

Artificial intelligence for assessing the security of electricity supply

Short study – Nuclear Power Plants in Germany (2023)

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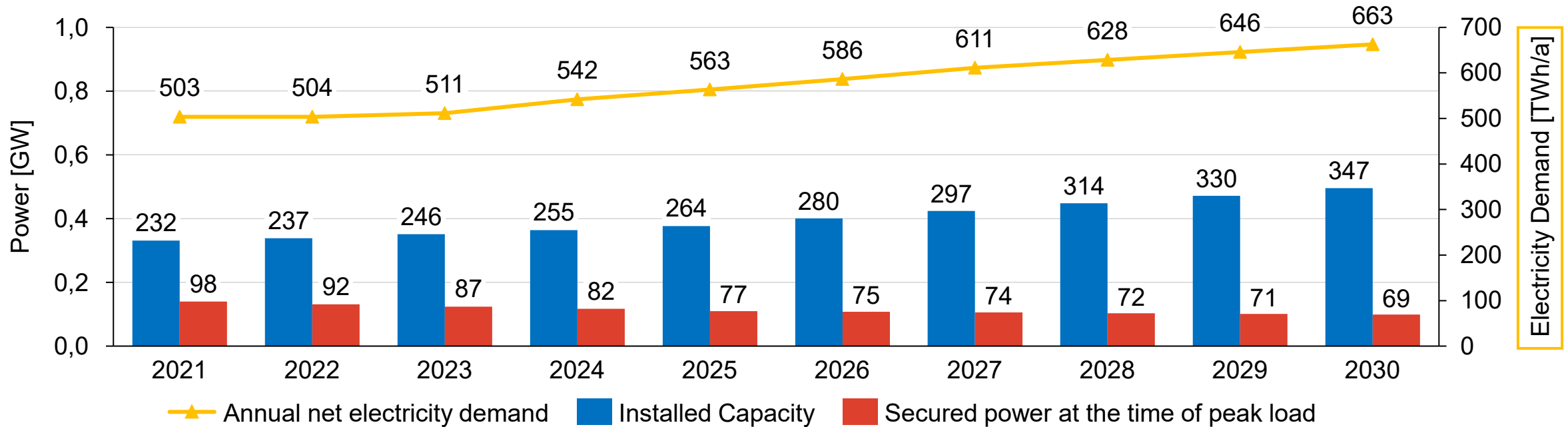


European Conference, Milan, Italy
July 26th, 2023

The energy transition: a challenge for the future security of supply ?



Forecast development of the electricity system in Germany

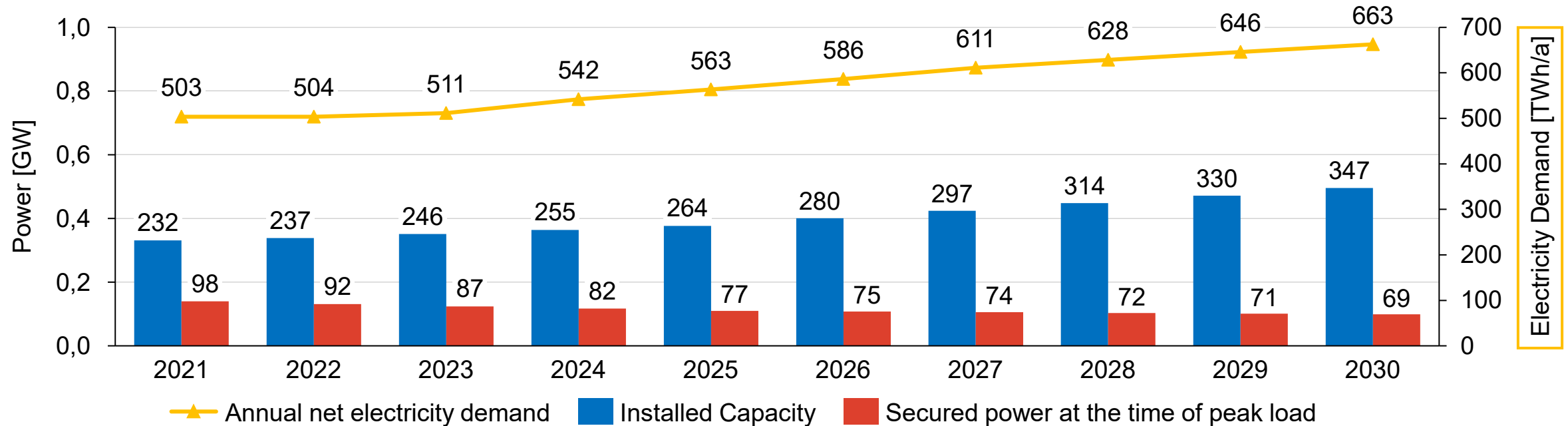


Source: Mittelfristprognose 2023-2027, Nolting, L. (2021). Die Versorgungssicherheit mit Elektrizität im Kontext von Liberalisierung und Energiewende, verschiedene Studienszenarien: dena KN100, SKN-Agora-KNDE2045, BDI - Klimapfade 2.0 Zielpfad, BMWK - LFS TN-Strom, Ariadne - REMIND-Mix, Ariadne - REMod-Mix

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- **Non-availability** of conventional generation plants as well as renewables, an increase in **electricity demand** as well as a lack of **flexibilities** can lead to **bottlenecks in the security of supply**
- The **assessment of the security of electricity supply** is therefore becoming increasingly important



Complexity vs. scenario scope

- Requirement for **probabilistic** assessment of security of supply (*ACER 2020, ERAA - European Resource Adequacy Assessment*)
- According to ERAA, only a **greatly reduced consideration of uncertainties** in generation, storage, grids and consumption is necessary
- **Uncertainty space** is only represented to a **very limited extent** due to the high **model complexity**

Source right: Köhnen, C.S., Priesmann, J., Nolting, L., Kotzur, L., Robinius, M., Praktiknjo, A., 2021. The potential of deep learning to reduce complexity in energy system modeling. International Journal of Energy Research.

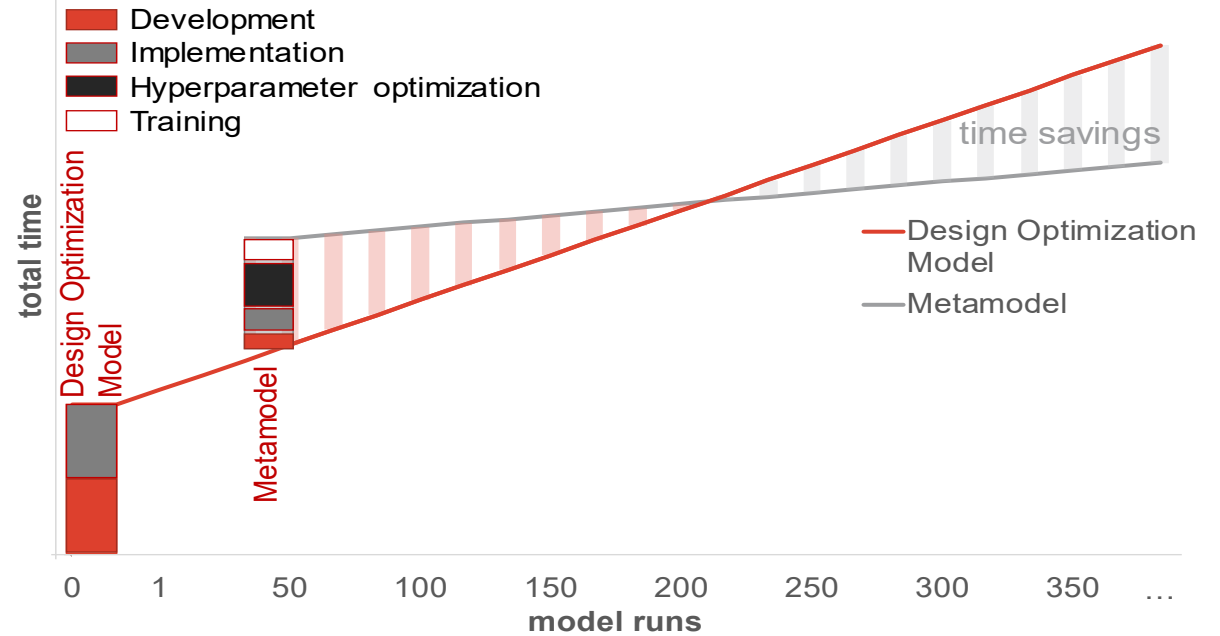
Assessment of the security of electricity supply

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A solution? Meta-modeling



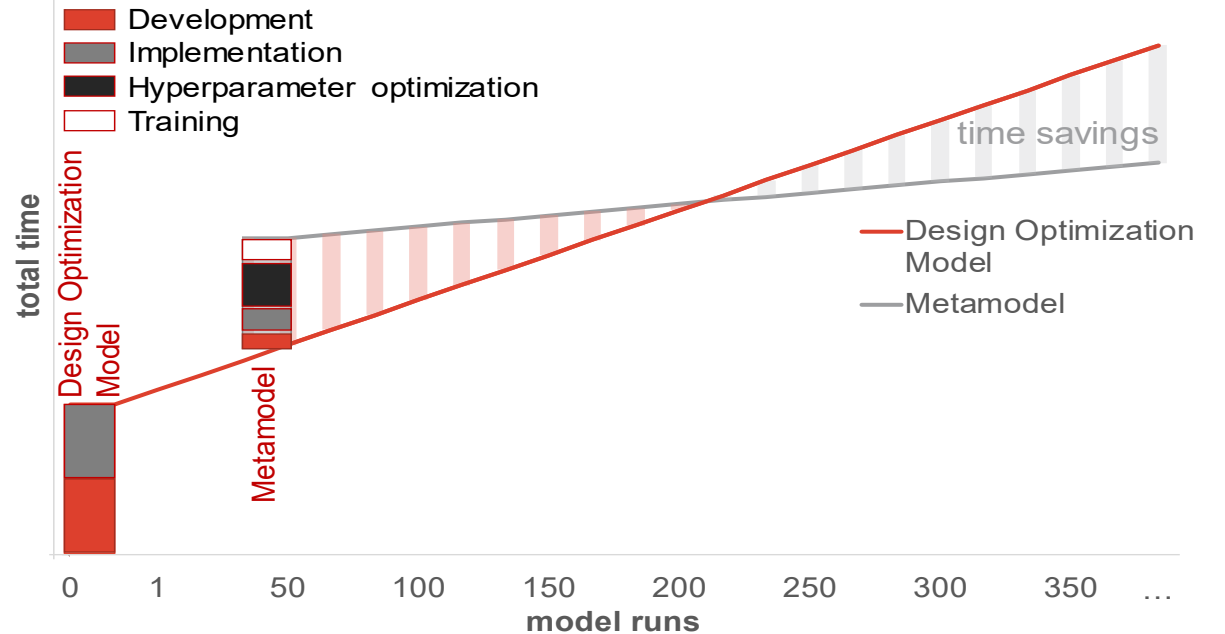
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Research questions

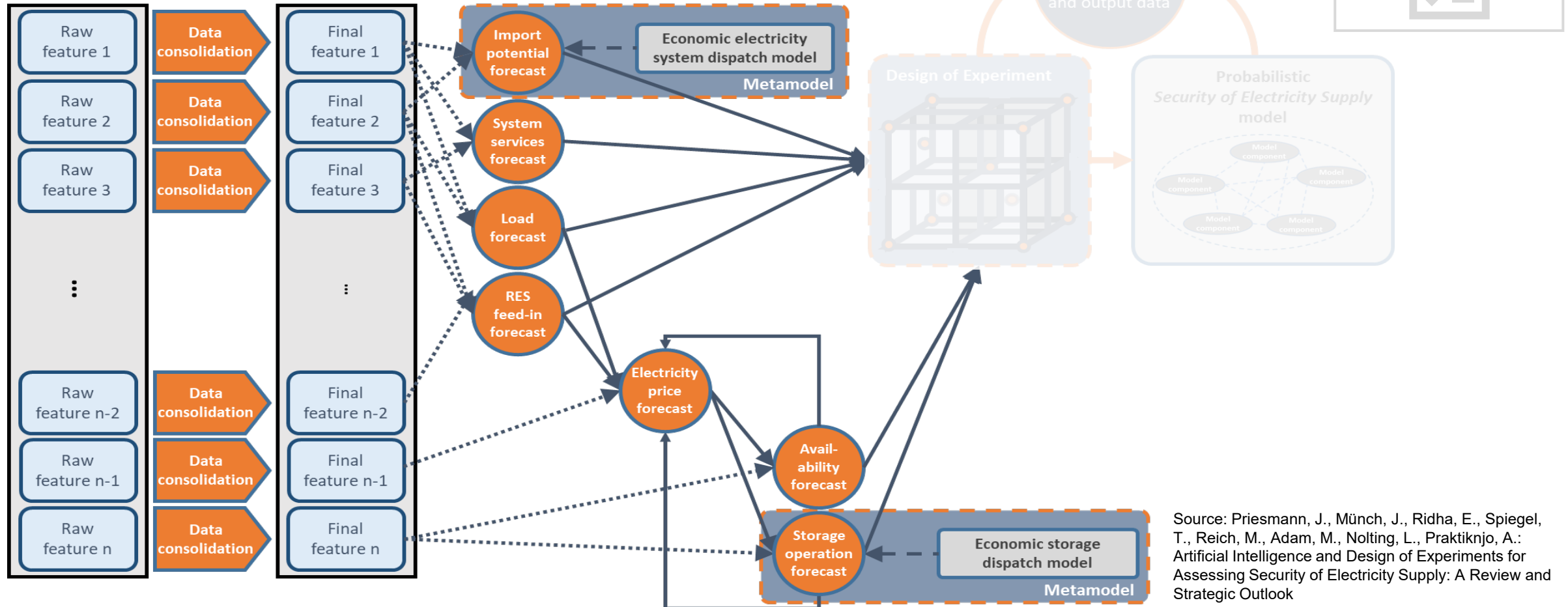
- To what extent can **metamodeling** help to reduce the **runtime** in the assessment of security of supply?
- And at what **cost**? Does the **accuracy of the model** remain sufficiently intact?
- **Case study**: Does the **extension of the operating lives** of the remaining **nuclear power plants in Germany** until 15 April 2023 improve the security of electricity supply?

Method pipeline and meta-modeling

Method



Development of a method pipeline for the integration of AI applications in security of supply analysis with electricity



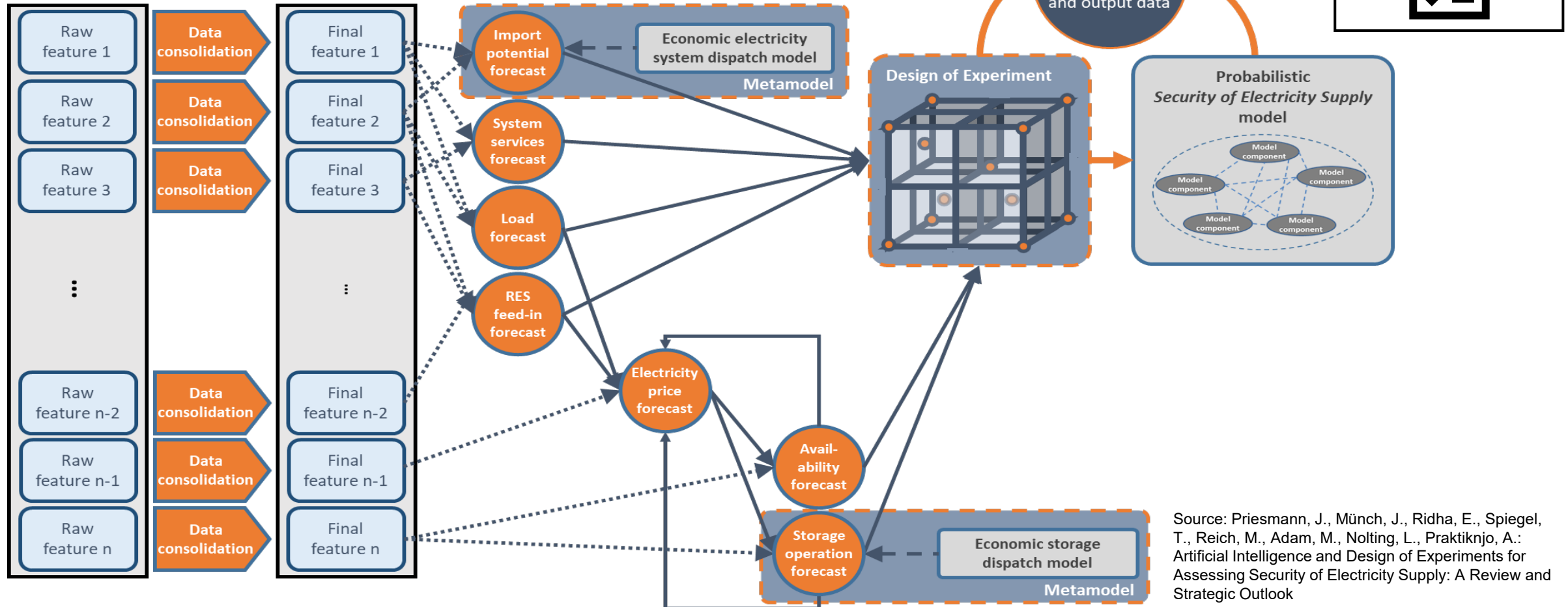
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Second approach of meta-modeling

Direct prediction of key figures of security of supply


Input data




Conventional
Power plant park
(controllable)




Renewable
Power plant park
(conditionally controllable)



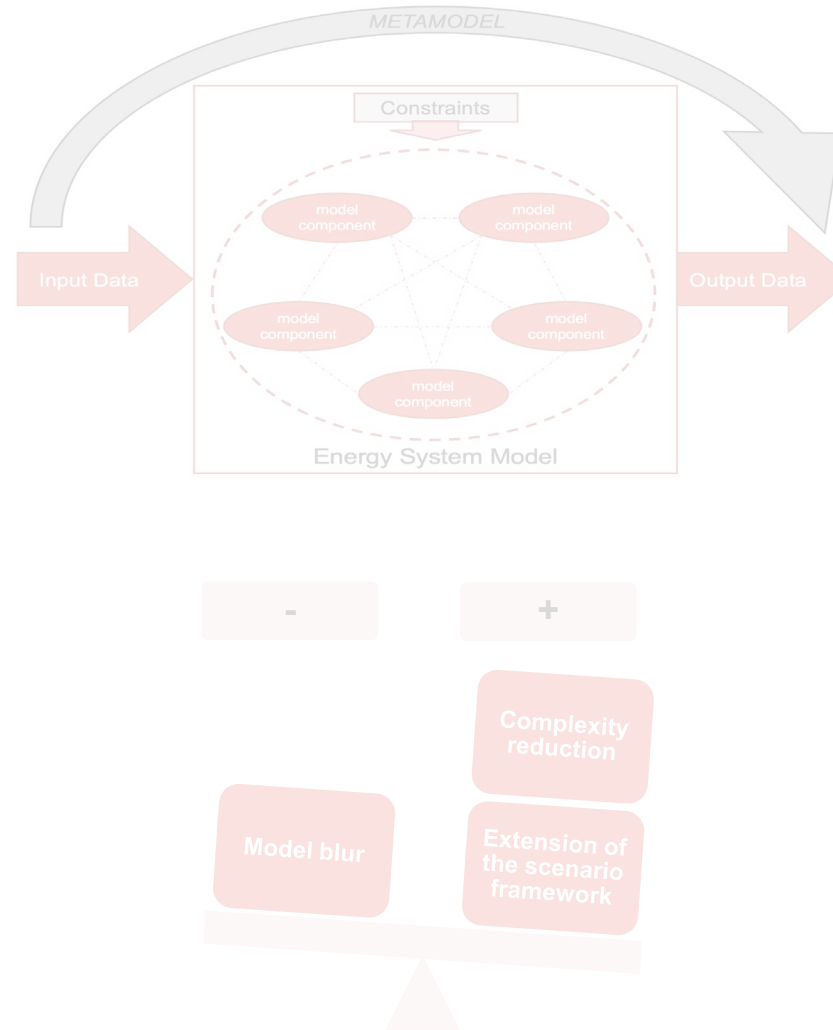
Import potential from
neighbouring countries



Electrical load
(*net electricity demand*)



(Sector coupling)
EV, heat pumps



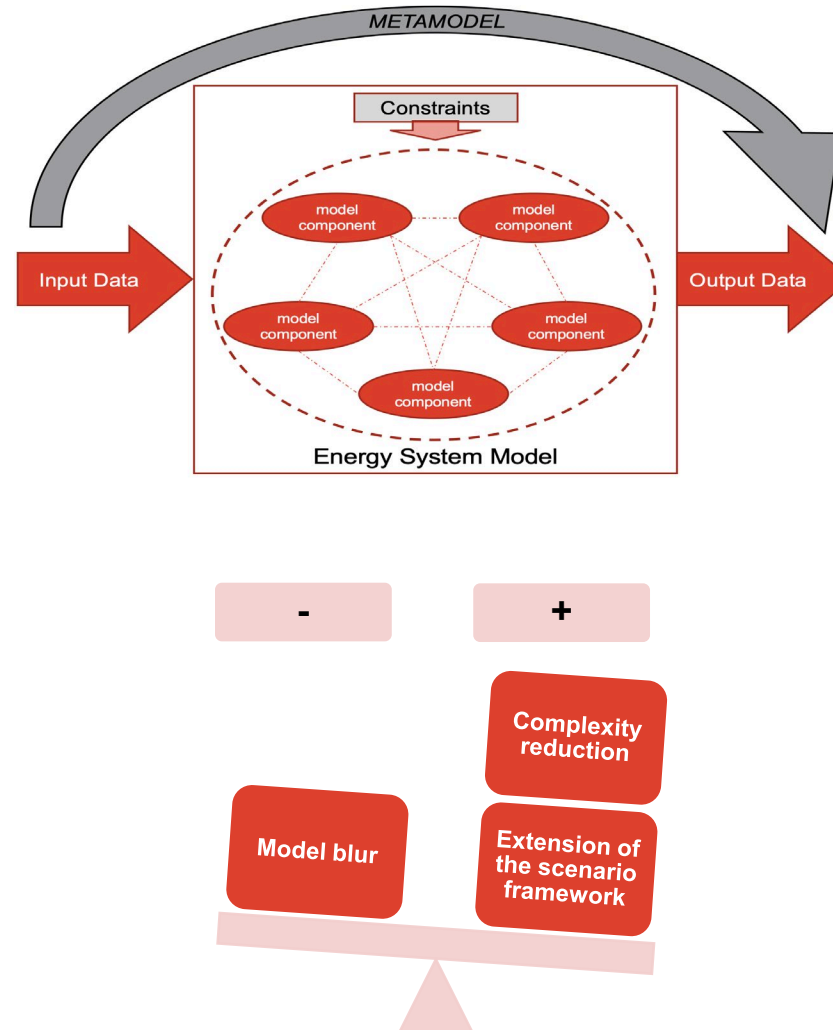


Second approach of meta-modeling

Direct prediction of key figures of security of supply

Input data

- Conventional Power plant park (controllable)
- Renewable Power plant park (conditionally controllable)
- Import potential from neighbouring countries
- Electrical load (net electricity demand)
- (Sector coupling) EV, heat pumps



Output data

Loss of Load Probability (LoLP)
 (Probability that the load cannot be met in one hour)

$$LoLP(t) = 1 - Pr_{Load\ coverage}(t)$$

Loss of Load Expected (LoLE)
 (expected duration of the load interruption in hours)

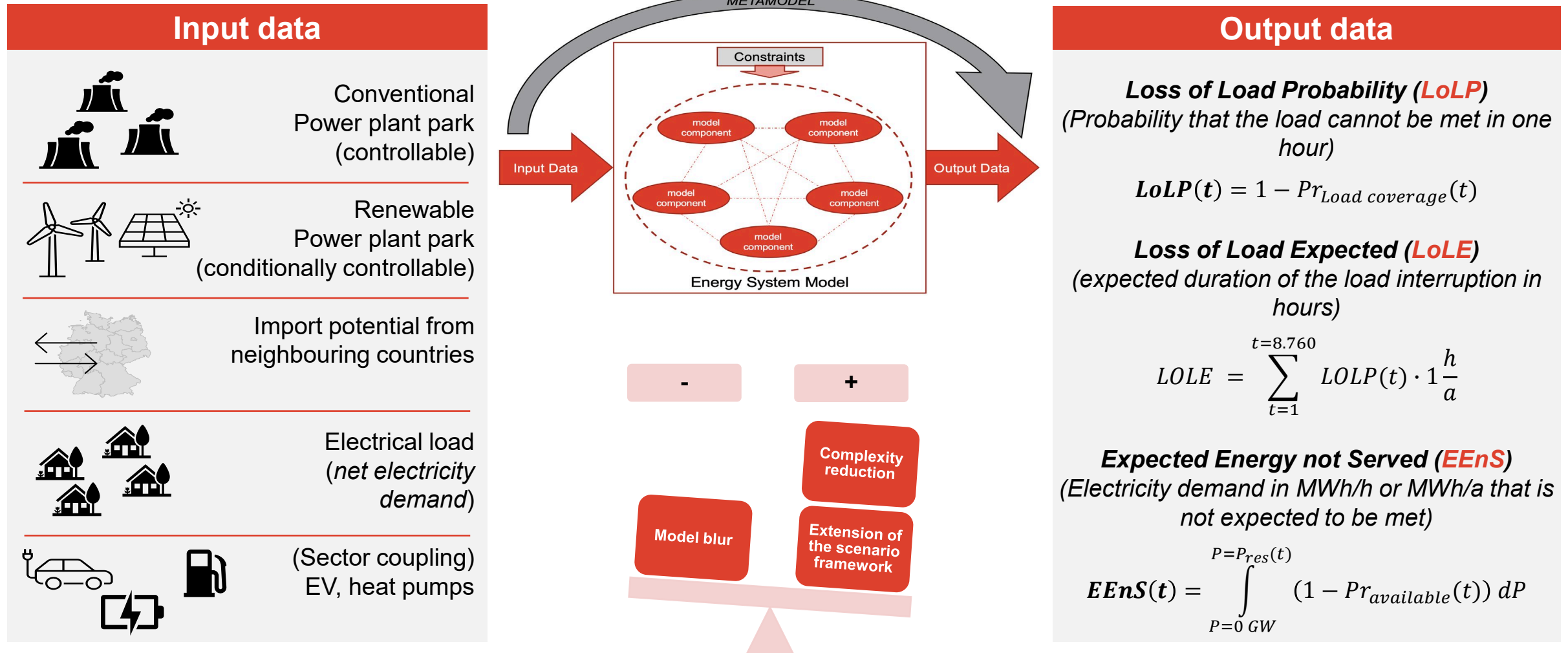
$$LOLE = \sum_{t=1}^{t=8.760} LOLP(t) \cdot 1 \frac{h}{a}$$

Expected Energy not Served (EEnS)
 (Electricity demand in MWh/h or MWh/a that is not expected to be met)

$$EEnS(t) = \int_{P=0\ GW}^{P=Pr_{res}(t)} (1 - Pr_{available}(t)) dP$$

Second approach of meta-modeling

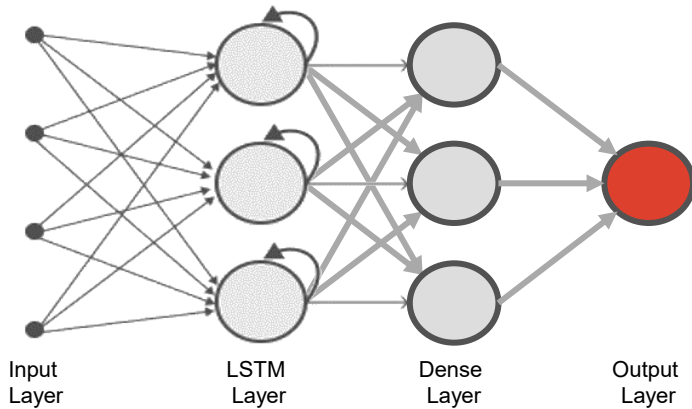
Direct prediction of key figures of security of supply



Meta-modeling: artificial neuronal network

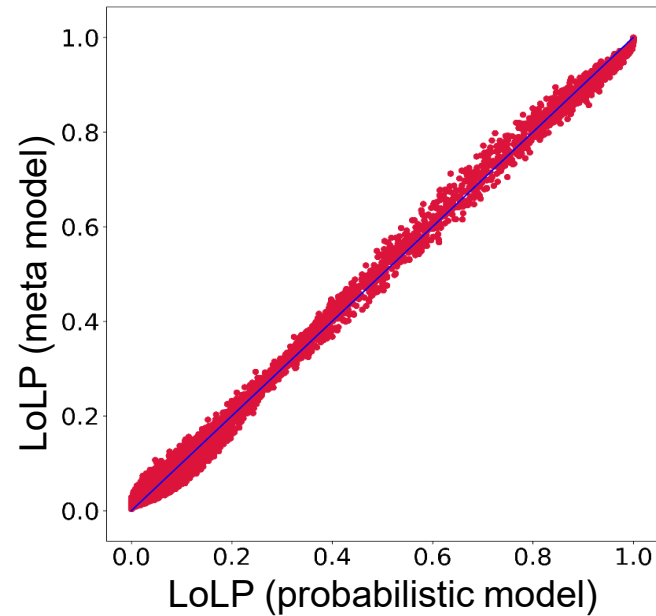
The simulation results: key figures of the training data

Metamodel

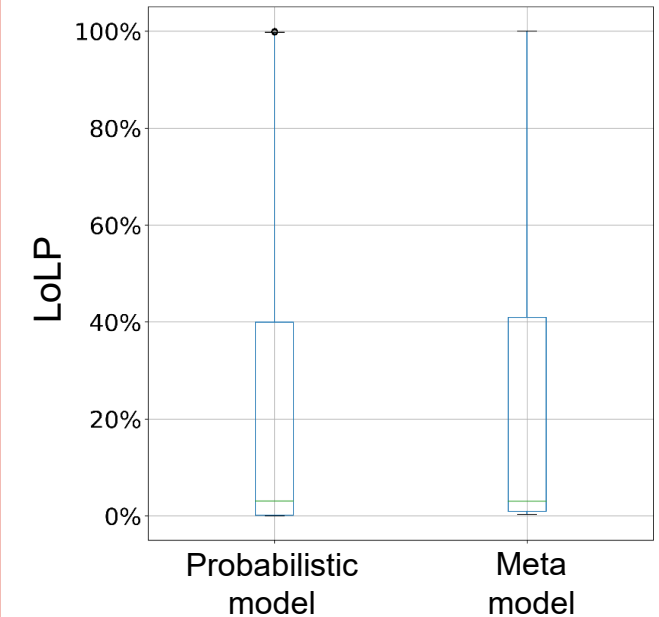


- **4 layers:** Input, LSTM, Dense and Output layers
- **3,081 Training weights**, trained with **262,800 input-output relations**

Forecast accuracy



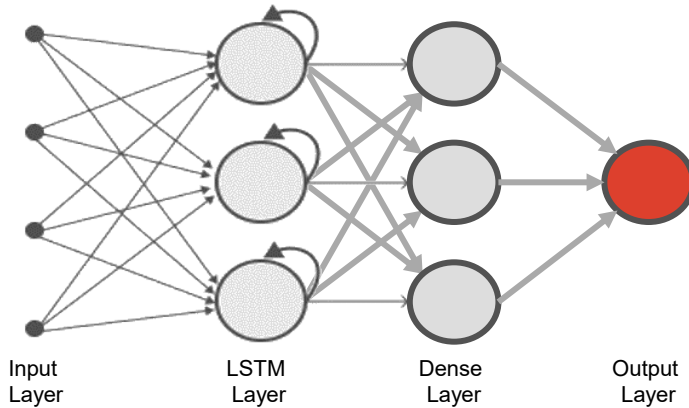
Distribution of the LoLPs



Meta-modeling: artificial neuronal network

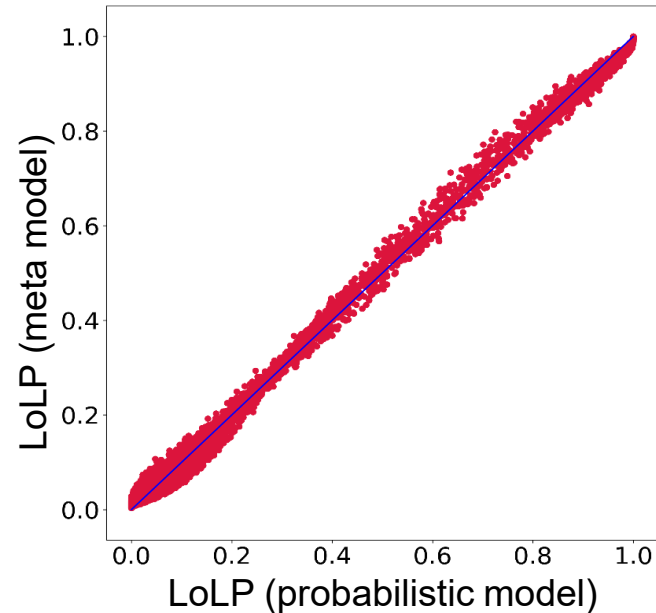
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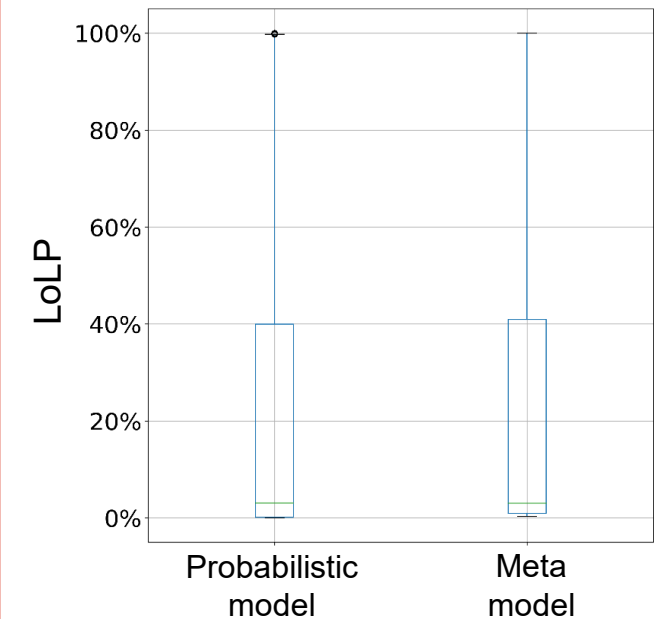


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Forecast accuracy



Distribution of the LoLPs



- Spread of errors is an important indicator of metamodel weaknesses
- **Best metamodel:** LSTN-NN (Long short-term memory-neuronal network)
- **The model approximates the simulation data with a coefficient of determination of $R^2 = 99,86\%$ and a mean absolute error of $MAE = 1\%$**



Short study – Nuclear Power Plants in Germany (2023)

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Aaron Praktiknjo, Jan Priesmann, Christina Kockel, Marius Tillmanns, Jakob Kulawik

 **RWTH AACHEN UNIVERSITY**

Arbeitspapiere energiewirtschaftliche Analysen 2023-001

Kurzstudie: Verbessert die Laufzeitverlängerung der verbleibenden Kernkraftwerke bis zum 15. April 2023 die Versorgungssicherheit mit Elektrizität?

Urteil-Prof. Dr.-Ing. Aaron Praktiknjo, Jan Priesmann, M.Sc., Christina Kockel, M.Sc., Marius Tillmanns, M.Sc., Jakob Kulawik, M.Sc.

Lehrstuhl für Energiesystemökonomik (FCN-ESE), RWTH Aachen, Mathieustr. 10, 52074 Aachen
E-Mail: apraktknjo@eonerc.rwth-aachen.de

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Zitierhinweis:
Praktiknjo, A., Priesmann, J., Kockel, C., Tillmanns, M., Kulawik, J., 2023. Kurzstudie: Verbessert die Laufzeitverlängerung der verbleibenden Kernkraftwerke bis zum 15. April 2023 die Versorgungssicherheit mit Elektrizität? Arbeitspapiere energiewirtschaftliche Analysen. Nr. 2023-001. Lehrstuhl für Energiesystemökonomik. Aachen.
DOI: 10.18154/RWTH-2023-00623

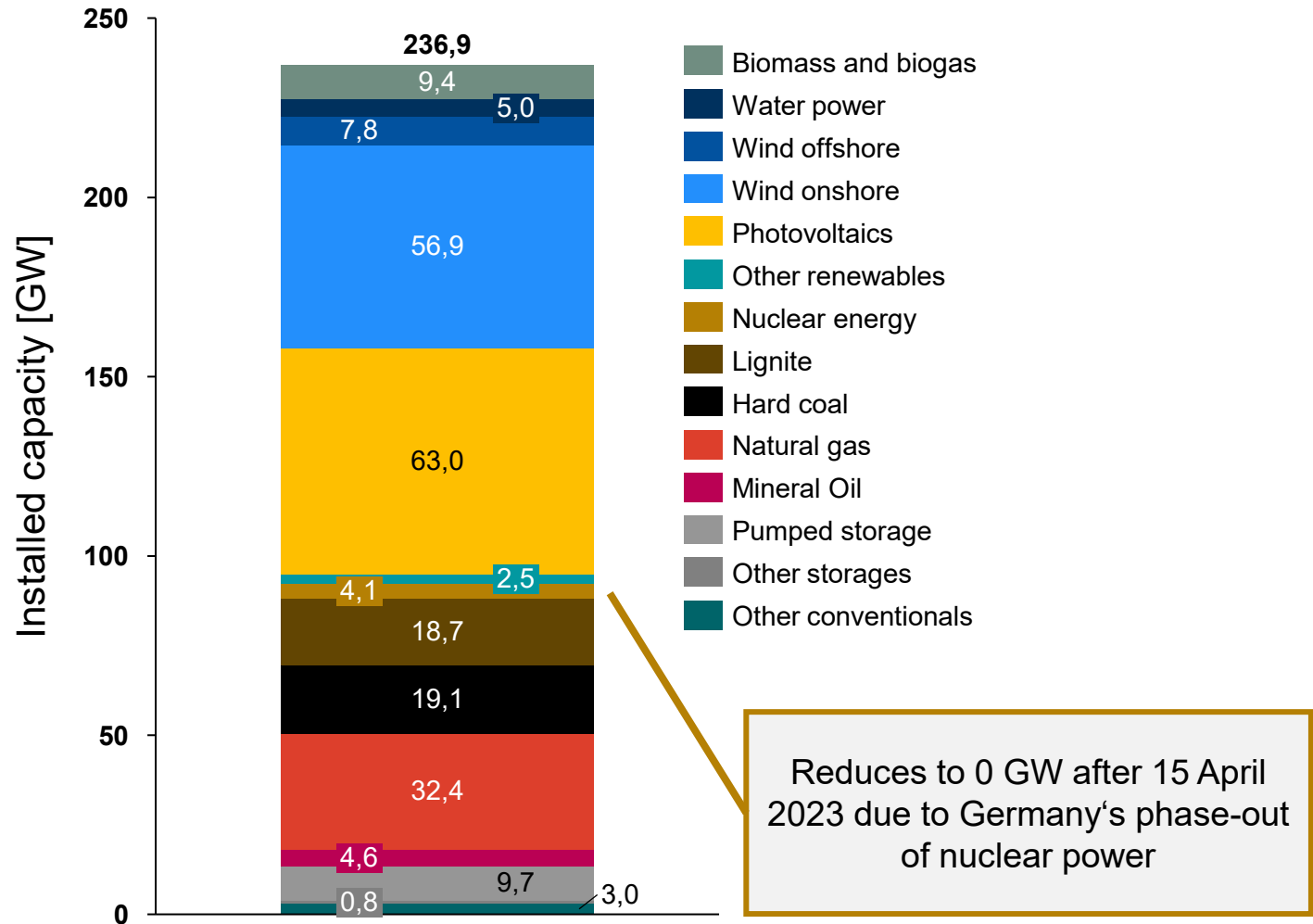
Lehrstuhl für Energiesystemökonomik
E.ON Energy Research Center
RWTH Aachen
Mathieustr. 10, 52074 Aachen
E-Mail: apraktknjo@eonerc.rwth-aachen.de

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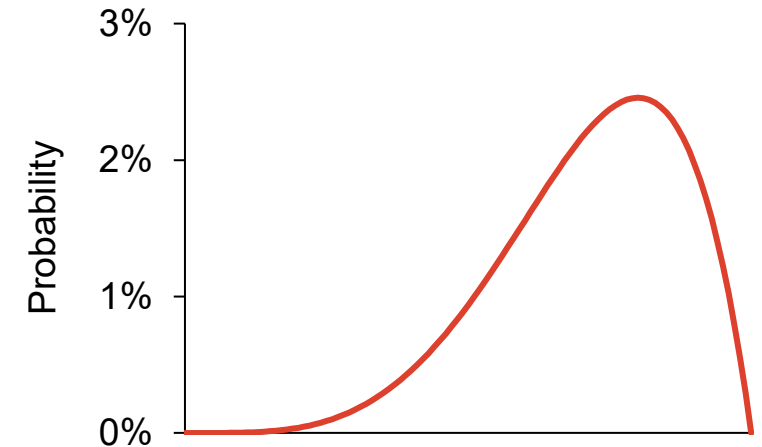
Scenario framework for the calendar year 2023

Power plant park in Germany (based on Federal Network Agency power plant list of 25 November 2022)



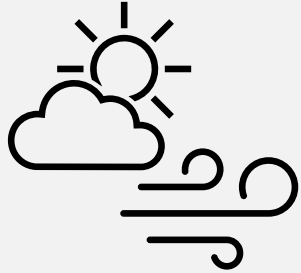
Further uncertainties considered

- Reduction of available **gas capacities** due to supply bottlenecks
- Reduction of **import potentials**
- Reduction of **electricity demand**

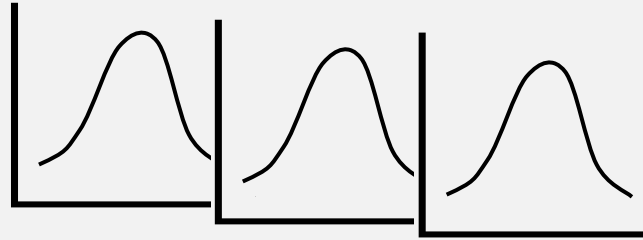


Scope of simulation and comparison of runtime to probabilistic model

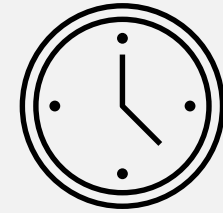
Weather years



Monte Carlo simulation of the further uncertainties



Hourly resolution



30

x

1000

x

8760

Variants

= 30,000 simulated years = 262.8 million simulated hours

Probabilistic Model

~4,000 – 8,000 hours (HPC)

Trained metamodel

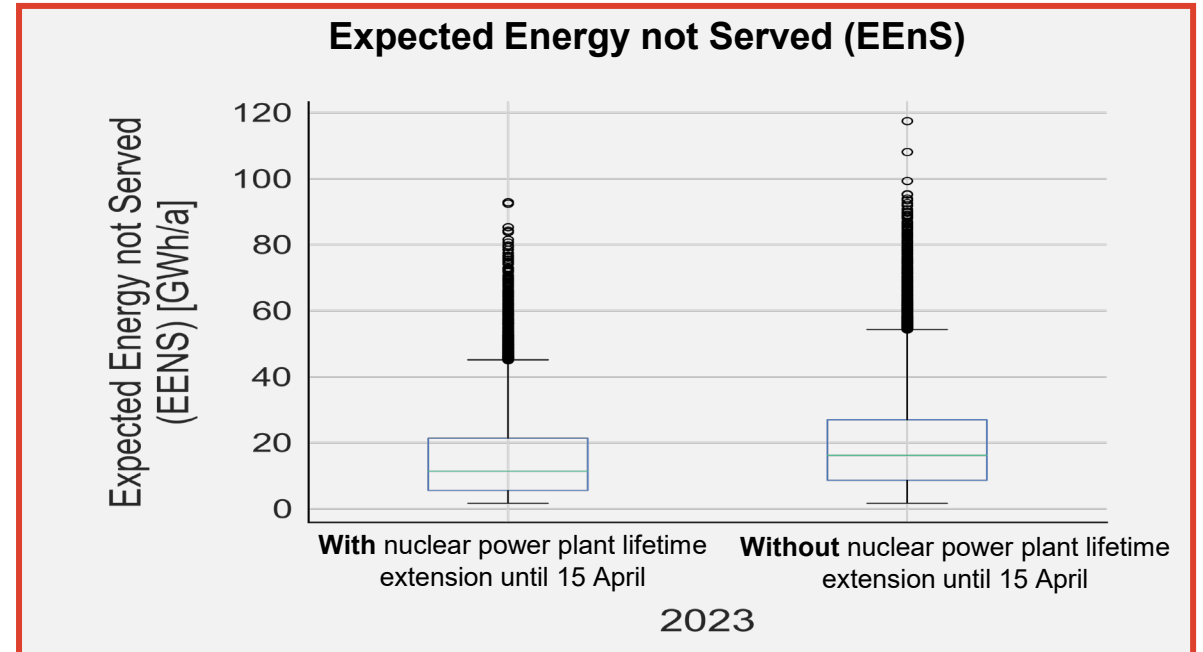
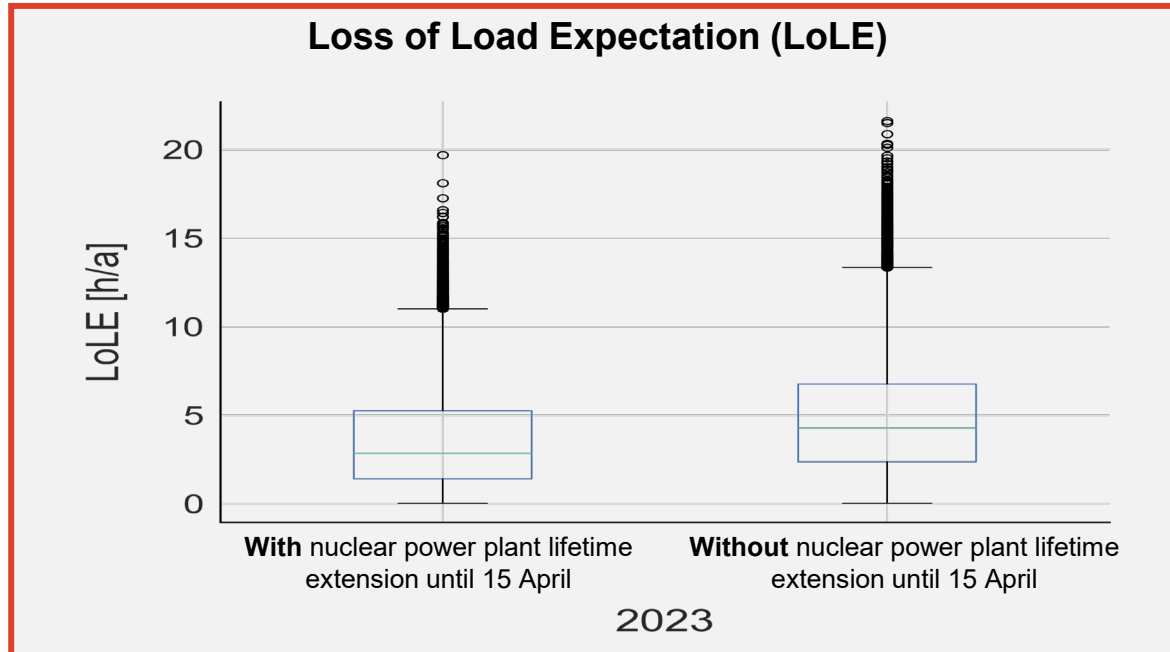
~30 minutes (PC)

Comparison of Running times



Distribution of the security of supply indicators: LoLE and EEnS

Results: influence of the extension of the operating lives of nuclear power plants on LoLE and EEnS in the period 1 January 2023 to 15 April 2023



- **With nuclear power plant runtime extension, undersupply time (LoLE) decreases by 1.3 hours on average and energy shortfall (EEnS) by 4.3 GWh on average.**
- **Depending on the scenario, the decrease for the LoLE due to the lifetime extension is between 0.0 and 3.2 hours and for the decrease in EEnS between 0.0 and 12.1 GWh in the 5 % and 95 % confidence interval.**



Key findings and outlook

Meta-modeling

- **Metamodels** show that the classic probabilistic convolution model can be approximated with **high accuracy**
- **New scenarios with 30 weather years** can be approximated **within seconds** instead of several hours

Case study - Nuclear Power Plants in Germany (2023)

- **Continued operation of** the nuclear power plants remaining in Germany until 15 April 2023 means that, according to our calculations, a **statistically positive contribution** to security of supply can be expected in the period under review
- Analysis cannot make **any statement on other aspects** such as the impact on the security of supply with natural gas and other energy sources, electricity prices, CO₂ emissions, risks of reactor accidents, final storage problems with radioactive waste and acceptance by the population.



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Outlook

- **Transfer of the developed methods** to further probabilistic models for the evaluation of supply security (time-coupled optimisation methods) → *forecast of storage dispatch and (non-)availabilities*
- Extension of the **methodology for the selection of support points (Design of Experiment)**
- The approximation introduces **additional fuzziness** into the analysis ("black box models") → **Explainable AI**

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Jan Priesmann
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Aaron Praktijnjo
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Backup



Artificial intelligence to study the security of electricity supply

Project duration: 01 June 2020 – 30 November 2023



Network partner



Chair of Energy System Economics (FCN-ESE) | RWTH Aachen University

Hochschule Düsseldorf
University of Applied Sciences



Centre for Innovative Energy Systems (ZIES) | Düsseldorf University

Practice
Advisory
Board





The security of electricity supply: background

Eight Challenges

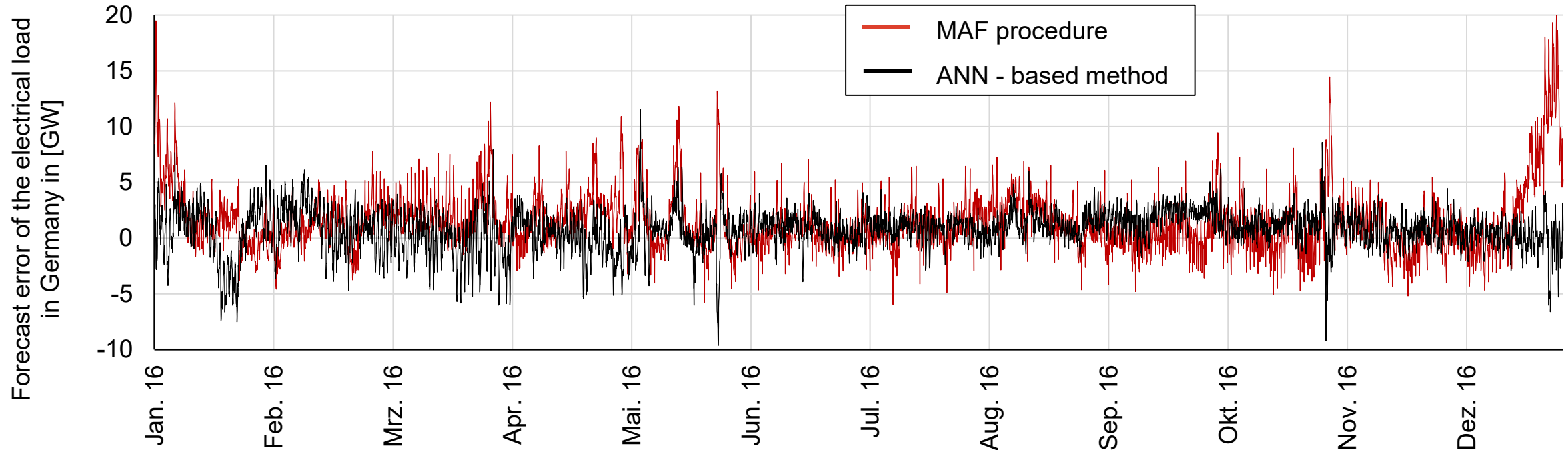


- 1 Forecasting loads and renewable feed-in: residual loads
- 2 Forecasting the unavailability of generation plants
- 3 Boundary-coupling services, mapping of international load flows
- 4 Complexity of the models: computing times and memory requirements
- 5 Mapping of uncertainties: increasing number of scenarios necessary
- 6 Water levels and temperatures: cooling water, supply chains, Run-of-river, storage water and pumped storage power plants
- 7 Integration of balancing power and balancing power markets
- 8 Mapping of market mechanisms and market behaviour

Time series forecast example: Weather dependence of the electrical load



Load forecast: Status quo (Midterm Adequacy Forecast, MAF) and ANN-based method (Artificial Neural Network) in Germany (Year 2016)



Source: Behm, C., Nolting, L., Praktiknjo, A. (2020). How to Model European Electricity Load Profiles using Artificial Neural Networks, Applied Energy, 277, 115564.

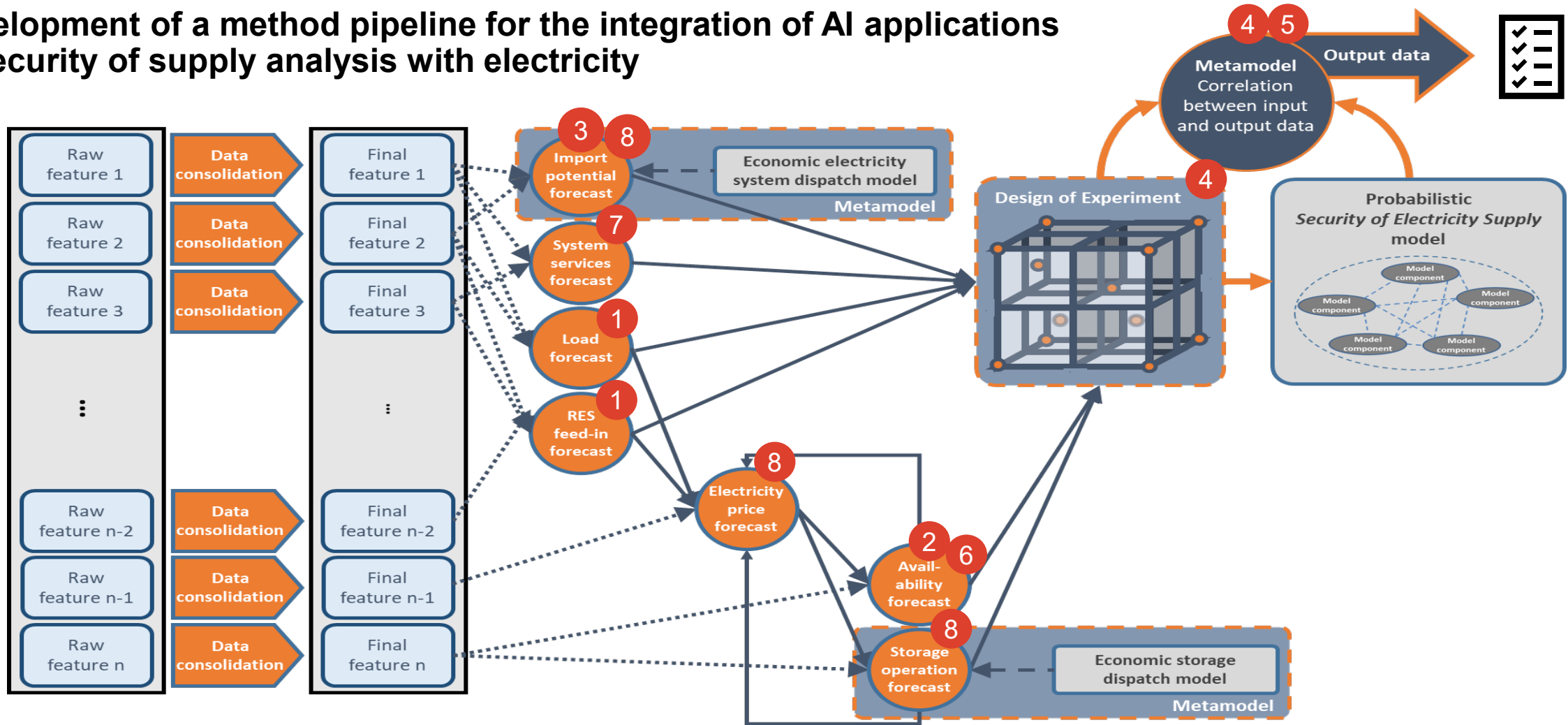
- Artificial neural networks can be used to **improve** the mapping of **weather effects** on **electrical load**
- Similar **improvements** are also feasible for the **weather-dependent feed-in power** of renewable energies

Research project: time series prediction and meta-modeling

Method

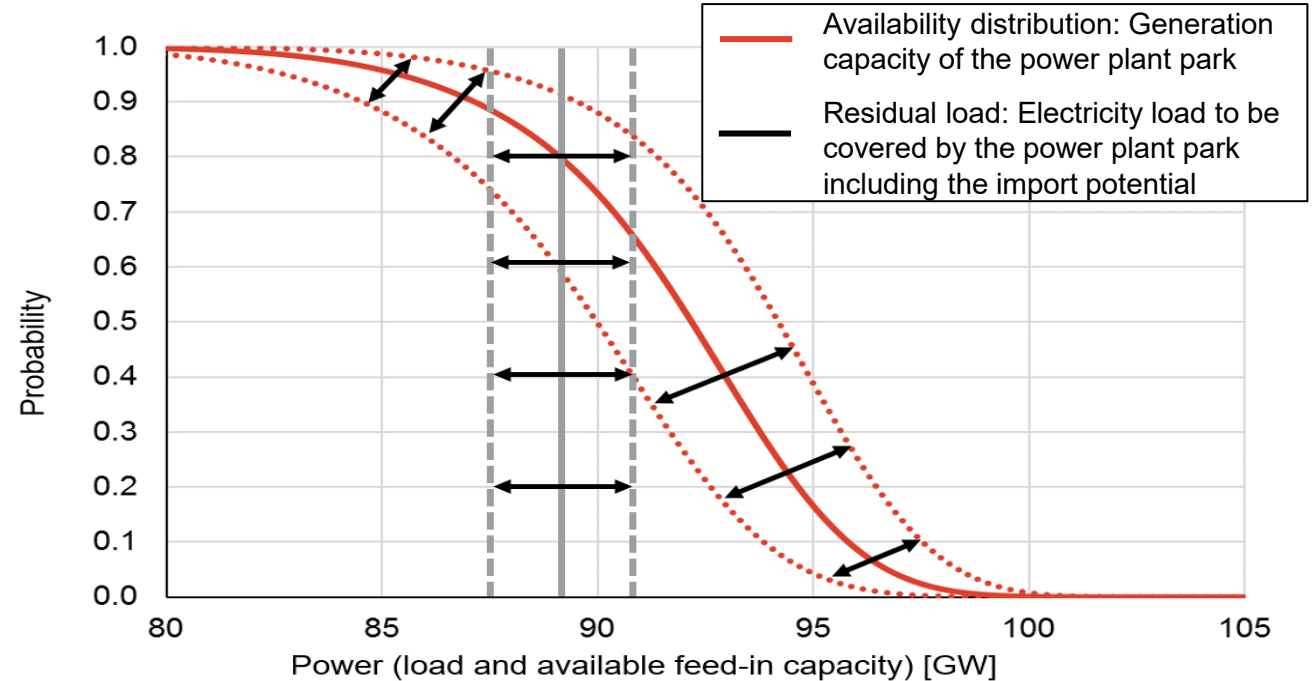
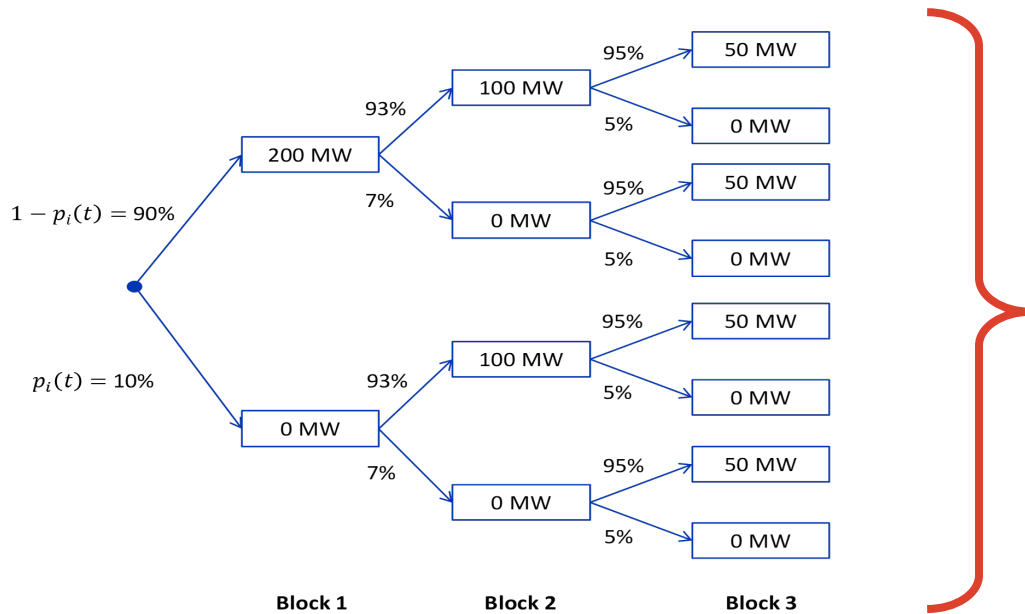


Development of a method pipeline for the integration of AI applications in security of supply analysis with electricity



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Basics of the probabilistic simulation model



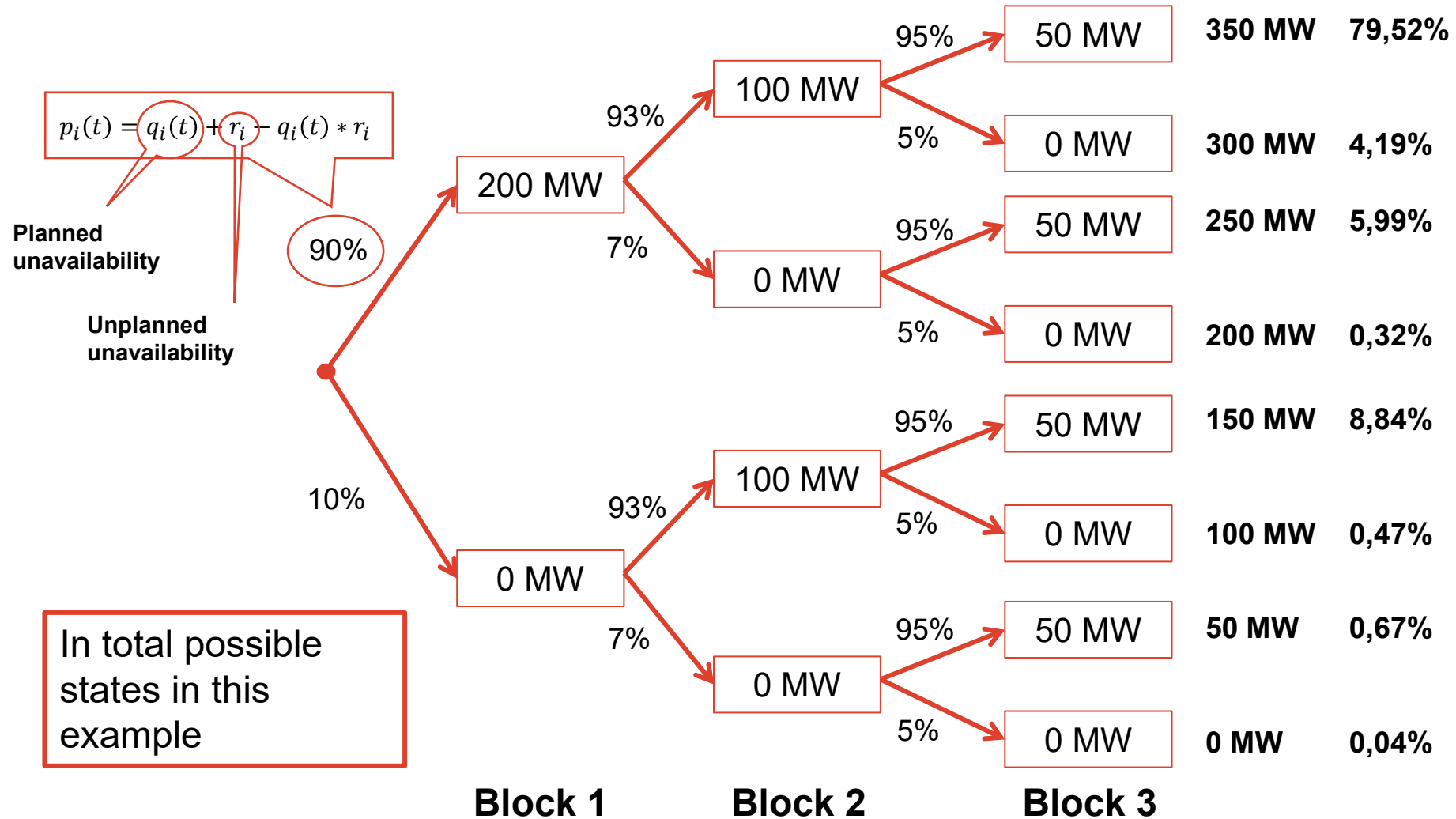
Mapping of the **distribution function of the secured feed-in power using recursive convolution:**

$$Pr_i(P_A > P) = Pr_{(i-1)}(P_A > P) \cdot (1 - p_i(t)) + Pr_{(i-1)}(P_A > (P - P_i)) \cdot p_i(t)$$

Cf. Brückl (2006)

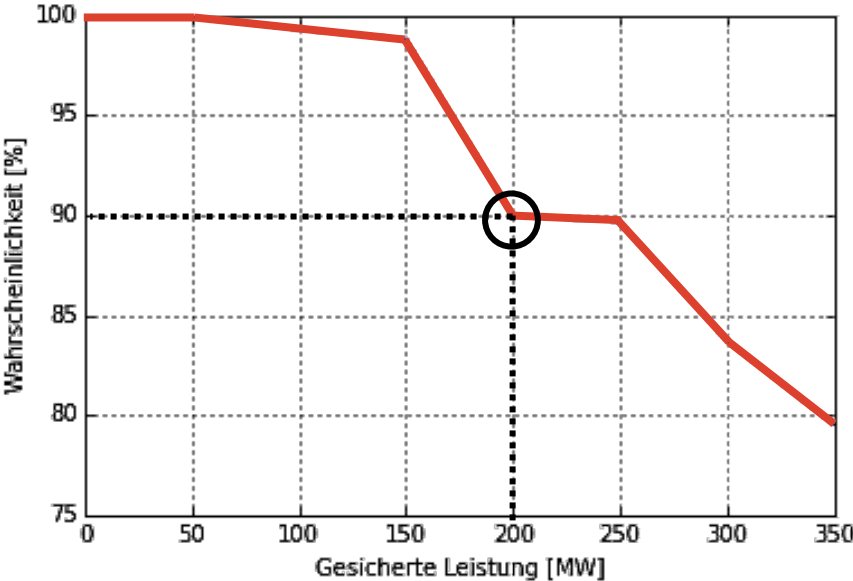
- Mapping of the **electrical load**, the **feed-in capacity of the renewable generation plants** (wind, PV and run-of-river) as well as the **import potentials** based on **30 weather years**
- Scenario-based mapping of the **flexibility potential of sector coupling technologies** such as heat pumps and electric vehicles

Example with 3 power plant units

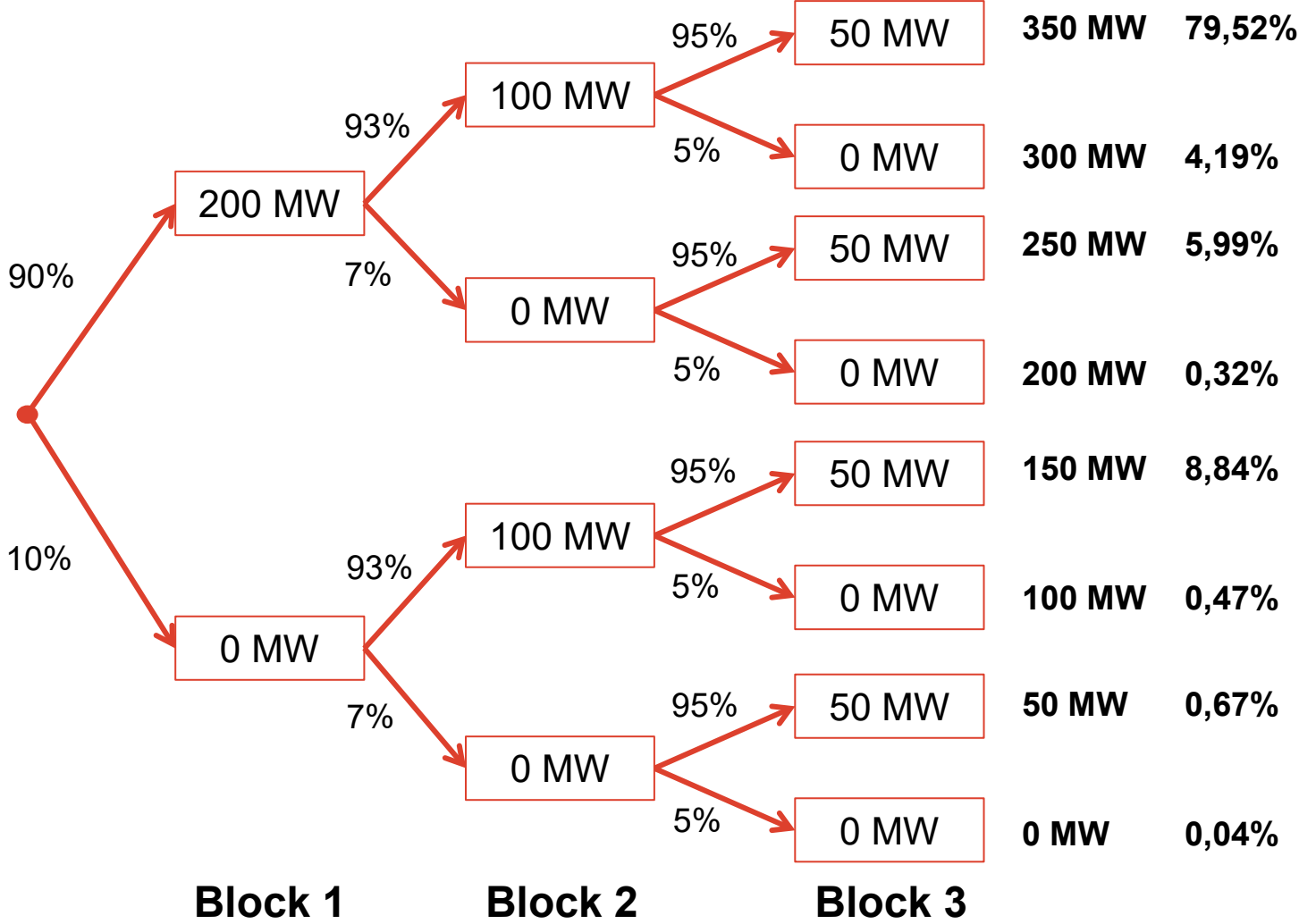


Tabular and graphical evaluation of the convolution

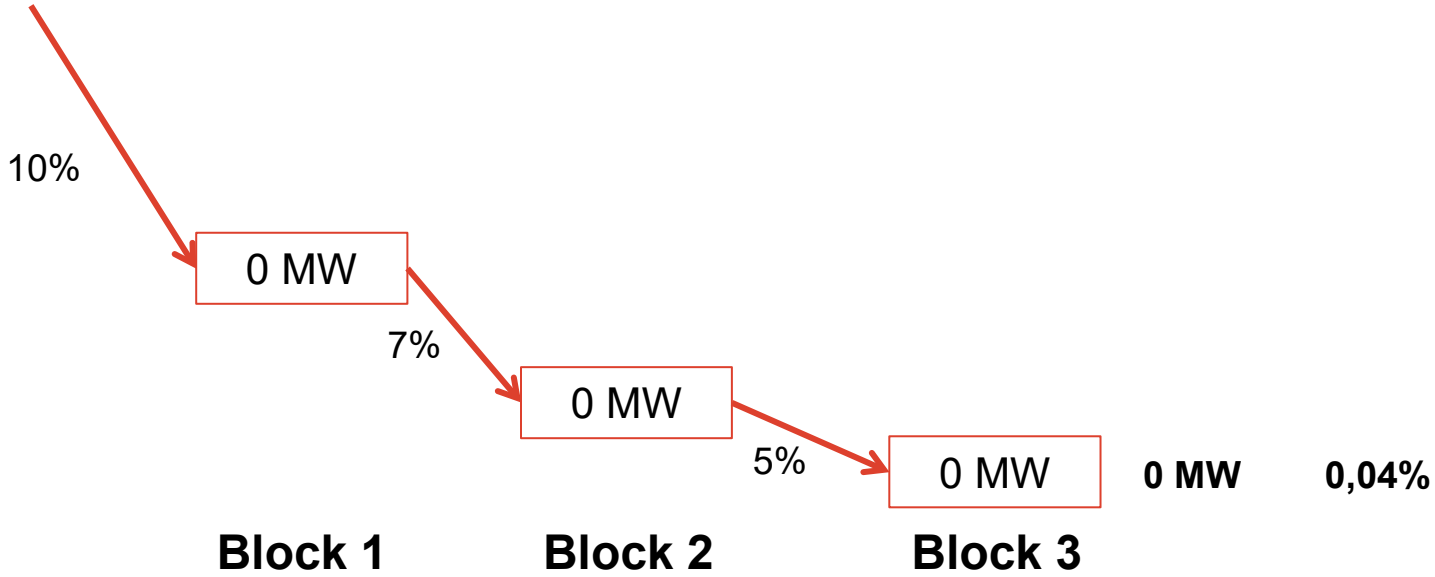
Non-availability [MW]	Assured performance [MW]	p [%]	p, cumulated [%]
0	350	79.52	79.52
50	300	4.19	83.70
100	250	5.99	89.69
150	200	0.32	90.00
200	150	8.84	98.84
250	100	0.47	99.30
300	50	0.67	99.97
350	0	0.04	100.00



Comparison with Monte Carlo simulation



Comparison with Monte Carlo simulation



Procedure for large numbers of power plant units: Recursive convolution

Number of possible states for n power plant units

With approx. 800 blocks in Germany Possible conditions

Therefore, use of the recursive formulation according to Brückl (2006) for the probability of a total failure of more than P_A of the installed capacity:

$$\Pr_i(P_A > P) = \Pr_{(i-1)}(P_A > P) * (1 - p_i(t)) + \Pr_{(i-1)}(P_A > (P - P_i)) * p_i(t)$$

With:

\Pr := Probability := Probability of default

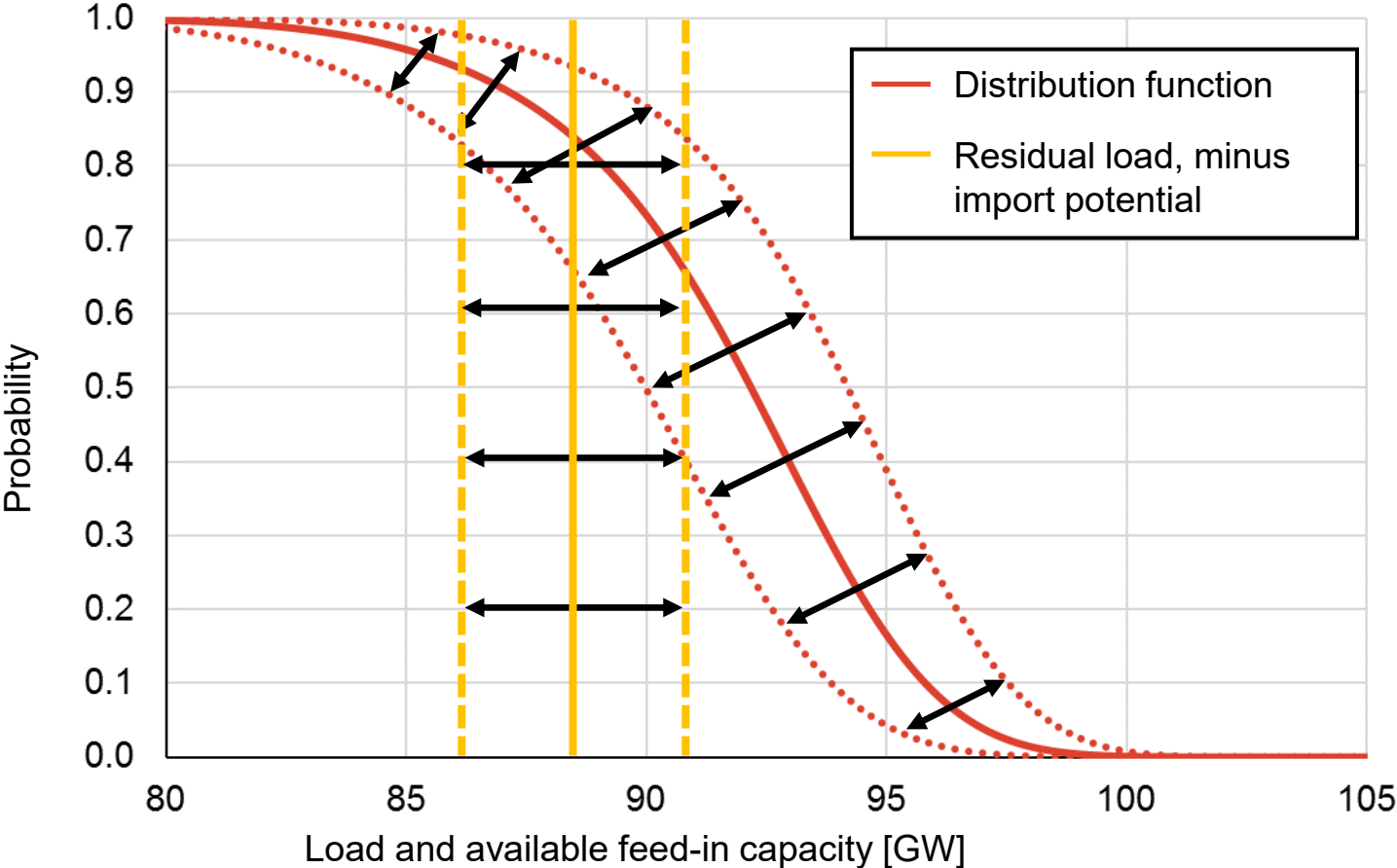
P := Power of block i

P_i := Power of power plant unit i

P_A := Power failure

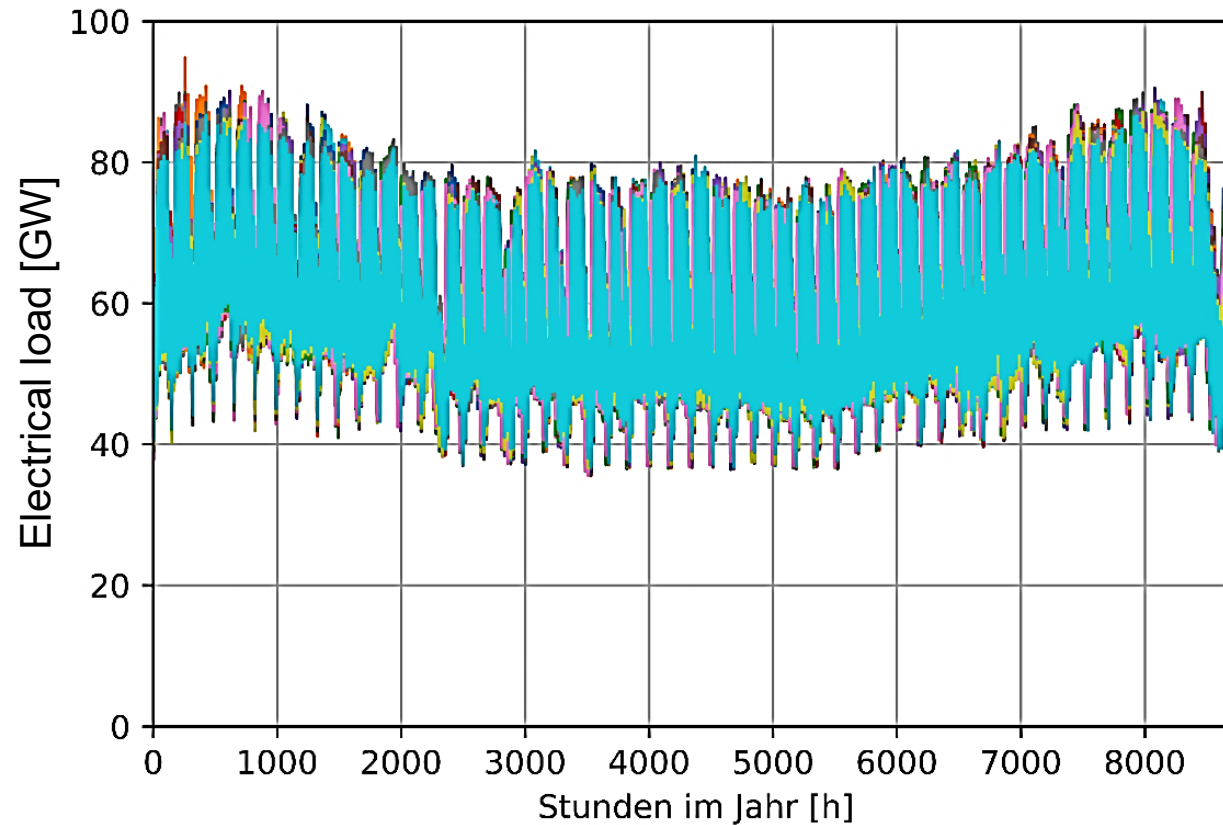
Models and input data: Security of supply model

Load-side consideration of the import potential



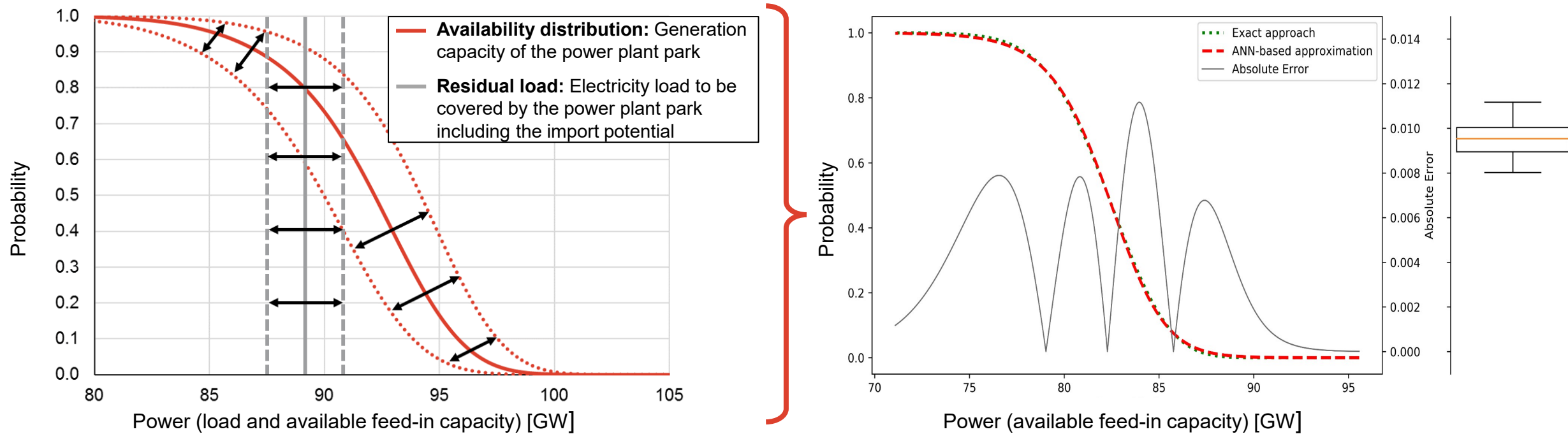
Scenario framework for the calendar year 2023: Weather influences

- Illustration of 30 weather years
- Influence of weather years on electrical load, RES-E generation, as well as import potentials



First approach of meta-modeling

Approximation of the convolution curve of the probabilistic simulation model via sigmoid function



- **Metamodel based on artificial neuronal network (ANN) shows very good results with deviations from the convolution curve of ~1 % mean square error**
- **ANNs can help to reduce computation time and avoid model complexity, per scenario year from originally ~8.5 h to now ~1.5 min (i.e. – 99.7 %)**
- **ANNs do not replace adapted (linear) metamodels. "Tailor-made" approach for convolution models is needed**



Second approach of meta-modelling

Direct prediction of key figures of security of supply

Input data

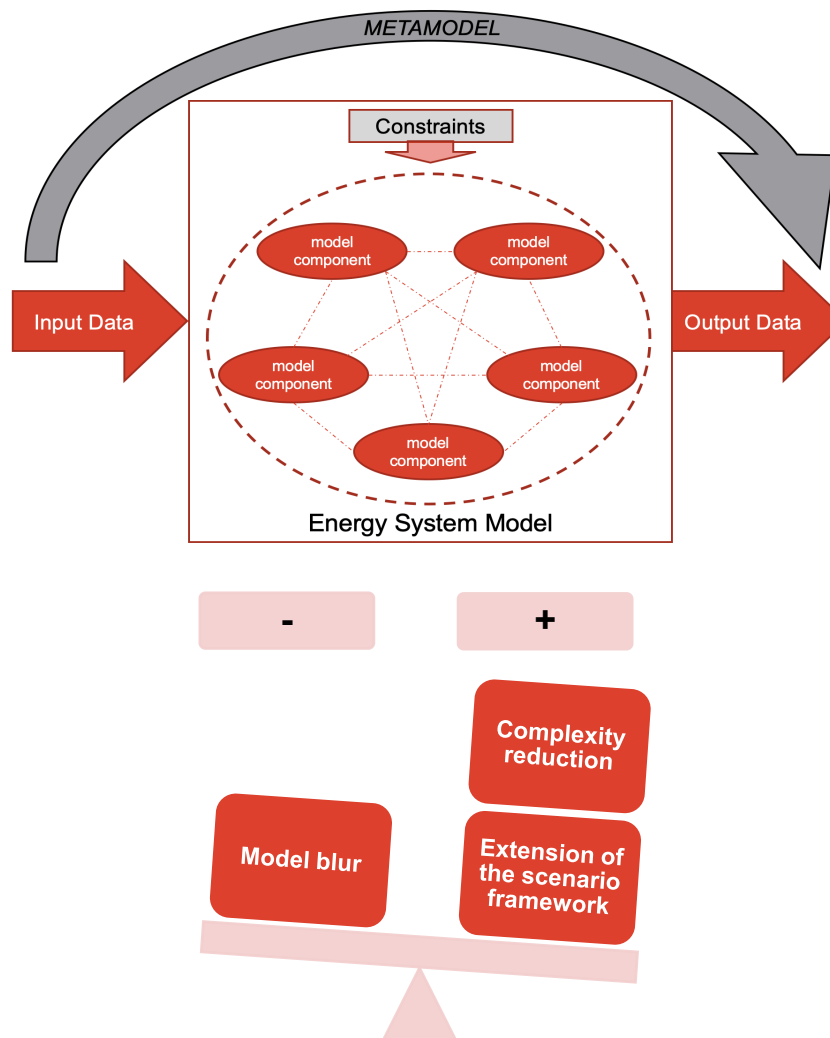
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Renewable
Power plant park
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Import potential from
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Electrical load
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Sector coupling
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Output data

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(Probability that the load cannot be met in one hour)

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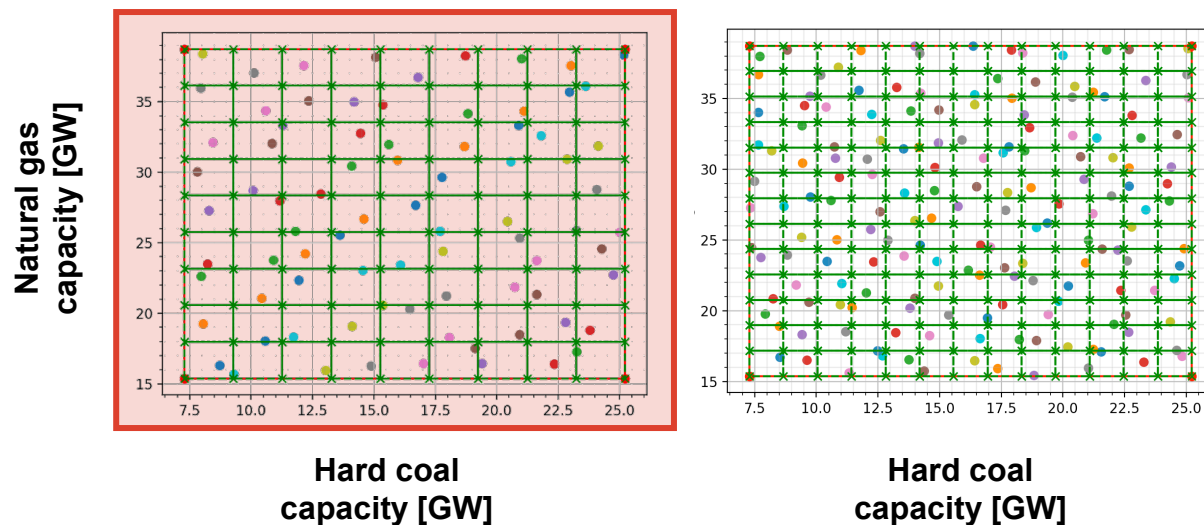
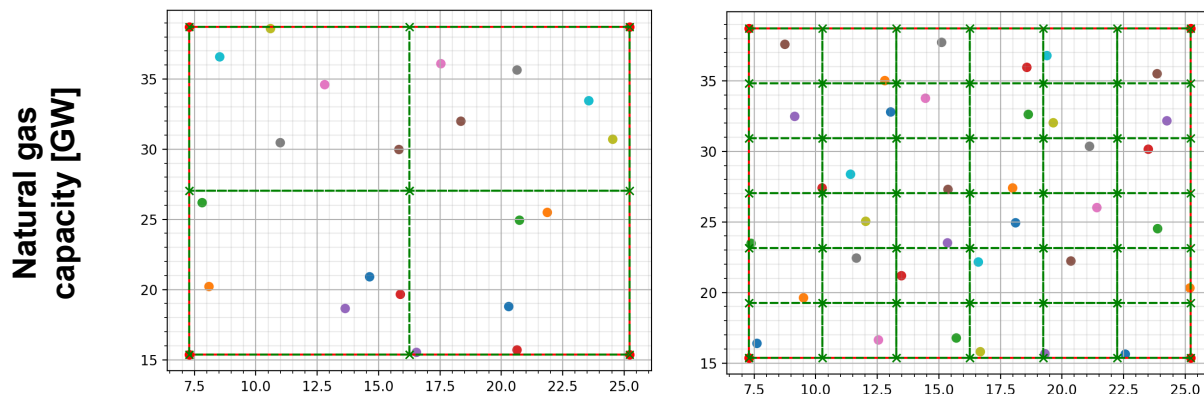
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Expected Energy not Served (EEnS)
(Electricity demand in MWh/h or MWh/a that is not expected to be met)

$$EEnS(t) = \int_{P=0\ GW}^{P=Pr_{res}(t)} (1 - Pr_{available}(t)) dP$$

Selection of training data with the help of statistical Design of Experiments

Support points are defined for training the metamodel, that span an experimental space



+ other variations of capacities for:

- Lignite
- Oil
- Other
- ...

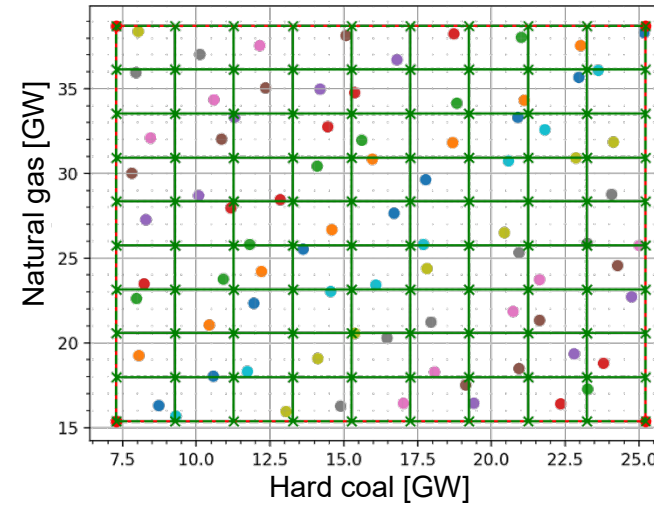
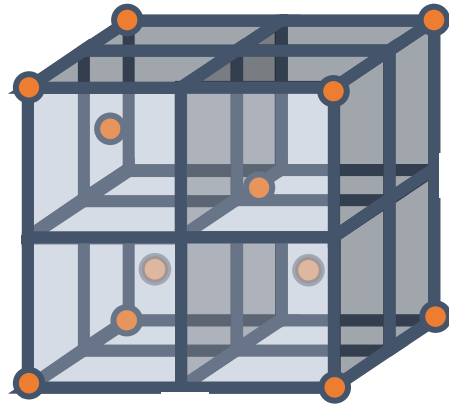
+ hourly Resolved weather years for:

- Electrical load
- Import potential
- Renewable feed-in
- Unavailabilities

→ A total of **~600 million** possible trial points

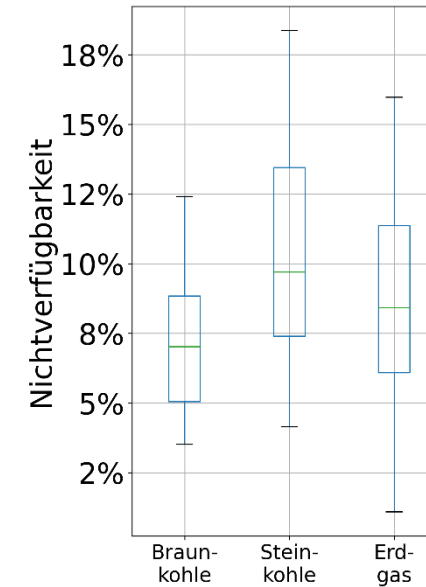
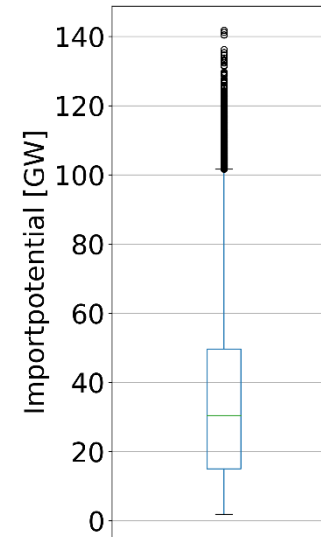
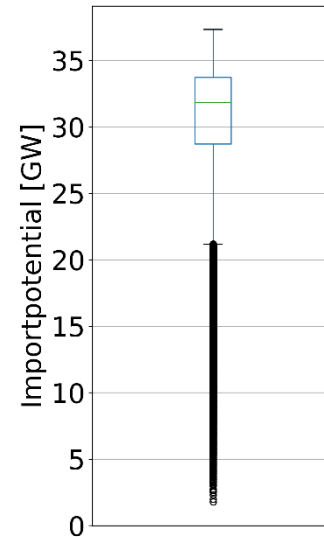
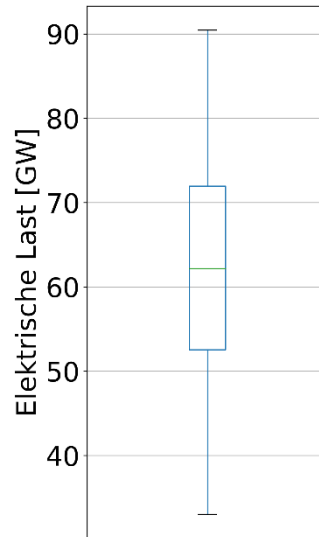
- Definition of **~20 variable input variables** for the metamodel
- From these, **~5,000 - 10,000 variants** are sampled for model training

Artificial neuronal network: The experimental room

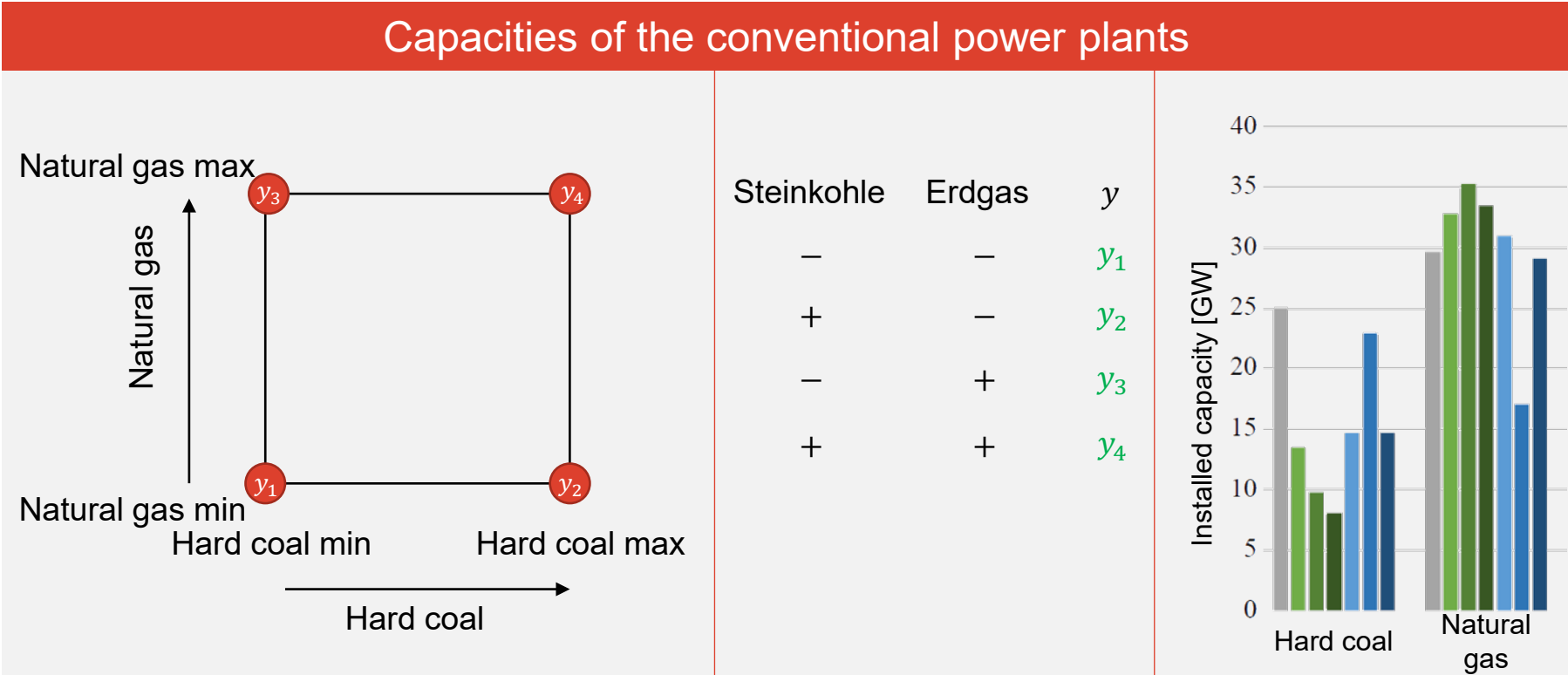


+ other variations of capacities for:

- Lignite
- Oil
- Other

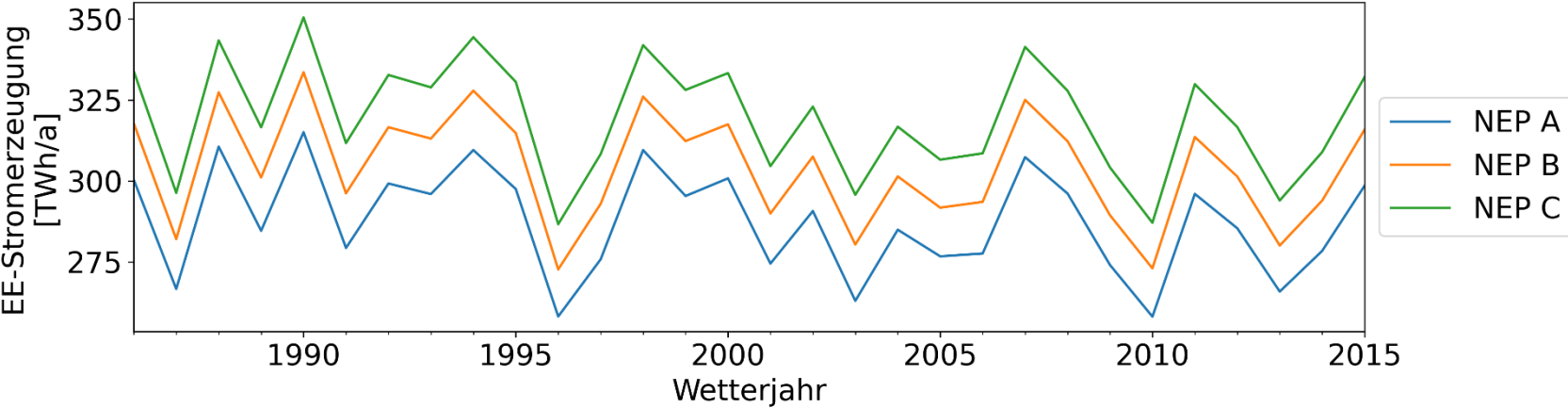
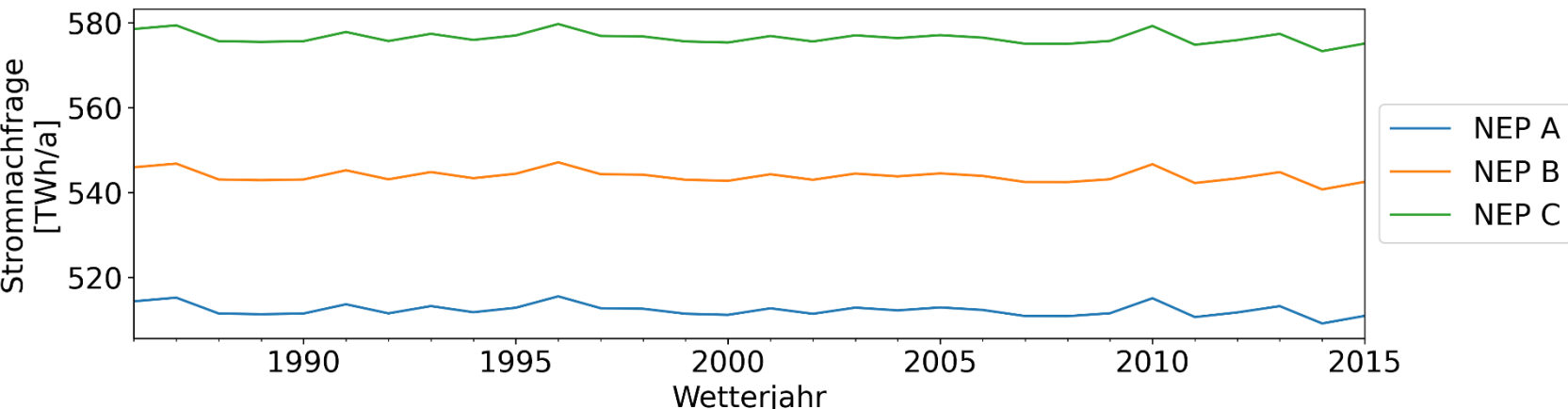


To train the metamodel, support points are defined that span an experimental space

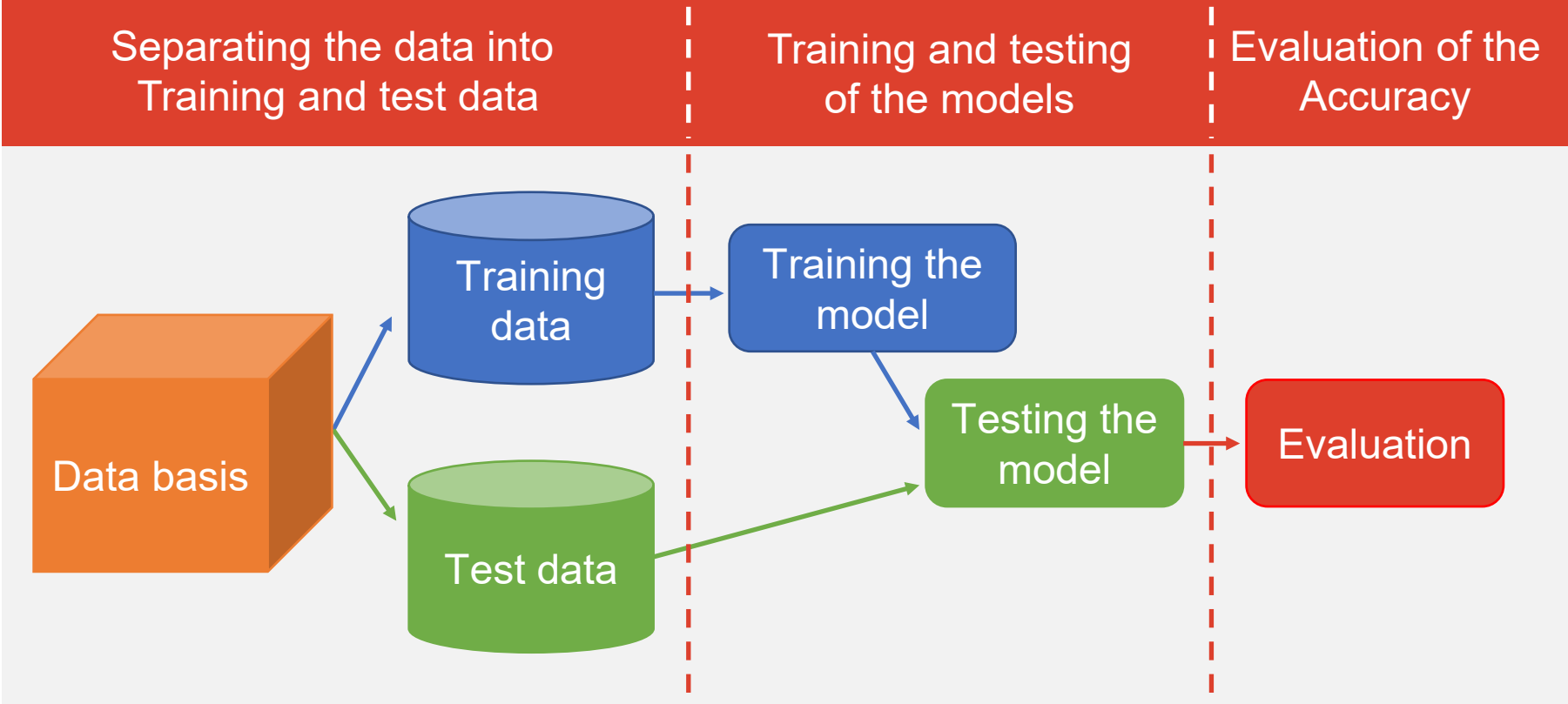


- Scenarios based on the **Grid Development Plan 2030** (as of 2019)
- Additional consideration of an **uncertainty band of +/- 10%**.

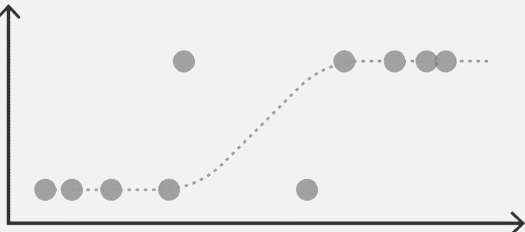
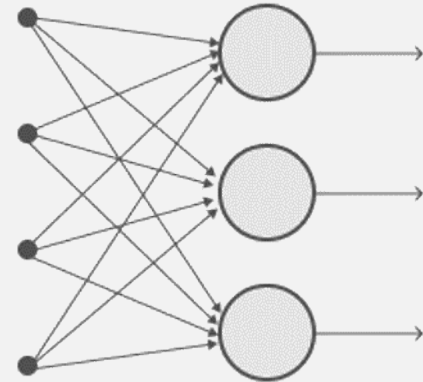
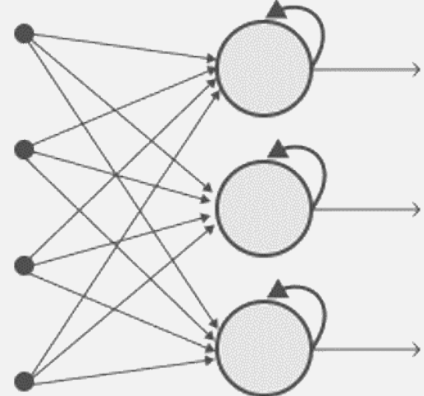
Mapping of different scenarios for the development of electricity demand and the expansion of renewable energies



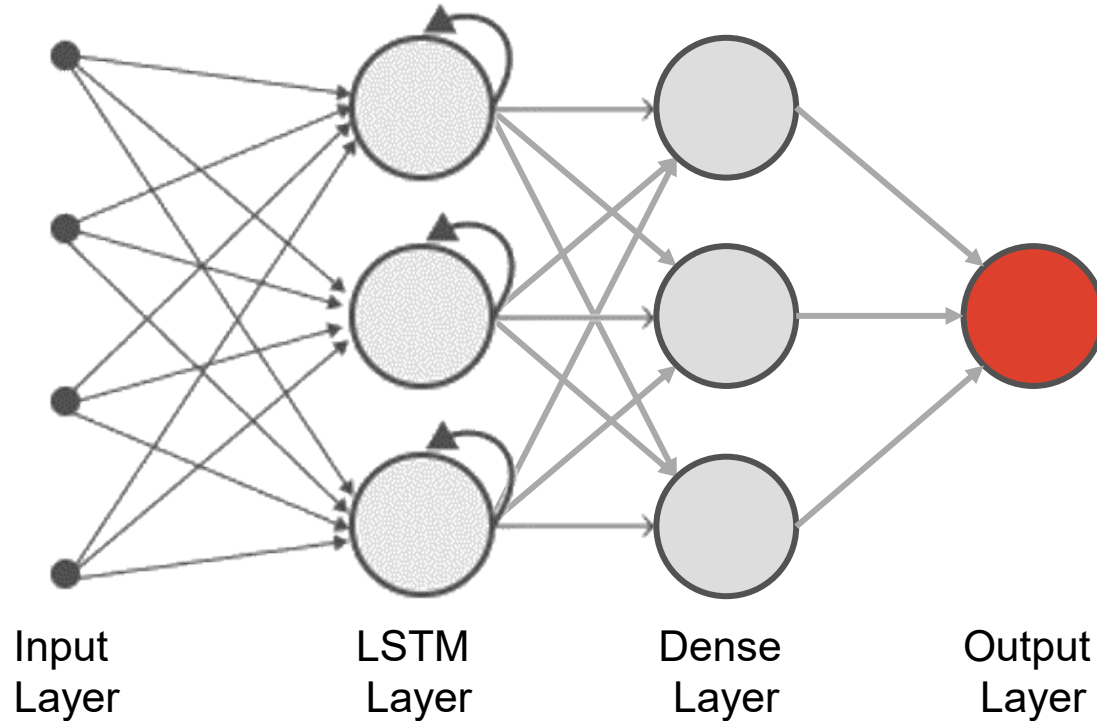
Procedure for training the metamodels



Testing different types of metamodels

Logistic regression (Logit)	Feed-Forward Neural Network	Long Short-Term Memory Neural Network
		
<ul style="list-style-type: none"> + Low training duration - Little possibility for modification 	<ul style="list-style-type: none"> + Diverse possibility for modification - Average training duration - Black box model 	<ul style="list-style-type: none"> + Diverse possibility for modification - High training duration - Black box model

The metamodel: Long Short-Term Memory (LSTM) Neural Network

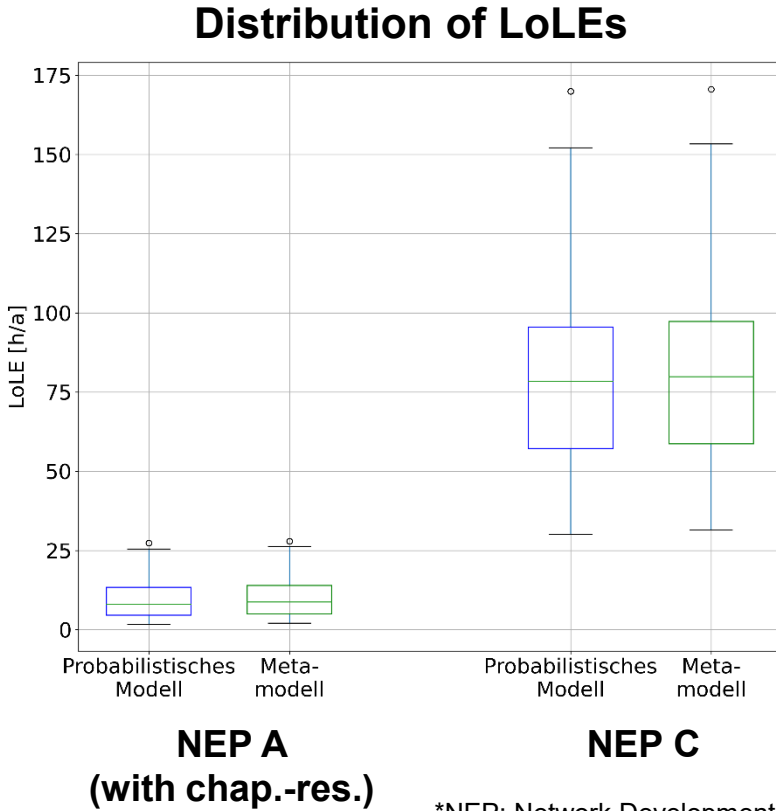
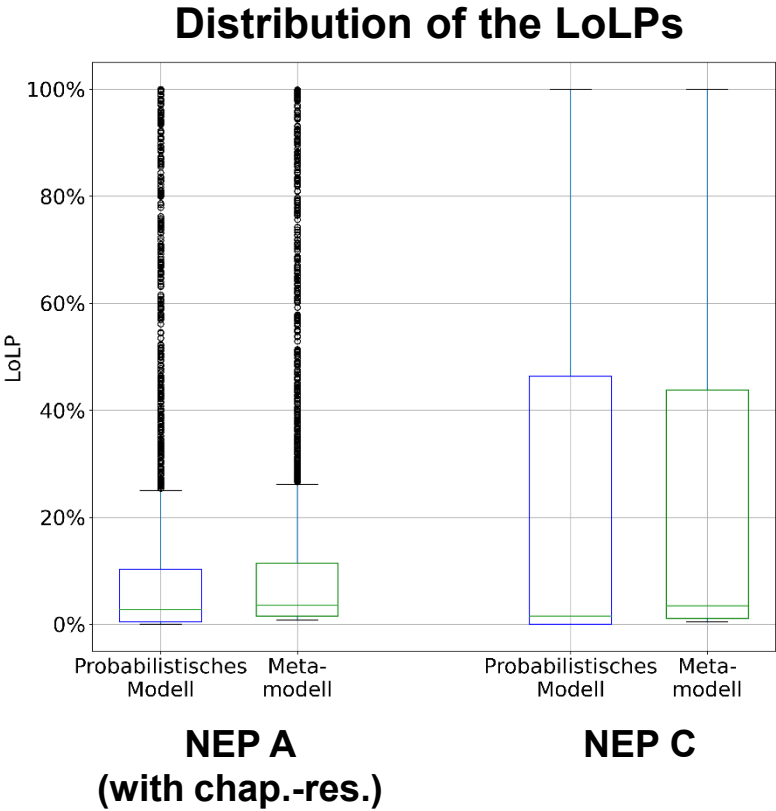


Key figures:

- 4 layers: Input, LSTM, Dense and Output layers
- 3,081 Training weights
- Trained with 262,800 input-output relations

In **comparison with** other tested meta-models, the **recurrent neural network** (here LSTM) shows the **highest accuracy** in the approximation of the simulations

Validation of the metamodel: comparison with scenarios of the NDP*



*NEP: Network Development Plan

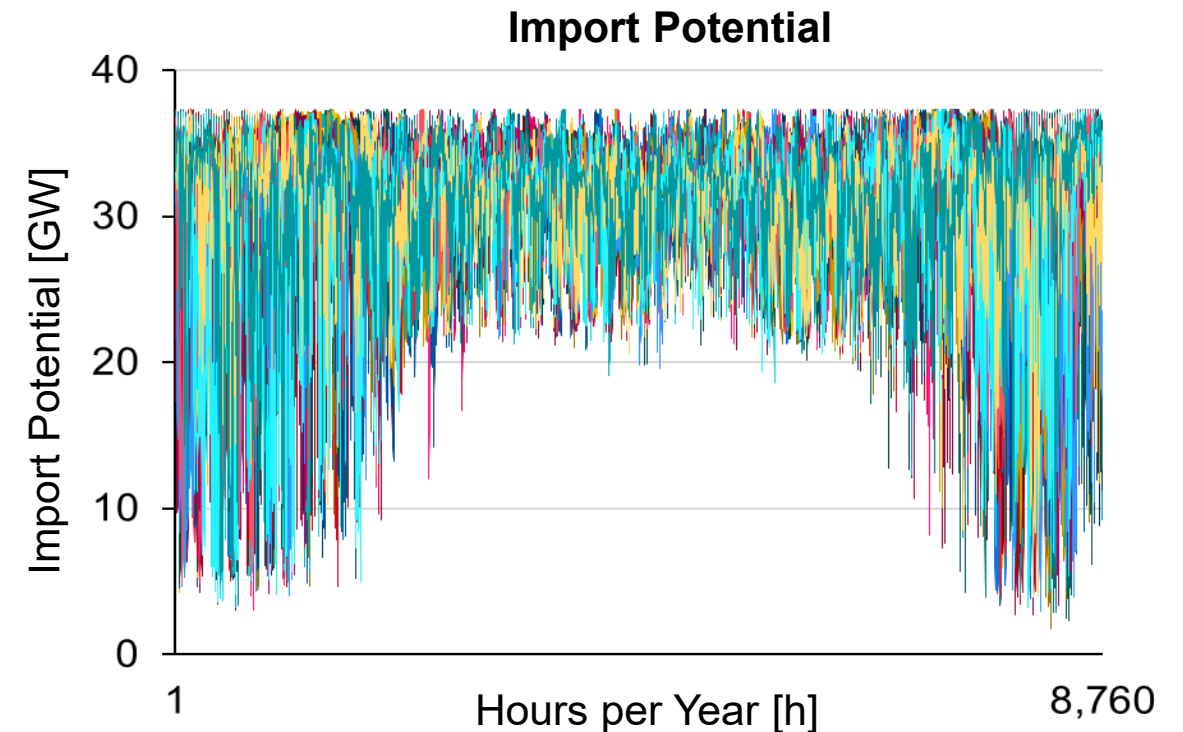
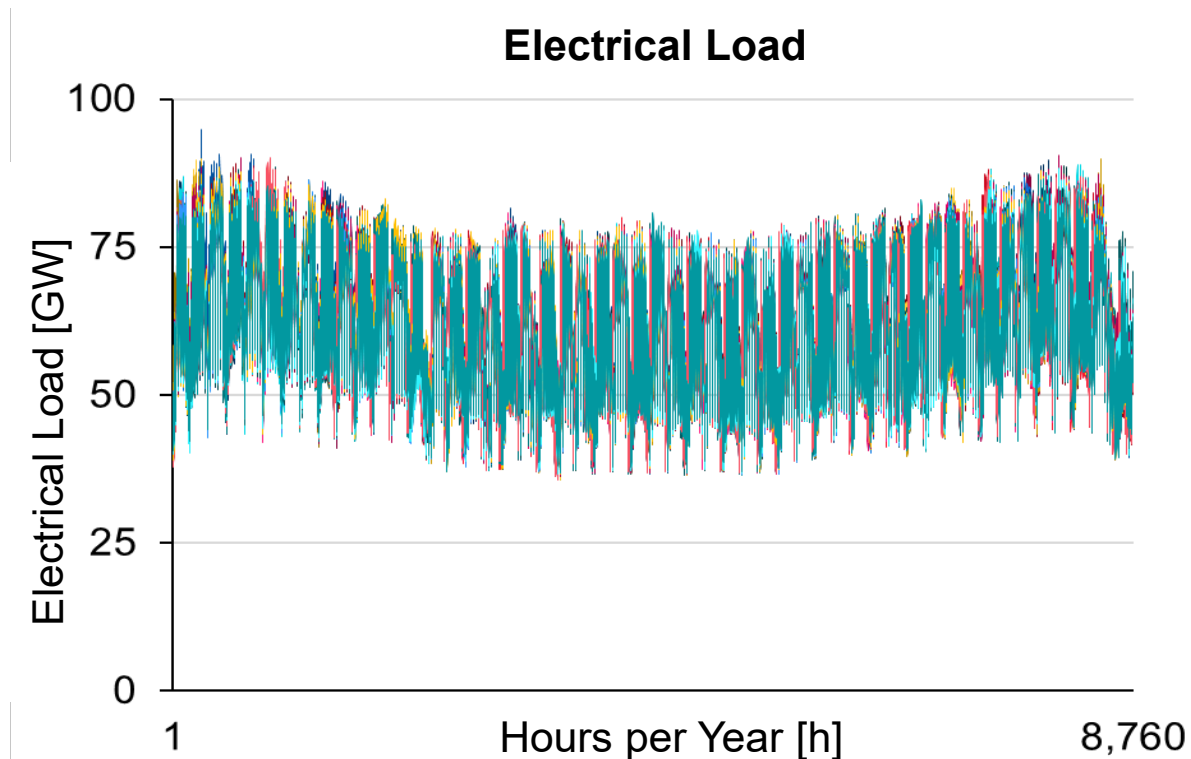
Both hourly (LoLP) and aggregated annual ratios (LoLE) are approximated with **high accuracy** and **low computation time** (seconds)



Scenario framework for the calendar year 2023

Weather influences

- Illustration of **30 weather years**
- Influence of weather years on electrical load, renewable sources of electricity (RES-E) generation, as well as import potentials





Results: Time course of the expected load shortfall

For each hour, 30.000 simulations were carried out

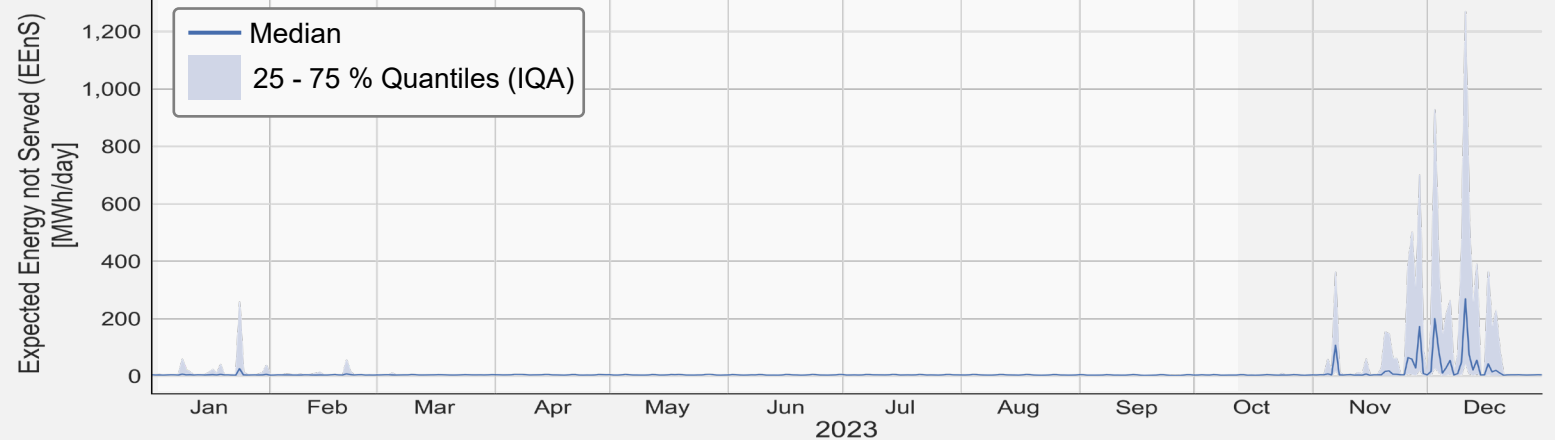
Variant A:

Nuclear power plant lifetime extension until 15 April 2023

Median: 11.4 GWh/a

IQA: 5.5 - 21.3 GWh/a

IQA: Interquartile range



Variant B:

Without nuclear power extension after 31 December 2022

Median: 16.1 GWh/a

IQA: 8.6 - 26.9 GWh/a

IQA: Interquartile range

