Master of Science in Information Systems

Business Analytics

Predicting the Norwegian Elspot markets: Evaluation of Methods and Price-drivers

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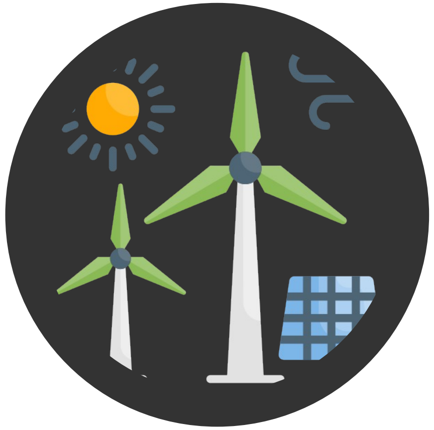
Background and Motivation

- Use of energy is strongly related to almost every conceivable aspect of development
- Forecasting is crucial in the efficient functioning of electricity markets
- Norwegian markets role in deregulation, renewable integration and recent disruption



Research questions

- Which price drivers shape the behaviour of the elspot markets in Norway?

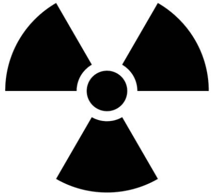
- Which methods are most effective in forecasting the hourly day-ahead elspot prices in Norway?

Page: 19-20

Background Theory

Electricity Consumption and Generation

- Electricity consumption
- Electricity production



Page: 4-6

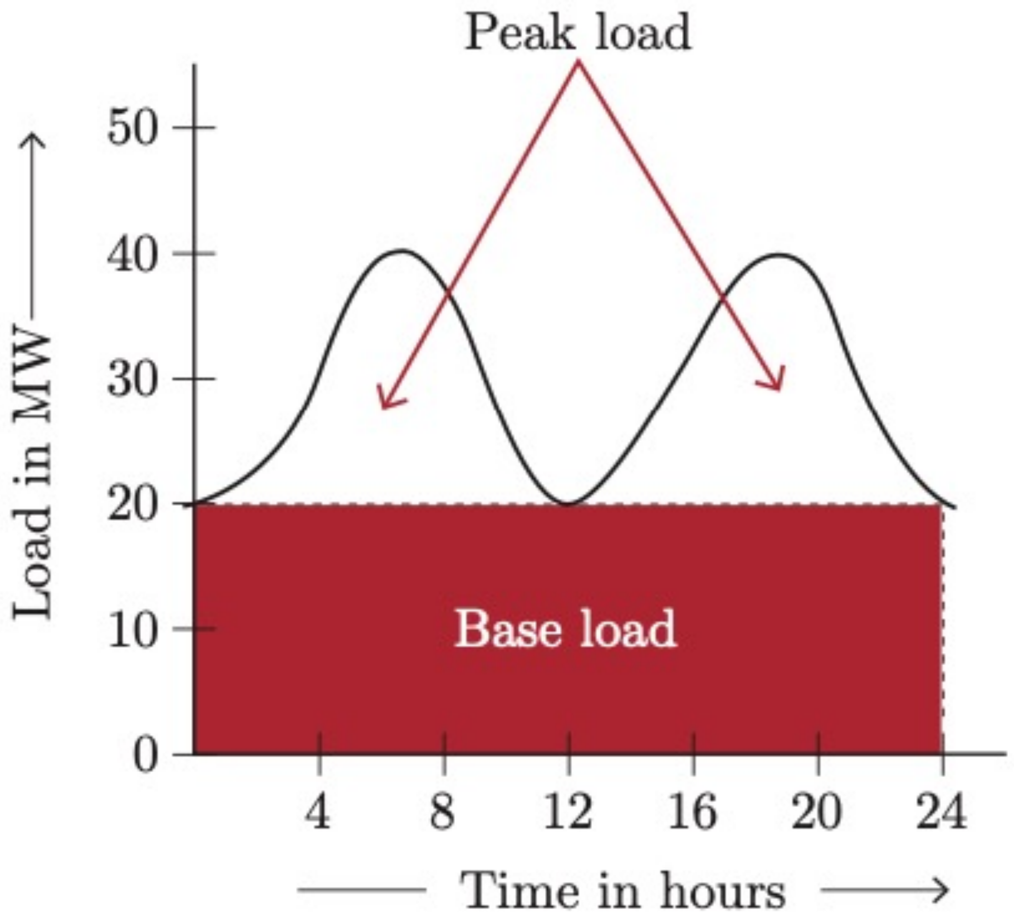


Figure 1: Base-load vs. Peak-load.

Electricity markets and pricing

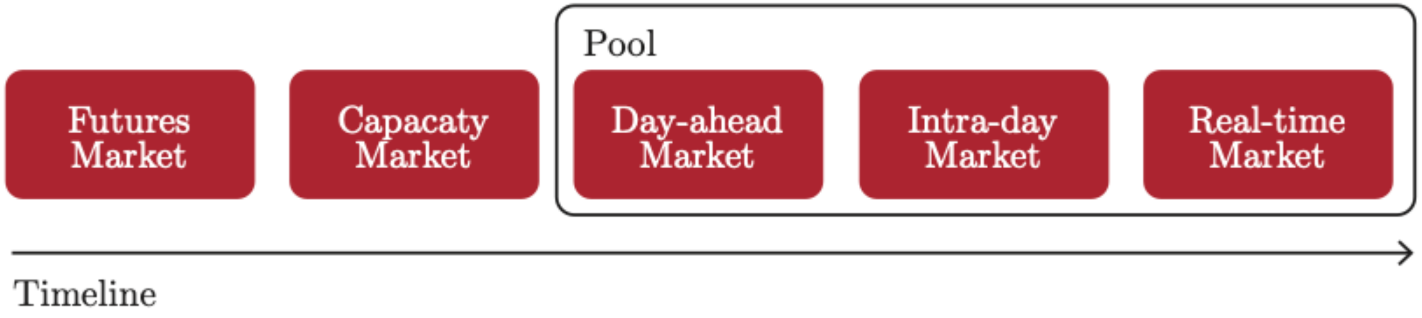


Figure 2: The Fragmented Market Scheme.

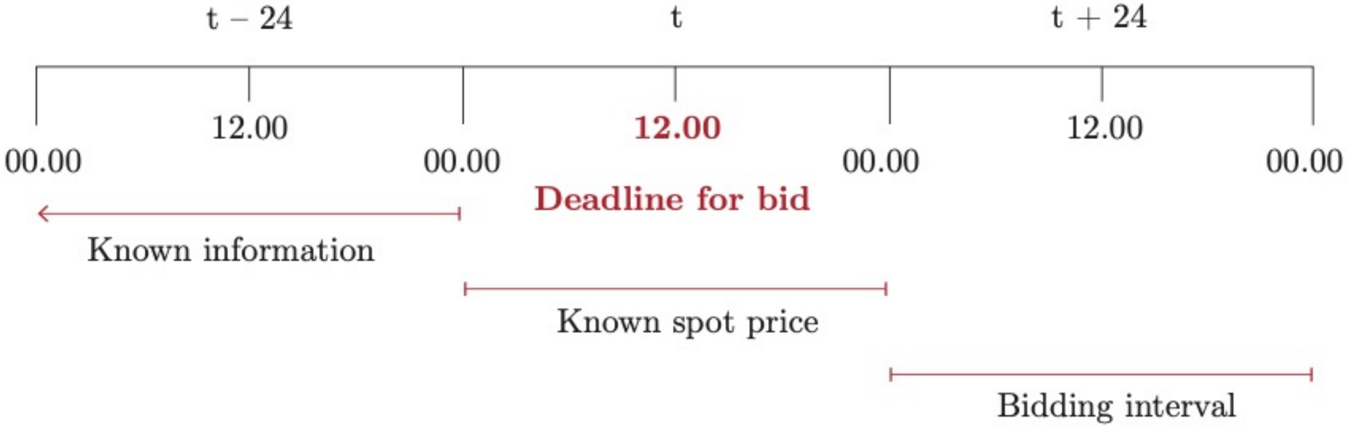


Figure 4: Deadline for bids.

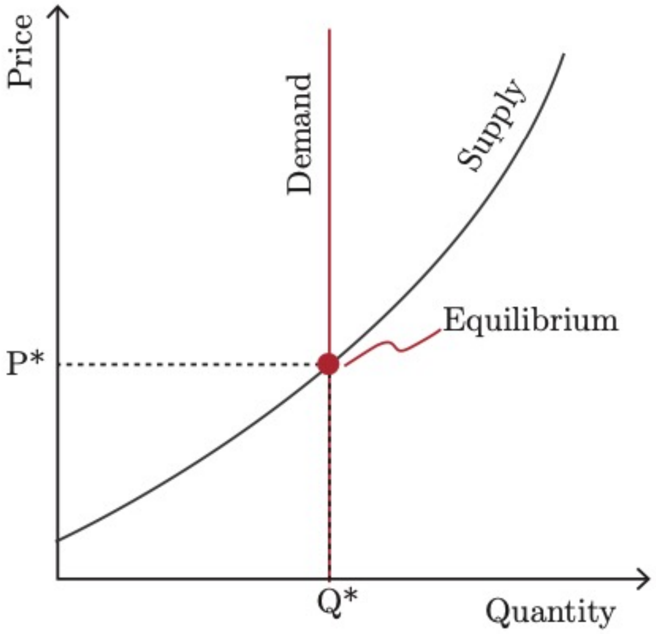


Figure 3: Equilibrium-curve for determining the market clearing price (spot-price).

Page: 6-9

Machine Learning

- Fits mathematical models to data
- ”no free lunch”
- Representation
- Evaluation
- Optimization
- Error components
- Bias-variance trade-off
- Regularization
- Ensembling
- Deep Learning

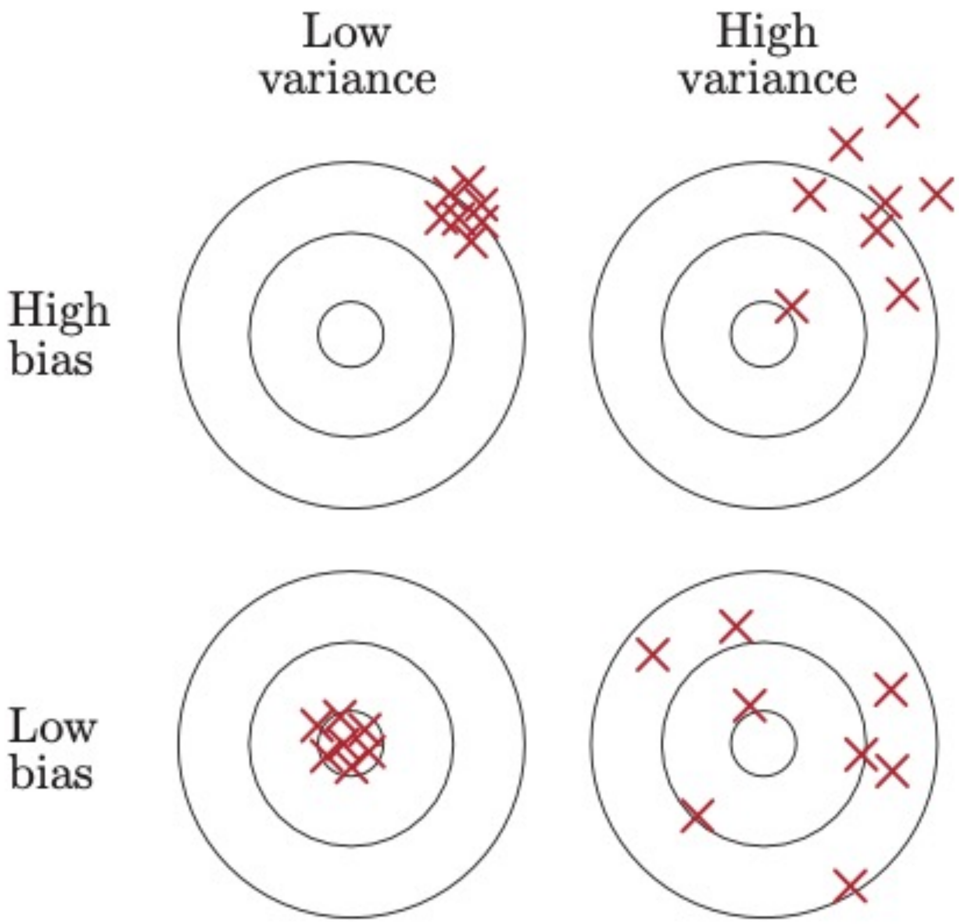


Figure 7: Bias and variance in dart-throwing.

Page: 9-18

Time Series Forecasting

$$X = X_{t}{}_{t=1}^{\infty} = (X_1, X_2, \ldots)$$

- Look-ahead-bias
- Stationarity
- Auto-correlation
- Smoothing
- Components
- Differencing

Page: 20-25

Related work

Approach	Papers
Long-term price modeling	[48, 24, 14]
Day-ahead-prices (spot) forecasting	[15, 32, 33, 51, 26, 39, 25, 6, 47, 4, 3, 16, 18]
Hourly prices (intraday) forecasting	[35, 23, 9, 10, 37]
Regulating price modeling	[42]

Table 1: Previous targets.

Input Variables	Papers
Previous prices	[3, 37, 18, 14, 25, 33, 35, 30, 15, 4, 42, 51, 26, 39, 16, 47, 6, 23, 9, 32, 10]
System loads	[37, 18, 25, 33, 35, 30, 39, 47]
Weather variables	[18, 48, 35, 26, 9]
Fuel costs	[28, 6, 9]
Sector indeces	[43]
Reserve margin	[30, 37, 42]
Generation costs	[30]

Table 2: Previous input-variables.

Pre-processing	Papers
Interpolation of Missing Values	[47]
Lagged Variables	[3]
Mean Normalization	[47, 9]
Min-max Scaling	[3, 10]
Wavelet Transform	[33, 15, 37, 51, 26, 10]
Differentiation	[16]

Table 3: Previous pre-processing techniques.

Feature Selection	Papers
Gaussian Radial Basis Function (GRBF) network	[28]
Principle Component Analysis (PCA)	[39]

Table 4: Previous feature-selection techniques.

Model Type	Papers
Fundamental Models	[14, 30]
Statistical Models	[42, 30, 48, 18, 33, 51, 18, 15, 26, 16, 47, 6, 23]
Deep-learning Models	[3, 25, 33, 35, 28, 30, 3, 37, 23, 18, 32, 10]
Ensemble Models	[6, 9]
Hybrid Models	[51, 37, 32]

Table 5: Previous model types.

Page: 26-31

Limitations of related work

- Lack of transparency and details
- Bias in model selection
- Convoluted
- Lack of baseline

Page: 30-31

Research Method

- Theoretical, empirical and practical
- Statistically rigorous and systematic
- Bottom-up approach
- Absolute terms

1. Research on price-drivers
   Data collection
   Exploratory data analysis
   Model interpretation
2. Research on methods
   Model evaluation
   Naive baseline
   Statistical/econometric
   Algorithmic ensemble
   Deep learning
   Experiments

Research on price-drivers

- Data selection and collection
- Exploratory analysis
  - Visualizations
  - Auto-correlation
  - Descriptive statistics
  - Correlation
  - Principal Component Analyis
  - ADF statistics
- Model interpretation
  - Univariate vs Multivariate configurations
  - XGBoost Feature importance
  - Comparing bidding-zones and performances on bidding-zones

Page: 32-35

Research on methods

- Model evaluation
- Experiments
  - 365-fold rolling forecast origin cross validation
  - Out-of-sample evaluation on recent hold-out test set
  - Total 84 forecast considering models, experiments and configurations
- Methods
  - Weak/general assumptions
  - Different theoretical vantage points
  - SOTA from each model-family

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{actual}_i - \mathrm{predicted}_i)^2$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{actual}_i - \mathrm{predicted}_i)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\mathrm{actual}_i - \mathrm{predicted}_i|$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\mathrm{actual}_i - \mathrm{predicted}_i}{\mathrm{actual}_i}\right| \times 100$$

$$RSS = \sum_{i=1}^{n}(\mathrm{actual}_i - \mathrm{predicted}_i)^2$$

Page: 35-43

Naïve baseline

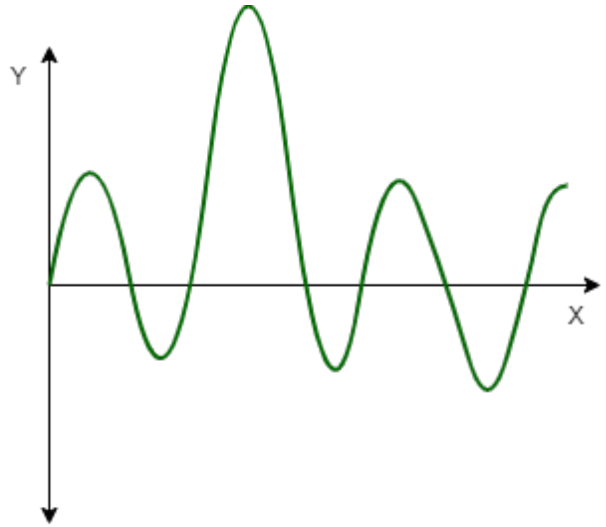
- Persistence forecast
- Heuristic (“price tomorrow is the same as the price today”)
- Predicts the current value as the value in 24-timesteps
- Easy to implement
- Surprisingly accurate
- Lower bound of performance

$$\hat{P}_t = P_{t-24}$$

Statistical/econometric apporach

- Autoregressive Integrated Moving Average (ARIMA(p,d,q))

$$Y_t = c + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \varepsilon_t - \sum_{j=1}^{q} \theta_j \varepsilon_{t-j}$$



- Y_t is the value of the timeseries at time t
- C is a constant term
- $\Phi_1, \Phi_2, \ldots, \Phi_p$ are the AR coefficients
- ε_t is the error term at time
- $\theta_1, \theta_2, \ldots, \theta_q$ are the MA coefficients
- P, d, q are integers that represent the order of the AR, differencing and MA components, respectively

Page: 38-39

Algorithmic ensemble apporach

- XGBoost: A gradient boosting framework
- Combines multiple weak models (decision trees) to make a strong prediction

The objective function for XGBoost can be written as:

$$\mathscr{L}(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

- Θ represents the set of model parameters
- *n* is the number of training examples
- *yi* is the true value of the *i*-th example
- *yˆi* is the predicted value
- *l*(*yi*,*yˆi*) is the loss function
- *K* is the number of weak models in the ensemble
- *fk* represents the *k*-th weak model
- Ω(*fk*) is the regularization term that penalizes complex models

The weak models used in XGBoost are decision trees, which can be expressed as:

$$f(x) = \sum_{t=1}^{T} w_t q_t(x), \quad w \in \mathbb{R}^T, \quad q : \mathbb{R}^d \to \{1, 2, \ldots, T\}$$

Page: 39-40

Deep learning approach

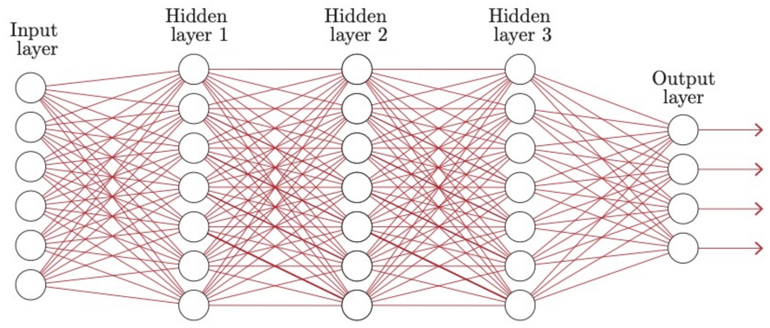


Figure 8: Deep Neural Network.

- LSTM (Long Short-Term Memory)
- Type of RNN (recurrent neural network) for seq-to-seq tasks
- Vanishing gradients
- Specialized memory unit
  - Input gates
  - Forget gates
  - Output gates
- Combined with feed-forward layers

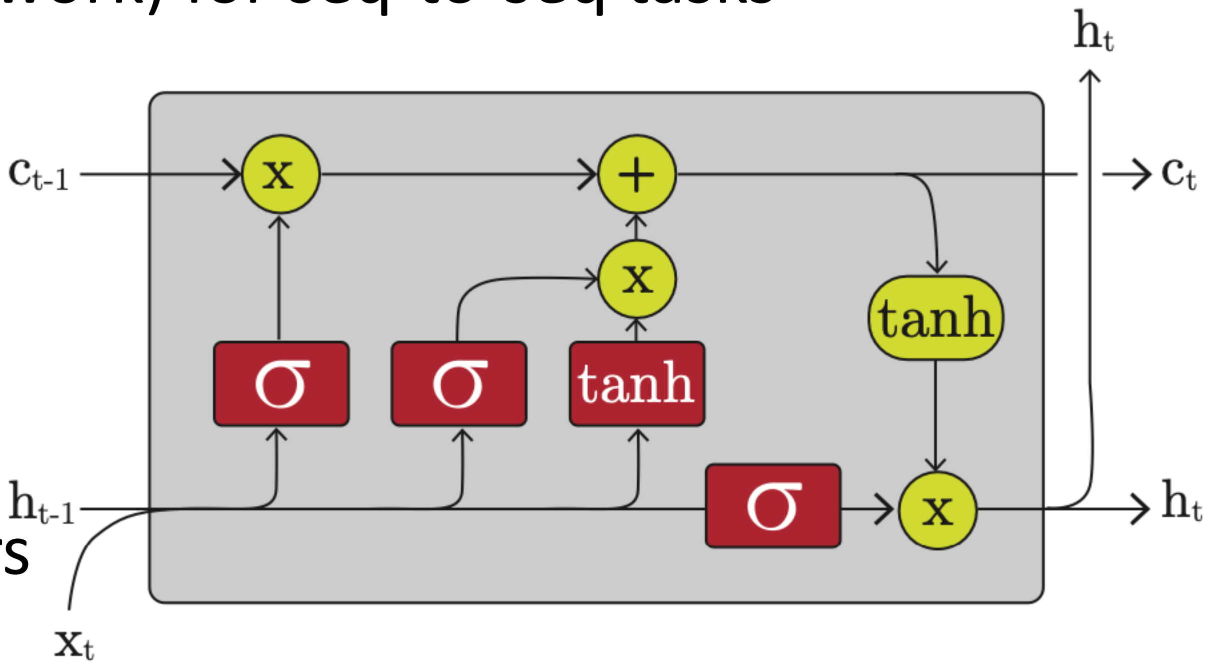
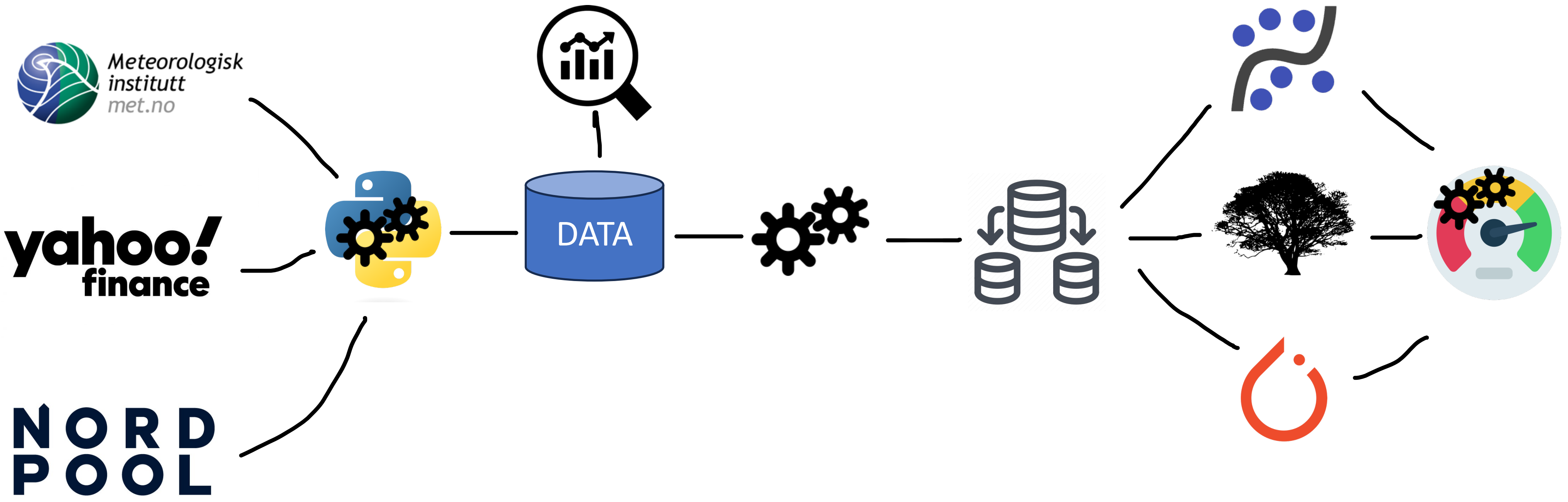


Figure 10: Long Short-Term Memory Network Diagram (LSTM).

Page: 40-42

Design and Implementation



Page: 44-69

Data collection

Period: 01.01.2020 – 30.03.2023

Variable (units) [granularity]	Description (source) [bidding-zones]
Elspot price (NOK/MWh) [h]	Settlement prices (Nordpool) [NO1-NO6].
Elspot day-ahead price (NOK/MWh) [h]	Day-ahead price targets (Nordpool) [NO1-NO6].*
Power production (MWh) [h]	Settlement of production bids (Nordpool) [NO1-NO6].
Power production prognosis (MWh) [h]	Day-ahead prognosis of production bids (Nordpool) [NO1-NO6].
Exchange (MWh) [h]	Exchange between bidding-zones including export/import (Nordpool) [NO1-NO6].
Power consumption (MWh) [h]	Total consumption (Nordpool) [NO1-NO6].
Reservoir levels (GWh) [w]	Hydro reservoir content (Nordpool).
Reservoir capacity (GWh) [w]	Total hydro reservoir content capacity (Nordpool).
Gas price (NOK/mmbtu) [d]	LNG-price per million british thermalunits (Yahoo-finance).
Oil price (NOK/barrel) [d]	Oil-price per barrel (Yahoo-finance).
OSEBX price (NOK/OSEBX) [d]	Oslo Børs Benchmark Index price (Yahoo-finance).
Air temperature (mean/degC) [d]	Temperature averaged by bidding-zones (Met) [NO1-NO6].
Wind speed (mean/ms) [d]	Wind speed averaged by bidding-zones (Met) [NO1-NO6].
Percipitation (sum/mm) [d]	Precipitation averaged by bidding-zones (Met) [NO1-NO6].

Table 6: Description of data.

*Target variables

Oparational data

NORD
POOL

Weather data

Meteorologisk institutt
met.no

django REST framework

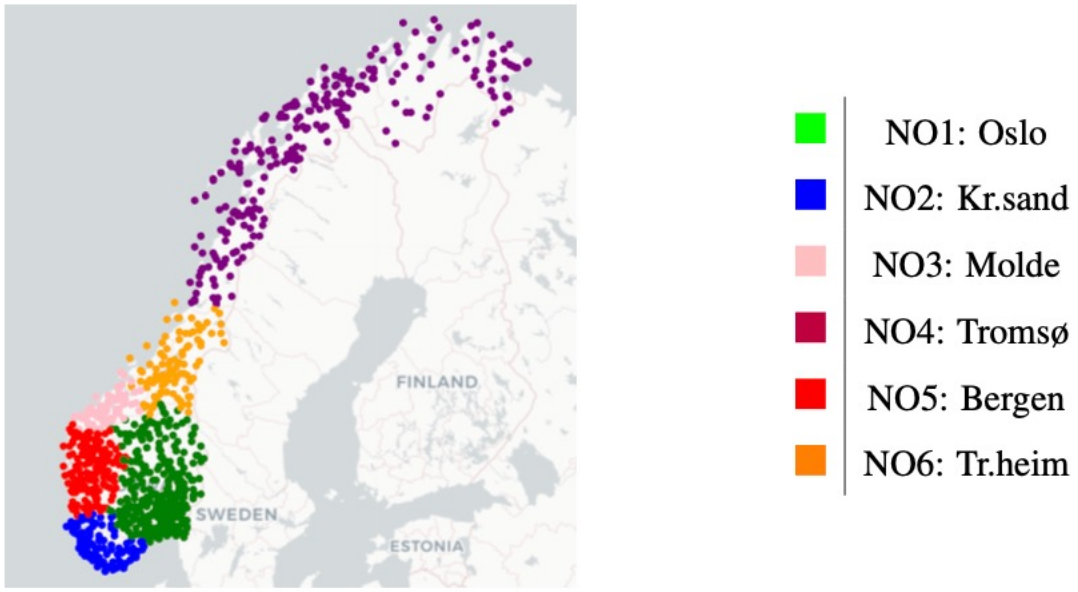
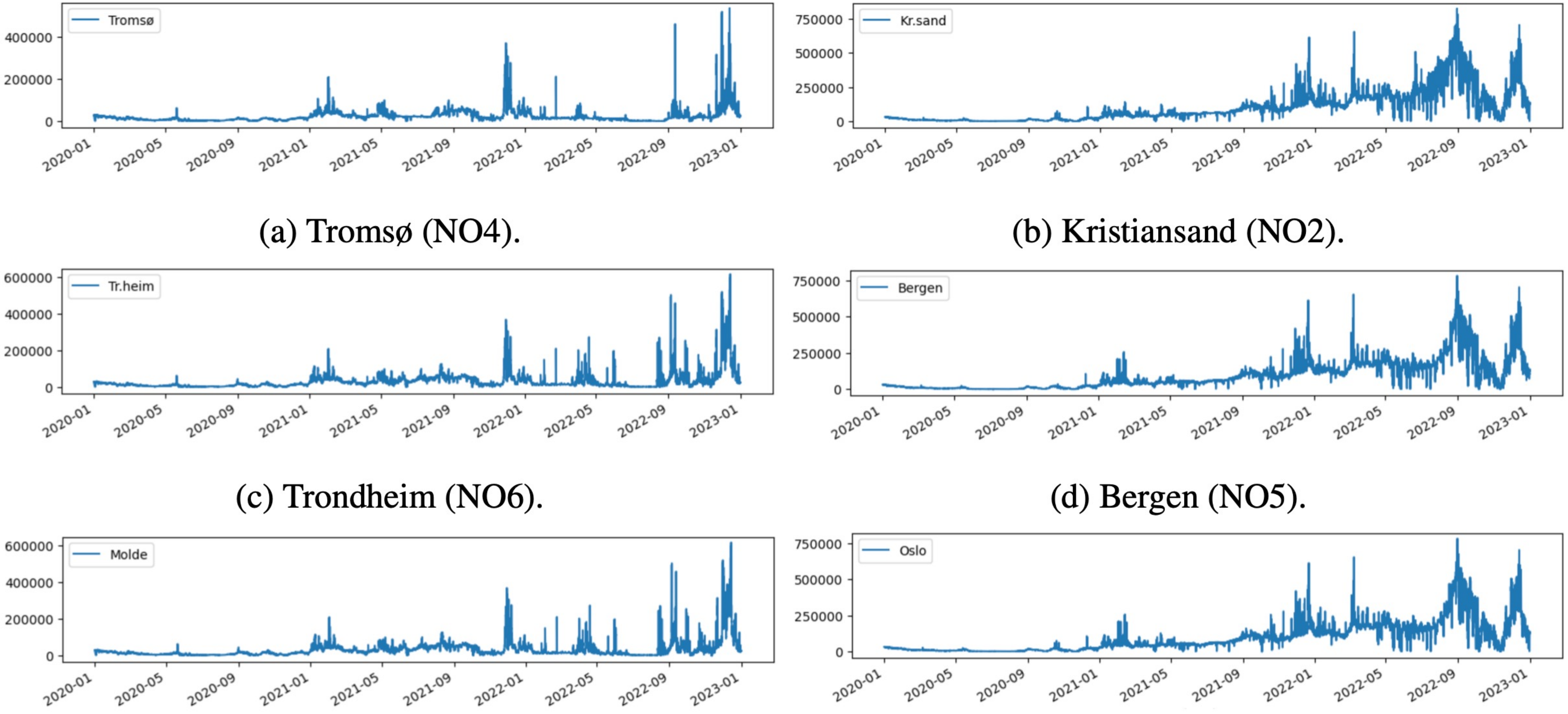


Figure 11: Locations of weather stations color-labeled by bidding zones.

Financial data

Exploratory analysis



(a) Tromsø (NO4).

(b) Kristiansand (NO2).

(c) Trondheim (NO6).

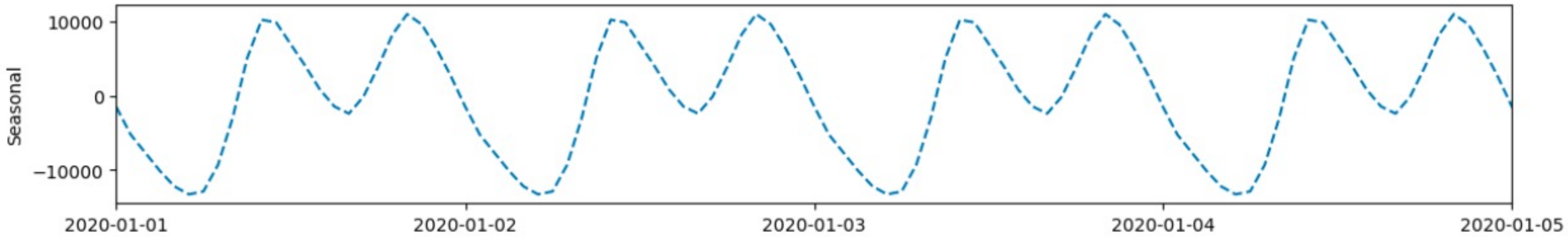
(d) Bergen (NO5).

(e) Molde (NO3).

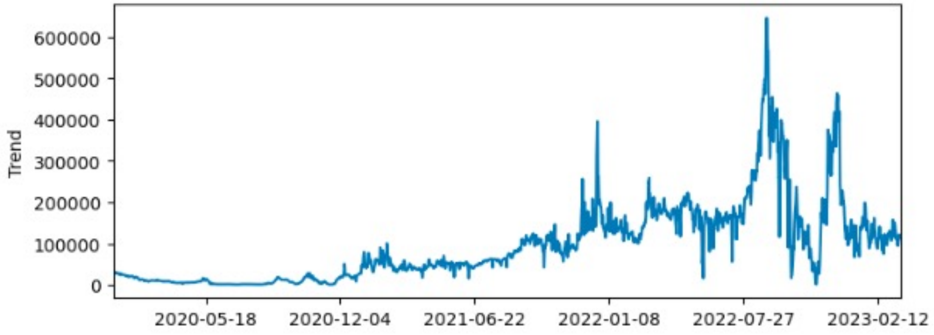
(f) Oslo (NO1).

Figure 12: Historical prices from 1.1.2020-31.12.2022 in each bidding zone.

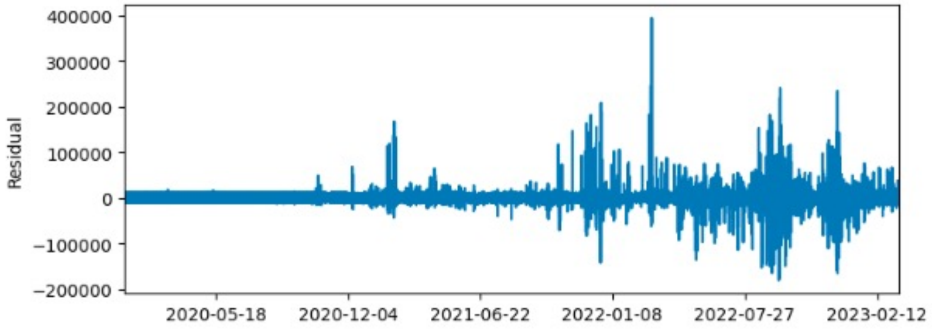
Decomposition



(a) Seasonal component.



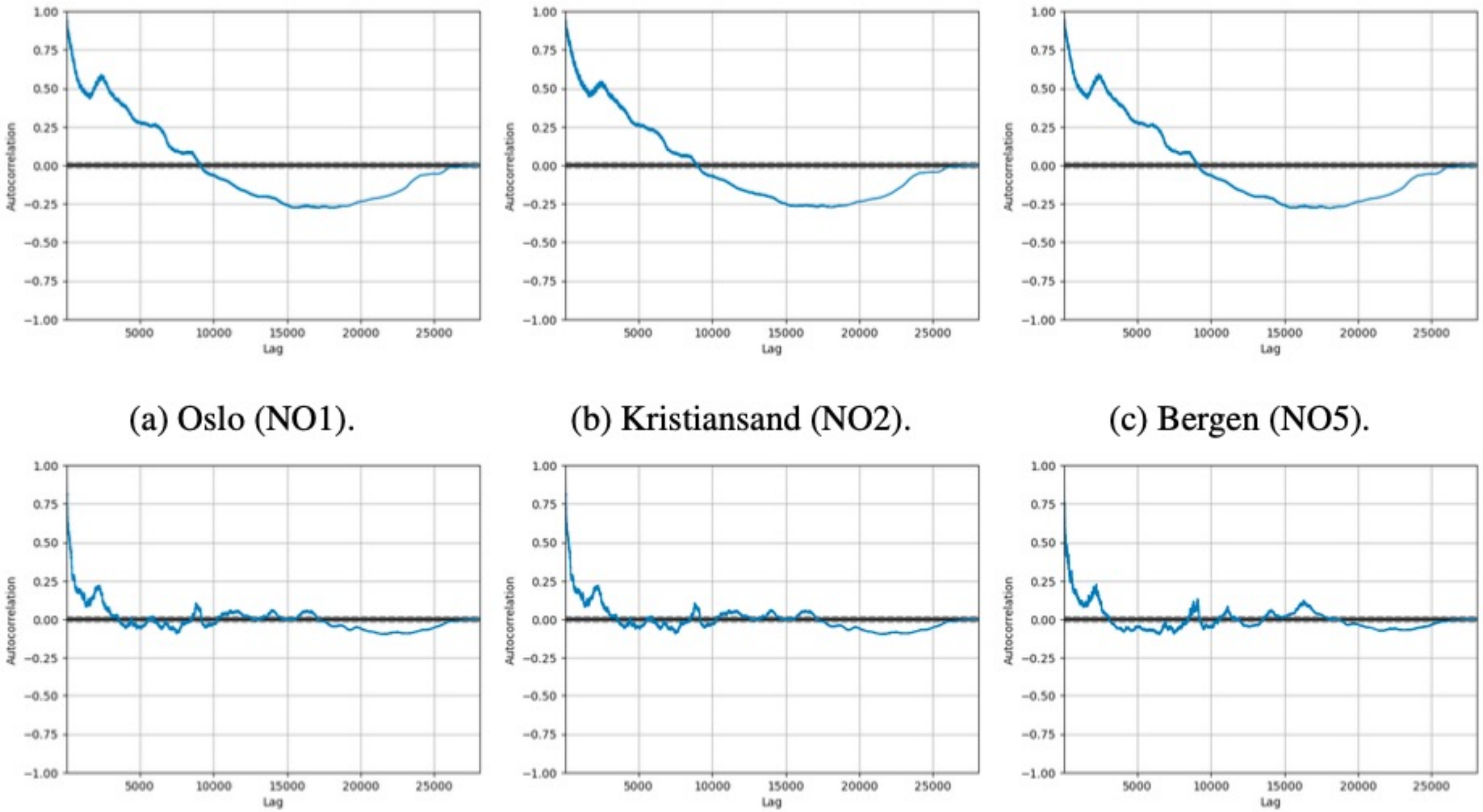
(b) Trend.



(c) Residual.

Figure 13: Additive decomposition of time series (NO1).

Autocorrelation



(a) Oslo (NO1).

(b) Kristiansand (NO2).

(c) Bergen (NO5).

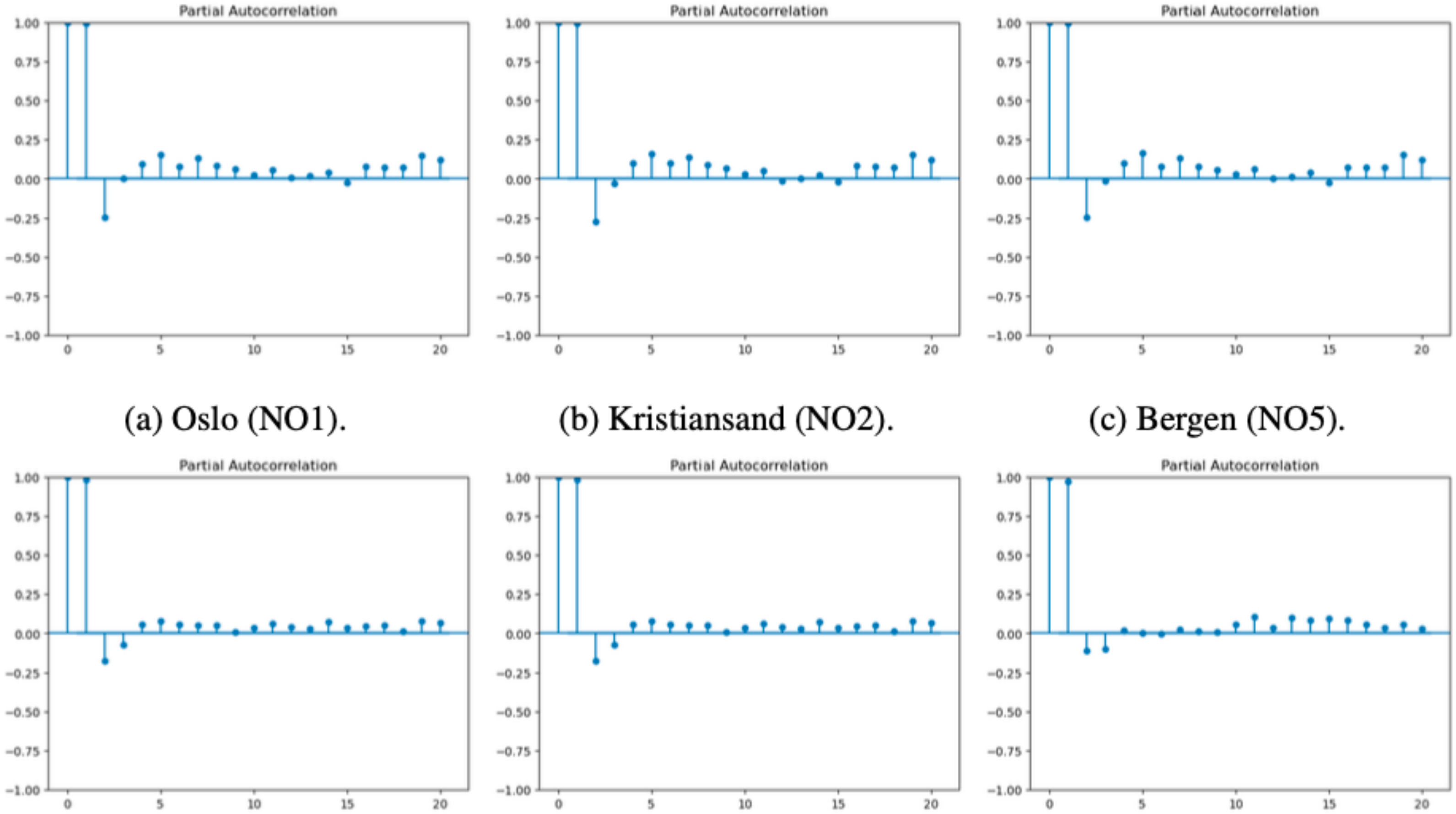
(d) Molde (NO3).

(e) Trondheim (NO6).

(f) Tromsø (NO4).

Figure 14: Auto-correlation function (ACF) of historical elspot prices.

Partial autocorrelation



(a) Oslo (NO1). (b) Kristiansand (NO2). (c) Bergen (NO5).

(d) Molde (NO3). (e) Trondheim (NO6). (f) Tromsø (NO4).

Figure 15: Partial auto-correlation function (PACF) of historical elspot prices.

Descriptive statistics

	Oslo	**Kr.sand**	**Bergen**	**Molde**	**Tr.heim**	**Tromsø**
mean	94888	100901	94641	33437	33437	24650
std	100203	111353	99828	45960	45960	31427
min	-1972	-1972	-96	-2137	-2137	-1058
25%	16089	16101	16300	9695	9695	8995
50%	62348	62670	62419	19904	19904	16580
75%	141576	143056	140894	43740	43740	28782
max	782033	822463	782033	617574	617574	533509

Table 7: Descriptive statistics of historical elspot-prices (NOK).

Visualizations

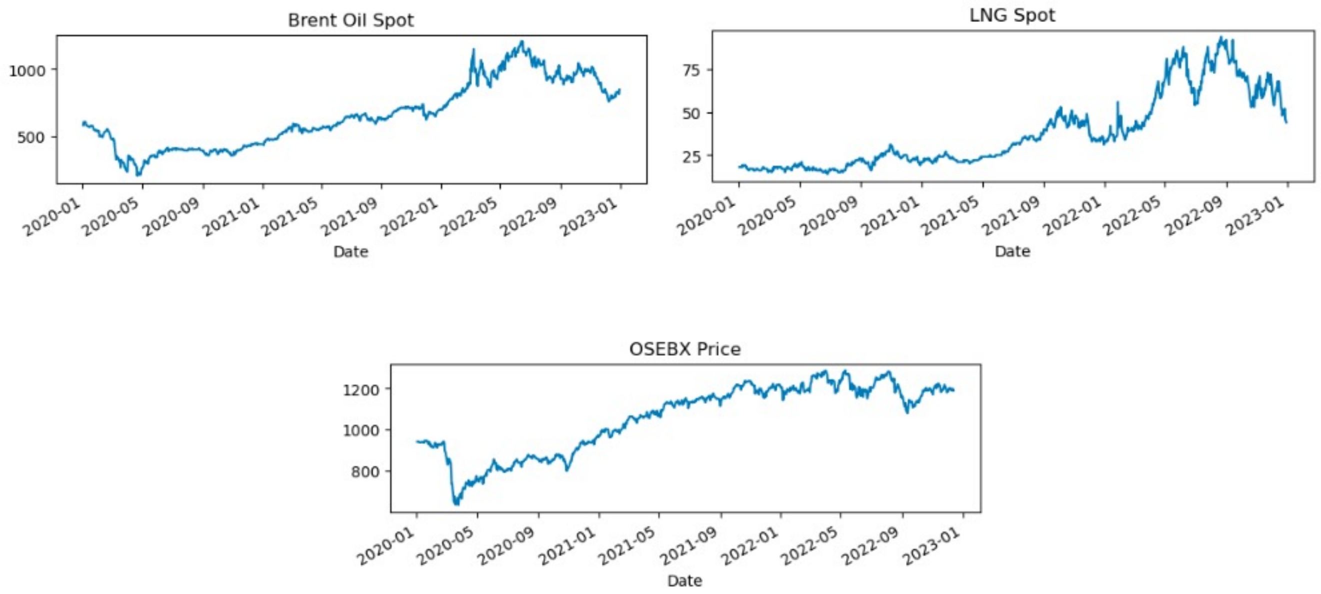


Figure 18: Historical economic variables (NOK).

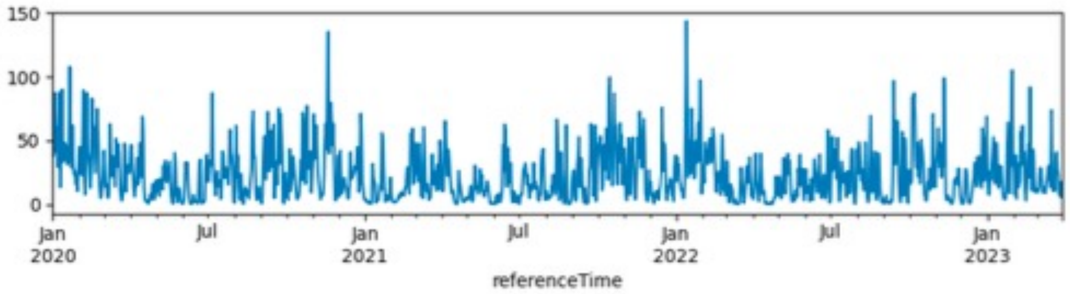


Figure 16: Precipitation.

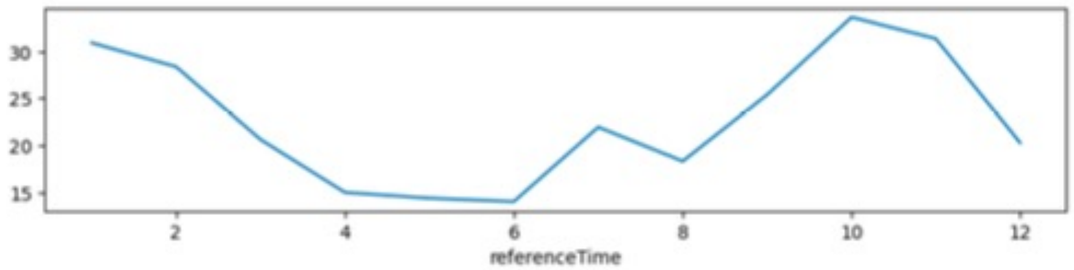
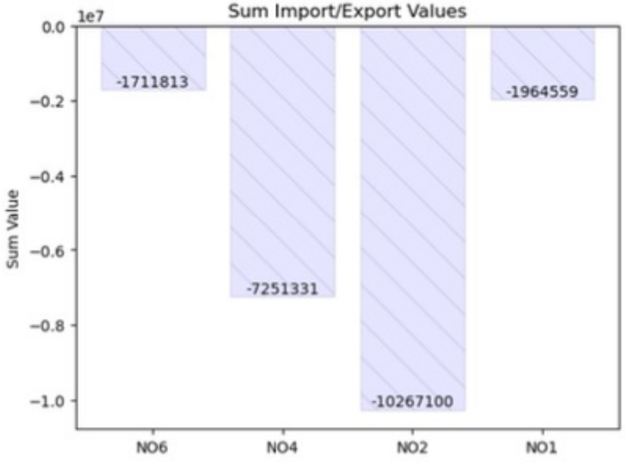
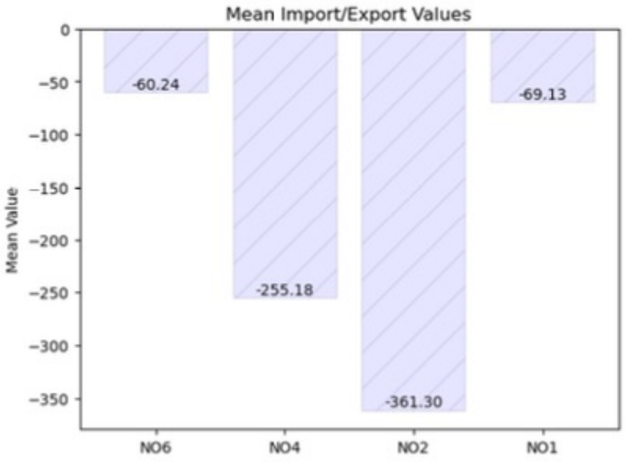


Figure 17: Precipitation averaged by month.

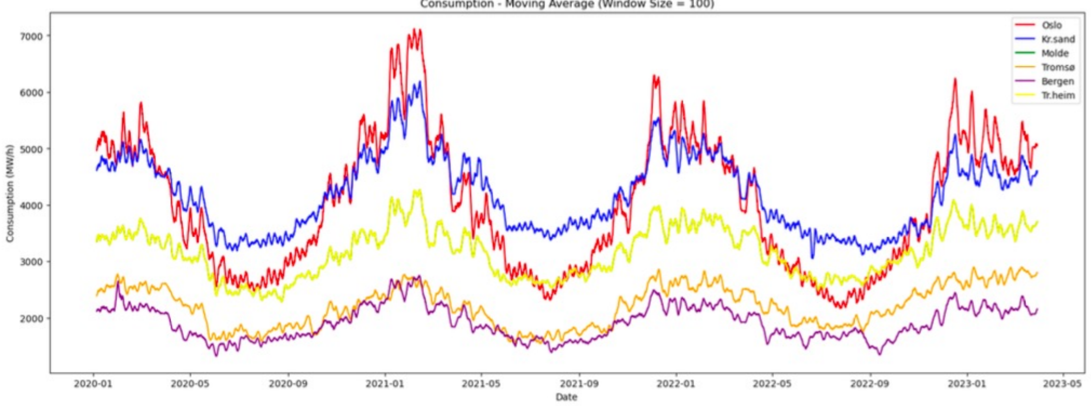


(a) Sum.

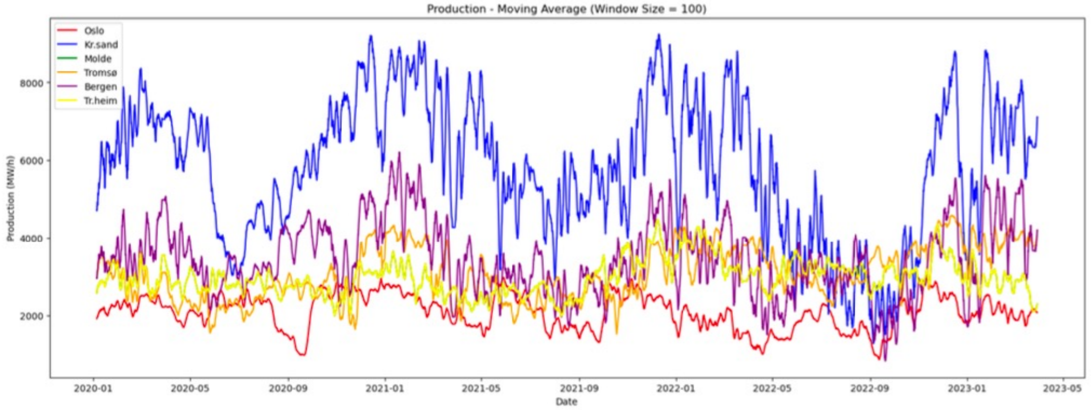


(b) Mean.

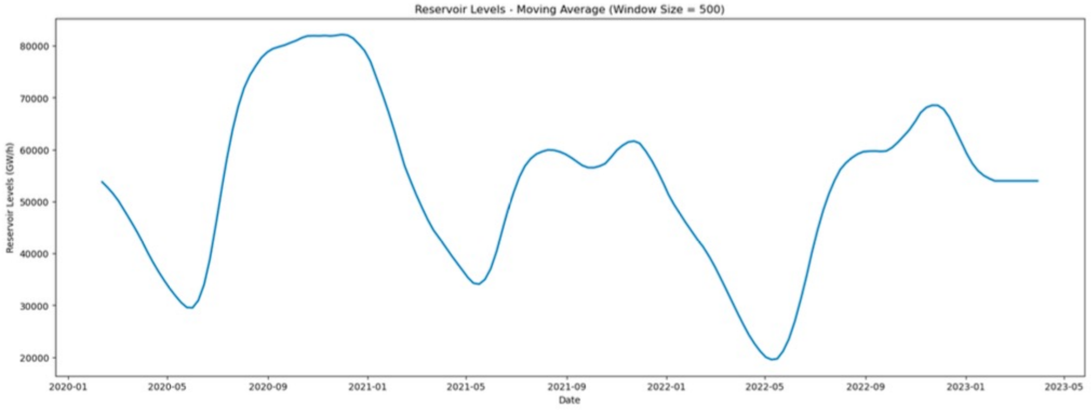
Figure 19: Inter-Country Import/Export of Electricity (MW/h).



(a) Moving average of historical consumption (MW/h).



(b) Moving average of historical production (MW/h).



(c) Historical reservoir levels in Norway (GW/h)

Correlation

	Oslo	**Kr.sand**	**Bergen**	**Molde**	**Tr.heim**	**Tromsø**
Oslo	1.0000	0.9719	0.9984	0.4722	0.4722	0.3562
Kr.sand	0.9719	1.0000	0.9703	0.3975	0.3975	0.2815
Bergen	0.9984	0.9703	1.0000	0.4728	0.4728	0.3572
Molde	0.4722	0.3975	0.4728	1.0000	1.0000	0.8104
Tr.heim	0.4722	0.3975	0.4728	1.0000	1.0000	0.8104
Tromsø	0.3562	0.2815	0.3572	0.8104	0.8104	1.0000

Table 9: Pearson correlation between bidding-zones.

Exogenous variables

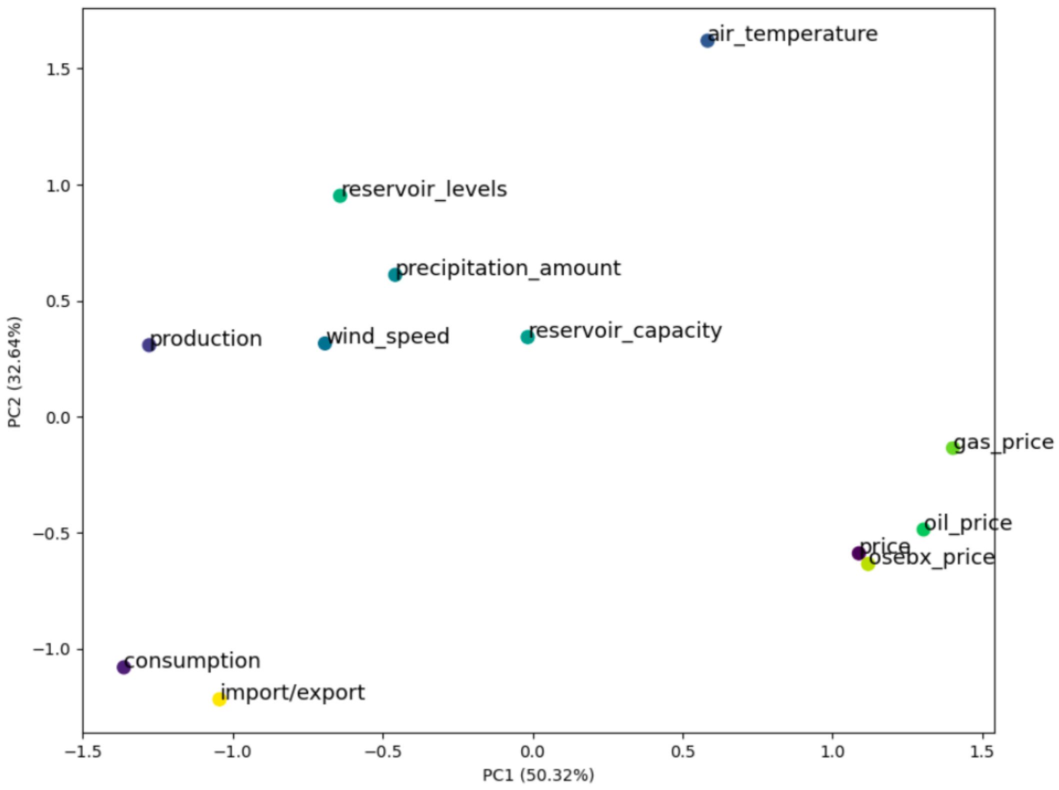


Figure 22: Approximation and projection of variables onto two-dimensional feature-space (PCA).

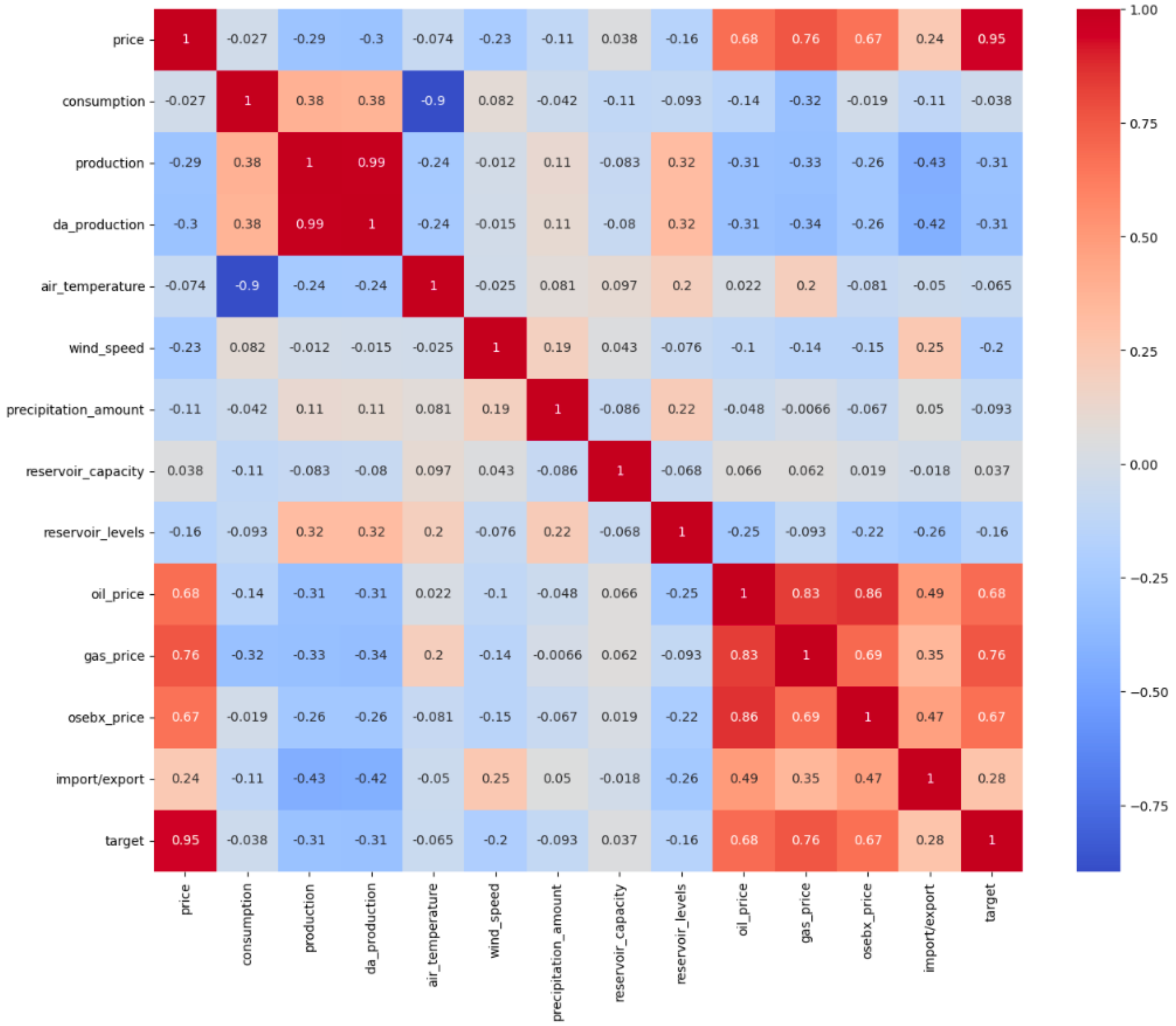


Figure 21: Correlation matrix Oslo (NO1).

Page: 56-58 (100-111 in appendix)

Testing for stationarity

Time Series	ADF Statistic	P-Value	Critical Value (1%)	Critical Value (5%)	Critical Value (10%)
Oslo	-4.019	0.001	-3.431	-2.862	-2.567
Kr.sand	-3.965	0.002	-3.431	-2.862	-2.567
Bergen	-3.967	0.002	-3.431	-2.862	-2.567
Molde	-7.567	< 0.001	-3.431	-2.862	-2.567
Tr.heim	-7.567	< 0.001	-3.431	-2.862	-2.567
Tromsø	-8.708	< 0.001	-3.431	-2.862	-2.567

Table 10: ADF Test Results for Target Time-series.

Data transformations

- Missing values
- Resampling
- Normalization
- Train-test split

Fold	Train Start	Train End	Val Start	Val End
1	2020-01-01 00:00:00	2021-12-31 23:00:00	2022-01-01 00:00:00	2022-01-01 23:00:00
2	2020-01-01 00:00:00	2022-01-01 23:00:00	2022-01-02 00:00:00	2022-01-02 23:00:00
3	2020-01-01 00:00:00	2022-01-02 23:00:00	2022-01-03 00:00:00	2022-01-03 23:00:00
4	2020-01-01 00:00:00	2022-01-03 23:00:00	2022-01-04 00:00:00	2022-01-04 23:00:00
5	2020-01-01 00:00:00	2022-01-04 23:00:00	2022-01-05 00:00:00	2022-01-05 23:00:00
...	...	...	...	...
365	2020-01-01 00:00:00	2022-12-28 23:00:00	2022-12-29 00:00:00	2022-12-29 23:00:00

Table 11: Rolling Forecast Origin Cross-validation Scheme.

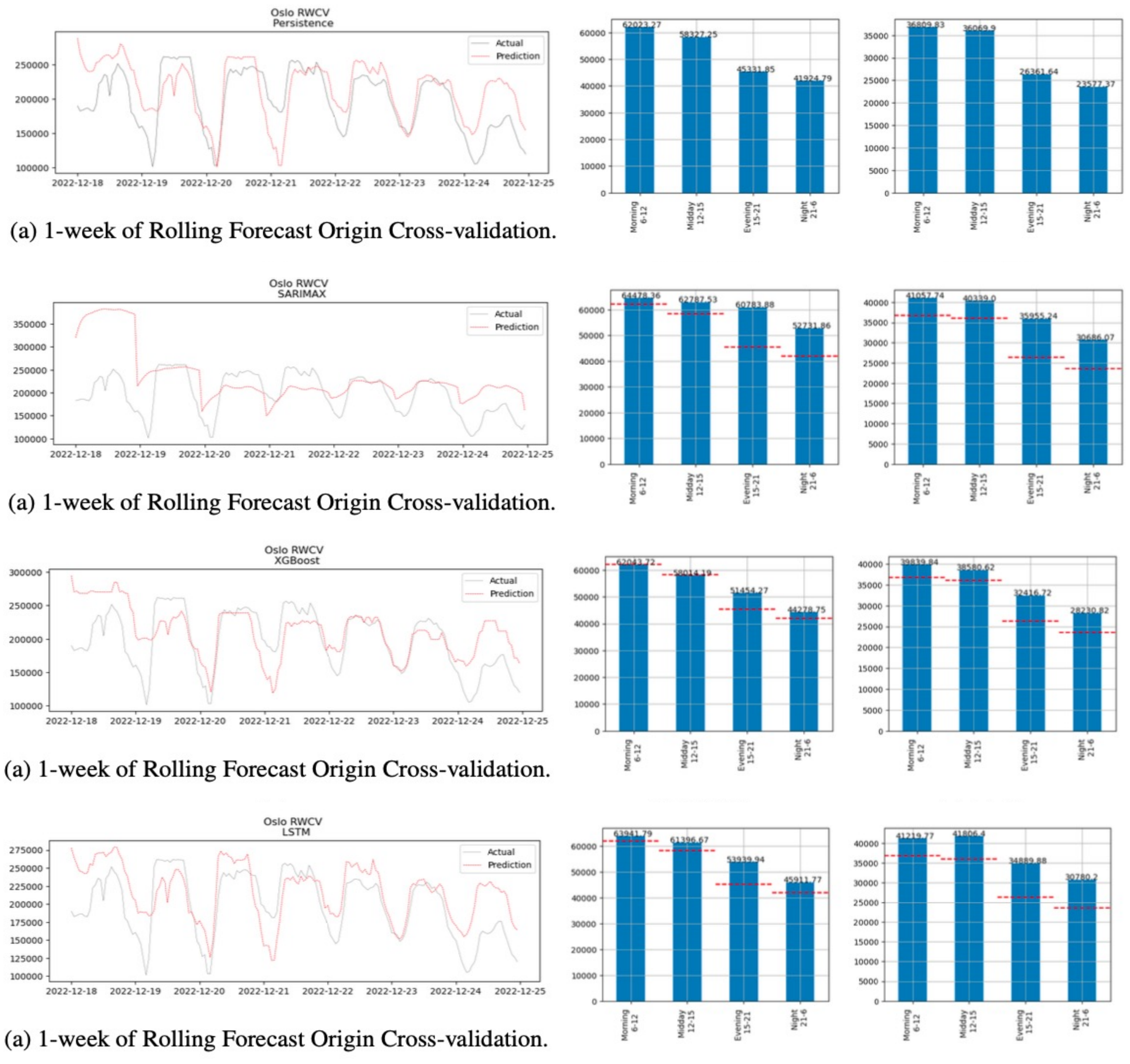
Hyperparameter optimization

1. ARIMA models
    - (p,d,q) = (AR,I,MA)
    - Grid search
    - Alkaline Information Criterion (AIC)
    - Bayesan Information Criterion (BIC)
2. XGBoost models
    - Depth
    - Loss function
    - Regularization (shrinkage)
3. LSTM models
    - Hidden size
    - Hidden layers
    - Sequence length
    - Batch size
    - Dropout (regularization)
    - Activation function
    - Loss function
    - Learning rate
    - Epochs

OPTUNA

Model evaluation

- Naïve baseline for comparisons against lower bound of performance
- Aggregated time-of-day scores (mornings 6-12, mid-days 12-15. evenings 15-21, nights 21-6)
- RMSE penalizes larger errors more than smaller ones (sensitive to outliers)
- MAE measures the absolute difference between predicted and actual price but weights the magnitude of errors equally
- Competing objectives between capturing the nuances of prices and generalizing trends and patterns



Oslo. (b) RMSE. (c) MAE.

Page: 65-69 (112-120 in appendix)

Results

- Univariate and multivariate (endogeneous and with exogeneous)
- All six bidding zones
- 365-fold rolling forecast cross validation (1 year)
- Out-of-sample evaluatiuon (3+months)
- 84 forecasts in total
- RMSE, MAE, MAPE and RSS
- XGBoost feature importance scores

Page: 70-78

Model performance

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	50595	/	**29143**	/	**81.82%**	/	**22.4e[12]**	/
SARIMA	43970	42118	37346	35802	193%	177%	$17.0e^{17}$	$17.0e^{17}$
XGBoost	40366	**39476**	33055	33473	92.84%	135%	$16.6e^{17}$	16.1^{17}
LSTM	40207	41640	33723	35795	126%	132%	$35.4e^{13}$	$34.2e^{13}$

Table 12: Results of 365-fold rolling forecast origin validation

Oslo (NO1).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	29469	/	19946	/	25.19%	/	$18.7e^{11}$	/
SARIMA	29469	44124	19946	36332	**25.18%**	36.84%	$18.7e^{11}$	$41.1e^{11}$
XGBoost	29156	27052	20268	**18838**	26.22%	26.92%	$17.9e^{11}$	$\mathbf{15.5e^{11}}$
LSTM	29174	**21109**	21035	20134	29.21%	26.69%	$17.9e^{11}$	$17.9e^{11}$

Table 13: Results of Out-of-sample evaluation

Oslo (NO1).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	59768	/	35868	/	**85.10%**	/	**31.3e^{12}**	/
SARIMA	52832	50904	45122	43598	194%	180.82%	$22.4e^{17}$	$22.2e^{17}$
XGBoost	47145	45920	**20268**	39101	96.31%	153%	$21.5e^{17}$	$21.5e^{17}$
LSTM	**46129**	46220	39067	39516	131%	155%	$43.1e^{13}$	$42.9e^{13}$

Table 14: Results of 365-fold rolling forecast origin validation

Kristiansand (NO2).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	29474	/	19943	/	25.19%	/	$18.7e^{11}$	/
SARIMA	29474	37216	19943	27932	25.18%	30.86%	$18.7e^{11}$	$29.2e^{11}$
XGBoost	29545	27259	20715	19266	26.77%	26.19%	$18.4e^{11}$	$15.7e^{11}$
LSTM	28354	**26431**	20317	**18173**	29.09%	**24.81%**	$16.9e^{11}$	**14.9e^{11}**

Table 15: Results of Out-of-sample evaluation

Kristiansand (NO2).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	44054	/	**17969**	/	inf%	/	$\mathbf{17.0e^{12}}$	/
SARIMA	**22587**	42118	18878	35802	inf%	inf%	$\mathbf{17.0e^{12}}$	$17.0e^{17}$
XGBoost	23386	23339	20715	19455	inf%	inf%	$58.1e^{16}$	$62.8e^{16}$
LSTM	24271	26279	20174	21622	inf%	inf%	$21.1e^{12}$	$29.7e^{12}$

Table 16: Results of 365-fold rolling forecast origin validation

Molde (NO3).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	30448	/	21069	/	37.58%	/	$20.0e^{11}$	/
SARIMA	30448	44907	21069	34139	37.57%	47.61%	$20.0e^{11}$	$42.6e^{11}$
XGBoost	28469	29069	19687	19666	35.79%	31.79%	$17.1e^{11}$	$17.8e^{11}$
LSTM	28438	**28381**	20462	**19228**	40.91%	**31.29%**	$17.1e^{11}$	$\mathbf{16.6e^{11}}$

Table 17: Results of Out-of-sample evaluation

Molde (NO3).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	33532	/	**9878**	/	inf%	/	$98.5e^{11}$	/
SARIMA	13169	12754	11019	10651	inf%	inf%	$19.1e^{16}$	/
XGBoost	**12333**	13179	19687	10946	inf%	inf%	$22.5e^{16}$	$23.9e^{16}$
LSTM	12580	15867	10231	13100	inf%	inf%	$\mathbf{82.8e^{11}}$	$95.9e^{11}$

Table 18: Results of 365-fold rolling forecast origin validation

Tromsø (NO4).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	21456	/	11705	/	25.28%	/	$99.4e^{10}$	/
SARIMA	21456	30875	11705	22584	25.27%	45.46%	$99.4e^{10}$	$18.7e^{16}$
XGBoost	20592	23149	11424	12507	25.43%	29.35%	$89.6e^{10}$	$11.3e^{11}$
LSTM	**19448**	21675	**10519**	13155	**22.76%**	28.05%	$\mathbf{79.9e^{10}}$	$96.1e^{10}$

Table 19: Results of Out-of-sample evaluation

Tromsø (NO4).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	49520	/	28290	/	**80.67%**	/	$\mathbf{21.4e^{12}}$	/
SARIMA	42755	41411	36593	35473	191%	183.02%	$16.9e^{17}$	$16.9e^{17}$
XGBoost	39208	39165	**11424**	33479	86.50%	154.40%	$16.5e^{17}$	$16.3e^{17}$
LSTM	**38759**	38818	32781	33351	126.24%	152.32%	$35.3e^{13}$	$36.3e^{13}$

Table 20: Results of 365-fold rolling forecast origin validation

Bergen (NO5).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	25240	/	**16953**	/	**15.75%**	/	$\mathbf{13.7e^{10}}$	/
SARIMA	25240	27679	**16953**	19177	**15.75%**	17.28%	$\mathbf{13.7e^{10}}$	$16.1e^{11}$
XGBoost	24950	**24156**	17137	17018	16.27%	15.94%	$13.1e^{11}$	$12.3e^{11}$
LSTM	25427	24584	18391	18189	17.80%	17.49%	$13.6e^{11}$	$12.9e9^{11}$

Table 21: Results of Out-of-sample evaluation

Bergen (NO5).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	44054	/	17969	/	inf%	/	$\mathbf{17.0e^{12}}$	/
SARIMA	22587	**22154**	18878	18547	inf%	inf%	$60.0e^{16}$	$61.2e^{16}$
XGBoost	23386	22915	**17137**	18979	inf%	inf%	$58.1e^{16}$	$61.6e^{16}$
LSTM	24050	25940	19957	21375	inf%	inf%	$21.0e^{12}$	$32.9e^{12}$

Table 22: Results of 365-fold rolling forecast origin validation

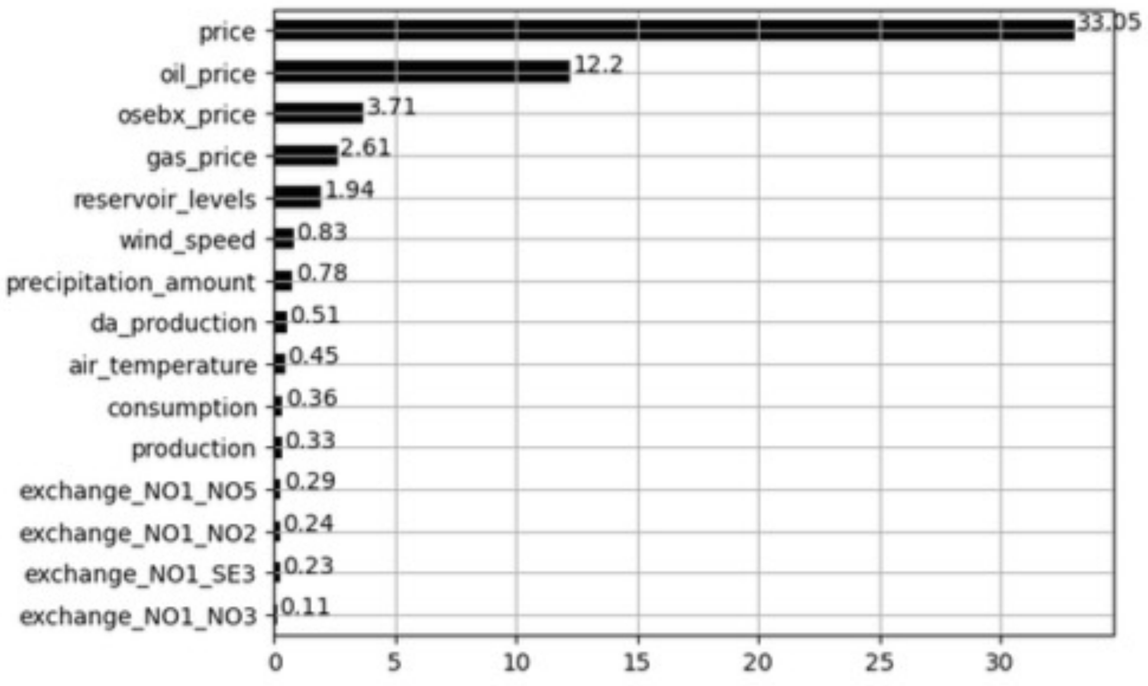
Trondheim (NO6).

	RMSE		MAE		MAPE		RSS	
	endog	w/ exog	endog	w/ exog	endog	w/ exog	endog	w/ exog
Baseline (naive)	30448	/	21069	/	37.58%	/	$20.0e^{11}$	/
SARIMA	30448	45333	21069	34465	37.57%	48.04%	$20.0e^{11}$	$43.4e^{11}$/
XGBoost	28469	**28326**	19687	**19532**	35.79%	**31.70%**	$17.1e^{11}$	$\mathbf{16.9e^{11}}$
LSTM	28438	30100	20462	22870	40.91%	48.58%	$17.1e^{11}$	$19.1e^{11}$

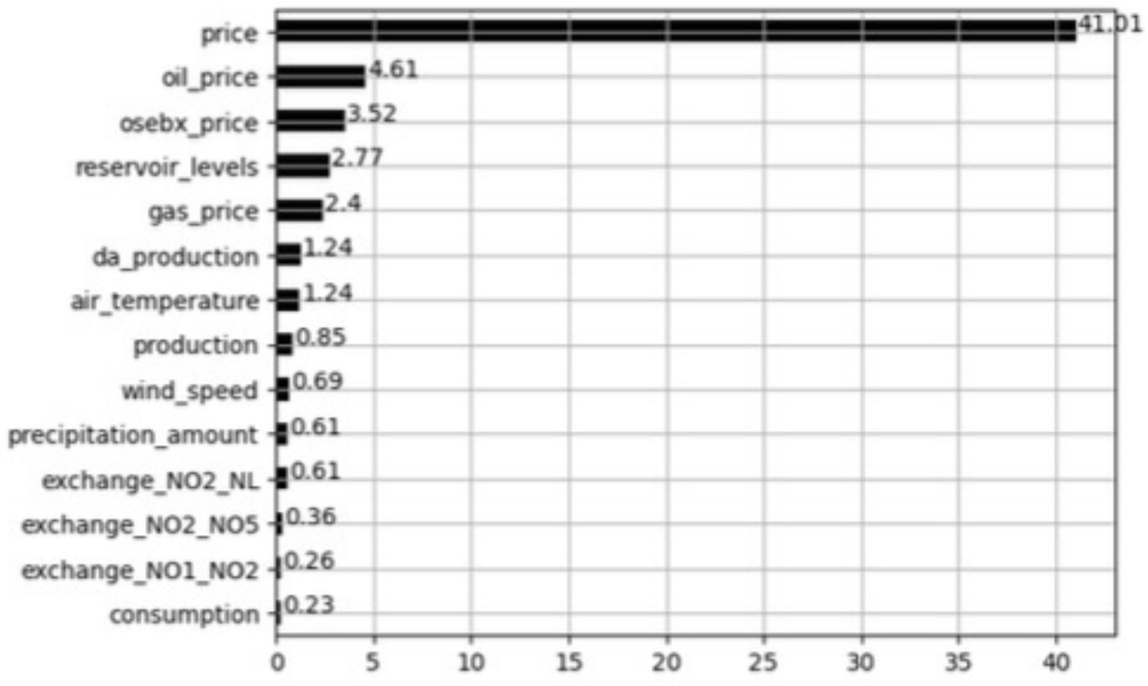
Table 23: Results of Out-of-sample evaluation

Trondheim (NO6).

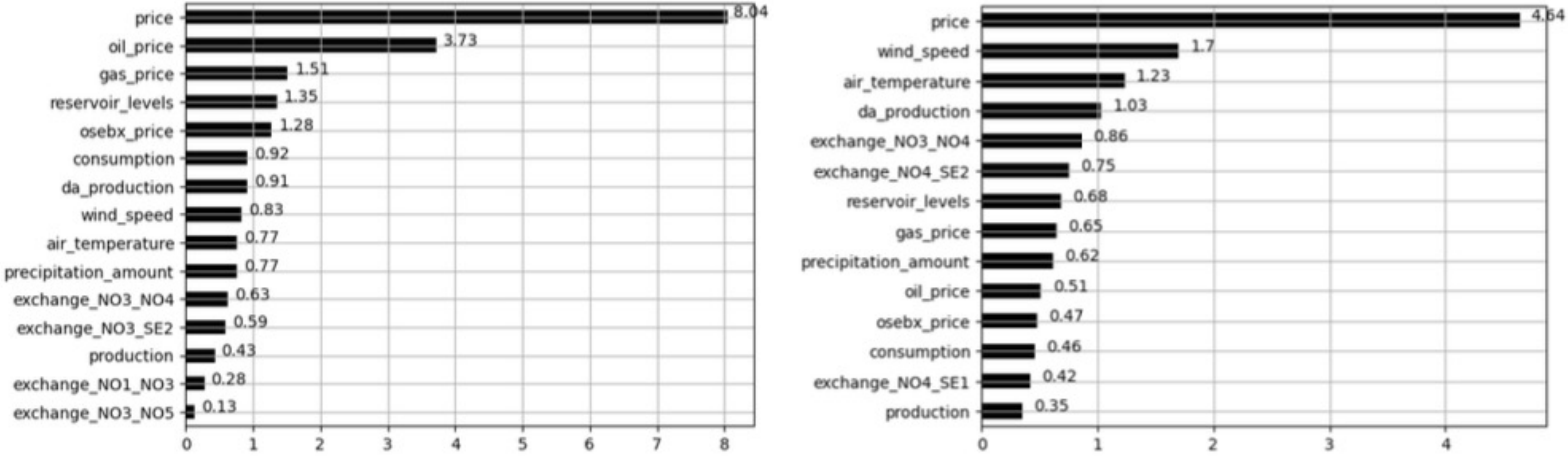
Feature importance



(a) Oslo (NO1).

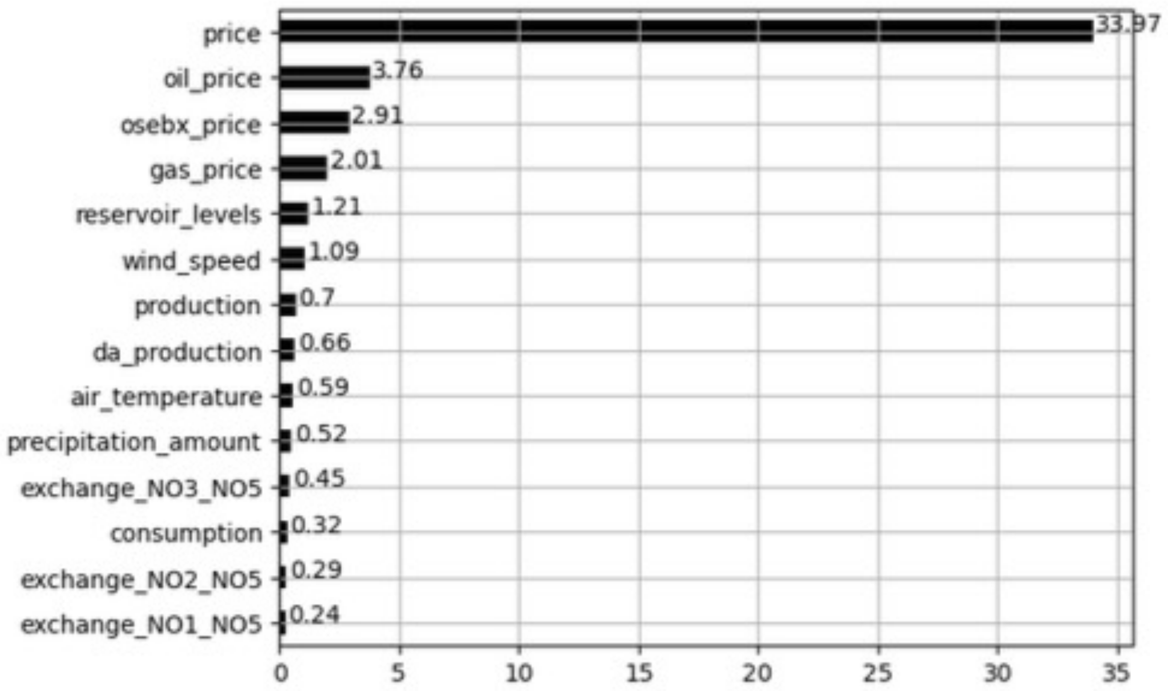


(b) Kristiansand (NO2).

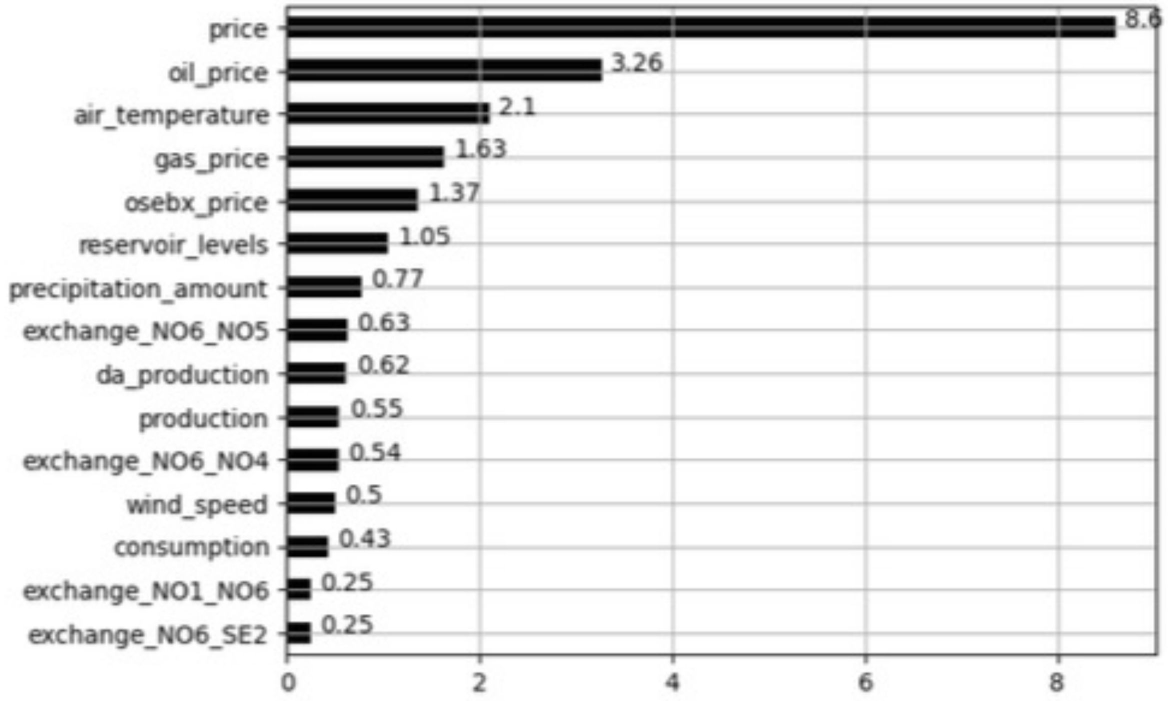


(c) Molde (NO3).

(d) Tromsø (NO4).



(e) Bergen (NO5).

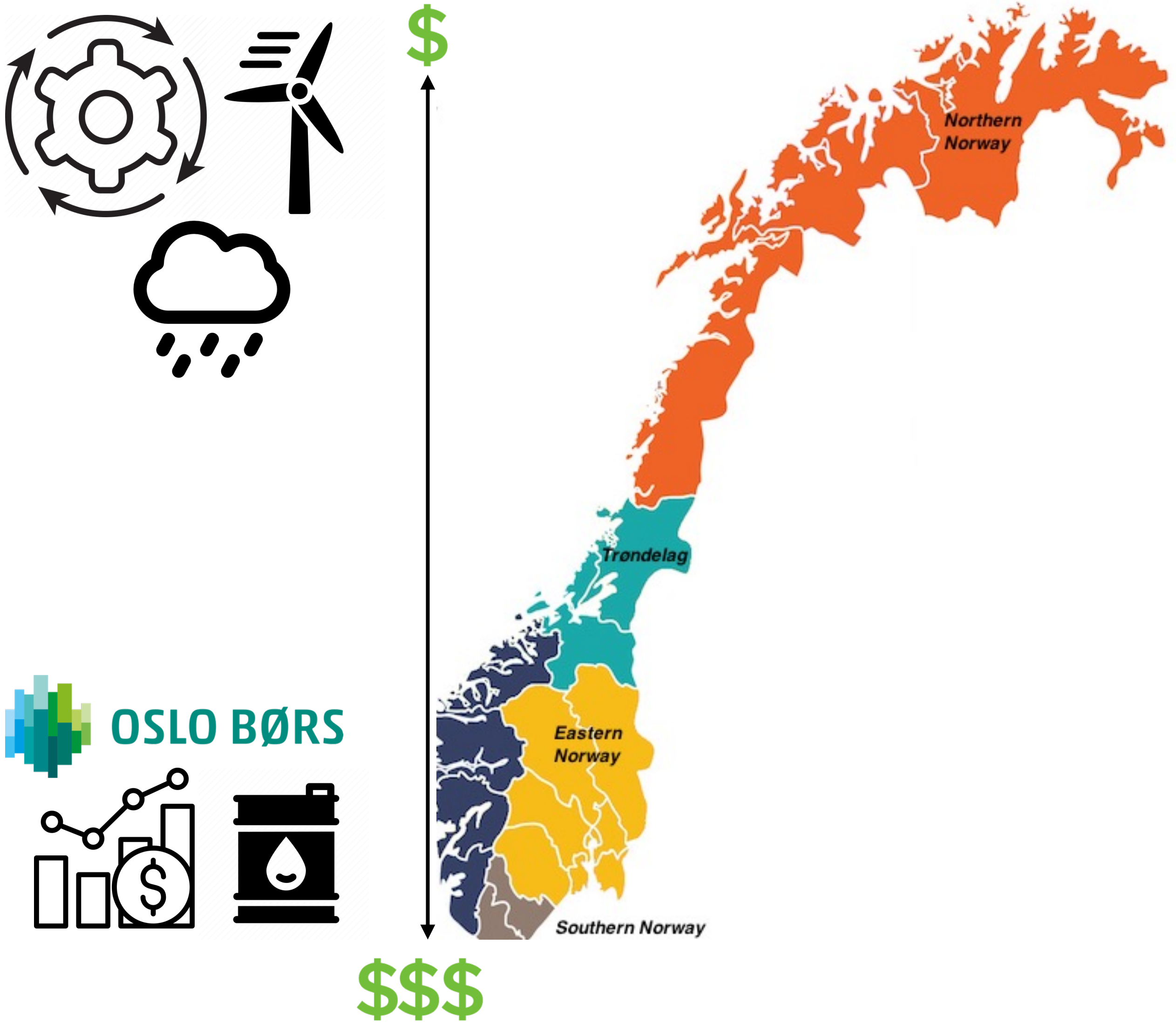


(f) Trondheim (NO2).

Discussion on price drivers

Period: 01.01.2020 – 31.03.2023

- Correlation, PCA and XGBoost scores
- Varying across bidding-zones
- Convenience yields as opposed to marginal cost of production
- Disruption of global energy after Ukraine



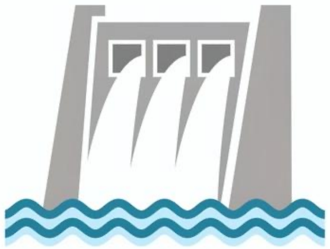
Page: 79-83

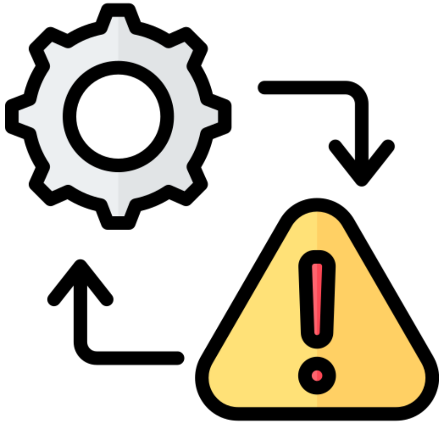
Discussion on methods

- ARIMA performs well on validation-set with short inference horizons

(but fails during further out-of-sample evaluation)

- LSTM and XGBoost manages to strike a balance in the bias-variance trade-off during out-of-sample evaluation
- XGBoost has the benefit of being interpretable
- LSTM performs better overall
- No one-size-fits-all model
- No one-size-fits-all metric



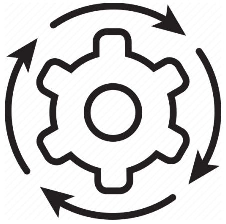


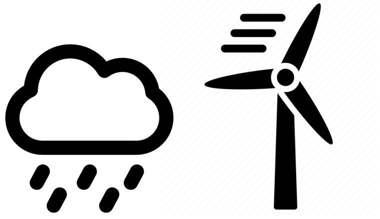
7 AFFORDABLE AND CLEAN ENERGY

Implications

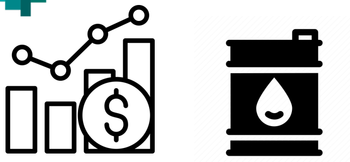
Page: 84-86

Conclusion





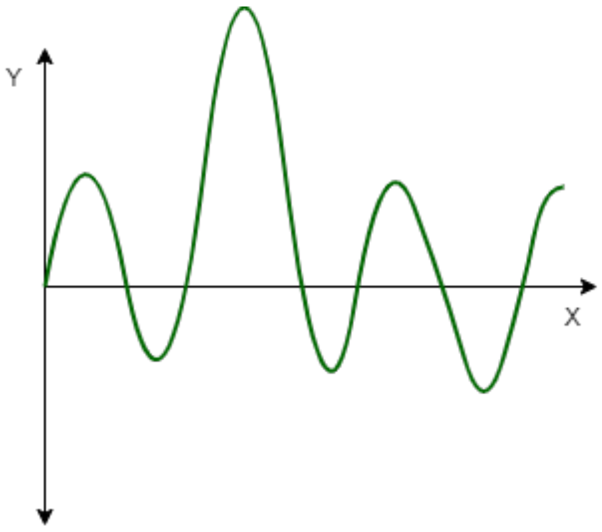
OSLO BØRS



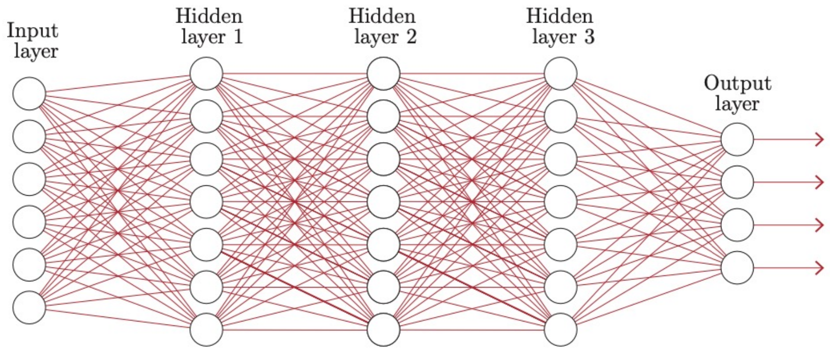
Which methods are most effective in predicting the Norwegian day-ahead elspot prices?

Which price-drivers shape the behaviour of the Norwegian elspot prices?

ARIMA



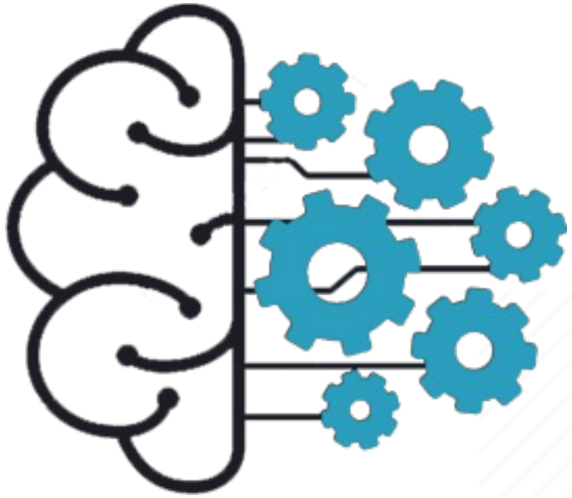
LSTM

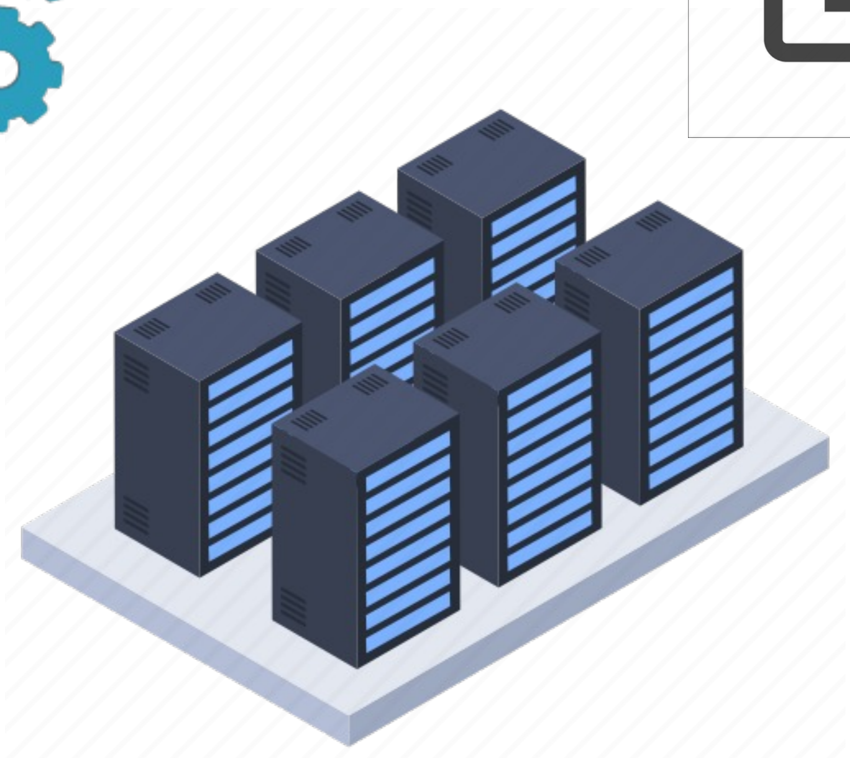


XGBoost

Page: 87-89

Limitations and Future Work





NLDL

Thank you!

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