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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Machine learning

- Building a model from sample inputs

![Heat load Karlskrona graph]

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www.4dh.eu      www.reinvestproject.eu      www.heatroadmap.eu
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)

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Feature selection

- Temperature forecast and historic thermal load
Feature selection

- Timing information

![Average thermal load (a)](image)

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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)\(^2\)

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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 $\ell$, set $\varepsilon$ of expert indices
2: for $k = 1, 2, \ldots$ 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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Real thermal load versus forecasted thermal load

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Results Expert Advice

Expert weights (a)

- LR
- ETR-lags
- ETR
- ANN

Time

Weight

2016-11-02 to 2017-02-22

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Results Expert Advice

MAPEs (b)

Time


MAPE [%]

8.5 -  8.0 -  7.5 -  7.0 -  6.5 -  6.0 -  5.5 -  5.0 -

LR  ETR-lags  ETR  ANN  Forecaster

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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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