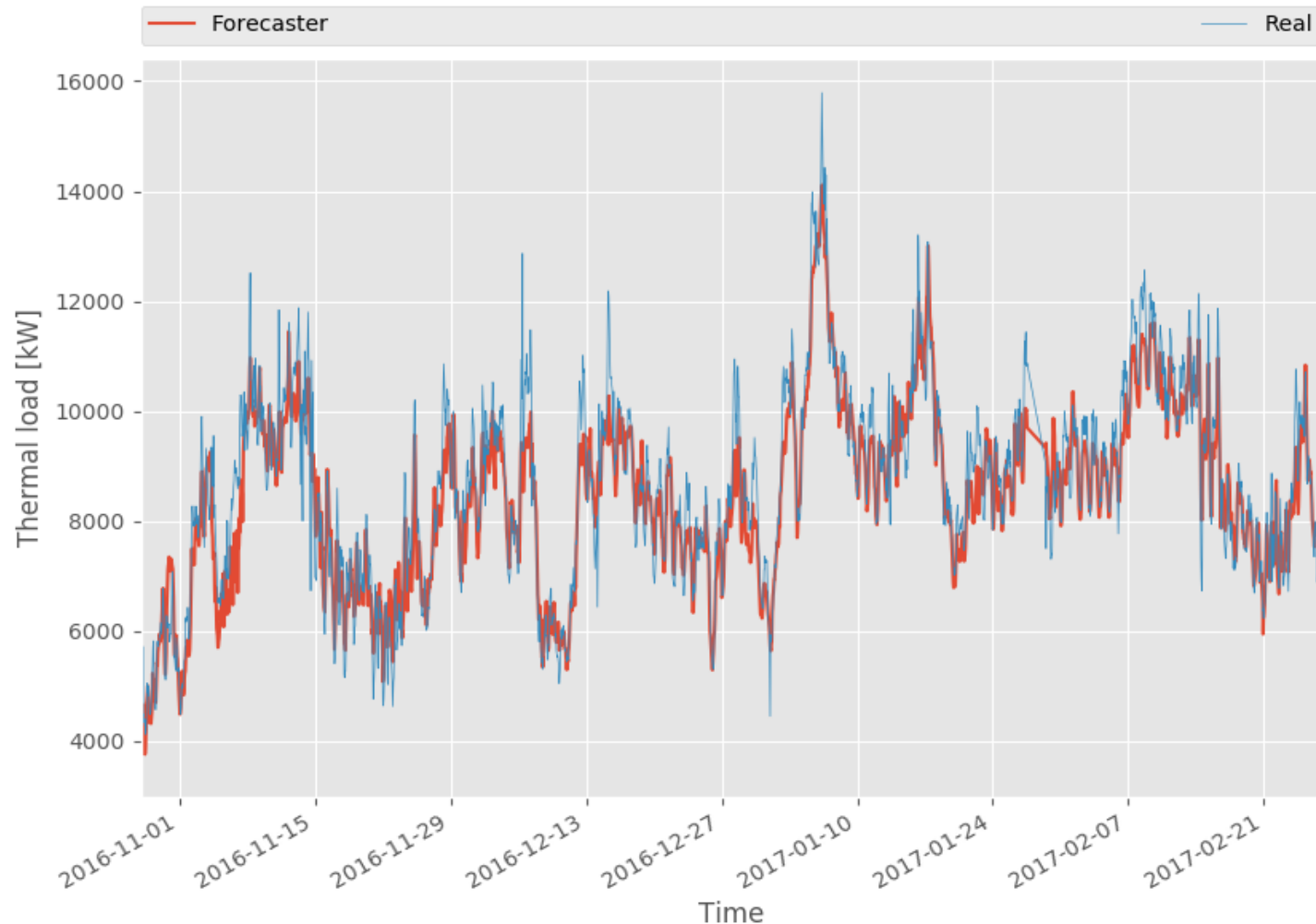
Part III Expert Advice

Part IV Results

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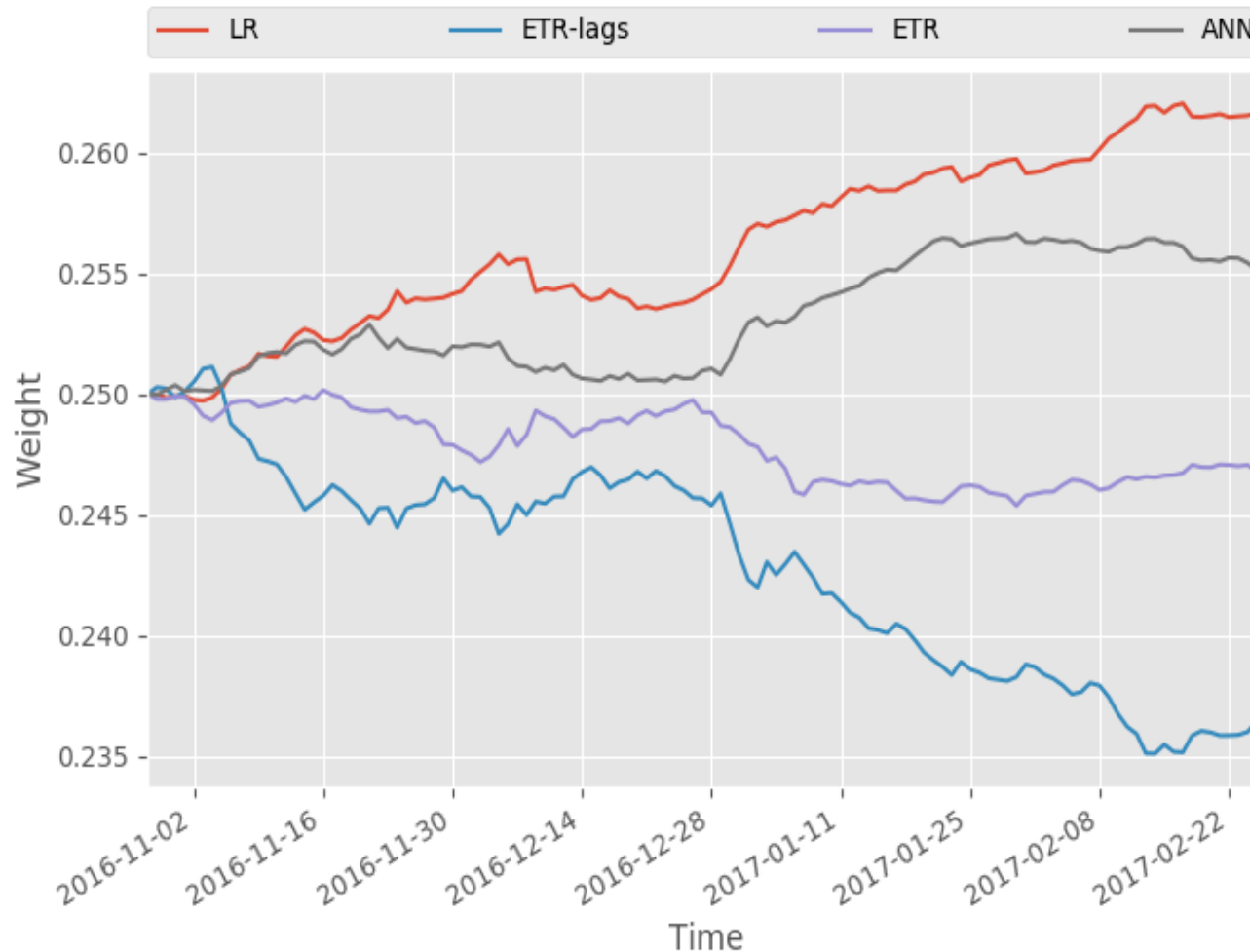
Results Expert Advice

Real thermal load versus forecasted thermal load

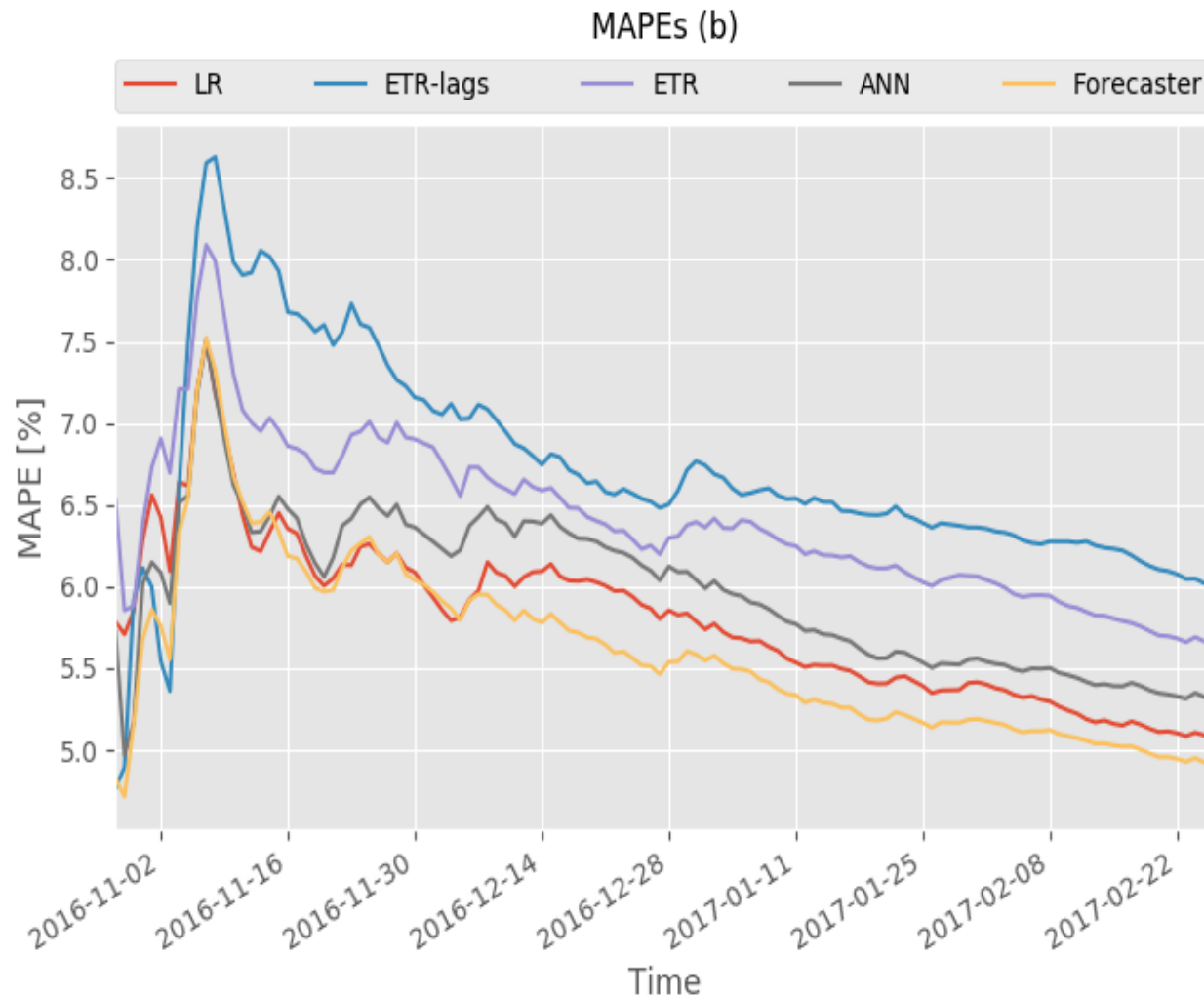


Results Expert Advice

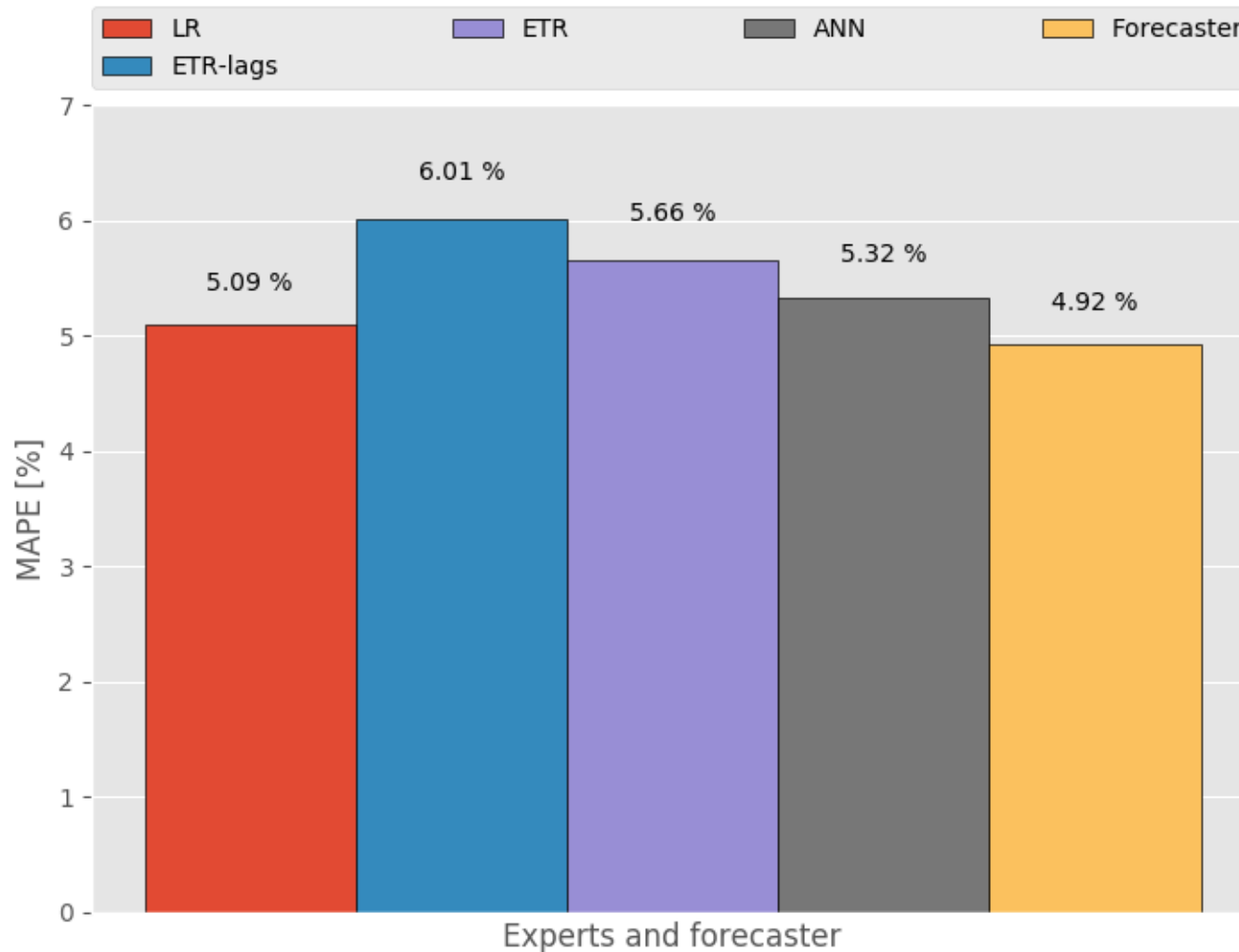
Expert weights (a)



Results Expert Advice



Results Expert Advice



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Conclusions



- **Robust and generic thermal load forecaster**
 - Easy to add and remove experts
 - Reduces susceptibility to changes in the DHS
 - Sufficient training data needed
 - Python 3.5, scikit-learn
- **Outperforms fractals**
- **Integration of forecaster in smart controller**
 - Shift peak production to integrate more renewables



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