Data Science Models Meet Fundamental Models: Moderne Ansätze zur Strompreisprognose

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Daten, fundamentale und stochastische Analysen
Wissenschaft trifft Energiewirtschaft

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Call-for-Papers for the 11th International Ruhr Energy Conference (INREC)

Uncertainties in Energy Markets

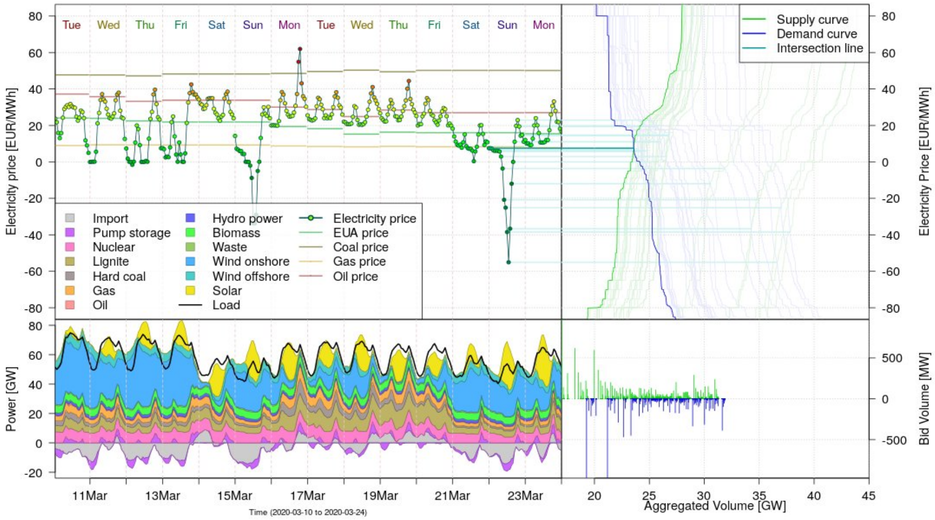
September 27-28, 2022, Essen, Germany

Conference objectives

Energy and electricity markets are characterised by a variety of long- and short-term risks and substantial uncertainties. Points in case are the Russian aggression against Ukraine, the accelerating switch to clean energy in Europe, as well as the transition and physical risks of climate change. Thorough investigations of various sources of uncertainty and risk in energy and financial markets are a key priority for researchers and practitioners. We welcome contributions from all areas of energy-related research in economics, finance, engineering, social sciences, data science and mathematics.

- Abstract submission deadline: July 04, 2022
- see www.inrec.org

German day-ahead electricity market



Motivation

- Past decades enormous progress for fundamental and data driven electricity price models

Reasons:

- Better availability and quality of data
- Better models and (optimization) algorithms

Objective of the talk:

- How can data science models improve further using fundamental models? (not combination/postprocessing or curve modeling)

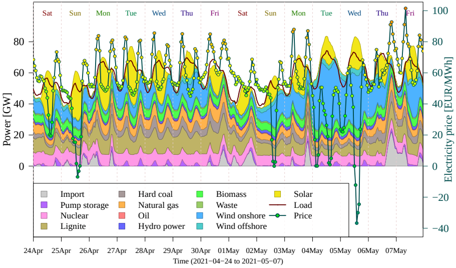
Literature:

- Ziel, F., & Steinert, R. (2018). *Probabilistic mid-and long-term electricity price forecasting*. **Renewable and Sustainable Energy Reviews**, 94, 251-266.
- Weron, R., & Ziel, F. (2019). *Electricity price forecasting*. In **Routledge handbook of energy economics** (pp. 506-521). Routledge.
- Petropoulos, F., Apiletti, D., Assimakopoulos, V., Babai, M. Z., Barrow, D. K., Taieb, S. B., . . . & Ziel, F. (2022). *Forecasting: theory and practice*. **International Journal of Forecasting**.

Two model classes for electricity price forecasting

i) Historic data based models

- Electricity price is modeled dependent on its history (and related inputs)
- Statistical/ML/AI methods, e.g. linear models, (deep) neural networks, GBMs, . . .
- Popular in short-term forecasting ⇒ operations managemant



Two model classes for electricity price forecasting

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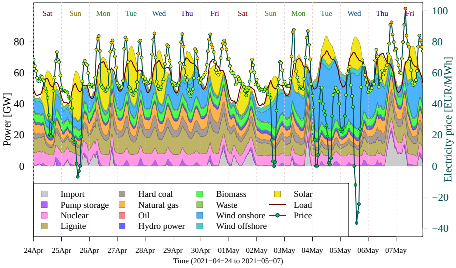
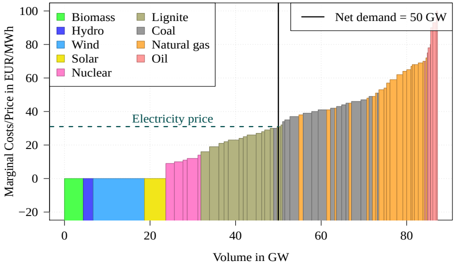


ii) Fundamental models

- Economically motivated
- Electricity price is match of supply and demand
- Popular in long-term fore-casting ⇒ policy making and invest-ment decisions



Data science models: Naive

The **naive** model is a very simple day-ahead forecasting model for hourly electricity price $Y_{d,h}$

$$Y_{d,h} = \begin{cases} Y_{d-1,h} & \text{if } d \text{ is on Tue, Wed, Thu, Fri} \\ Y_{d-7,h} & \text{if } d \text{ is on Mon, Sat, Sun} \end{cases} + \varepsilon_{d,h} \tag{1}$$

- Very low model complexity
- No estimation risk
- $\Rightarrow$ Very low accuracy

- Recommended as (trivial) benchmark

Data science models: Linear model

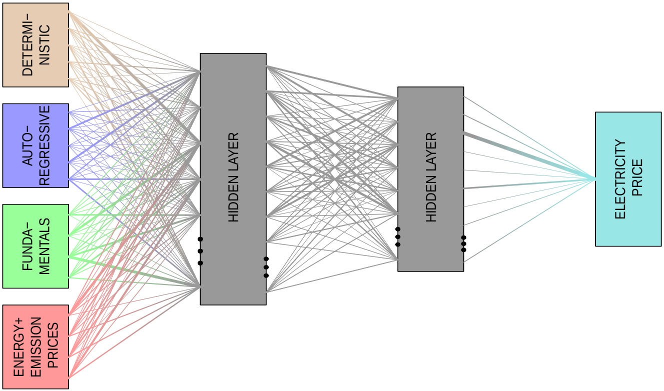
A **linear model (LM)** (often referred as expert model) for $Y_{d,h}$:

$$
\begin{aligned}
Y_{d,h} = & \underbrace{\beta_0 + \beta_1 \text{Sat} + \beta_2 \text{Sun} + \beta_3 \text{Mon} + \beta_4 \text{Holiday}}_{\text{deterministic inputs (esp. calendar information)}} \\
& + \underbrace{\beta_5 Y_{d-1,h} + \beta_6 Y_{d-2,h} + \beta_7 Y_{d-7,h} + \beta_8 Y_{d-1,H} + \beta_9 Y_{d-1,\max}}_{\text{autoregressive (= past price) information}} \\
& + \underbrace{\beta_{10} \text{DA-Load}_{d,h} + \beta_{11} \text{DA-Wind}_{d,h} + \beta_{12} \text{DA-Solar}_{d,h}}_{\text{day-ahead forecasts of fundamentals}} \\
& + \underbrace{\beta_{13} \text{EUA}_d + \beta_{14} \text{Coal}_d + \beta_{15} \text{NGas}_d + \beta_{16} \text{Oil}_d}_{\text{current related market information (fuels+emission prices)}} + \varepsilon_{d,h} \qquad (2)
\end{aligned}
$$

- Low model complexity
- Low estimation risk
- $\Rightarrow$ Low to moderate accuracy

Data science models: Neural network model

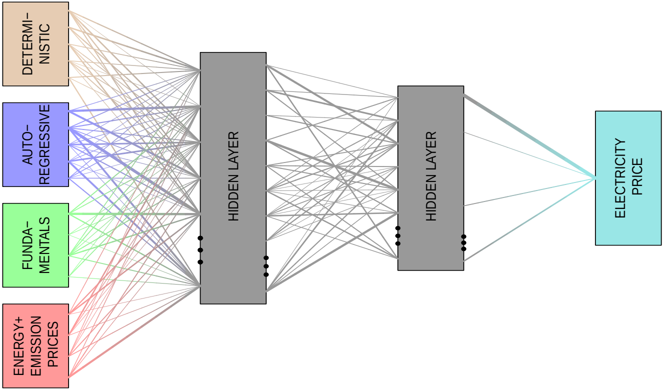
A simple **artificial neural network (ANN)** (often MLP or recurrent) for $Y_{d,h}$:



- Moderate model complexity
- Moderate estimation risk
- $\Rightarrow$ Good accuracy

Data science models: Neural network model

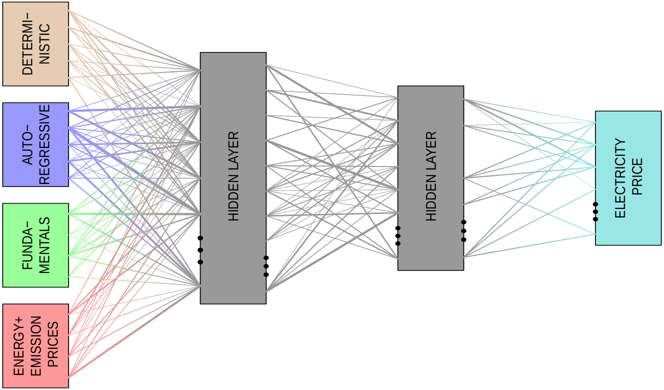
A simple **artificial neural network (ANN)** (often MLP or recurrent) for $Y_{d,h}$:



- Moderate model complexity
- Moderate estimation risk
- $\Rightarrow$ Good accuracy

Data science models: Neural network model

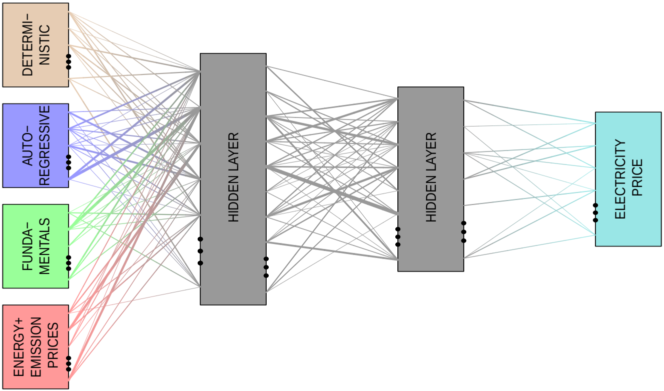
A simple **artificial neural network (ANN)** for $Y_{d,1}, \dots, Y_{d,24}$:



- Moderate model complexity
- Moderate estimation risk
- $\Rightarrow$ Good accuracy

Data science models: Neural network model

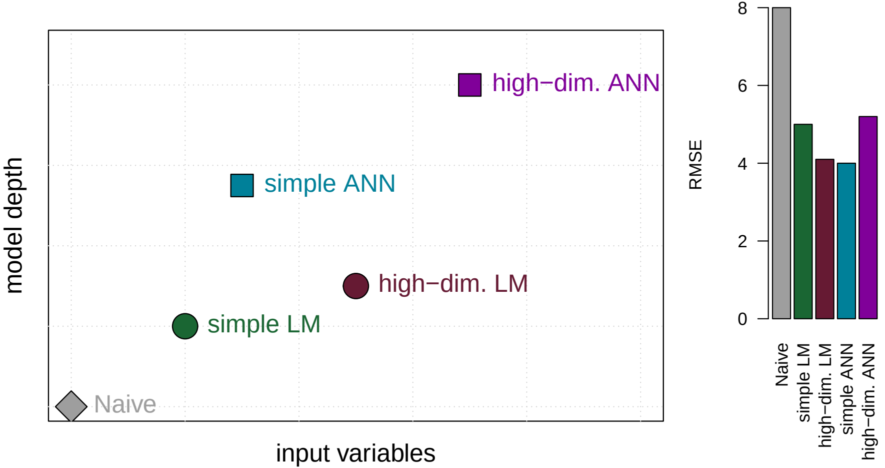
A high-dim. **artificial neural network (ANN)** for $Y_{d,1}, \ldots, Y_{d,24}$:



- High model complexity
- High estimation risk
- $\Rightarrow$ Poor accuracy

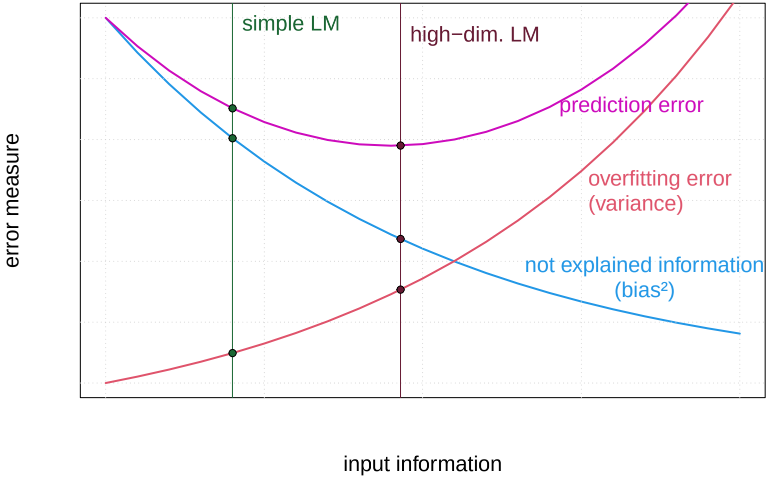
Data science models: Overview on complexity

Decomposition of model complexity into input size and model depth



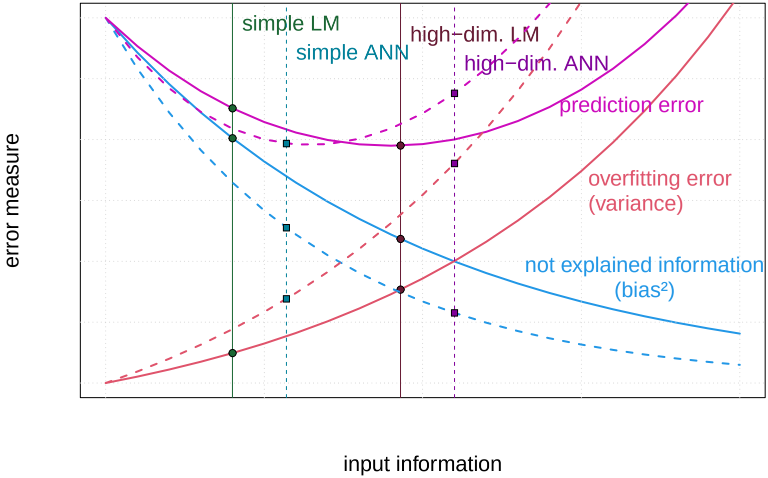
- complexity and prediction error for **naive**, **linear model (LM)** and **artificial neural networks (ANN)**

Explained information and overfitting



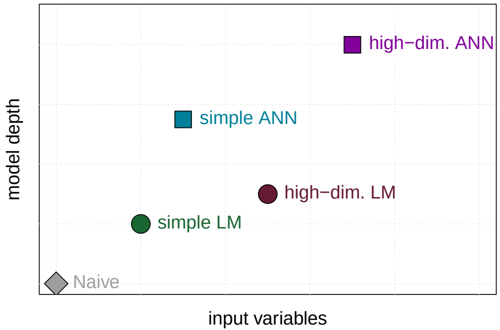
- simple LM has moderate prediction error (poor variance-bias trade-off)
- high-dim. LM has low prediction error (good variance-bias trade-off)

Explained information and overfitting



- simple ANN has high pred. error (good variance-bias trade-off)
- high-dim. ANN has high pred. error (poor variance-bias trade-off)

Can we do better?



a) model like **high-dim. LM with higher model depth**?

$\Rightarrow$ increase model depth by **adding only relevant non-linearities**

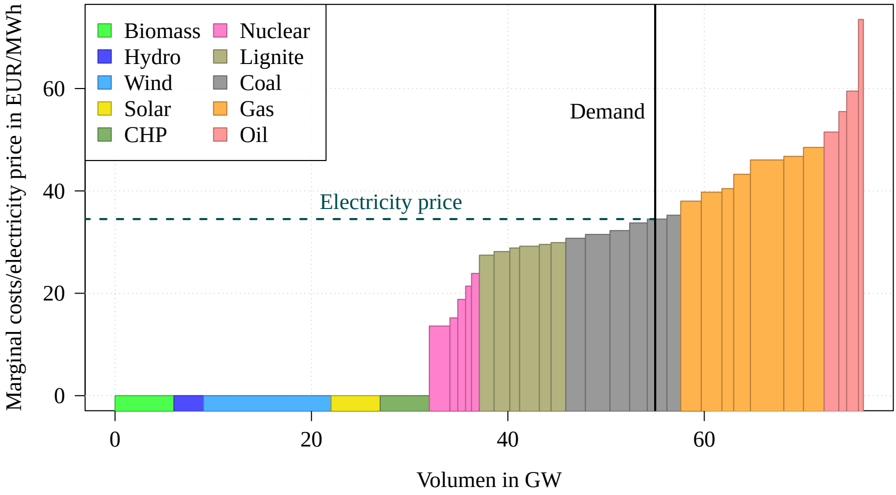
b) model like **simple ANN with more inputs**?

$\Rightarrow$ increase input size while **controlling for model depth**

$\Rightarrow$ **Utilize fundamental electricity price models** to learn restrictions for model design in a) and b)

How to use fundemental models?

For illustration purpose consider simple supply-stack model:



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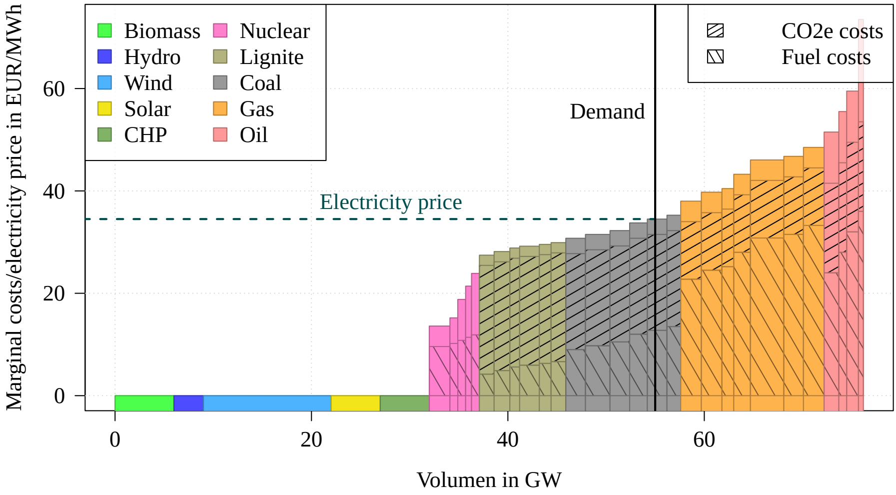
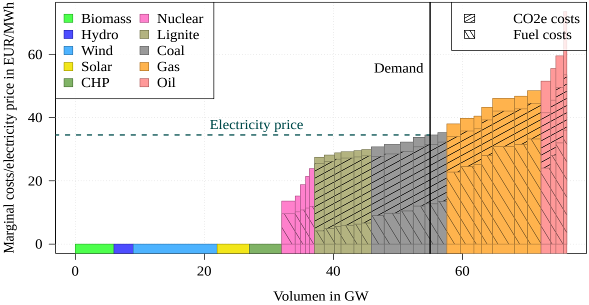
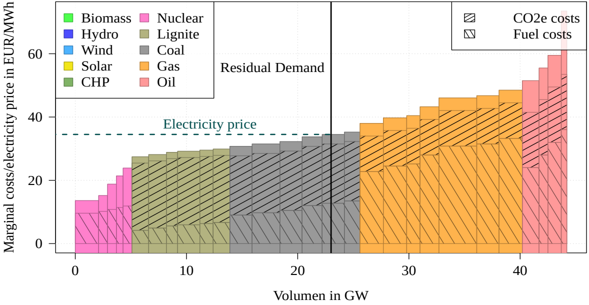
For illustration purpose consider simple supply-stack model:

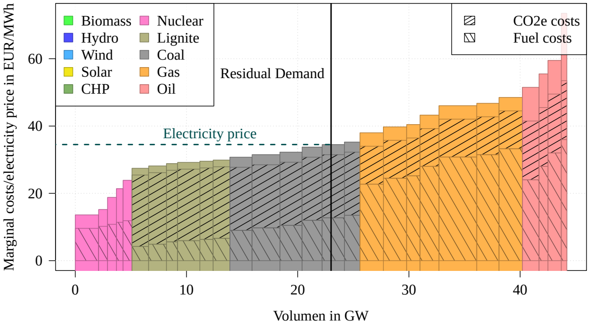


Change supply stack model to residual load/demand perspective:





The supply stack model.



- Consider merit order curve/ supply stack
- Formal electricity price model

$$Y_{d,h} = \text{MO}_{d,h}(\text{DA-ResLoad}_{d,h}) + \varepsilon_{d,h}$$

Supply stack model with 1 fuel.

- Very simple assumption: Constant supply stack with only one fuel:

$$\text{MO}_d(x) = \alpha_0 + \alpha_1 \text{EUA}_d + \alpha_2 \text{NGas}_d \tag{3}$$

- Simple assumption: Linear supply stack with only one fuel:

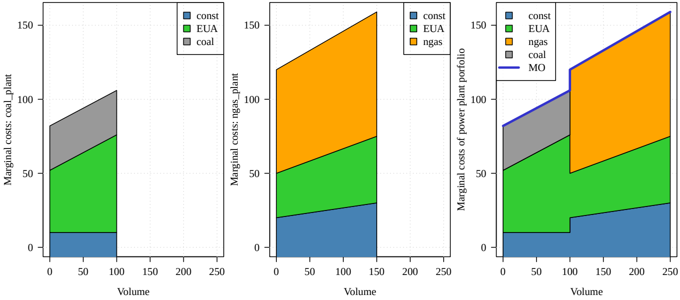
$$\text{MO}_{d,h}(x) = \alpha_{00} + \alpha_{01}\text{EUA}_d + \alpha_{02}\text{NGas}_d + (\alpha_{10} + \alpha_{11}\text{EUA}_d + \alpha_{12}\text{NGas}_d)x$$

$\Rightarrow$ for the electricity price $Y_{d,h}$ we receive with $x = \text{DA-ResLoad}_{d,h}$:

$$\begin{aligned} Y_{d,h} =& \text{MO}_{d,h}(\text{DA-ResLoad}_{d,h}) + \varepsilon_{d,h} \\ =& \alpha_{00} + \alpha_{01}\text{EUA}_d + \alpha_{02}\text{NGas}_d \\ & + (\alpha_{10} + \alpha_{11}\text{EUA}_d + \alpha_{12}\text{NGas}_d)\text{DA-ResLoad}_{d,h} + \varepsilon_{d,h} \end{aligned} \tag{4}$$

- Interactions $\text{EUA}_d\text{DA-ResLoad}_{d,h}$ and $\text{NGas}_d\text{DA-ResLoad}_{d,h}$ candidate regressors in linear model

Supply stack model with 2 fuels.



- Case 1, non-overlapping price regions (C is capacity of first fuel):

$$Y_{d,h} = \alpha_{00} + \alpha_{01}\text{EUA}_d + \alpha_{02}\text{NGas}_d + \varepsilon_{d,h}$$

$$+ \text{DA-ResLoad}_{d,h}\mathbf{1}_{\{\text{DA-ResLoad}_{d,h}<C\}}(\alpha_{10} + \alpha_{11}\text{EUA}_d + \alpha_{12}\text{NGas}_d)$$

$$+ \text{DA-ResLoad}_{d,h}\mathbf{1}_{\{\text{DA-ResLoad}_{d,h}\geq C\}}(\alpha_{22} + \alpha_{21}\text{EUA}_d + \alpha_{22}\text{EUA}_d)$$

- Terms e.g. $\text{DA-ResLoad}_{d,h}\mathbf{1}_{\{\text{DA-ResLoad}_{d,h}\geq C\}}\text{NGas}_d$

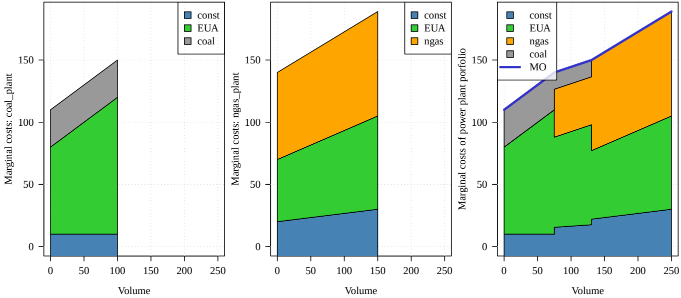
Supply stack model with 2 fuels.

- Resulting termse.g. (selected)

$$\underbrace{\text{DA-ResLoad}_{d,h}\left(\alpha_{01}+\alpha_{11}\mathbf{1}_{\{\text{DA-ResLoad}_{d,h}<C\}}+\alpha_{21}\mathbf{1}_{\{\text{DA-ResLoad}_{d,h}\geq C\}}\right)}_{=f(\text{DA-ResLoad}_{d,h})\text{ (non-linear function)}}\text{EUA}_d$$

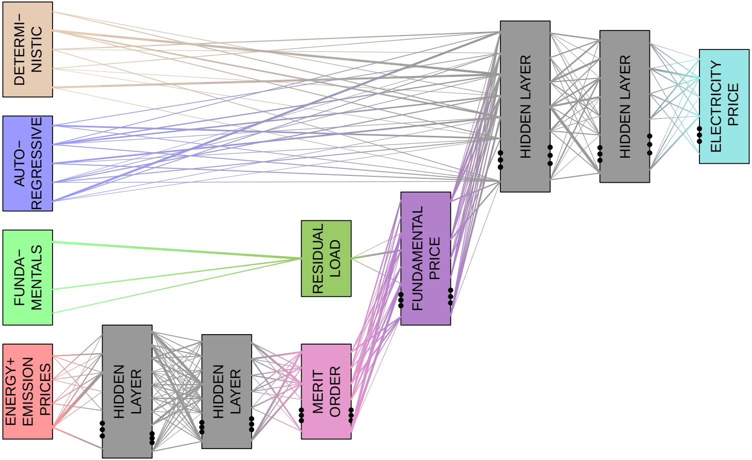
$\Rightarrow$ GAMs (generalized additive models) suitable framework

- Case 2, overlapping price regions:



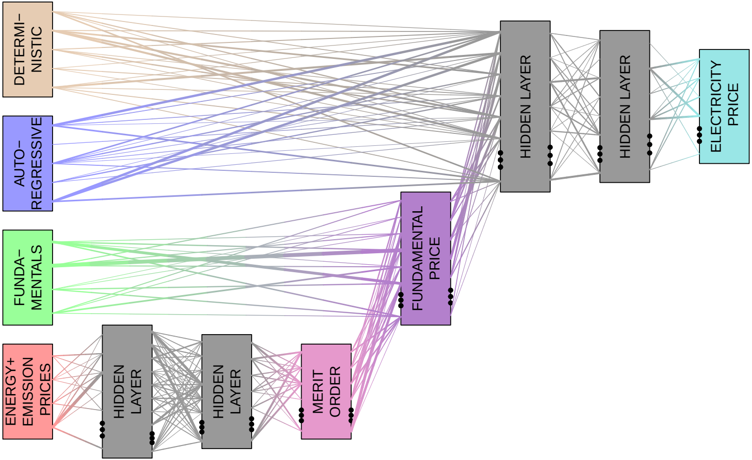
- Same conclusion (f is only more complicated)

Example ANN structure for fundamental information.



- Feed information in the network as in fundamental model
  $\Rightarrow$ only allow for reasonable non-linear relationships
- *black boxes* receive (some) interpretation

Example ANN structure for fundamental information.



- Allow for reasonable *black boxes*

On Coupled electricity markets.

- Consider two market areas (bidding zones) A and B
- prices with no interconnection:
  $P_{d,h}^{\mathsf{A}} = \mathsf{MO}_{d,h}^{\mathsf{A}}(\mathsf{ResLoad}_{d,h}^{\mathsf{A}}) + \varepsilon_{d,h}$ and
  $P_{d,h}^{\mathsf{B}} = \mathsf{MO}_{d,h}^{\mathsf{B}}(\mathsf{ResLoad}_{d,h}^{\mathsf{B}}) + \varepsilon_{d,h}$
- price with unlimited interconnection:
  $P_{d,h}^{\mathsf{A}\cup\mathsf{B}} =$
  $$\underbrace{\left((\mathsf{MO}_{d,h}^{\mathsf{A}})^{-1} + (\mathsf{MO}_{d,h}^{\mathsf{B}})^{-1}\right)^{-1}}_{=\mathsf{MO}_{d,h}^{\mathsf{A}\cup\mathsf{B}}}(\mathsf{ResLoad}_{d,h}^{\mathsf{A}} + \mathsf{ResLoad}_{d,h}^{\mathsf{B}}) + \varepsilon_{d,h}$$

$\Rightarrow$ Even for simple linear supply stack assumption with one fuel $\mathsf{MO}_{d,h}^{\mathsf{A}\cup\mathsf{B}}$ is quite highly nonlinear, involving shape of the supply stack and fuel/emission prices - but no residual load.

- For limited interconnection situation is even more complicated, but of the same structure.

Conclusions

- Data science models have challenges concerning their complexity: input size vs model depth
- Fundamental models help to find relevant features and non-linearities
- Fundamental models help to get (more) interpretable price models

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Thank you for your attention.

Further Literature:

- h Ziel, F., & Weron, R. (2018). *Day-ahead electricity price forecasting with high-dimensional structures: Univariate vs. multivariate modeling frameworks*. **Energy Economics**, 70, 396-420.
- Alasseur, C., & Féron, O. (2018). *Structural price model for coupled electricity markets*. **Energy Economics**, 75, 104-119.
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