Wrocław University of Science and Technology

Electricity price forecasting in BESS management – linking statistical and economic measures

Katarzyna Maciejowska, Bartosz Uniejewski

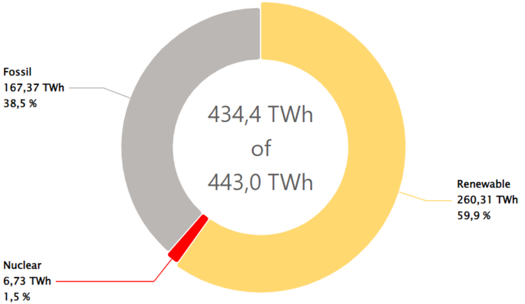
Wrocław University of Science and Technology, Poland

11.12.2024,Sydney

Generation structure

Change of the generation structure:

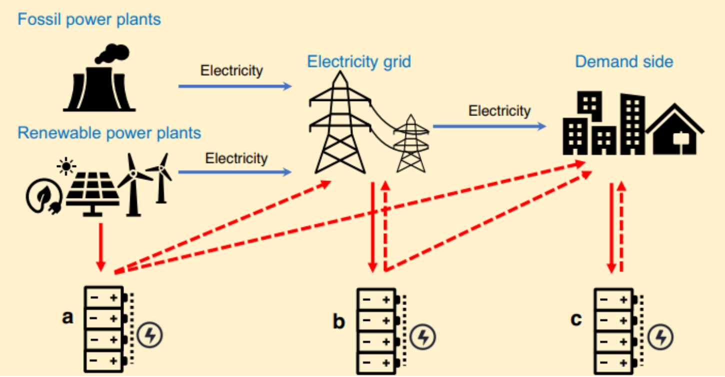
- Technological development → Renewable Energy Sources (RES)
- Nuclear accident in Japan → reduction of nuclear power
- Ukraine war → turbulence in fuel markets



Generation in Germany, 2023: https://www.energy-charts.de/

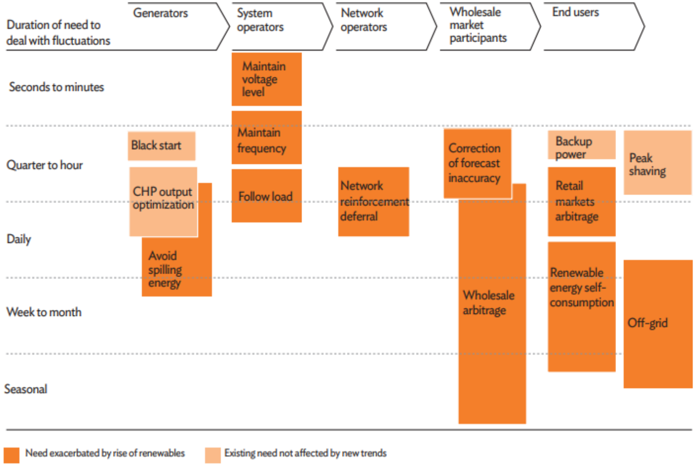
BESS

Battery energy storage systems (BESS) → essential for speeding up the replacement of fossil fuels with RES



Source: Peng et al, 2023, nature.com/articles/s41467-023-40337-3

Usage of BESS



Source: ROLAND BERGER GMBH (2017). R. Berger, "Business models in energy storage – Energy Storage can bring utilities back into the game," May.

BESS operation

In this research, it is assumed that the battery earns from wholesale arbitrage:

- buys in off-peak hours at low prices
- sells in peak hours at high prices
- places unlimited bids – accepts the market price
- charging and discharging efficiency – 90%

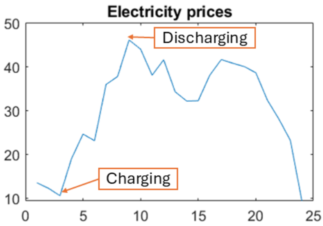
BESS operation

Profit on day t

$$\pi_t = 0.9DA_{t,h_{discharge}} - 1/0.9DA_{t,h_{charge}} - C$$

depends on selection of charging and discharging hours. Choice is:

- made on the day before delivery
- insignificant costs: $C = 0$
- based on price forecasts: $h_{charge} < h_{discharge}$
- operate when $\pi_t \geq 0$



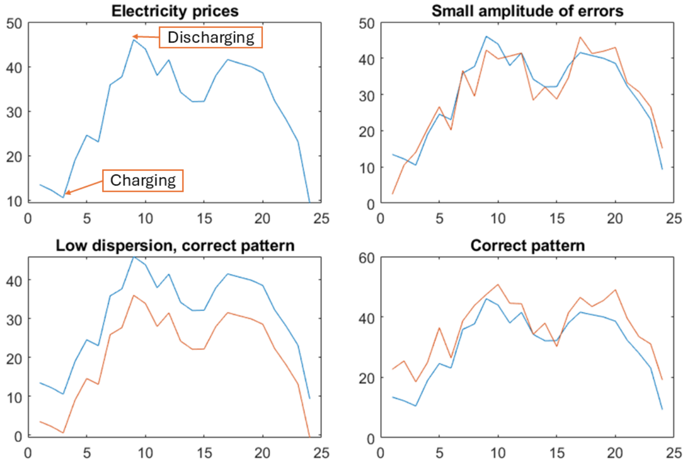
Between economic and statistical measures

Profit depends on selection of charging and discharging hours $\rightarrow$ choice is based on forecasts

- no forecast errors (oracle) $\rightarrow$ optimal decision
- various aspects of forecasts may impact the income differently:
  - magnitude of errors
  - dispersion of errors
  - pattern across the day ...
  - ... $\rightarrow$ hour selection

Question Which property of forecasts is the most important? How can be measured?

Statistical measures of forecast accuracy



Measuring magnitude of errors

Two measures based on the out-of-sample forecast errors:

$$e_{t,h} = P_{t,h} - \hat{P}_{t,h}$$

$$RMSE = \sqrt{\frac{1}{24}\frac{1}{T}\sum_{h}\sum_{t}(e_{t,h})^2}$$

$$MAE = \frac{1}{24}\frac{1}{T}\sum_{h}\sum_{t}|e_{t,h}|$$

Measuring dispersion of errors

Two measures based on the (24×1) vector of forecast errors:
$e_t = [e_{t,1}, ..., e_{t,24}]'$

- Determinant of second non-central moment of forecast errors

$$D = log(det(\frac{1}{T}\sum_t e_t e_t'))$$

- similar to Dawid-Sebastiani measure

$$DS = log(det(\Sigma)) + \frac{1}{T}\sum_t e_t'\Sigma^{-1}e_t',$$

where Σ is the variance-covariance matrix of e_t

Measuring dispersion of errors

Both measures:

- increase with the dispersion $\rightarrow$ the less diversified the forecast errors the smaller the measures
- increase with the magnitude of errors

It can be notices that DS-like measure:

- when $\Sigma = I \rightarrow$ MSE
- when errors are normally distributed $\rightarrow$ DS proportional to the log-likelihood function

Measuring correct pattern

Lets denote by P_t and $\hat{P}_t$ the (24×1) vectors of prices and their forecast in a day t and by ρ_t their Pearson correlation

$$\rho_t = corr(P_t, \hat{P}_t)$$

Then

$$\rho = \frac{1}{T} \sum_t \rho_t$$

Measuring quality of hour selection

Lets denote by h_{min} and h_{max} the hour of the minimum and the maximum price within the day (oracle) and by $\hat{h}_{min}$ and $\hat{h}_{max}$ their predictions. Then the selection quality can be measured using two forecast errors:

- difference of hours

$$e_{t,min}^{(Hours)} = h_{min} - \hat{h}_{min}$$

$$e_{t,max}^{(Hours)} = h_{min} - \hat{h}_{max}$$

- difference of prices in selected hours:

$$e_{t,min}^{(Prices)} = P_{t,h_{min}} - P_{\hat{h}_{min}}$$

$$e_{t,max}^{(Prices)} = P_{t,h_{max}} - P_{\hat{h}_{max}}$$

Measuring quality of hour selection

Using the forecast errors $e_{t,min}^{(i)}$ ans $e_{t,max}^{(i)}$, we can compute

$$RMSE^{(i)} = \sqrt{(MSE_{min}^{(i)} + MSE_{max}^{(i)})/2}$$

$$MAE^{(i)} = (MAE_{min}^{(i)} + MAE_{max}^{(i)})/2$$

Models used for forecasting

In order to examine the relationship between forecast accuracy measures and the profit, we calculate forecasts using models:

- ARX expert models
- mARX - models of the deviation of prices from their daily mean + the model of the daily mean
- LEAR models

ARX

Expert model (Misiorek et al. 2006; Ziel, Weron, 2018)

$$P_{t,h} = D_t\alpha_h + \underbrace{\sum_{p\in\{1,2,3,7\}} \theta_{h,p} P_{t-p,h}}_{\text{AR component}} + X_{t,h}\beta_h + \varepsilon_{t,h},$$

where $X_{t,h}$ is a vector of exogenous variables:

- Previous day effect: $P_{t-1,min}$, $P_{t-1,max}$
- Forecasted fundamental variables: $L_{t,h}$, $RES_{t,h}$
- Past gas and CO_2 allowance prices from day $t-2$

mARX

We predict separately:

- average daily price: $\bar{P}_t$
- deviation from the mean: $\tilde{P}_{t,h} = P_{t,h} - \bar{P}_t$

Two models:

$$\bar{P}_t = D_t\alpha + \sum_{p\in\{1,2,7\}} \theta_p \bar{P}_{t-p} + \bar{X}_t\beta + \varepsilon_t$$

$$\tilde{P}_{t,h} = D_t\alpha_h + \sum_{p\in\{1,2,7\}} \theta_{h,p} \tilde{P}_{t-p,h} + \tilde{X}_{t,h}\beta_h + \varepsilon_{t,h}$$

LEAR

Huge model that includes 251 variables:

- all 24 prices from days:$t-1$, $t-2$, $t-3$ and $t-7$
- predicted load and RES for all 24 prices for days: t, $t-1$, $t-7$
- past fuel and CO_2 allowance prices from day $t-2$
- seven weekday dummies

The model is estimate with LASSO method (Uniejewski et al., 2016; Uniejewski, Weron, 2018)

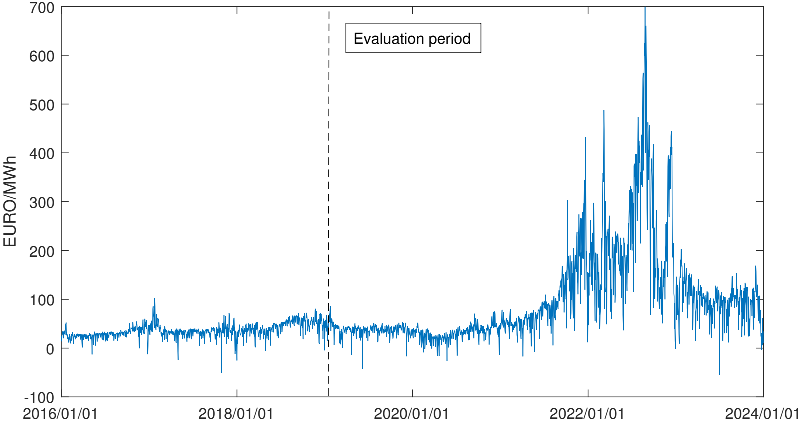
Models specification and estimation

Additionally:

- each model is estimated using windows of length: 1095,750, 365, 182, 112, 84, 56 days
- variance stabilizing transformation: no or asinh
- ARX, mARX models $\rightarrow$ individual models are fit to each hour or pooled estimator is used
- forecasts are next averaged over:
  - window sizes (for a particular model)
  - models (for a particular window length)
  - windows and models

For each day/hour, 90 forecasts are computed!

EPEX: average daily day-ahead prices, 01.01.2016–31.12.2023



RMSE relative to ARX: average over years

RMSE (relative to ARX, window 1095)

	1095	730	365	182	112	84	56	Ave
ARX	1	1.003	0.9666	0.936	0.9179	0.9312	0.9651	0.8841
mARX	1.07	1.077	1.047	1.001	0.96	0.9614	0.9876	0.933
ARX-pooled	1.109	1.119	1.076	0.9995	0.9514	0.9331	0.9277	0.9516
mARX-pooled	1.042	1.049	1.012	0.9574	0.9237	0.9199	0.9271	0.918
LEAR	0.8933	0.9166	0.8965	0.8864	0.8775	0.9016	0.9183	0.831
asinh-ARX	1.156	1.104	1.144	1.041	0.9711	1.081	1.121	1.084
asinh-mARX	1.067	1.075	1.047	1.003	0.9575	0.9815	1.088	0.9338
asinh-ARX-pooled	1.109	1.138	1.091	1.062	0.9594	0.9322	0.9447	0.9185
asinh-mARX-pooled	1.062	1.067	1.023	0.9678	0.9327	0.9274	0.9313	0.9267
asinh-LEAR	0.8112	0.8687	0.8496	0.8643	0.8308	0.85	0.8874	0.7639
Ave	0.9328	0.9487	0.9156	0.886	0.8497	0.8582	0.903	0.8368

RMSE relative to ARX: average over years

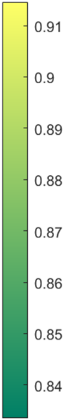
RMSE (relative to ARX, window 1095)

	1095	730	365	182	112	84	56	Ave
ARX	1	1.003	0.9666	0.936	0.9179	0.9312	0.9651	0.8841
mARX	1.07	1.077	1.047	1.001	0.96	0.9614	0.9876	0.933
ARX-pooled	1.109	1.119	1.076	0.9995	0.9514	0.9331	0.9277	0.9516
mARX-pooled	1.042	1.049	1.012	0.9574	0.9237	0.9199	0.9271	0.918
LEAR	0.8933	0.9166	0.8965	0.8864	0.8775	0.9016	0.9183	0.831
asinh-ARX	1.156	1.104	1.144	1.041	0.9711	1.081	1.121	1.084
asinh-mARX	1.067	1.075	1.047	1.003	0.9575	0.9815	1.088	0.9338
asinh-ARX-pooled	1.109	1.138	1.091	1.062	0.9594	0.9322	0.9447	0.9185
asinh-mARX-pooled	1.062	1.067	1.023	0.9678	0.9327	0.9274	0.9313	0.9267
asinh-LEAR	0.8112	0.8687	0.8496	0.8643	0.8308	0.85	0.8874	0.7639
Ave	0.9328	0.9487	0.9156	0.886	0.8497	0.8582	0.903	0.8368

Profit relative to oracle: average over years

Profits (relative to oracle)

	1095	730	365	182	112	84	56	Ave
ARX	0.8792	0.8803	0.8754	0.8659	0.8656	0.856	0.8379	0.8876
mARX	0.8933	0.8892	0.8904	0.8812	0.8789	0.8692	0.8648	0.896
ARX-pooled	0.8851	0.8883	0.8966	0.9022	0.9007	0.8991	0.9003	0.9022
mARX-pooled	0.8819	0.8883	0.8989	0.9047	0.9026	0.9047	0.9037	0.9032
LEAR	0.8831	0.8788	0.8723	0.8621	0.8572	0.8459	0.8335	0.8923
asinh-ARX	0.8769	0.8768	0.8723	0.86	0.8647	0.8514	0.8339	0.887
asinh-mARX	0.9	0.8958	0.8973	0.8787	0.8762	0.8651	0.86	0.8984
asinh-ARX-pooled	0.8973	0.8992	0.903	0.907	0.9074	0.9058	0.9062	0.9081
asinh-mARX-pooled	0.8996	0.9009	0.9054	0.9078	0.906	0.9052	0.9058	0.9076
asinh-LEAR	0.8998	0.8965	0.8845	0.873	0.8706	0.8617	0.8461	0.9034
Ave	0.9086	0.9086	0.91	0.9106	0.9102	0.9052	0.9013	0.9146



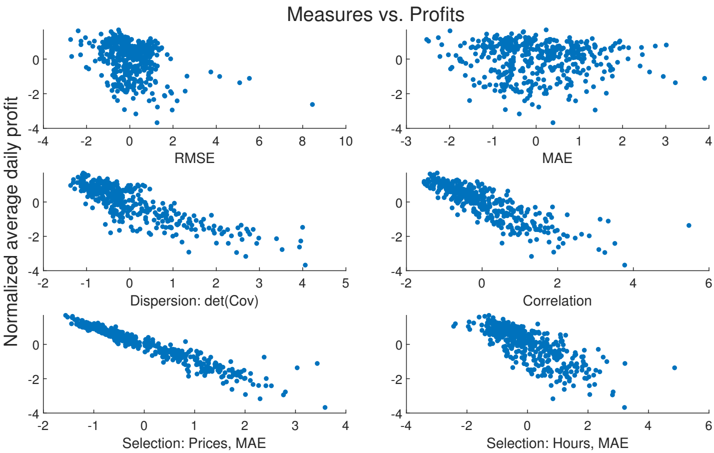
Profit relative to oracle: average over years

Profits (relative to oracle)

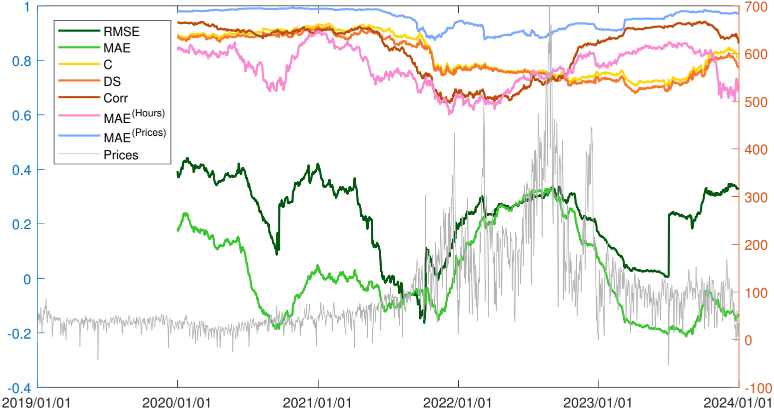
	1095	730	365	182	112	84	56	Ave
ARX	0.8792	0.8803	0.8754	0.8659	0.8656	0.856	0.8379	0.8876
mARX	0.8933	0.8892	0.8904	0.8812	0.8789	0.8692	0.8648	0.896
ARX-pooled	0.8851	0.8883	0.8966	0.9022	0.9007	0.8991	0.9003	0.9022
mARX-pooled	0.8819	0.8883	0.8989	0.9047	0.9026	0.9047	0.9037	0.9032
LEAR	0.8831	0.8788	0.8723	0.8621	0.8572	0.8459	0.8335	0.8923
asinh-ARX	0.8769	0.8768	0.8723	0.86	0.8647	0.8514	0.8339	0.887
asinh-mARX	0.9	0.8958	0.8973	0.8787	0.8762	0.8651	0.86	0.8984
asinh-ARX-pooled	0.8973	0.8992	0.903	0.907	0.9074	0.9058	0.9062	0.9081
asinh-mARX-pooled	0.8996	0.9009	0.9054	0.9078	0.906	0.9052	0.9058	0.9076
asinh-LEAR	0.8998	0.8965	0.8845	0.873	0.8706	0.8617	0.8461	0.9034
Ave	0.9086	0.9086	0.91	0.9106	0.9102	0.9052	0.9013	0.9146

Colour scale: 0.84, 0.85, 0.86, 0.87, 0.88, 0.89, 0.9, 0.91

Normalized profits across years vs. statistical measures



Correlation with profit, window: 365 days



Summary

- In this research, 90 different models and model specifications are considered
- Results show that
  - **LEAR** minimizes the magnitude of errors: RMSE, MAE
  - **pooled ARX** and **mARX** models leads to the highest profits
  - forecast averaging improves both RMSE and profits
- Magnitude of forecast errors is not a good indicator of profits

Summary

Seven different measures of forecast properties are evaluated and their correlation with profits is calculated

- **RMSE and MAE** are only weakly related to profits, their average correlation are **0.2253 and 0.0205**
- price selection accuracy measured with the **MAE of profits** has the strongest correlation with profits, which reaches **0.9529**
- MAE of hours performs worse, with correlation of 0.7752
- both **dispersion measures** perform similarly, the correlations are **0.8243 and 0.8092**
- **Corr** is the second best measure with the average correlation of **0.8443**

Team

Bartek Uniejewski

Tomek Serafin

Weronika Nitka

Tomek Weron

Arek Lipiecki

Rafał Weron

https://kbo.pwr.edu.pl

Kasia Maciejowska