Modelling forecast errors for day-ahead electricity market prices

8th INREC 2019 - Uncertainties in Energy Markets
September 25th

Christoph Schimeczek — Christoph.Schimeczek@dlr.de
Felix Nitsch — Felix.Nitsch@dlr.de

German Aerospace Center (DLR)
Institute of Engineering Thermodynamics
Department of Energy Systems Analysis
Pfaffenwaldring 38-40 | 70569 Stuttgart

Motivation

Reality:

- Price forecasts are an important decision-making basis for actors in the electricity market

Modelling:

- Energy System Analysis using Agent Based Modelling is in need of forecasts
- Forecast errors are essential to model more realistic agent behavior

Problem:

- Simply adding Gaussian error to historic prices does not lead to good results

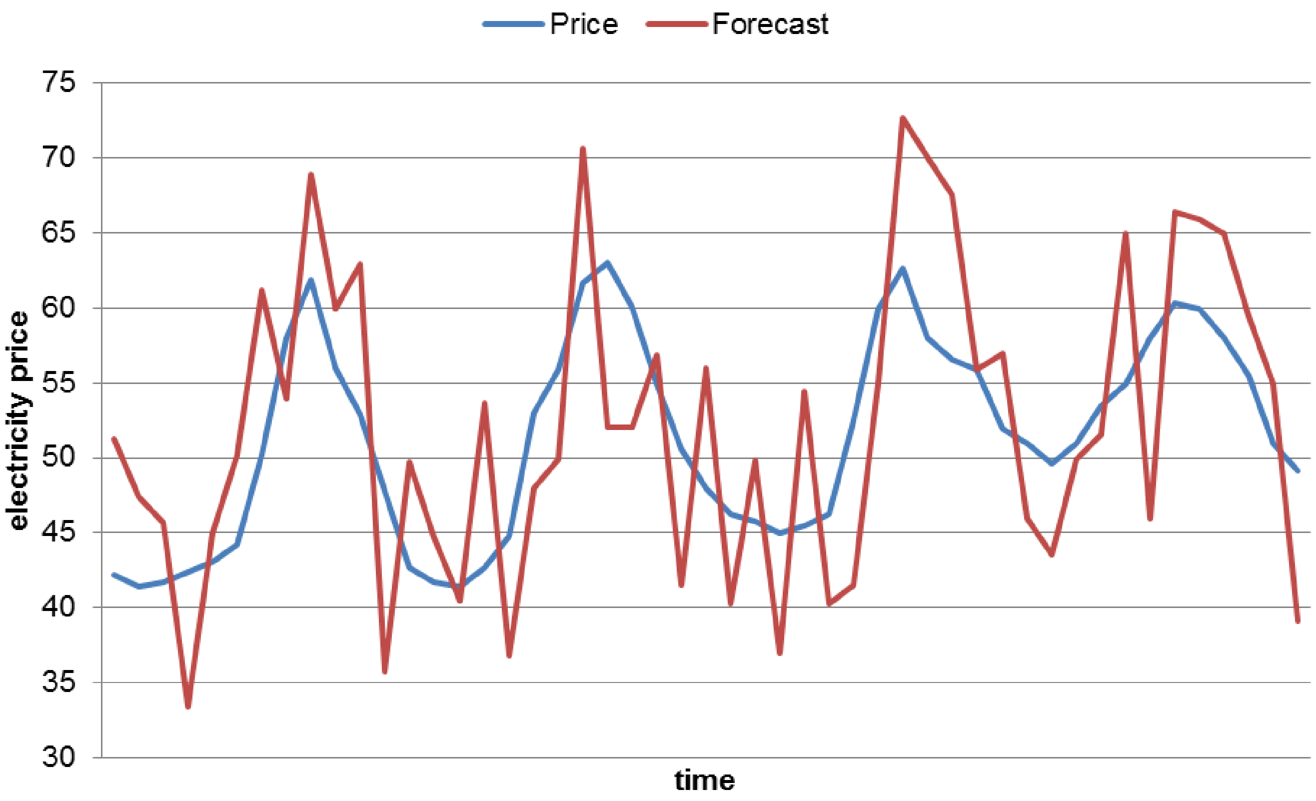


Fig.1: Historical prices (blue) and a simple attempt to map forecast uncertainties using a Gaussian function (red)


INSPECT

DISMANTLE

CONSTRUCT


INSPECT

Real forecast data from professional forecast provider

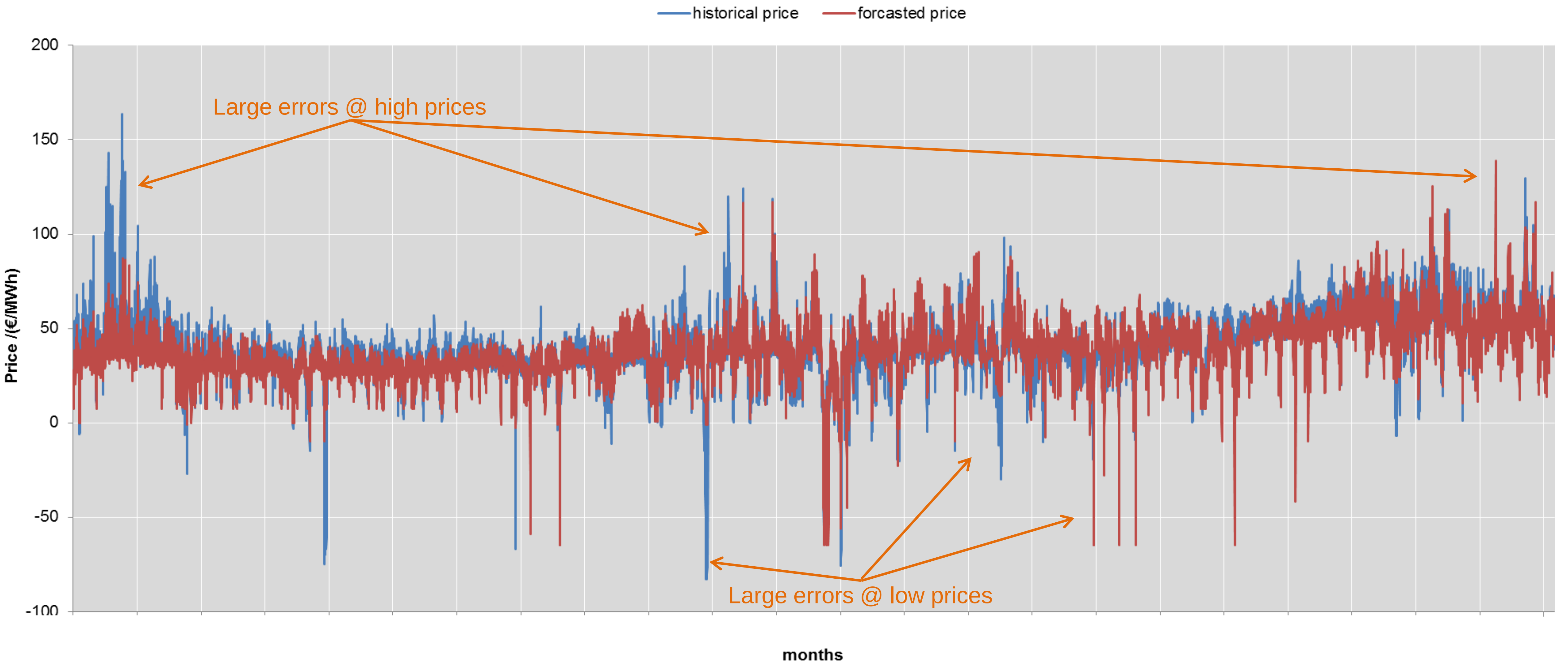


Fig.2: Historical prices (blue) and a forecasted prices by a professional provider (red) for 24 months

INSPECT

Real forecast data from professional forecast provider, detailed look

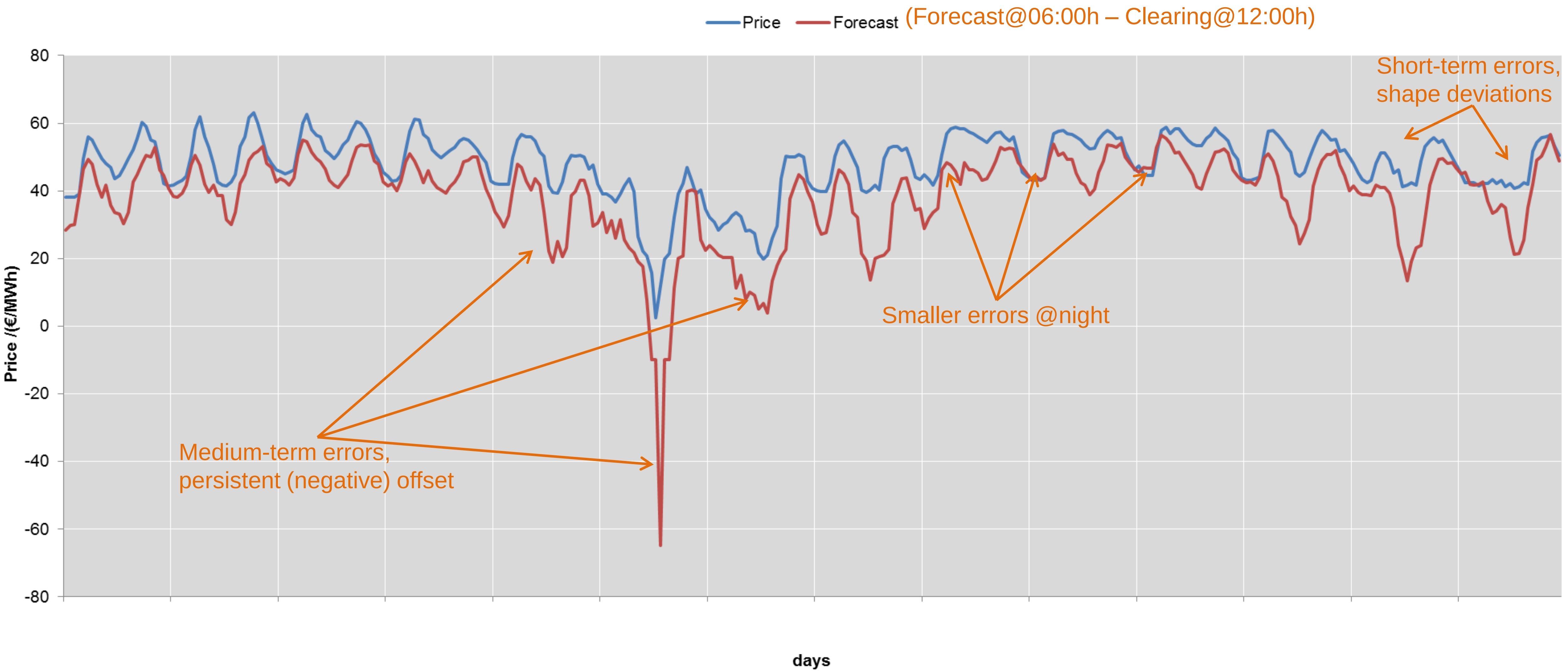


Fig.3: Historical prices (blue) and a forecasted prices by a professional provider (red) for a randomly selected period of two weeks in summer

DLR

Identified error components

Very large errors at
- high prices
- low prices

Small errors at
- average prices
- night

Merit order gradient

24h cycle PV & demand

Explained by Theory

Medium-term errors
persistent offsets
days to weeks

Autocorrelation

Short-term errors
e.g. shape deviations

Random fluctuations

Explained by forecast Model


DISMANTLE

Error components: Merit order gradient

Theory

Price forecast uncertainty ΔP

Residual load uncertainty ΔE

Price sensitivity on residual load $\frac{\delta \mathrm{P}}{\delta E}$

$$\Delta P = \Delta E \, \frac{\delta \mathrm{P}}{\delta E}$$

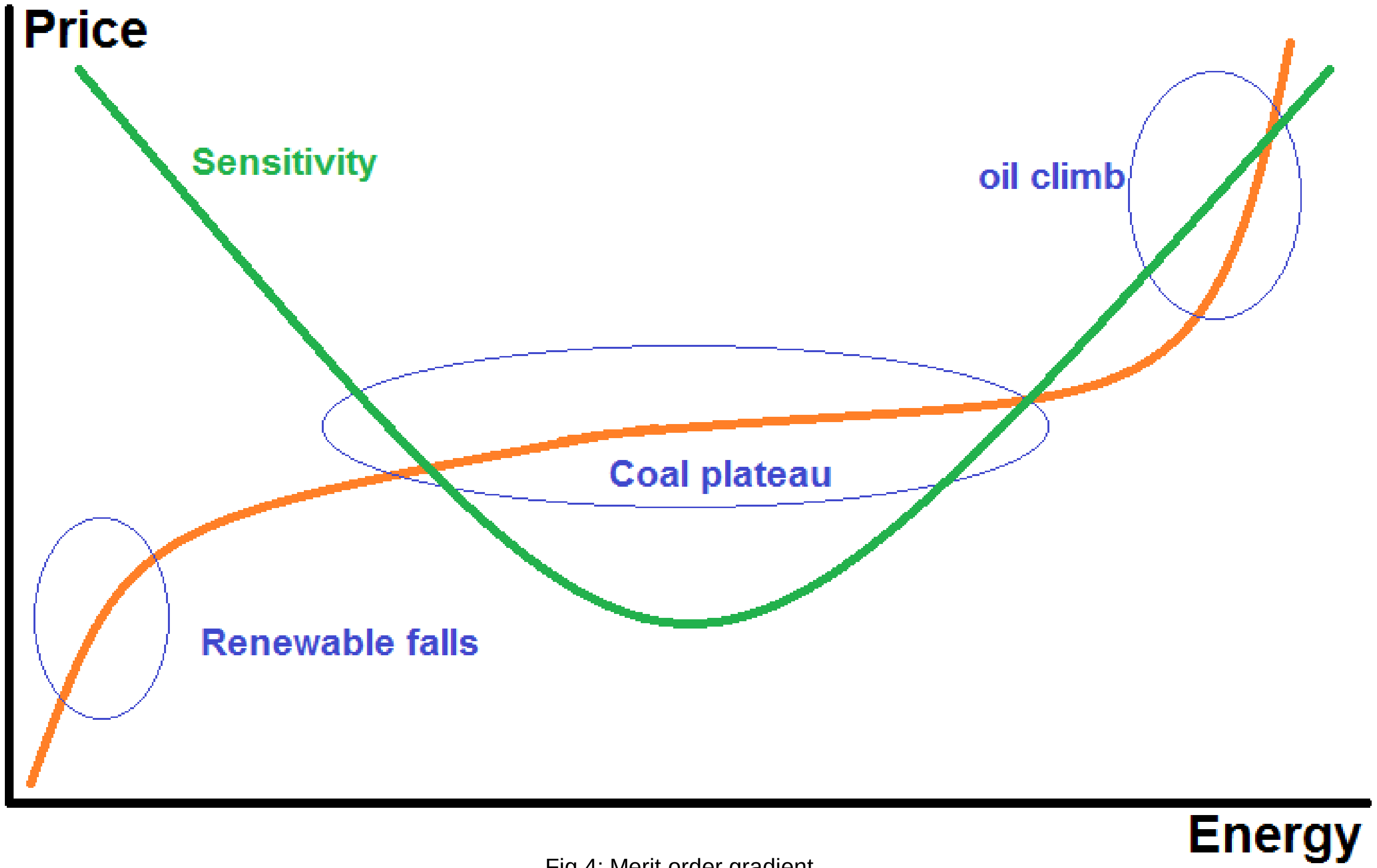


Fig.4: Merit order gradient

DISMANTLE

Error components: Merit order gradient

Theory

Price forecast uncertainty ΔP

Residual load uncertainty ΔE

Price sensitivity on residual load $\frac{\delta \mathrm{P}}{\delta E}$

$$\Delta P = \Delta E \, \frac{\delta \mathrm{P}}{\delta E}$$

Absolute errors

→ match theory

Signed errors

“compression” of prices

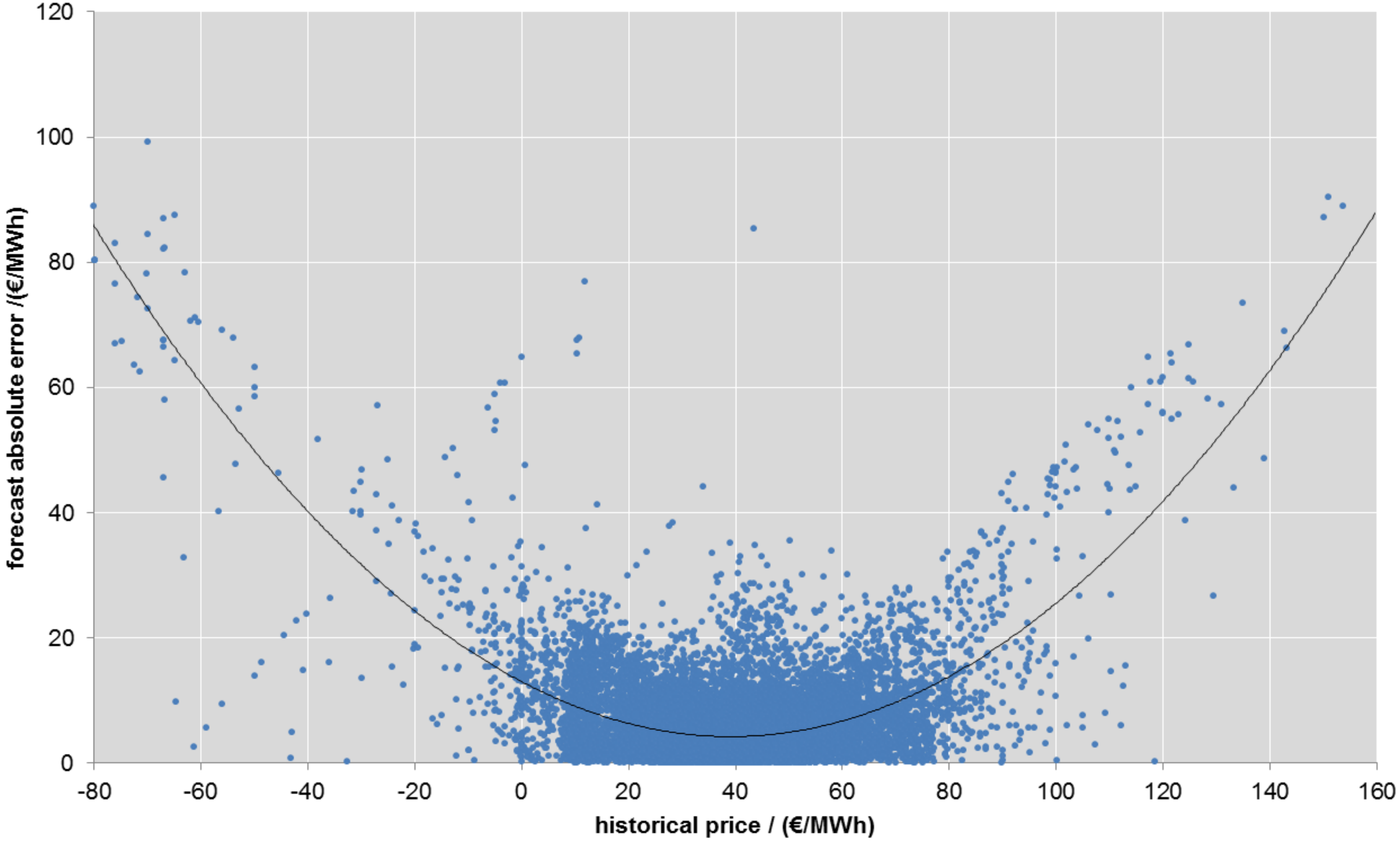


Fig.5: Absolute forecast errors at historical prices

DLR

Error components: Merit order gradient

Refinement #1

Subtract fitted curve from errors

Remaining errors

- no offset
- slightly smaller
- uncorrelated to prices

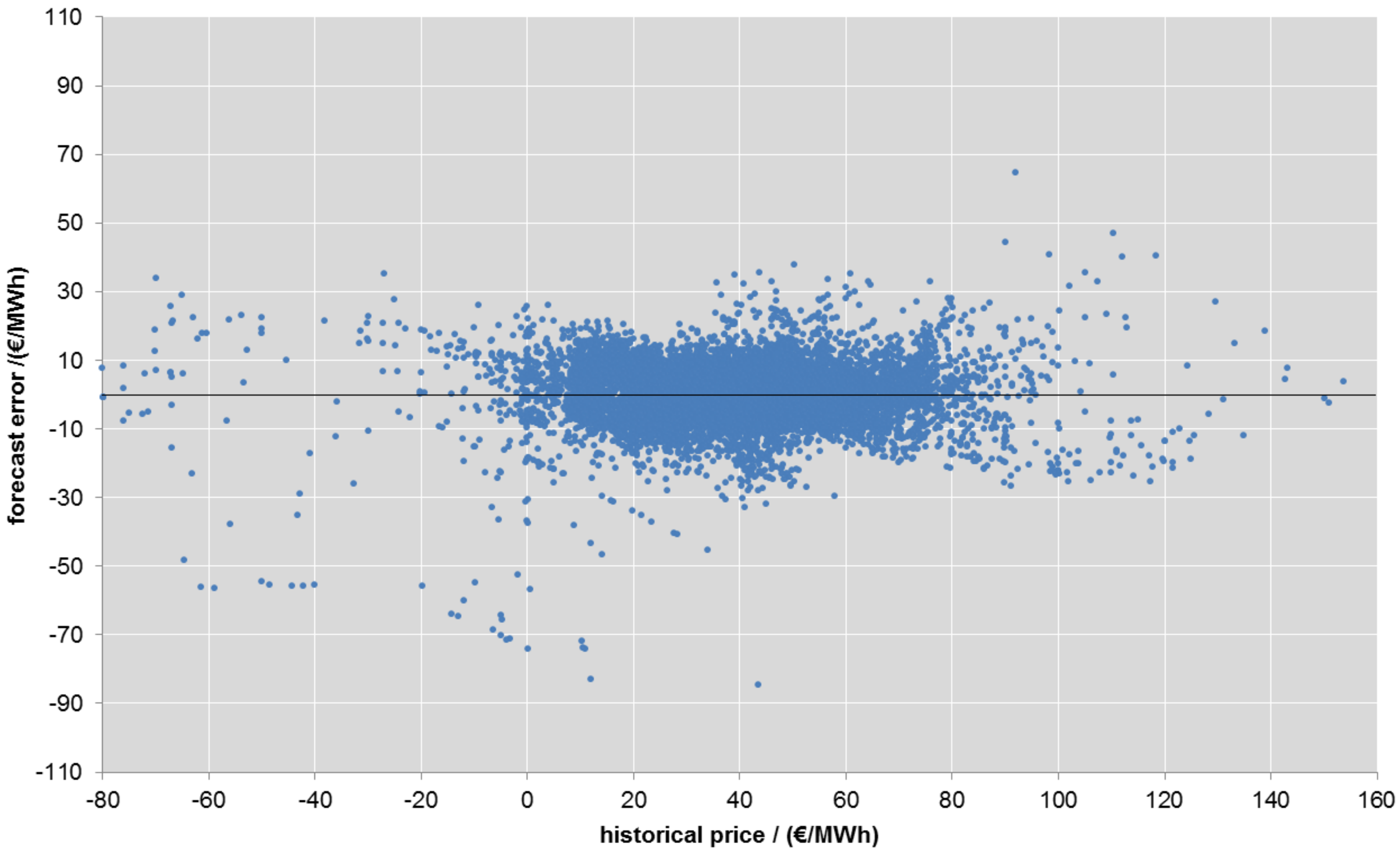


Fig.6: Forecast errors at historical prices

DISMANTLE

Error components: 24h cycle

Refinement #2

address time-of-day dependency

similar patterns of forecast errors for price, load & RE generation

Correlation with price error

Corr. with RE forecast error	Corr. with load forecast error
79.4%	87.1%

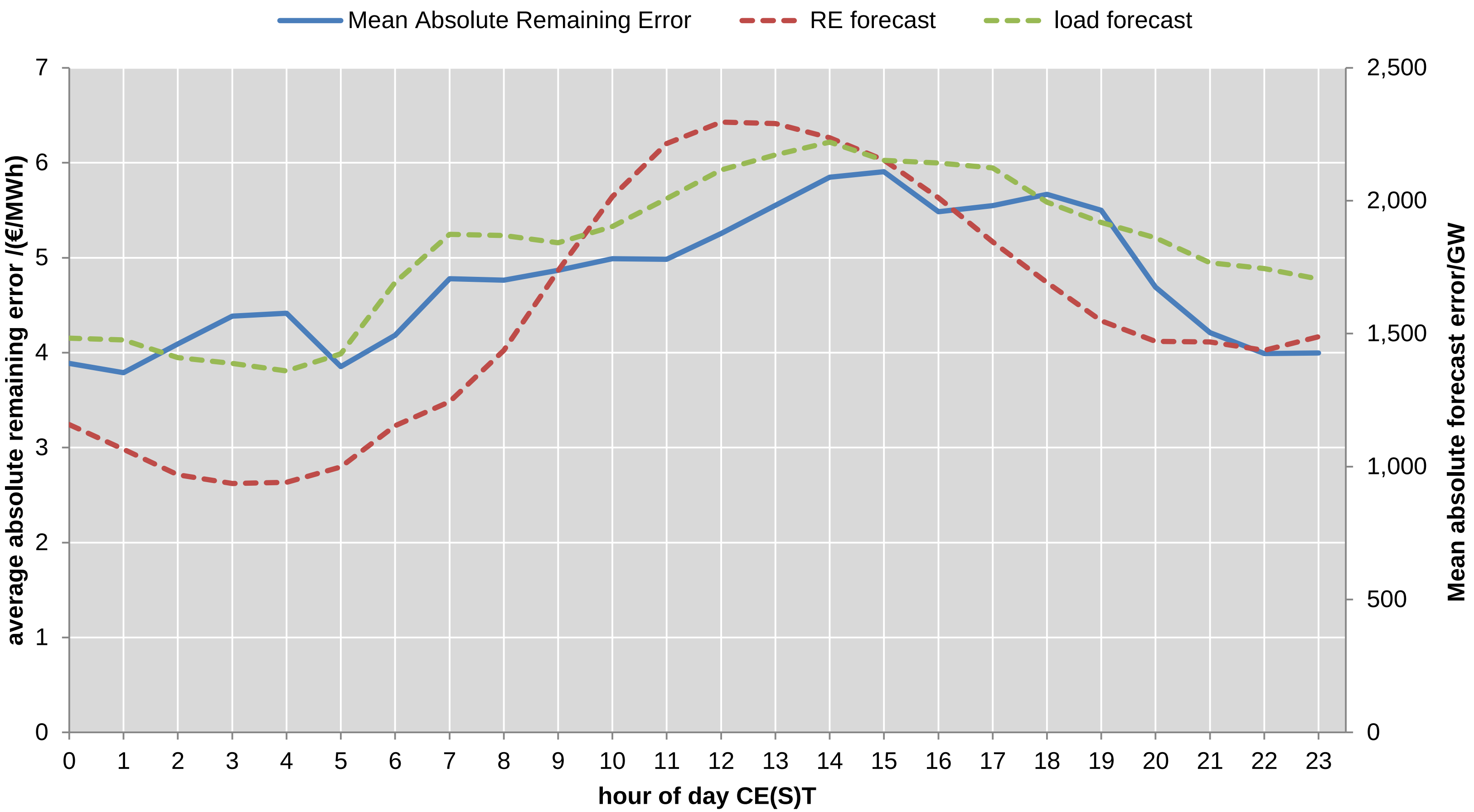


Fig.7: Mean absolute remaining forecast error (red), renewable energy production forecast (red) and load forecast (green)

Error scaling factors: Medium-term effects

Refinement #3

address medium-term effects

Optical Inspection

- long-term effects
- medium-term effects
- short-term fluctuations

Check Autocorrelation

- long-term: ~ 500 h
- medium-term: ~ 36 h

Problem:

Generated random values are uncorrelated

➔We need uncorrelated data

➔Add correlations later

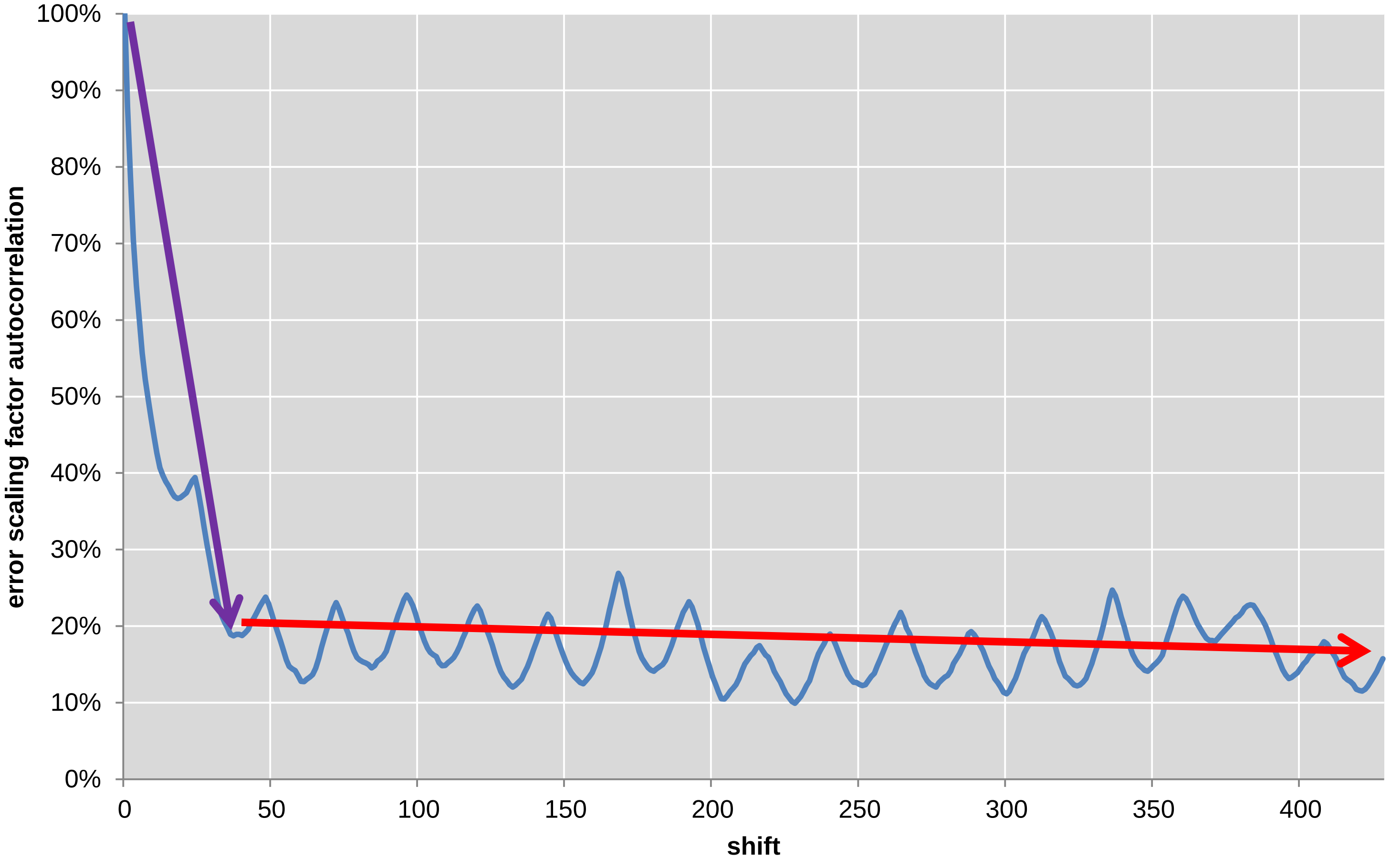


Fig.8: Autocorrelation for medium-term (purple) and long-term (red) effects

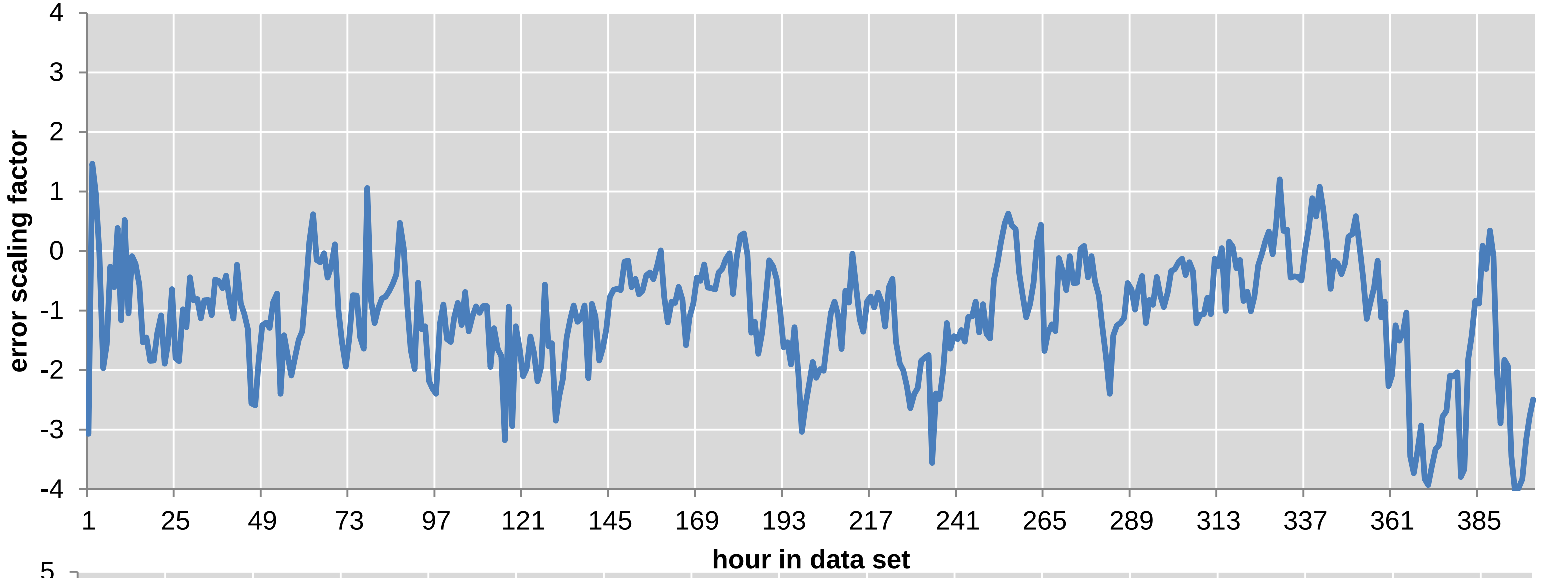
DISMANTLE

Error scaling factors: Uncorrelate data

Refinement #4

Calculate change of error scaling factors

Measure	Scaling factors	Scaling factor changes
Average value	0.00	0.00
Mean absolute	1.00	0.46
Autocorrelation length /h	36	0



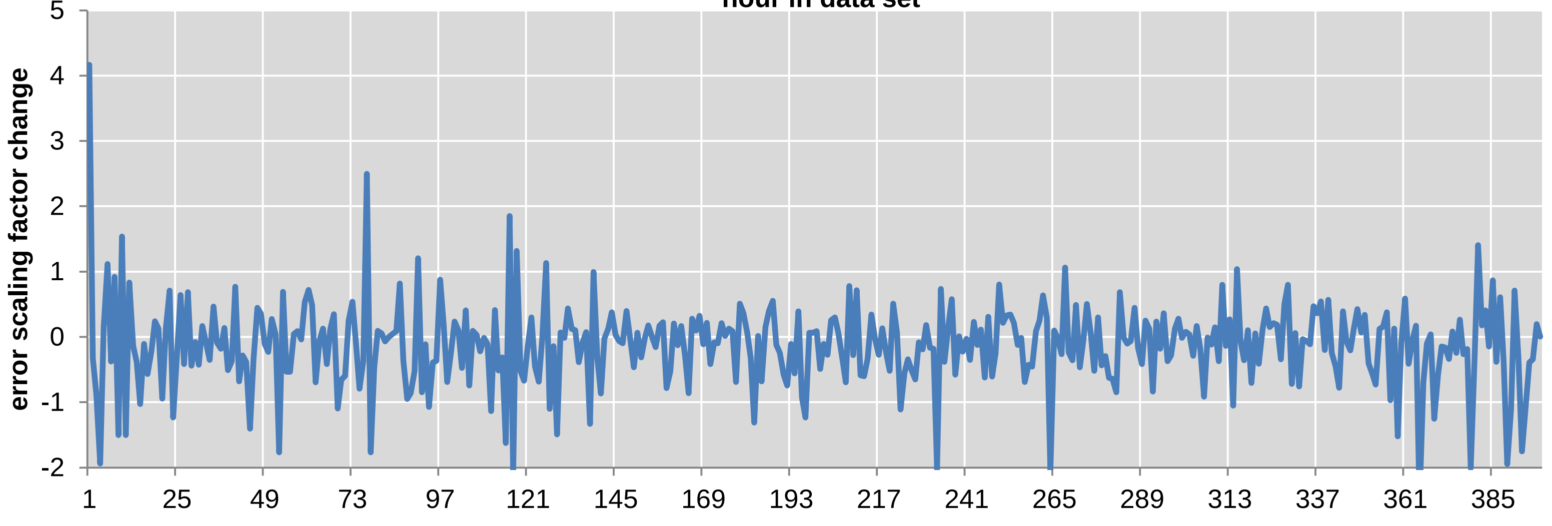


Fig.9: Error scaling factor

DLR

Error scaling factors: Uncorrelate data

Refinement #4

Calculate change of error scaling factors

Measure	Scaling factors	Scaling factor changes
Average value	0.00	0.00
Mean absolute	1.00	0.46
Autocorrelation length /h	36	0

Problem:

Correlated to scaling factor

➔ Subtract linear fit from scaling factor changes in **Refinement #5**

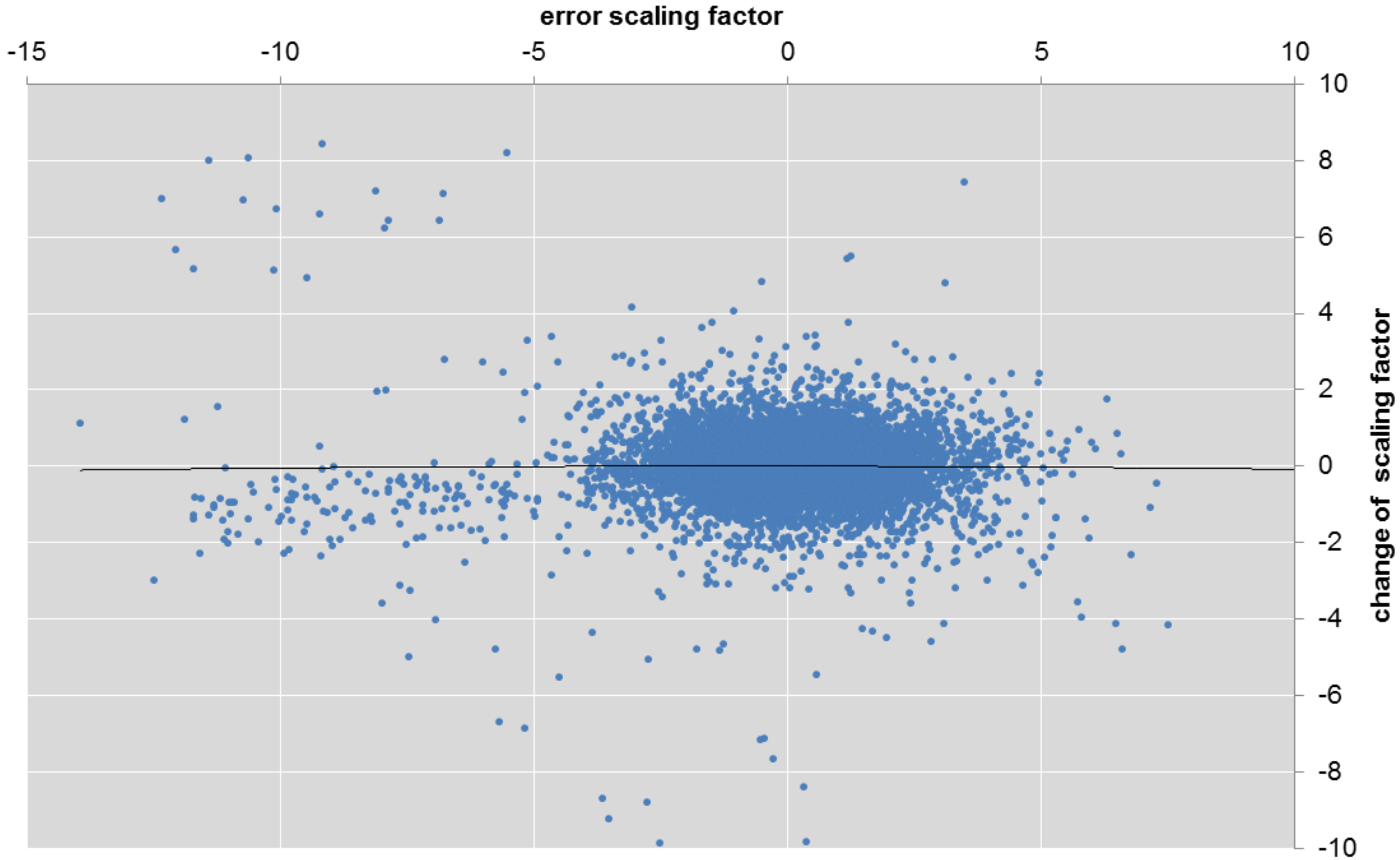


Fig.10: Uncorrelated error scaling factor in dependence of change of scaling factor

Error scaling factor changes: Distribution

Histogram

Probability distribution of corrected scaling factor changes

Fit Function

- “spiky” (high kurtosis)
- symmetrical to 0
- exponential decay

$$f(x) = a\, b^{-|cx|}$$

Dissection completed

➔ Let’s build our own errors

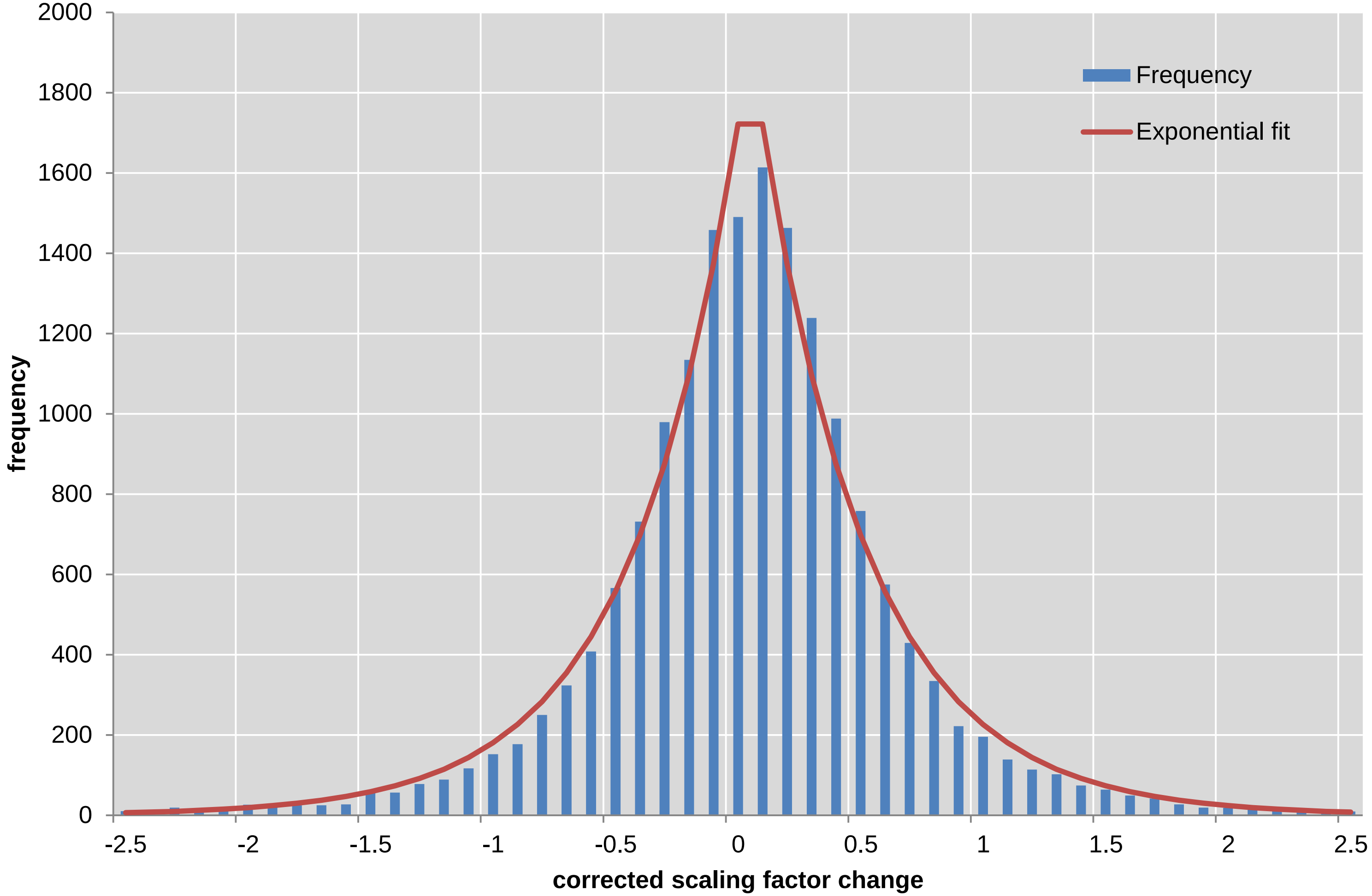


Fig.11: Historgram showing the frequency of corrected scaling factor change


CONSTRUCT

Generate Errors   Scaling factors

Generation Steps

1. Pick *corrected scaling factor changes* according to probability distribution

2. Add correlation to *scaling factor*

3. Sum scaling factor changes & add autocorrelation

➔Correlated hourly error scaling factors

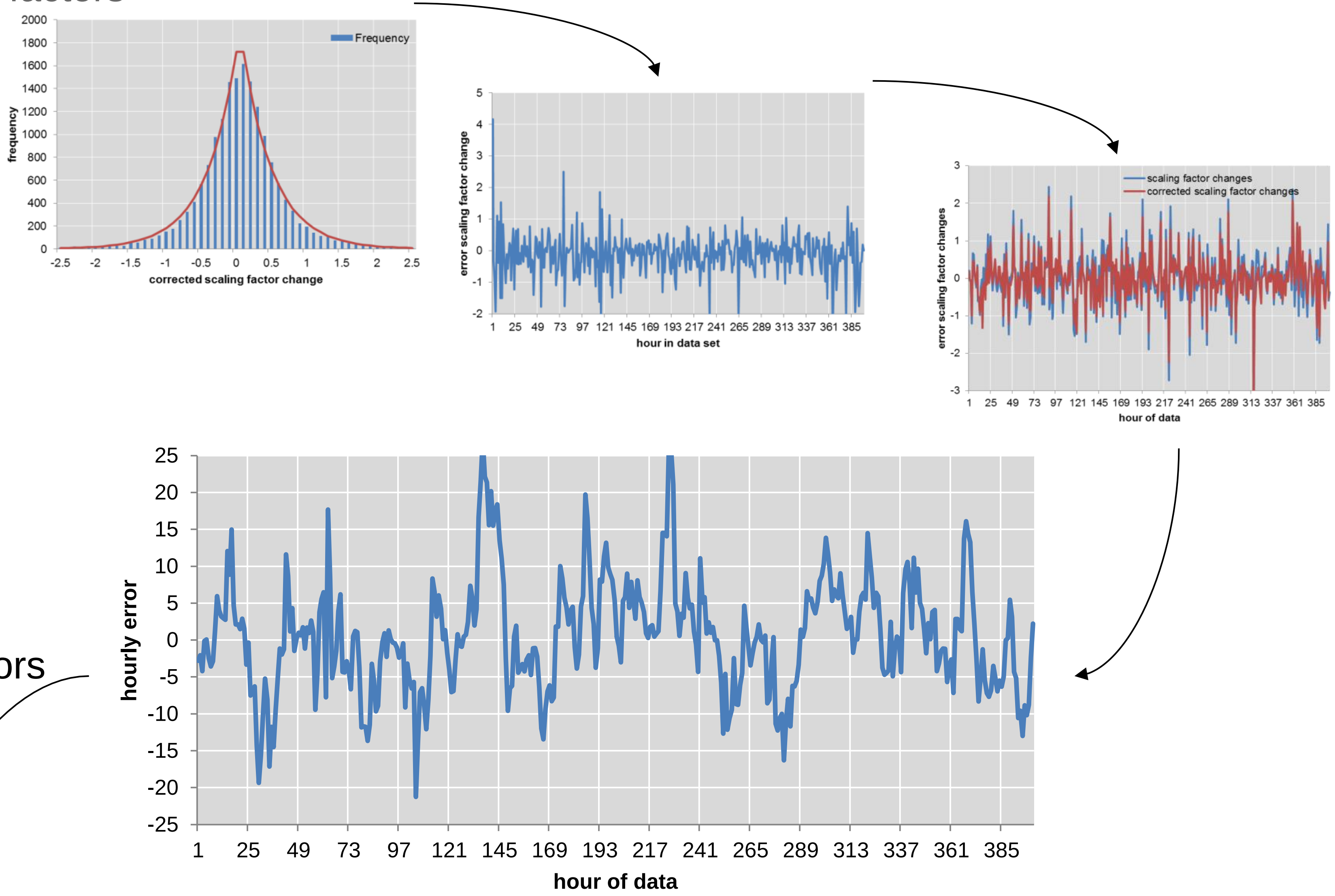
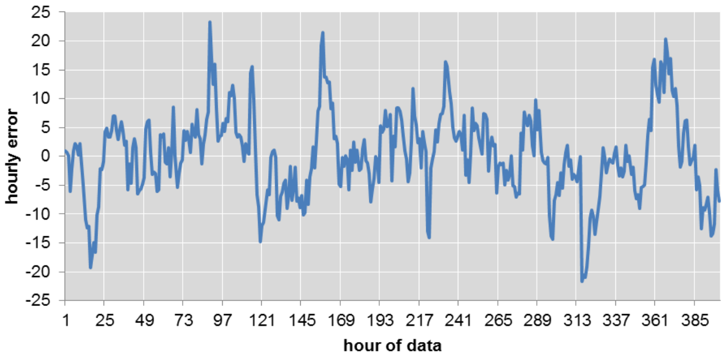


Fig.12: Steps to generate scaling factors

CONSTRUCT

Generate Errors   Price forecast

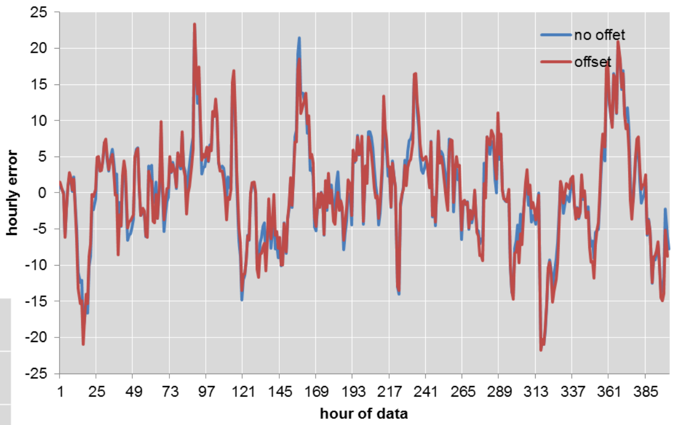


Generation Steps

4. Multiply error scaling factors with hour-of-day error average value

5. Add hour-of-day specific offset

6. Add price correlation



Finally:

➔ Compare artificial to actual errors

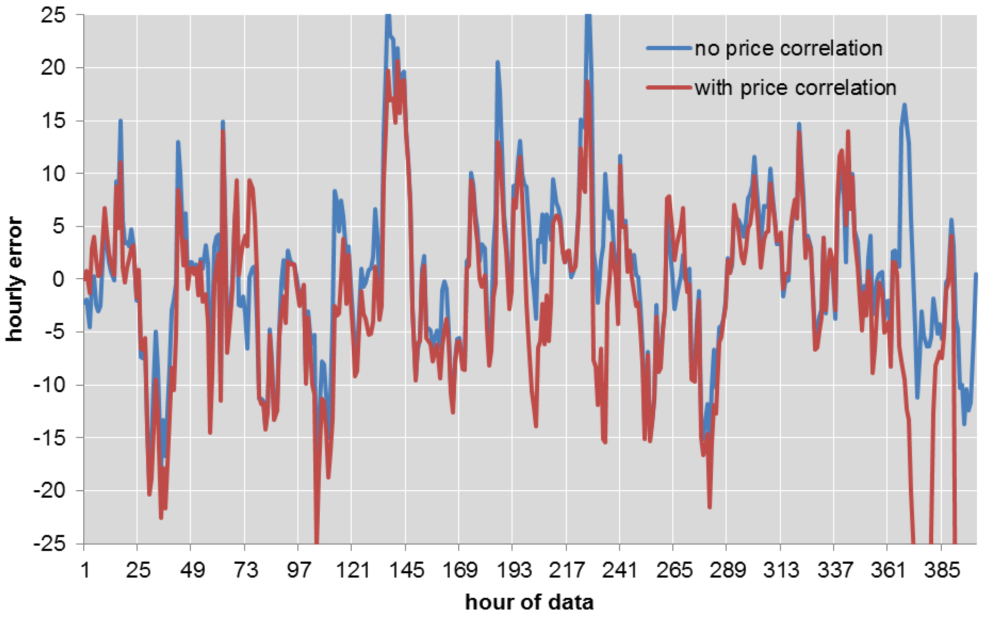


Fig.13: Steps to generate price forecast

DLR

Final result

Measure	Artificial error	Original error
Average /(€/MWh)	-0.13	0.00
Mean absolute Error /(€/MWh)	6.16	6.12
Standard deviation /(€/MWh)	8.94	9.66

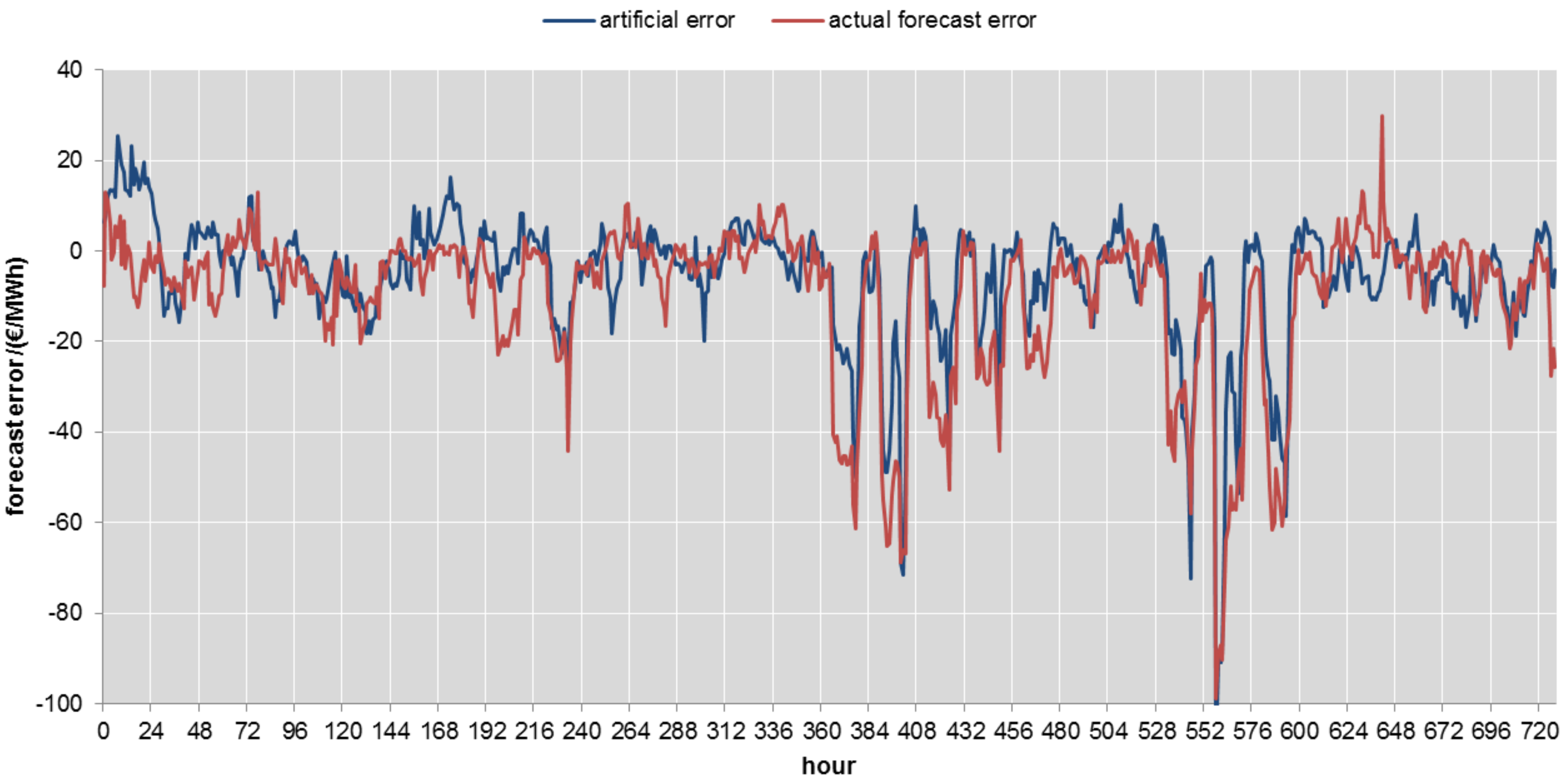


Fig.14: Sample of a final artificially generated forecast error (blue) and actual forecast error (red)

Conclusion

- Price forecasts are essential for actors on the electricity markets
- We analysed a day-ahead electricity price forecast of a professional provider and identified its key error components
- Based on our analysis, we are able to create artificial day-ahead price forecasts with similar forecast error characteristics as found in the industry
- The results of this research are applied in our Energy System Models, especially Agent-Based-Modelling enabling more realistic agent-behaviour

Thank you for your attention!

8th INREC 2019 - Uncertainties in Energy Markets
September 25th

Christoph Schimeczek   Christoph.Schimeczek@dlr.de
Felix Nitsch   Felix.Nitsch@dlr.de

German Aerospace Center (DLR)
Institute of Engineering Thermodynamics
Department of Energy Systems Analysis
Pfaffenwaldring 38-40 | 70569 Stuttgart