Brandenburgische Technische Universität Cottbus - Senftenberg

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Bridging Fundamental model with the econometric approach for electricity price forecasting

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Energy Finance Christmas (EFC) Workshops

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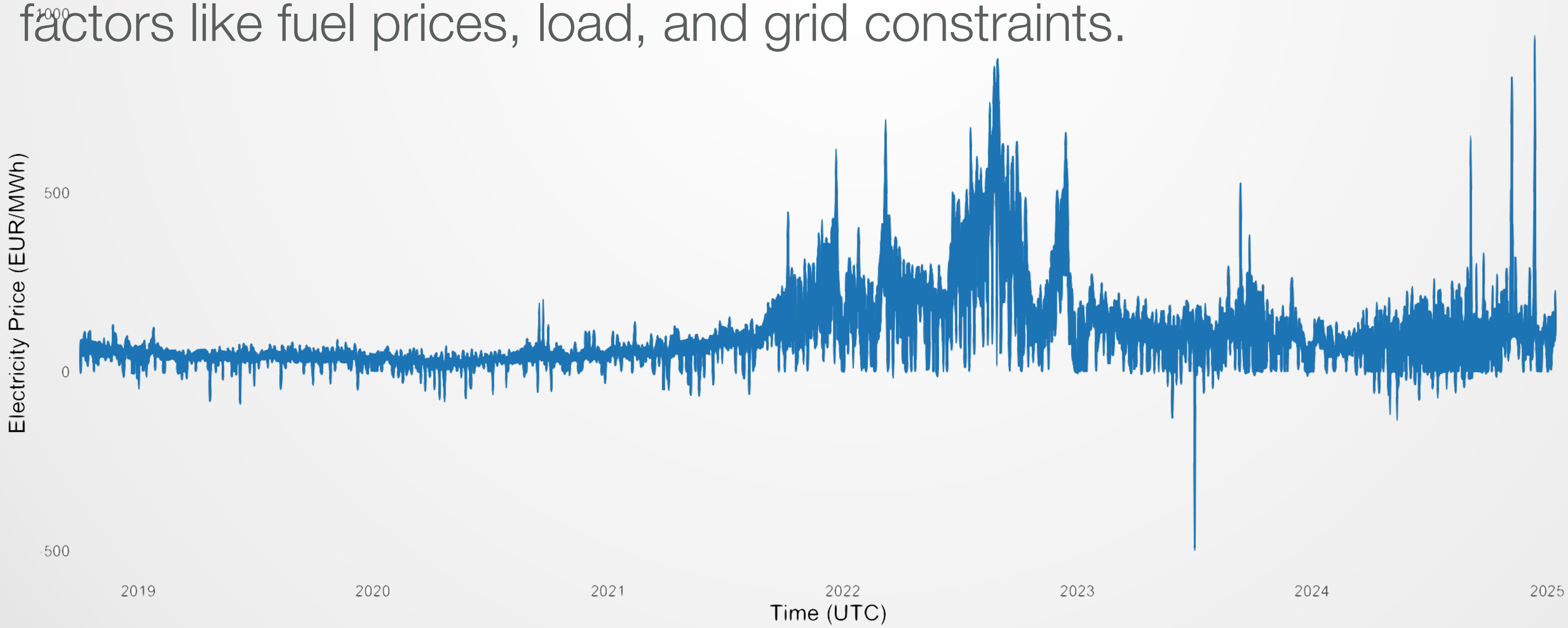
Electricity Price Forecasting (EPF): Interest

- For Market Participants: Enhanced Profitability & Risk Management
  - Optimal Bidding Strategies
  - Mitigated Financial Risk
  - Informed Investment

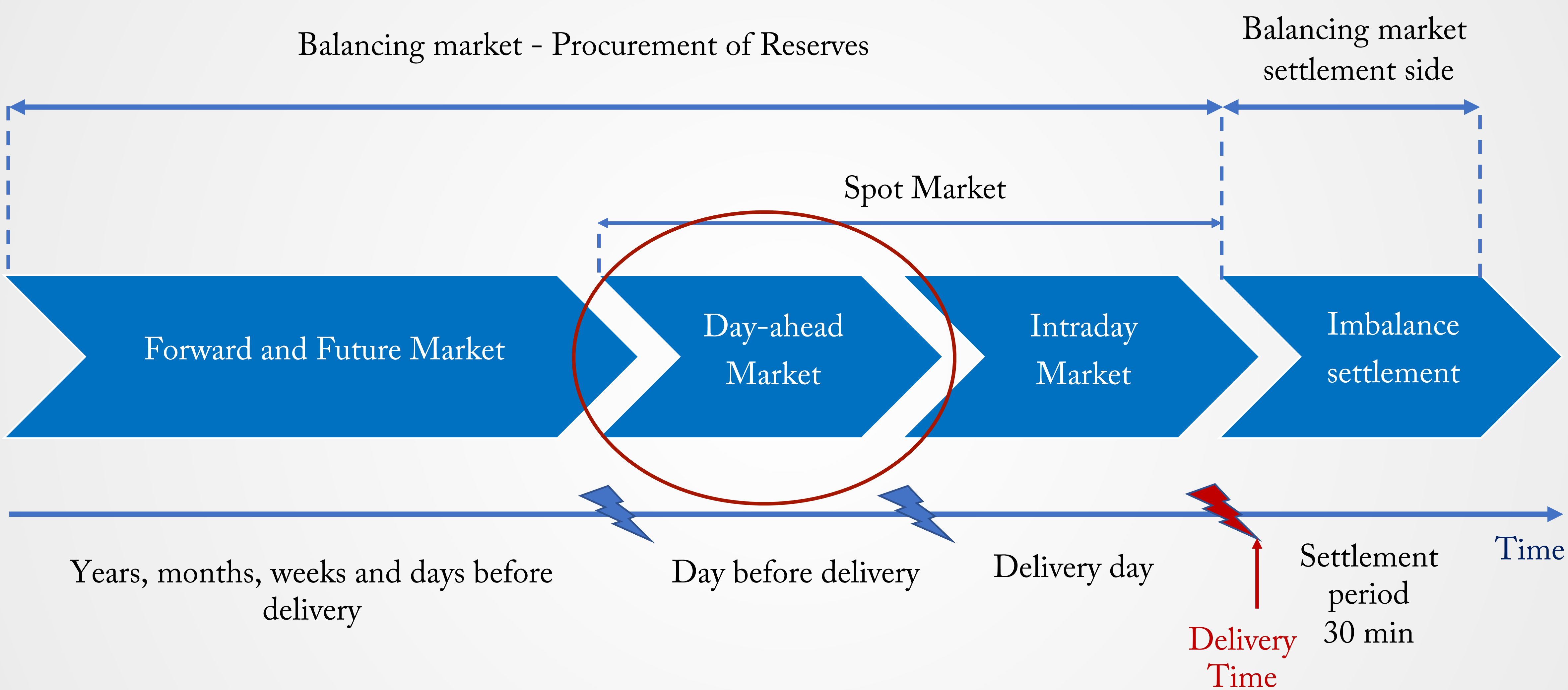
- For Grid & Market Operations: Improved Stability & Efficiency
  - Grid Reliability & Security
  - Efficient Market Operations
  - Renewable Energy Integration

Electricity prices: Features

- Non-storable, so supply and demand must balance instantly, causing sharp price movements.
- Prices are highly volatile, with frequent spikes and even negative prices.
- Renewable generation is weather-dependent, making forecasts uncertain and less predictable.
- Market dynamics are complex and nonlinear, driven by many interacting factors like fuel prices, load, and grid constraints.

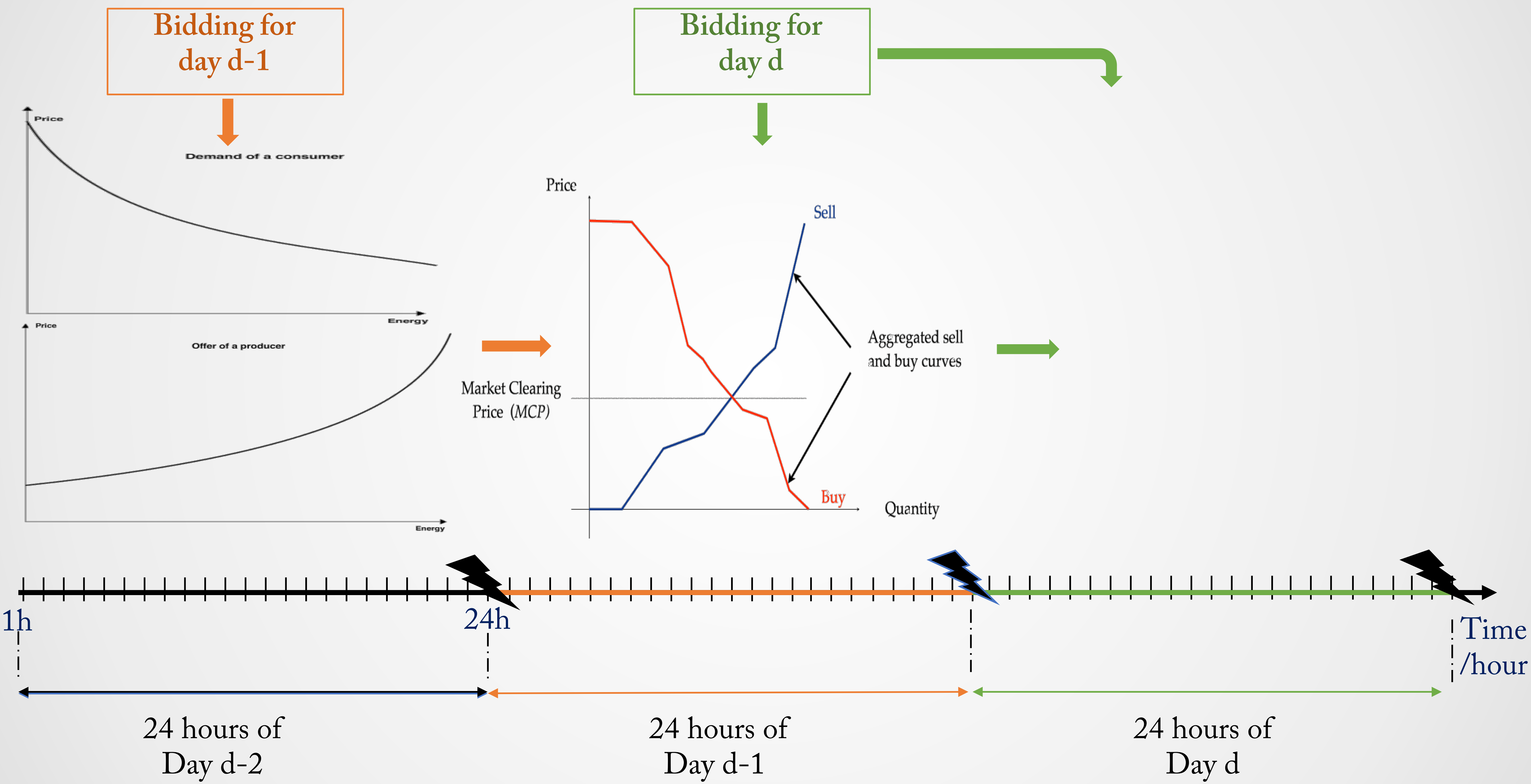


Electricity Market design in Europe



Different types of electricity markets regarding their time dimension

Day Ahead Market



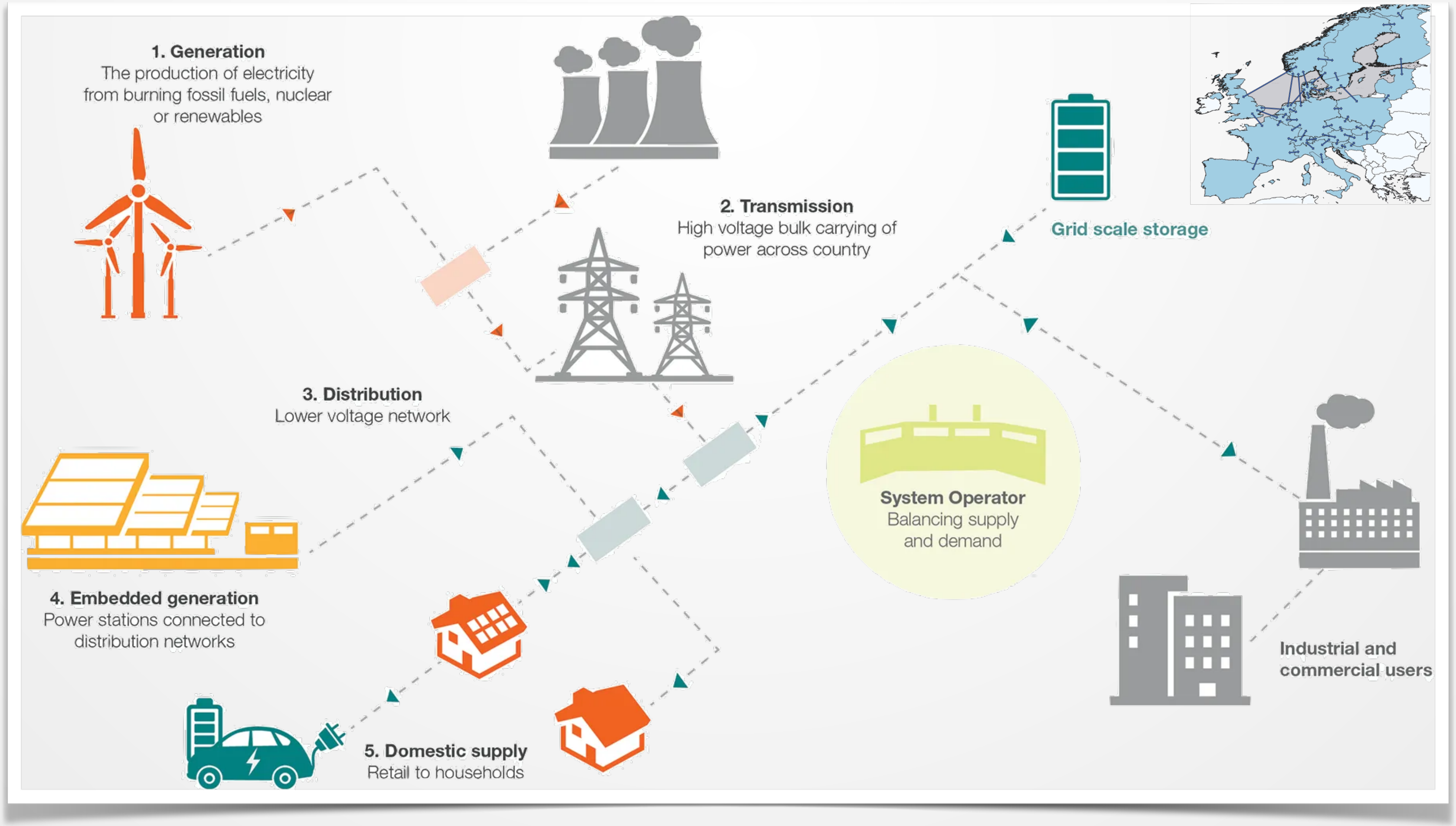
On day $d-1$, agents must submit their bids and offers for the delivery of electricity during each hour of day d

Econometric model

- Take into consideration the statistical characteristics related to the electricity market: high volatility, long memory behaviour,..
- Captures the revealed behavioural aspects of market participants, such as strategic and speculative behaviour
- Not able to fully incorporate market dynamic and operations into their forecasts.
- Rely on the assumption that history repeats itself.

Fundamental model

- Market clearing price is estimated using fundamental models,
- Model the power market by including all generation technologies
- Includes information related to renewable energy, demand and supply,..
- The generation units, technical features including the production cost
- Poor performance in capturing the short term price dynamics,..



Bridging Fundamental and econometrics models

- The capability to consider the most relevant, economic drivers of electricity market prices
- Fundamentals: supply, demand, unit commitment, dispatch, and technical constraints.
- Econometrics: linear/non-linear modelling capabilities,…
- The behaviour and operation of the power market are successfully incorporated to the electricity price forecasts,
- Great interest for market participants.

Outline

1. Motivation ✔
2. Fundamental models
3. Econometrics models
4. Results and Interpretation
5. Closing remarks

Fundamental Model

- *em.power dispatch model*
- The objective function minimises total system costs:

$$\min TC = \underbrace{\sum_{i,n,t} G_{i,n,t}\, vc^{FL}_{i,n,t}}_{\text{fuel and variable operating costs}} + \underbrace{\sum_{i,n,t} SU_{i,n,t}\, sc_{i,n,t}}_{\text{start-up costs}}$$

$$+ \underbrace{\sum_{i,n,t} (P^{on}_{i,n,t} - G_{i,n,t})\,(vc^{ML}_{i,n,t} - vc^{FL}_{i,n,t})\,\frac{g_i^{min}}{1 - g_i^{min}}}_{\text{part-load efficiency penalty}}$$

$$- \underbrace{\sum_{stl,n,t} CL_{stl,n,t}\, wv_{stl,n,t}}_{\text{water value of long-term storage}} + \underbrace{\sum_{n,t} SHED_{n,t}\, voll}_{\text{value of lost load}}$$

$$+ \underbrace{\sum_{n,t} CURT_{res,n,t}\, curtc}_{\text{renewable curtailment cost}}$$

▶ Go to details

Fundamental Model

- Market clearing is ensured by:

$$d_{n,t} = \underbrace{\sum_{i} G_{i,n,t}}_{\text{generation}} - \underbrace{\sum_{stm \subset I} CM_{stm,n,t}}_{\text{mid-term storage charging}} - \underbrace{\sum_{stl \subset I} CL_{stl,n,t}}_{\text{long-term storage charging}}$$
$$+ \underbrace{SHED_{n,t}}_{\text{load shedding}} + \underbrace{\sum_{nn} \left(FLOW_{nn,n,t} - FLOW_{n,nn,t} \right)}_{\text{net imports}}$$
$$\forall\, n, nn \in N,\ t \in T$$

- The demand restriction is differentiable at each point and can thus be interpreted as a wholesale market price estimator.

Lasso Estimated AutoRegressive (LEAR) model

- The LEAR to predict price $p_{d,h}$ on day d and hour h is:

$$p_{d,h} = f(\underbrace{p_{d-1}, p_{d-2}, p_{d-3}, p_{d-7}}_{\text{lagged prices}}, \underbrace{x_d^1, x_{d-1}^1, x_{d-7}^1}_{\text{load + lags}}, \underbrace{x_d^2, x_{d-1}^2, x_{d-7}^2}_{\text{RES + lags}},$$

$$\underbrace{x_d^3}_{\text{gas}}, \underbrace{x_d^4}_{\text{coal}}, \underbrace{x_d^5}_{\text{CO2}}, \underbrace{\theta_h}_{\text{params}}) + \epsilon_{d,h}$$

Where $\theta_h = [\theta_{h,1}, \ldots, \theta_{h,247}]$ are the parameters of LEAR for hour h, estimated using LASSO:

$$\widehat{\theta_h} = \underset{\theta_h}{\operatorname{argmin}} \left\{ \text{RSS} + \lambda \parallel \theta_h \parallel_1 \right\} = \underset{\theta_h}{\operatorname{argmin}} \left\{ \text{RSS} + \lambda \sum_{i=1}^{247} |\theta_{h,i}| \right\}$$

Lasso Estimated AutoRegressive (LEAR) model

- Lasso Estimation for θ_h,

$\text{RSS} = \sum_{d=8}^{N_d} \left(p_{d,h} - \hat{p}_{d,h}\right)^2$ is the sum of squares,

$\hat{p}_{d,h}$ is the price forecast,

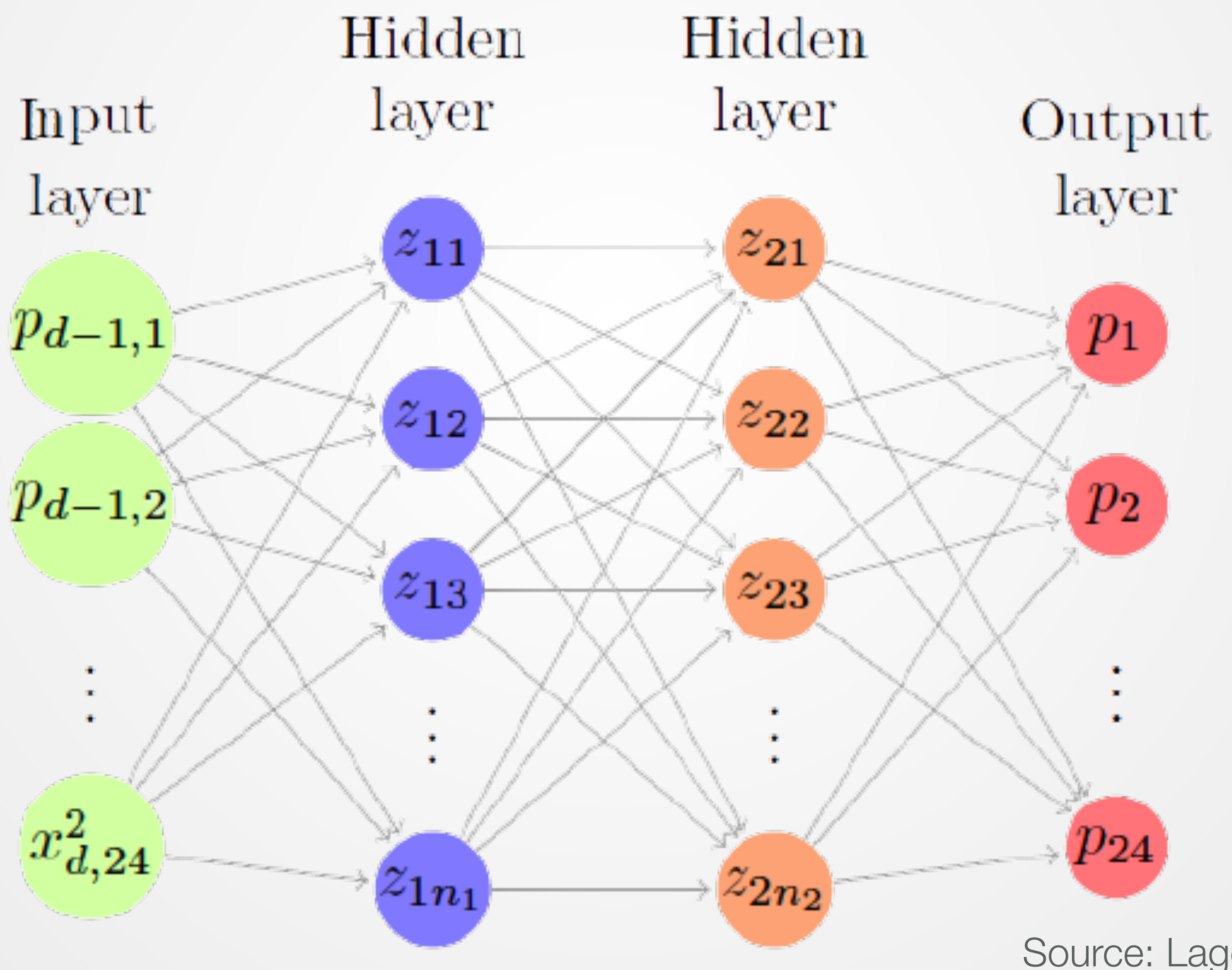
N_d is the number of days in the training dataset,

$\lambda \geq 0$ is is the tuning (or regularization) hyperparameter of LASSO.

- Selecting the regularization hyperparameter: a hybrid approach
  - Estimate the hyperparameter using the LARS method with the in-sample AIC
  - Optimal λ from the LARS method, recalibrate the LEAR

Deep Neural Network (DNN)

- The DNN estimated using Adam, hyperparameters and input features are optimized using the tree Parzen estimator



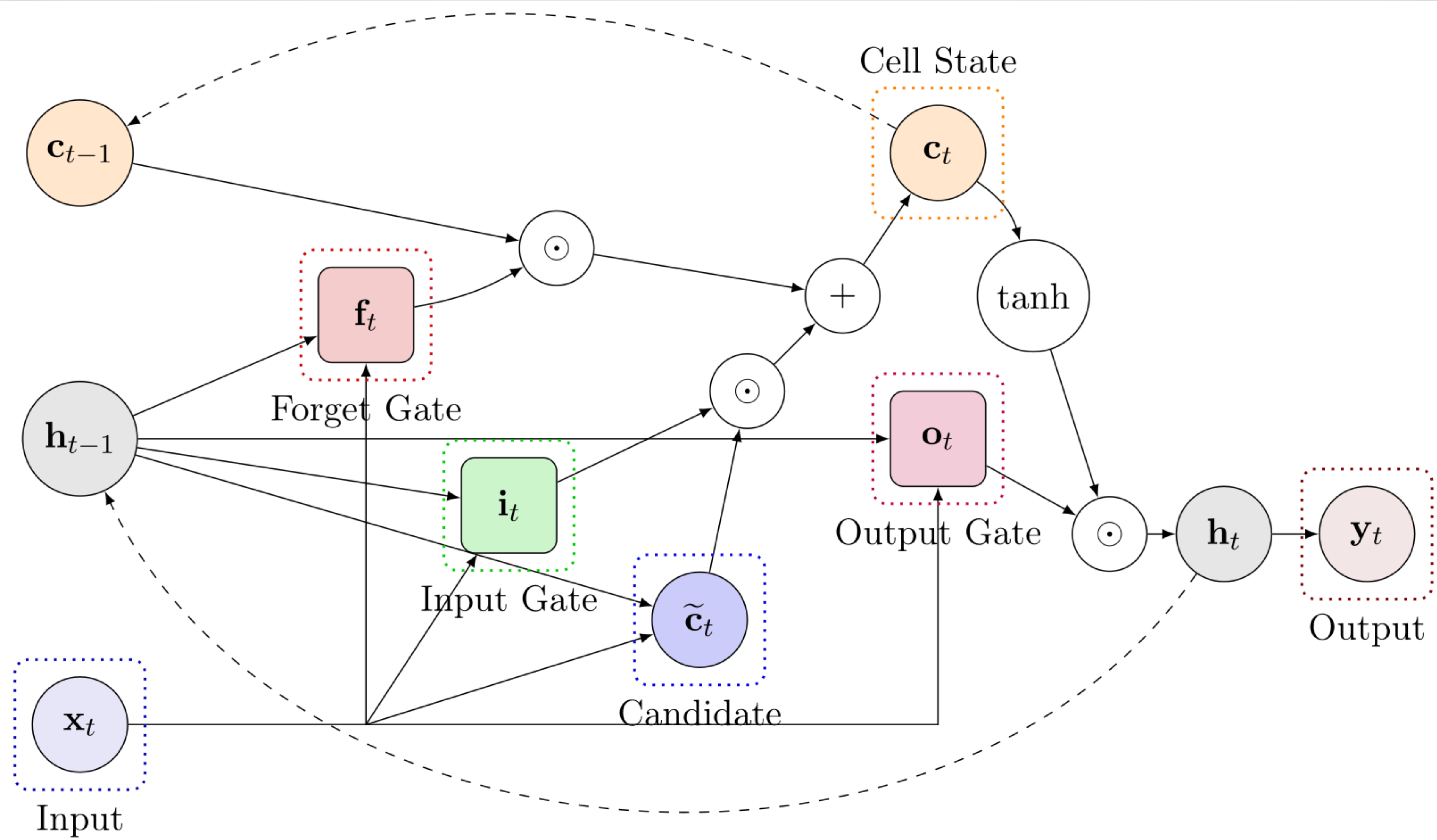
Source: Lago et al (2021)

LSTM, Hochreiter and Schmidhuber (1997)

- Overcome the vanishing gradient problem in RNN
- The information used in the transformation of the input is controlled by three gates:
  - One reset gate: $r_t = \sigma\left(W_r x_t + U_r h_{t-1}\right)$
  - One update gate: $z_t = \sigma(W_z x_t + U_z h_{t-1})$
  - One output gate: $o_t = \sigma\left(W_o x_t + W_o h_{t-1} + b_o\right)$
  - Current memory content $h'_t = \tanh\left(W x_t + r_t \odot U h_{t-1}\right)$
    Use of the *reset* gate to drop irrelevant information
  - Final memory at t: $h_t = z_t \odot h_{t-1} + \left(1 - z_t\right) \odot h'_t$
    Use of the update gate to learn how much information from the previous step will carry over the current step

where $\odot$ is pointwise multiplication.

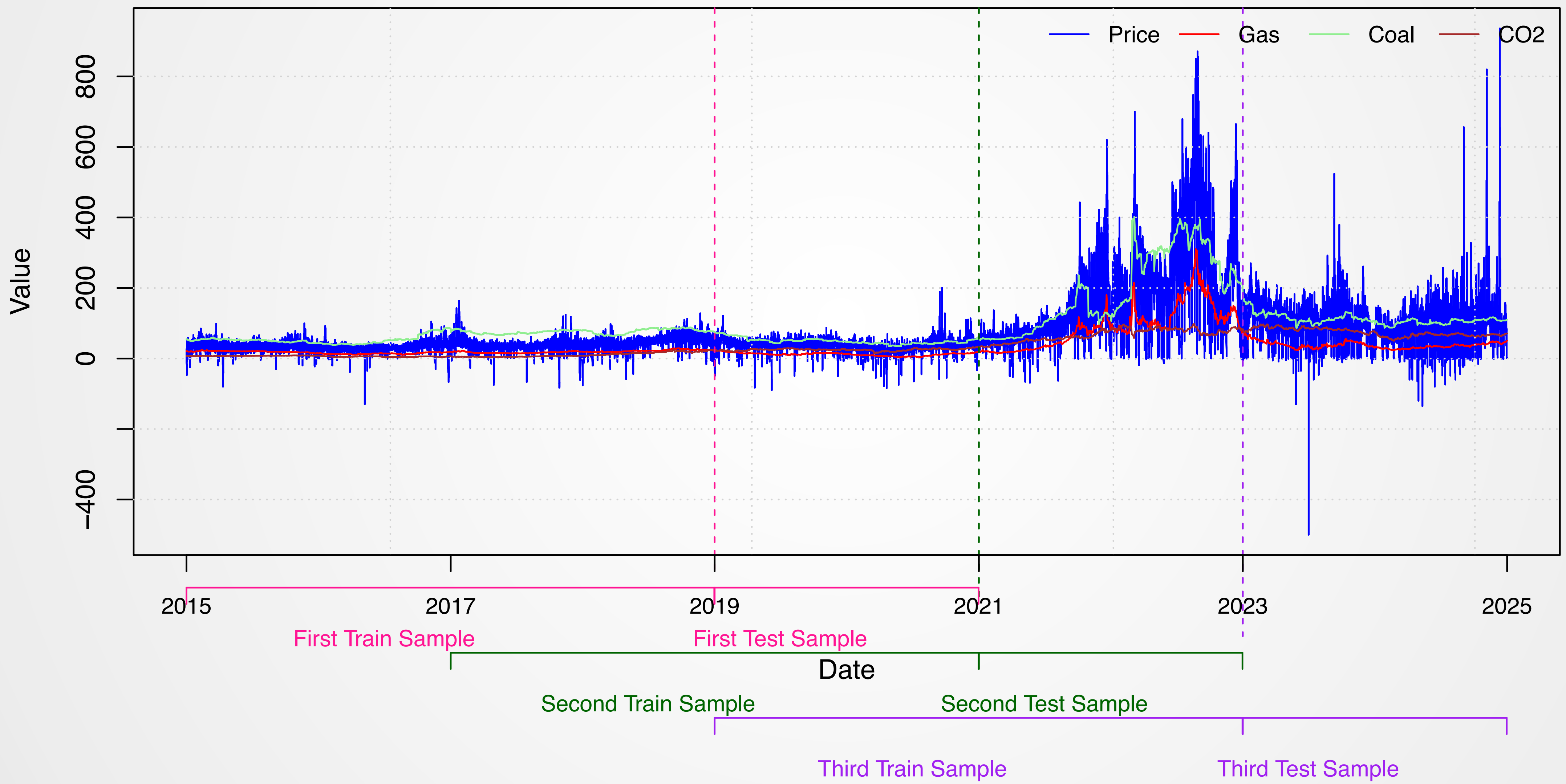
LSTM memory block



LSTM cell

Data: Germany-Luxembourg Market

1. Long enough, analyse out-of-sample datasets that span 1-2 years,
2. Three different Test samples: before, during, and after the energy Crisis.



Electricity prices vs Fuel Prices (Gas, Coal and CO2) and Time series split for First Test Sample (2019-2020), Second Test Sample (2021- 2022), and Third Test Sample (2023-2024)

Three-test samples average evaluation metrics

Model	MAE	RMSE	sMAPE
ESM	22.808	38.457	28.046
Ens-DNN	11.206	19.752	19.990
DNN	14.267	28.565	23.286
Ens-LEAR	13.361	22.067	22.507
LEAR	14.340	23.940	22.636
LSTM	15.297	25.805	23.729
ESM–Ens-DNN +	**10.582**	**18.455**	**18.839**
ESM–DNN +	12.235	20.662	20.339
ESM–Ens-LEAR +	12.297	21.819	20.169
ESM–LEAR +	13.046	23.034	20.563
ESM–LSTM +	14.483	23.912	22.746
ESM–Ens-DNN	11.491	19.729	19.847
ESM–DNN	11.960	20.184	20.440
ESM–Ens-LEAR	12.518	22.083	20.354
ESM–LEAR	13.387	23.427	21.070
ESM–LSTM	19.446	30.740	27.065

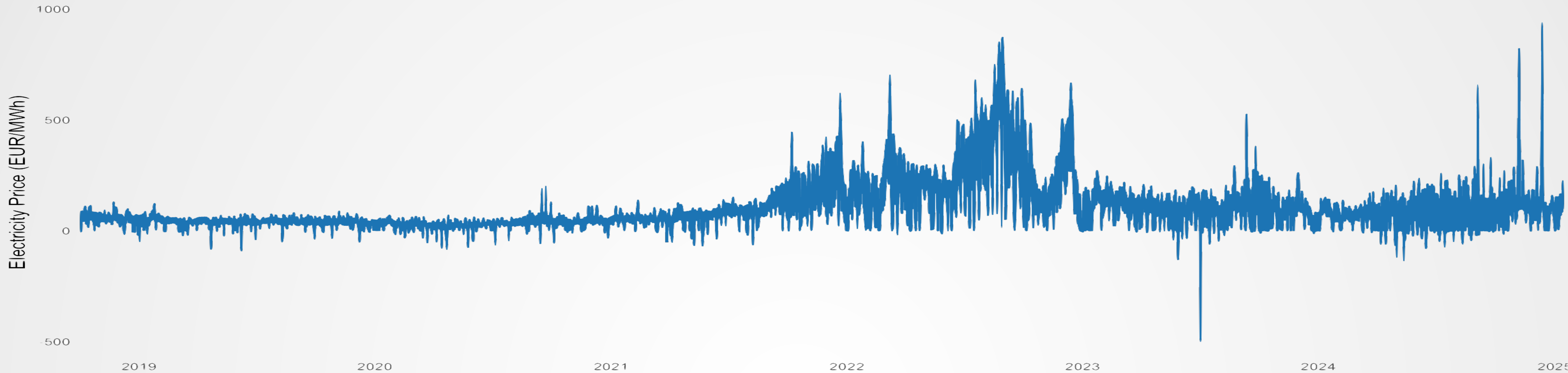
Forecasting Results

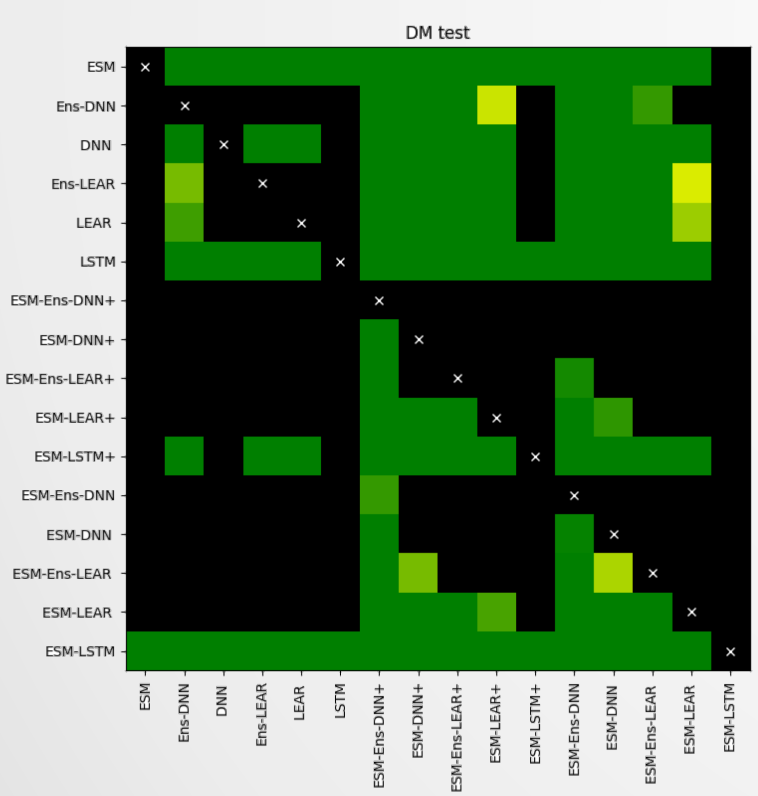
Model	2019-2020			2021-2022			2023-2024		
	MAE	RMSE	sMAPE	MAE	RMSE	sMAPE	MAE	RMSE	sMAPE
ESM	6.101	9.366	23.950	**45.953**	**77.320**	**29.337**	16.370	28.686	30.852
Ens-DNN	4.248	7.190	19.127	18.092	29.263	15.961	11.278	22.804	24.881
DNN	5.051	8.236	21.263	24.919	53.603	21.993	12.831	23.856	26.601
Ens-LEAR	4.065	6.822	19.810	22.820	35.562	19.179	13.198	23.818	28.533
LEAR	4.109	6.975	19.363	25.552	40.137	20.430	13.358	24.707	28.115
LSTM	4.808	7.684	21.421	26.552	43.644	20.807	14.532	26.088	28.958
ESM–Ens-DNN +	**3.485**	**5.891**	**16.631**	**17.312**	**27.297**	**15.433**	**10.949**	**22.178**	**24.454**
ESM–DNN +	3.763	6.357	17.684	21.372	33.177	17.963	11.569	22.453	25.371
ESM–Ens-LEAR +	3.670	6.098	17.715	20.117	37.146	17.419	11.199	22.146	25.425
ESM–LEAR +	3.834	6.283	17.965	23.812	39.915	18.294	11.491	22.903	25.431
ESM–LSTM +	4.417	7.388	19.951	25.106	40.061	20.024	13.925	24.287	28.264
ESM–Ens-DNN	3.838	6.244	17.987	19.376	30.821	16.726	11.258	22.122	24.827
ESM–DNN	3.967	6.271	18.351	20.079	31.659	17.349	11.833	22.623	25.620
ESM–Ens-LEAR	3.885	6.273	18.156	21.951	36.963	17.337	11.719	23.014	25.570
ESM–LEAR	4.145	6.613	18.976	23.807	39.910	18.292	12.209	23.759	25.941
ESM–LSTM	5.717	8.660	23.425	34.742	54.524	25.081	17.879	29.036	32.688

Statistical testing Results

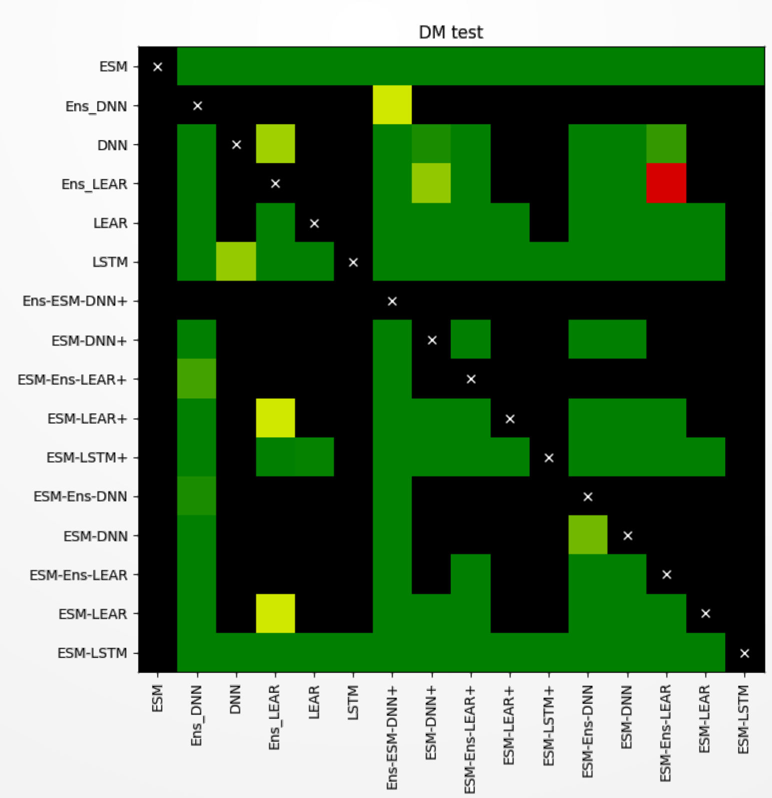
- The Diebold-Mariano test: Diebold and Mariano (1995)

▶ Go to details

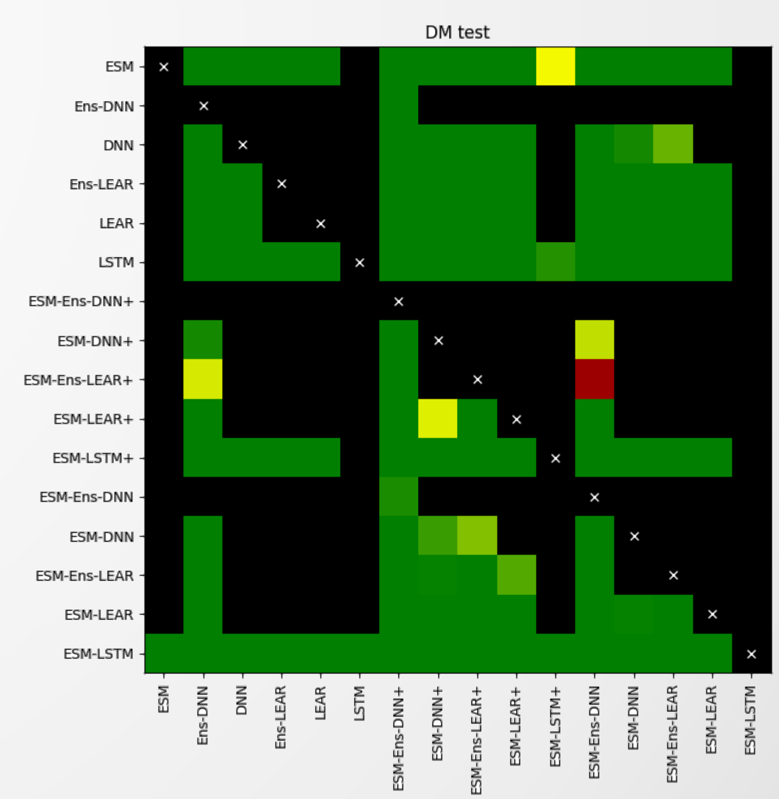




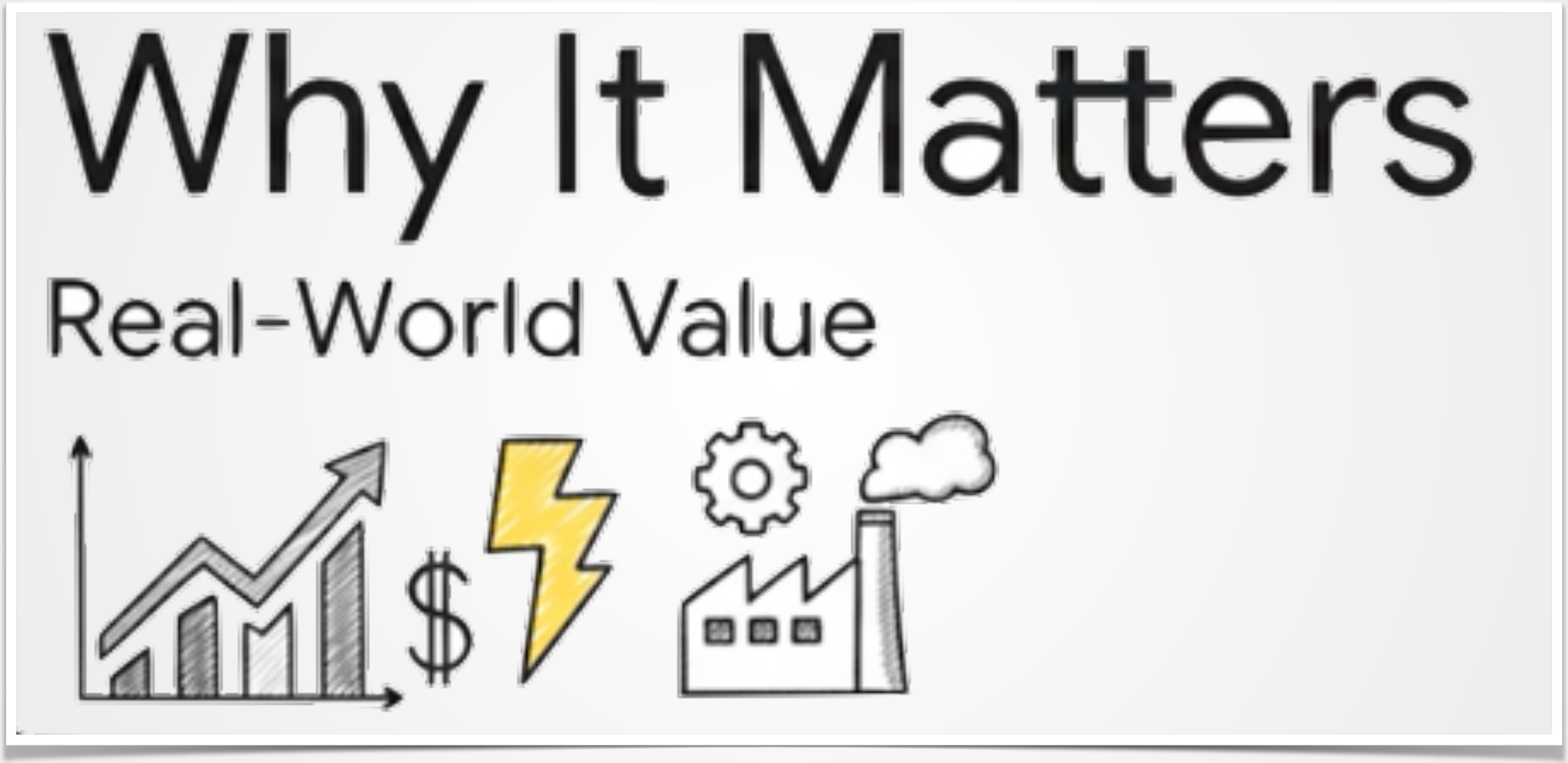
2019-2020



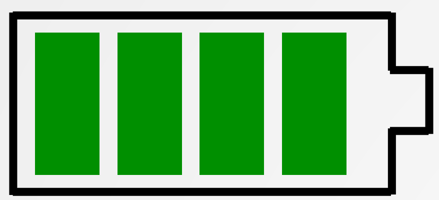
2021-2022



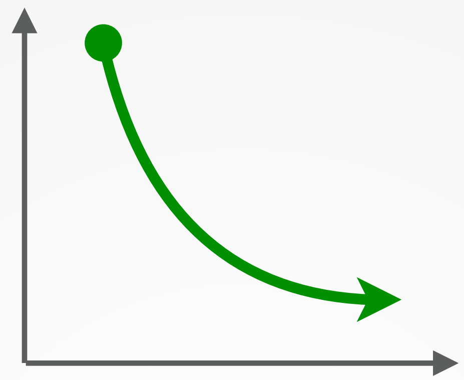
2023-2024


Why It Matters
Real-World Value

Profit contribution of a storage application



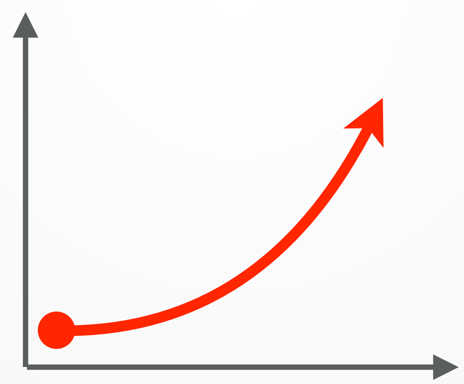
Battery Charge



Price decrease

BUY

Battery discharge



Price increase

SELL

Profit

Energy Storage Model

- Maximise the daily profit of a storage unit that buys energy at low prices and sells at high prices (using forecasted prices):

$$\max_{C_{d,h},\, G_{d,h}} \Pi = \sum_{d,h} \left(\hat{p}_{d,h} G_{d,h} - \hat{p}_{d,h} C_{d,h} \right)$$

- Actual realised profit (using real prices):

$$\Pi^{\text{act}} = \sum_{d,h} \left(p_{d,h} G_{d,h} - p_{d,h} C_{d,h} \right)$$

$G_{d,h}$ electricity generation, $C_{d,h}$ charging power

- Storage fully cycles daily to avoid shifting across days
- The ratio of the realised profit contribution to the optimal profit contribution

▶ Go to Constraints

Energy Storage Model Results

- **Storage 1:** Long-duration unit (7 h) with lower efficiency (75%).
- **Storage 2:** Medium-duration unit (3 h) with medium efficiency (80%).
- **Storage 3:** Short-duration unit (1 h) with high efficiency (90%).

Model	Storage 1	Storage 2	Storage 3
ESM	0,916	0,934	0,917
Ens-DNN	0,911	0,932	0,903
DNN	0,842	0,869	0,848
Ens-LEAR	0,895	0,923	0,895
LEAR	0,885	0,916	0,884
LSTM	0,727	0,751	0,738
ESM–Ens-DNN+	0,917	0,936	0,906
ESM–DNN+	0,888	0,907	0,859
ESM–Ens-LEAR+	0,902	0,917	0,884
ESM–LEAR+	0,899	0,917	0,881
ESM–LSTM+	0,782	0,809	0,765
ESM–Ens-DNN	0,906	0,927	0,897
ESM–DNN	0,890	0,915	0,888
ESM–Ens-LEAR	0,902	0,920	0,892
ESM–LEAR	0,894	0,913	0,879
ESM–LSTM	0,642	0,664	0,603

Conclusion

- Combining ESM with Econometric models significantly improves day-ahead price forecasts.
- The ESM's Market Clearing Price provides unique structural information not captured by historical-data models alone.
- Hybrid models (especially ESM–Ens-DNN+) deliver the highest accuracy across calm, crisis, and post-crisis market periods.
- Improved forecasts translate into meaningful economic gains, such as higher battery storage revenues.

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International Ruhr Energy Conference
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House of
Energy,
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Markets, Systems and Decisions

Fundamental Model

$G_{i,n,t}$: Electricity generation of unit i at node n

$vc^{FL}_{i,n,t}$: The variable cost of full load operation,

$sc_{i,n,t}$: Startup costs;

$SU_{i,n,t}$: Start-up decision of a generation unit,

$P^{on}_{i,n,t}$: Running capacity

$vc^{ML}_{i,n,t}$: Variable generation costs at minimum load

g^{min}_{i}: The minimum generation of a running power plant

$CL_{slt,n,t}$: States of the electricity consumption of long term storage

$SHED_{n,t}$: Cost for involuntary load shedding

$voll$: Load shedding costs

$CURT_{res,n,t}$: Curtailing renewables generation weighted by its penalty payments $curtc$

▶ Back

Fundamental Model

- Market clearing is ensured by:

$$d_{n,t} = \sum_{i} G_{i,n,t} - \sum_{stm \subset I} CM_{stm,n,t} - \sum_{stl \subset I} CL_{stl,n,t} + SHED_{n,t} + \sum_{nn} \left(FLOW_{nn,n,t} - FLOW_{n,nn,t} \right)$$

$CM_{stm,n,t}$: electricity consumption of mid-term energy storage
$CL_{stl,n,t}$: long-term energy storage
$SHED_{n,t}$: load shedding
$FLOW_{nn,n,t}$: electricity imports
$FLOW_{n,nn,t}$: electricity exports

Back

Improved Day-Ahead Load Forecast

- ENTSO-E TSO load forecasts contain systematic errors (structural bias).
- We improve them using an error-correction model based on weekly seasonality + $SARMA(1,1)(1,1)_{24}$ dynamics.
- The improved load forecast is the sum of the TSO forecast and the predicted error:

$$\hat{L}_t^* = \hat{L}_t + \hat{\varepsilon}_t$$

- Error Decomposition: $\varepsilon_t = SC_t + RC_t$
- Seasonal Component:

$$SC_t = \sum_{h=1}^{24} \sum_{d=1}^{7} HoW_t^{h,d} \cdot HS^{h,d}$$

- SARMA Model (for the remaining component)

Back

$$RC_t = \phi_0 + \phi_1 RC_{t-1} + \phi_{24} RC_{t-24} - \phi_1 \phi_{24} RC_{t-25}$$
$$+\omega_1 \psi_{t-1} + \omega_{24} \psi_{t-24} + \omega_1 \omega_{24} \psi_{t-25} + \psi_t$$

Evaluation metrics

- Mean absolute error MAE

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|P_t^a - P_t^f\right|$$

- Symmetric mean absolute percentage error (sMAPE)

$$\mathrm{sMAPE} = \frac{1}{24N_\mathrm{d}}\sum_{d=1}^{N_\mathrm{d}}\sum_{h=1}^{24} 2\frac{\left|p_{d,h} - \hat{p}_{d,h}\right|}{\left|p_{d,h}\right| + \left|\hat{p}_{d,h}\right|}$$

- The relative MAE

$$\mathrm{rMAE} = \frac{\frac{1}{24N_\mathrm{d}}\sum_{d=1}^{N_\mathrm{d}}\sum_{h=1}^{24}\left|p_{d,h} - \hat{p}_{d,h}\right|}{\frac{1}{24N_\mathrm{d}}\sum_{d=1}^{N_\mathrm{d}}\sum_{h=1}^{24}\left|p_{d,h} - \hat{p}_{d,h}^{\text{naive}}\right|}$$

Source: Lago (2021)

Statistical testing: The Diebold-Mariano test

- The loss differential series:

$$\Delta_{d,h}^{\mathrm{A,B}} = L\left(\varepsilon_{d,h}^{\mathrm{A}}\right) - L\left(\varepsilon_{d,h}^{\mathrm{B}}\right) \text{ is zero,}$$

$\varepsilon_{d,h}^{Z} = p_{d,h} - \hat{p}_{d,h}$: the prediction error of model Z for day d and hour h,
$L(\cdot)$ is the loss function.
we compute the statistic:

$$\mathrm{DM} = \sqrt{N}\frac{\hat{\mu}}{\hat{\sigma}}$$

1. Null hypothesis $H_0 : E\left(\Delta_{d,h}^{\mathrm{A,B}}\right) \leq 0$
2. The alternative hypothesis $H_1 : E\left(\Delta_{d,h}^{\mathrm{A,B}}\right) \geq 0$

Back

Energy Storage Model: Operational Constraints

- Power capacity constraint:

$$G_{d,h} + C_{d,h} \leq \text{cap}$$

- State of charge (SOC):

$$SL_{d,h} = SL_{d,h-1} + \eta\, C_{d,h} - G_{d,h}$$

- No discharge beyond available storage:

$$G_{d,h} \leq SL_{d,h-1}$$

- Storage energy capacity:

$$SL_{d,h} \leq \text{cap} \,.\, ecr$$

- Daily cycle reset: $SL_{d,1} = \eta\, C_{d,1}, \qquad SL_{d,24} = 0$
- Non-negativity: $G_{d,h} \geq 0, \quad C_{d,h} \geq 0, \quad SL_{d,h} \geq 0$

Back