

Can energy system modeling benefit from artificial neural networks? Application of two-stage metamodels to reduce computation of security of supply assessments



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ARTICLE INFO

Keywords:

Metamodeling
Complexity reduction
Simulation
Security of electricity supply
Artificial neural networks

ABSTRACT

Assessments of security of electricity supply are of high necessity for decision-makers in politics and industry. Based on scientifically sound and reliable advices, better decisions can be made concerning potential interventions in the energy system. With growing shares of intermittent renewable energy generation, probabilistic methods with high temporal resolution are increasingly important to simulate key indicators of security of electricity supply. However, these simulations are computationally complex and thus very time demanding. For this reason, we propose a two-stage metamodeling approach to reduce computational effort while maintaining high levels of accuracy. In the first step, we represent probability distribution curves of available power plant capacities using sigmoid functions. In the second step, we approximate the relevant regression coefficients. We apply both, linear regression methods and more advanced approaches based on artificial neural networks in this second stage. Our results indicate that computational time can be reduced from ~10 h to ~2 min. Further, the accuracy of the linear regression approach is relatively high and does not comprise the interpretation of relevant key indicators for the assessment of security of electricity supply. However, our results also show that no further accuracy gains can be achieved using artificial neural networks, indicating strong linear relationships. Overall, our approach reduces modeling complexity and therefore allows the investigation of a higher number of different scenarios, thus allowing for deepened insights about the future energy system. Based on our results, we can state that rather simple, but tailor-made approximation methods can outperform more sophisticated approaches if the latter are not suitable for the specific use-case. For future research, the application of artificial neural networks to approximate non-linear relationships within the assessment of security of electricity supply is highly recommended.

1. Introduction

Against the backdrop of ongoing phase-outs of thermal power plants in Germany and other European states, assessments of security of electricity supply are becoming increasingly important. The German government has decided to phase-out all existing nuclear power plants by 2023 as a direct reaction to the Fukushima Daiichi nuclear disaster (German Government, 2011). Moreover, there is an ongoing debate about the possible mothballing of coal-fired power plants to decrease CO₂-emissions. The Commission on “Growth, Structural Change and Employment” that has been appointed by the German Federal Cabinet suggested phasing out all coal-fired power plants in Germany by the year 2038 (Commission for Growth, Structural Change and Employment, 2019). Reduced capacities of controllable power plants

and growing shares of intermittent producing renewables might lead to situations in which electricity supply is not sufficient to cover load, thus e.g. causing load-shedding measures (see Praktiknjo, 2016).

If local and time-limited electricity blackouts occur, German industry will be affected. As the German electricity system has historically been among the world’s most reliable, most industrial sites do not have sufficient back-up systems to maintain production during electricity outages. In recent years, only few electricity supply interruptions due to grid instabilities have occurred. The annual interruption duration per customer in Germany, the so-called system average interruption duration index (SAIDI), has ranged well below 20 min throughout the last ten years (BNetzA, 2018a). During these years, no outages due to a lack of power generation have occurred. However, this might change as a result of the aforementioned changes in the German electricity system

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<https://doi.org/10.1016/j.cie.2020.106334>

Available online 31 January 2020

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Nomenclature			
AC	available capacities	P_i	installed capacity of plant unit i
ANN	artificial neural network	$p_i(t)$	probability for non-availability of block i during hour t
b_0	regression coefficient for intersection	P_0	outage power
b_i	regression coefficient for main effects	Pr	probability
b_{ij}	regression coefficient for interaction effects	\widehat{Pr}	approximated probability
DoE	design of experiments	$q_i(t)$	probability for planned non-availability of block i during hour t
i	index of power plant block	$r_i(t)$	probability for unplanned non-availability of block i during hour t
LoLE	loss of load expectation	SAIDI	system average interruption duration index
LoLP	loss of load probability	ζ_k	curve parameter
MAF	mid-term adequacy forecast	$\widehat{\zeta}_k$	approximated curve parameter
n	number of power plant blocks		
P	threshold power		

and additionally planned generation capacity reductions in other European states.

The needed probabilistic assessments require advanced computer simulations of weather influences and capacity availabilities in order to predict the future security of electricity supply in Germany. Due to the hourly resolution of such simulation models, 8760 evaluations of the probability distribution of available power plants need to be performed for each scenario under investigation. As the calculation of these probability distributions is very computationally intensive, high runtimes limit the possibilities of analyzing a large variety of different scenarios for future power plant parks. However, such system analyses are of special importance to provide independent scientific advice for decision makers in politics and industry as future developments are inherently subject to uncertainties.

Considering real-life use-cases for the assessment of electricity supply in Germany as introduced in Section 5, we therefore focus on the efficient acceleration of runtimes using two-stage metamodels based on linear response and artificial neural networks (ANNs). Our research questions are as follows:

1. Can energy system modeling benefit from the application of ANNs to decrease computational effort?
2. What would be the gains in runtime and losses in accuracy of the approximation based on linear regression and the ANN-based approach?

The remainder of this paper is structured as follows: In Section 2, we provide an overview on relevant literature and carve out the existing research gap. In Section 3, we introduce the simulation model that is used to assess security of electricity supply. In Section 4, we then present the methodological approaches used for runtime accelerations. We then briefly summarize necessary input data and the scenarios that were chosen to assess security of electricity supply in Section 5. Section 6 shows our results and provides discussions with regards to both, runtime accelerations and accuracy losses. Finally, we provide a conclusion and outlook for possible future research in Section 7.

2. Literature review

Here we briefly summarize the current scientific state of the art regarding the computational assessment of security of electricity supply as well as approximation methods based on linear response and ANNs. We then conclude the existing research gap.

2.1. Assessment of security of electricity supply

For the assessment of security of electricity supply, two different approaches are commonly applied: Firstly, a variety of studies use deterministic balance sheets of available capacities and peak load as used by transmission grid operators (cf. entso-e (2015), German

Transmission System Operators (2018)), regulating authorities (cf. BNetzA (2018a)), and consultancies (cf. Agora Energiewende (2017), Energy Brainpool (2015), Öko-Institut (2012) and Prognos (2015)). Secondly, other studies perform probabilistic simulations in high temporal resolution that reflect the weather dependency of load and renewable feed-in (c.f. Praktijnjo and Dittmar (2016)). This probabilistic approach has also been applied by grid operators (cf. entso-e (2017) and Pentalateral Energy Forum (2018)) and consultancies (cf. Consentec & r2b energy consulting (2015), EICOM (2017), and frontier economics, FORMAET Services (2014)) in varying degrees of accuracy.

There are two features that distinguish these approaches. Firstly, the complexity of calculations is much higher for probabilistic approaches. Secondly, the results of deterministic approaches need to be interpreted differently from those of stochastic calculations. Balance sheets of available capacities and peak load rely on rather simple spreadsheet calculations, whereas probabilistic assessments require advanced simulations of weather influences and capacity availabilities.

However, the results of probabilistic simulations reflect the stochastic character of real-world conditions more closely than deterministic approaches. E.g., the authors of the EU Clean Energy Package state that a deterministic approach to assess security of electricity supply “does not give a reliable picture of the adequacy situation due to the increase in renewable energies in electricity systems” (Meeus & Nouicer, 2018). To account for this, we have developed a python-based probabilistic module as part of the JERICH0 energy system model from RWTH Aachen University to assess security of electricity supply. The module that is briefly presented in this paper (see Section 3) incorporates stochastic fluctuations of both renewable feed-in and electricity demand as well as volatile availabilities of power plant capacities. In order to reflect the stochasticity of weather influences, we perform hourly simulations for 30 different weather years (1986–2015). This enables us to conduct scientifically sound assessments of security of electricity supply for different future scenarios. However, we face runtime constraints that prevent us from analyzing a multitude of different scenarios. As this problem is common for probabilistic simulations of security of electricity supply, it is of high importance to decrease computational effort so as to allow for a broader applicability of the models.

2.2. Metamodeling using linear regression and artificial neural networks

To increase computational efficiency and to lower runtimes, linear regressions and ANNs are used among other approaches as metamodels to reflect a functional relationship between input and output variables based on a gathered set of information. While conducting linear regressions can be described as a rather simple and straightforward approach for the task of function approximation, the implementation of ANNs tends to be more sophisticated and requires more specific knowledge. This difference in complexity is reflected in the possibilities

that arise when using the approaches to model a functional relationship: linear regressions are useful when the underlying functional relationship can be assumed to be *linear*, while ANNs are suitable for also approximating *non-linear* functional relationships.

Linear regressions, or in more general terms polynomial functions, have a fixed parametric form consisting of regressors and their corresponding regression coefficients. The latter are evaluated using least square methods.¹ To gather information that is useful for a statistically sound analysis, design of experiments (DoE) is used to sample appropriate information very efficiently in an experimental environment where experiments can be time consuming and costly. A good overview of DoE is provided by [Montgomery \(2017\)](#).

Once real-world experiments are substituted by computer-aided experiments, the situation changes: while simulations can still be very time consuming and costly, the simulation setup can be changed at low effort, allowing to sample the space of interest with a higher resolution. For many use-cases, simulations have a rather complex nature resulting in more non-linear responses that ordinary polynomial functions cannot map. For this purpose, the aforementioned ANNs can be used. A short and use-case oriented introduction to ANNs is given in [Section 4.2](#).²

These more elaborated approaches often outperform classical approaches as shown by [Reich, Adam, and Lambach \(2017\)](#), who deal with the approximation of energy supply system responses with the goal of optimizing the system's structure and dimension. [Biedermann, Reich, Kameier, Adam, and Paschereit \(2018\)](#) show that, under certain circumstances, the more sophisticated approaches can even be utilized for experimental setups. Thus, we can conclude, based on the existing literature that the application of linear regression methods and ANNs are promising approaches to decrease runtimes of probabilistic simulation models to assess security of electricity supply. Hence, the implementation of both approaches seems reasonable and the comparison will allow us to work out which is the best suited approach.

2.3. Existing research gap

Our literature review demonstrated that

- (1) complex, probabilistic simulation models might reflect the stochastic nature of real world conditions more realistically, but come with high runtimes that prevent from analysing a multitude of scenarios,
- (2) both linear regression methods and ANNs are promising methods to reduce computational effort of simulation models in the sense of metamodeling.

To the best of the authors' knowledge a combination of metamodeling approaches and probabilistic simulation of security of electricity supply has not been analysed, yet. Thus, we introduce a probabilistic model and assess the runtime gains and accuracy losses of different metamodeling approaches in the following.

3. Description of simulation model

In this section, we briefly present our current state-of-the-art simulation model for assessing security of electricity supply. First, we introduce our approach for modeling the availability of a single power plant unit. Second, we demonstrate the computationally high-demanding process (so-called *recursive convolution*) that is used to aggregate the availabilities of all installed plant units to one probability

¹ For further readings on linear regression, we refer readers to [Moré \(2012\)](#) and [Meeus and Nouicer \(2013\)](#).

² A more detailed introduction is provided by [Zurada \(1992\)](#). A more recent overview on current processes in the field of ANNs, machine learning and computational intelligence is provided by [Biedermann et al. \(2018\)](#).

distribution curve. Finally, we summarize all other model parts that are not within the focus of this study but necessary to calculate scientific key indicators of security of electricity supply.

3.1. Power plant availabilities

The aggregated amount of available power plant capacities follows a stochastic distribution. This distribution can be derived based on the realistic assumption that each block of the controllable power plant portfolio has two possible states: complete availability or non-availability. Thus, each power plant block follows a discrete *Bernoulli distribution* independently of all other blocks. The state of non-availability for a power plant block with index i at a given time t occurs with probability $p_i(t)$. Accordingly, the probability that the block is fully available is given by the converse probability $1 - p_i(t)$.

When deriving the probability of non-availability, we differentiate the two categories, planned and unplanned non-availability, according to [VGB e.V. \(2017\)](#). We define planned unavailability such that the start and duration of the unavailability are determined at least four weeks before their occurrence. If the lead-time is shorter, we designate this an unplanned unavailability.

In the following, the probability of a planned unavailability is referred to as $q_i(t)$. The probability of an unplanned unavailability is defined as $r_i(t)$.

According to [Fig. 1](#), the probability of non-availability of a power plant unit $p_i(t)$ is the cumulative probability of planned unavailability and unplanned unavailability in the case of no maintenance. It can be calculated as follows:

$$p_i(t) = q_i(t) + (1 - q_i(t)) \cdot r_i(t) = q_i(t) + r_i(t) - q_i(t) \cdot r_i(t) \quad (1)$$

3.2. Recursive convolution

Having shown the derivation of the time-dependent outage probability of an individual power plant unit in the above paragraphs, we now extend this consideration by merging a large number of individual units into one system.

The fact that each block of the controllable power plant portfolio can take two discrete states results in a total of 2^n possible states when abstracting to n blocks. Hence, there exist about $6.7 \cdot 10^{240}$ possible states for a total of approximately 800 power station units in Germany. For the assessment of security of electricity supply, the probability that a given capacity is available needs to be calculated. As a direct calculation is not computationally feasible due to the high number of possible states, we apply the mathematical concept of *recursive convolution*. This implies that the calculation is extended recursively by adding one power plant unit after another. The probability $\Pr_i(P_O > P)$ that the outage power P_O exceeds a given threshold P in a system with i power plant units can be formulated recursively, according to [Brückl \(2006\)](#), as:

$$\Pr_i(P_O > P) = \Pr_{(i-1)}(P_O > P) \cdot (1 - p_i(t)) + \Pr_{(i-1)}(P_O > (P - P_i)) \cdot p_i(t) \quad (2)$$

Where:

$$\begin{array}{ll} Pr: = \text{Probability} & P_O: = \text{Outage power} \\ P: = \text{Threshold power} & P_i: = \text{Installed capacity of plant unit } i \end{array}$$

The flowchart in [Fig. 2](#) summarizes the necessary processes to calculate the distribution of available capacities considering n blocks. This process needs to be carried out for each hour under investigation as the probability of non-availability $p_i(t)$ varies accordingly.

The process as described above finally provides a probability distribution of available capacities. Hence, a curve is calculated, which assigns probability values to capacities, as shown by the example in [Fig. 3](#).

However, the complexity of numerical simulations initially led to high computational times despite using the efficient formulation of the

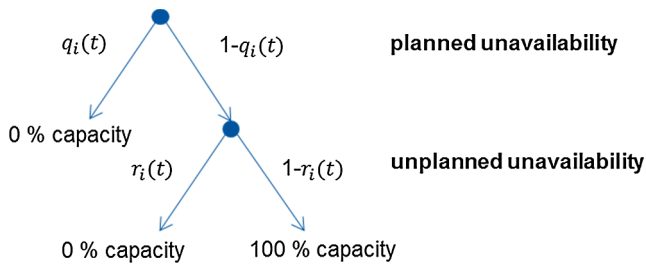


Fig. 1. Planned and unplanned unavailability.

convolution algorithm as published by Ibanez and Milligan (2012). This is caused by the hourly resolution leading to 8760 convolutions per year under investigation. For this reason, we use the computing cluster of RWTH Aachen University for the simulations. Here, we requested the

smp-l-bull cluster, providing 32 cores at 2.0 GHz with total RAM memory of 256 GB. Despite using high-performance computers and parallelizing the program code, the runtime per scenario still ranged in an order of magnitude of 10 h (for a more detailed runtime analysis, see Section 6). Hence, we applied more advanced techniques to accelerate computational time by using metamodels. Section 4 shows these approaches in more detail.

3.3. Calculation of scientific key indicators for security of electricity supply

Having derived the distribution curve of available capacities, in the following paragraphs we briefly summarize all additional steps that are necessary to scientifically evaluate security of electricity supply. However, as their computational effort is significantly lower than the runtime of the recursive convolution algorithm, the latter parts of the model are not within the focus of this paper. Thus, only a short

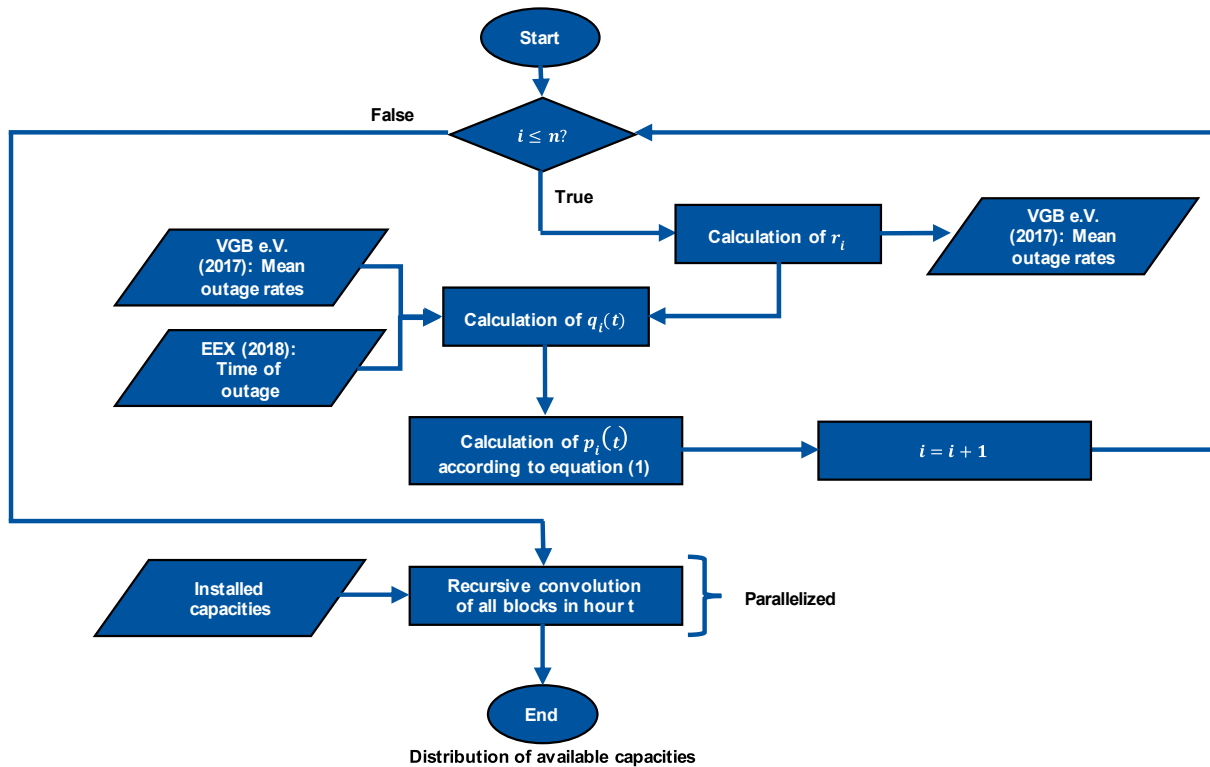


Fig. 2. Calculating the distribution of available capacities – flowchart.

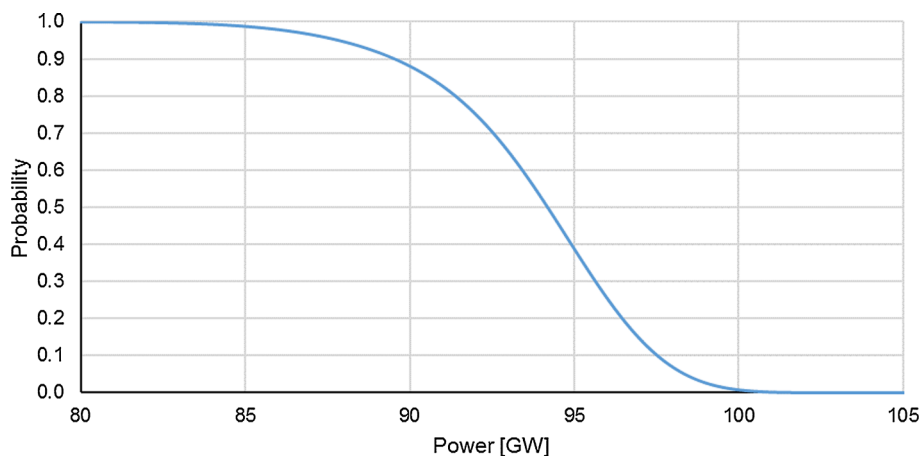


Fig. 3. Sample distribution of available capacities.

overview is provided here in order to enable a comprehensive analysis.

Once the probability distribution of available controllable power plants has been conducted, the following steps need to be performed: (1) modeling of electricity load and renewable feed-in in hourly resolution for each scenario under investigation, (2) implementation of contributions from neighboring countries, and (3) calculation of scientific key indicators for the assessment of security of electricity supply.

3.3.1. Electricity load and renewable feed-in

As the calculated probability distribution only reflects the availability of *controllable* power plants, the contribution of fluctuating renewables needs to be accounted for on the load side within the model. For this reason, residual load (i.e. electricity load minus renewable feed-in) is calculated. To do so, two factors need to be determined for each hour under investigation: first, electricity load and second, the feed-in of fluctuating renewables.

To simulate the temperature dependency of loads in the countries studied, we derived country-specific functions, which depict the relationship between electricity load and temperature. We simulated the temperature sensitivity of electricity loads using these functions, historical weather data, and the normalized electricity load profiles that are published in the *Mid-term Adequacy Forecast* (MAF) by [entso-e \(2016\)](#).

To model the feed-in of fluctuating renewable energies, we used two data sets by [González Aparicio et al. \(2016\)](#) and [González Aparicio, Huld, Careri, Monforti, and Zucker \(2017\)](#). These data sets comprise standardized, hourly feed-in hydrographs for wind (off- and onshore) and photovoltaics for 30 weather years (1986–2015). In addition, we used data as published by [Copernicus \(2018\)](#) on daily feed-in of run-of-the-river power plants, and interpolated this to hourly resolution.

Finally, residual load can be calculated as the difference between electricity load and renewable feed-in. The intersection of the distribution curve of available capacities, as derived within [Section 3.2](#) and the residual load determines the probability that the electricity load in a given hour for a given weather year can be covered, as depicted in [Fig. 4](#). Here, the probability to cover residual load in the presented hour emerges as 90%.

3.3.2. Contributions from neighbouring countries

The purely national approach as described above is extended by taking into account potential foreign contributions to cover the electricity load in Germany. Within our simulations, contributions from Austria, Belgium, Switzerland, Czech Republic, Denmark, France, the Netherlands, Norway, Poland, and Sweden are considered due to the countries' direct electrical connection to the German grid. This potential from neighboring countries is accounted for on the load side. Potential imports are subtracted from the residual load within Germany.

3.3.3. Determination of key indicators

To reflect realistic conditions, probabilistic influences need to be accounted for within the model. On the load side, this comprises temperature effects and fluctuating import potentials. On the supply side, both weather effects on renewable feed-in and hourly changing power plant availabilities need to be considered. This leads to hourly shifting probabilities to cover residual load, as shown in [Fig. 5](#).

Stochastic key indicators reflect this fluctuating behavior. Based on the model outputs, the hourly *Loss of Load Probability (LoLP)* can be calculated as complementary probability according to the following equation:

$$LoLP = 1 - P_{load_coverage} \quad (3)$$

LoLP reflects states in which available capacities are not sufficient to cover electricity load completely. An evaluation of *LoLPs* is especially interesting for hours of peak load and peak residual load.

By aggregating *LoLP* values over the course of a year, one can determine the so-called *Loss of Load Expectation (LoLE)*. This indicator reflects the expected loss of load duration stated in hours. Thus, the *LoLE* value represents all stochastic influences on both the demand and on the supply sides that occur within the period under consideration.

$$LoLE = \sum_{t=1}^{t=8760} LoLP_t \cdot 1h \quad (4)$$

4. Reducing computational effort

As stated in [Section 3.2](#), the computational effort for calculating the hourly resolved distribution of available capacities in current state-of-the-art models is very high, ranging in the order of magnitude of 10 h per simulation run. However, this time effort is already relatively low when directly compared to the six days that each run took before utilizing the high-performance computer cluster and a parallel code structure. Since the computational effort is mainly caused by the high number of hours being evaluated, the goal is to further decrease computing time by performing fewer convolutions while still being able to evaluate the indicators mentioned in [Section 3.3.3](#) as precisely as possible.

The proposed method of two-stage metamodelling to further reduce the computational effort can be explained as follows:

Stage 1: Representing the probability distribution of available capacities

The availability distributions for each hour of the year (see [Fig. 3](#)) have the general form of a sigmoid functions. Though it can be represented by other functional relationships, as for example different

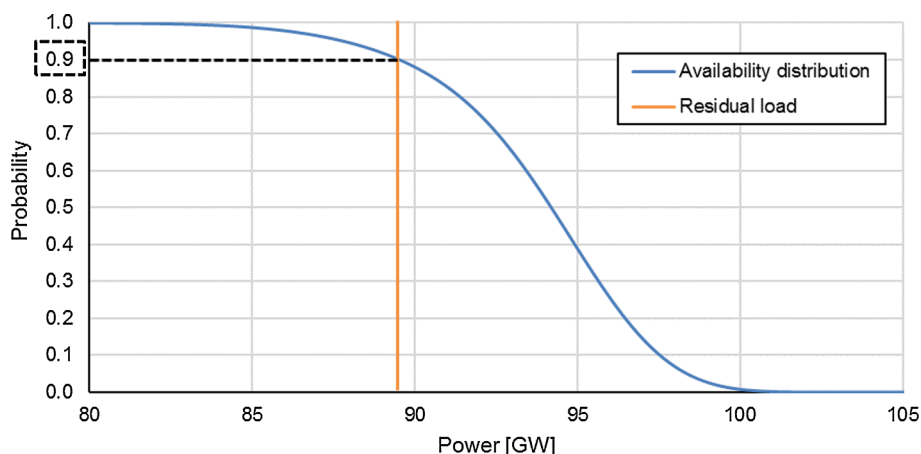


Fig. 4. Sample calculation of probability to cover residual load.

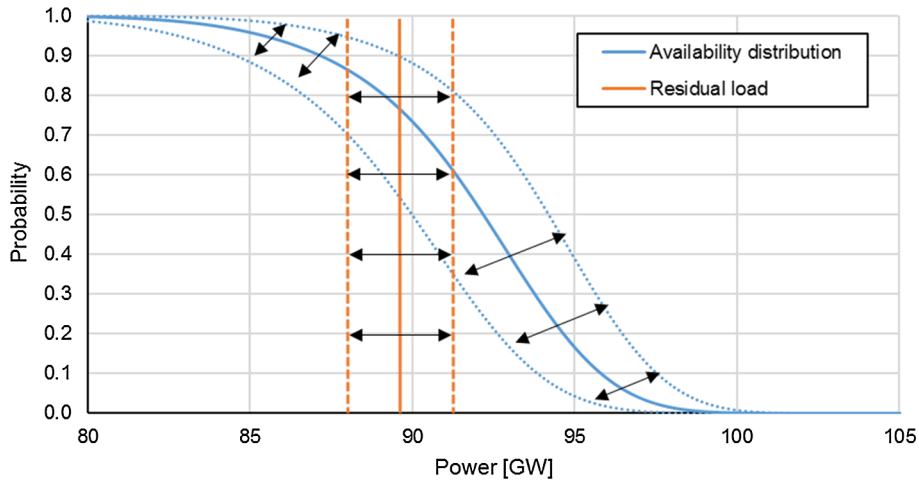


Fig. 5. Time dependency of capacity distribution and residual load.

kind of distribution functions, in the scope of this paper we have focused on a sigmoid function according to Eq. (5). Thus, the first-stage of our metamodeling approach is to approximate the availability distribution using the sigmoid function.

$$\widehat{Pr} = \left(1 + \exp\left(\frac{AC - \zeta_1}{\zeta_2}\right) \right)^{-\zeta_3} \quad (5)$$

where

AC := Available capacity \widehat{Pr} := Approximated probability
 ζ_k := Curve parameter, $k = 1..3$

In detail, the originally calculated distribution is approximated by determining three influencing curve parameters, namely the vector ζ_k . This is performed by utilizing a least-squares method solved with the Levenberg-Marquardt algorithm (Moré, 1978). Step 1 does not need to be carried out for each of the 8760 h of the year, but rather for certain well-defined combinations of probabilities for non-availability of power plant units p_i . The calculation of the best fitting combinations mainly depends on the assumed underlying type of relations (i.e. linear or non-linear) as discussed in more detail below.

Stage 2: Approximating the regression coefficients

If the distribution changes during the course of the year due to variations of $p_i(t)$, the curve parameters ζ_k need to be adjusted accordingly. Thus, if the functional relationship of $\zeta_k(p_i(t))$ can be estimated, the distribution for every hour of the year can be approximated, too.

The first step in determining $\zeta_k(p_i(t))$ is to construct the so-called design space, in which the functional relationship is required to be valid. For this, the maximum and minimum of $p_i(t)$ are determined. Consequently, the design space covers combinations of p_i that are not part of the original time series $p_i(t)$.

In this design space, information is gathered to model ζ_k using a linear approximation as well as an ANN. Both metamodels are used and compared in this study. The choice of linear regression methods implies the assumption of linear relations, whereas ANNs are especially suitable for non-linear relations between the input parameters (changing $p_i(t)$) and the output parameters (i.e. $\zeta_k(p_i(t))$) in this case).

To gather appropriate information, designs are set up that define certain factor level combinations of p_i . With those factor level combinations, the time-dependency of $p_i(t)$ vanishes. Both approximation models as well as their corresponding designs are explained in more detail in the following subsections. Fig. 6 visualizes the workflow for the two-stage metamodeling. The depicted procedure results in approximations of the original distribution curves, causing negligible

computational effort. This in turn allows us to approximate the key indicators stated in Section 3.3.3 for any given time series of $p_i(t)$.

4.1. Linear response considering interactions and two-level factorial design

The functional relationship for approximating the vector ζ_k assumes a linear response and can be written as follows:

$$\widehat{\zeta}_k = b_0 + \sum_{i=1}^n b_i p_i + \sum_{i=1}^{n-1} \sum_{j=i+1}^n b_{ij} p_i p_j \quad (6)$$

where

$\widehat{\zeta}_k$:= Approximated curve parameter, $k = 1..3$
 b_0 := Regression coefficient for intersection
 b_i := Regression coefficient for main effects
 b_{ij} := Regression coefficient for interaction effects
 n := Number of power plant units

To determine b_0 , b_i and b_{ij} , a system of linear equations needs to be solved. This is done using the least square method (Moré, 1978). Performing simulations using a full factorial two-level design (sampling all extreme value combinations, more details are given in Section 4.2)

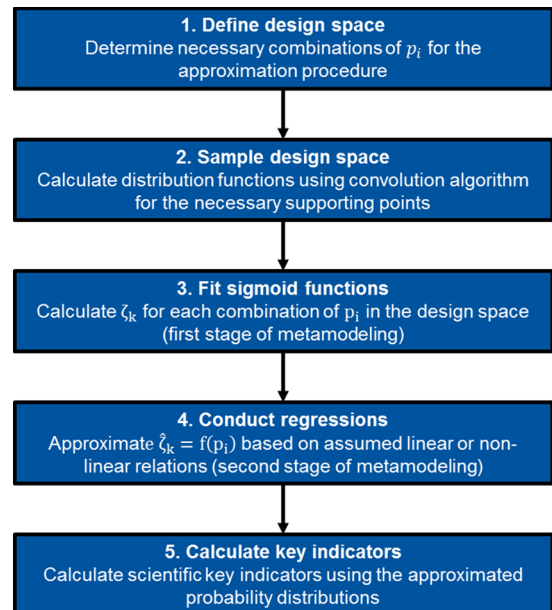


Fig. 6. Workflow of two-stage metamodeling.

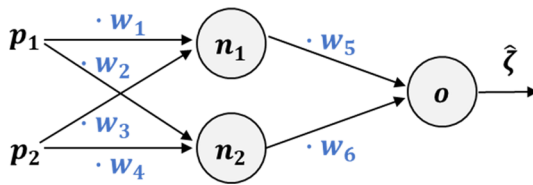


Fig. 7. Simplified schematic of an artificial neural network architecture. The inputs (p_1 and p_2) are multiplied by according weights $w_{i=1,\dots,4}$ and summed, as well as transformed within the neurons n_1 and n_2 using an activation function.

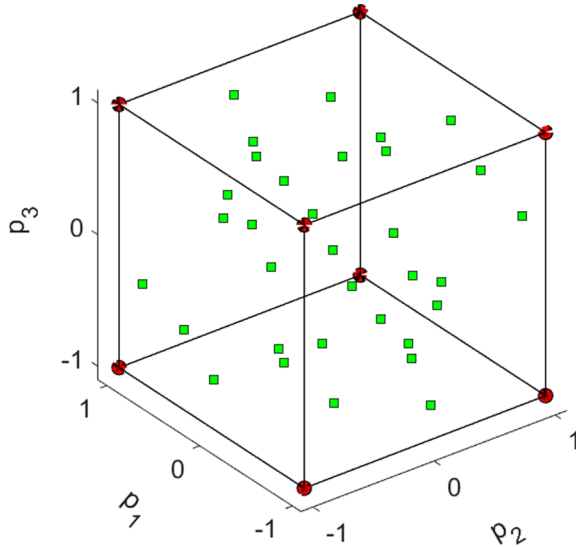


Fig. 8. Two-level factorial design (red dots) in the normalized p_i design space to determine a linear regression as well as combined with a *Latin Hypercube Design* (green rectangles) to train an ANN.

Table 1
Investigated scenarios.

Year	Additional phase-out of coal-fired power plants	
	0 GW	8 GW
2020	2020	2020_–8GW
2022	2022	2022_–8GW
2023	2023	2023_–8GW

Table 2
Evaluation of runtimes and memory usage.

Scenario	Number of simulations [/]	Total runtime [sec]	Total runtime [h]	Average memory [MB]	Max memory [MB]
<i>Exact approach</i>					
2020	8760	37,085	10.30	6847	8859
2022	8760	34,705	9.64	6718	8643
2023	8760	35,428	9.84	6620	8405
2020_–8GW	8760	32,039	8.90	6586	8393
2022_–8GW	8760	30,602	8.50	6593	8367
2023_–8GW	8760	27,834	7.73	6500	8170
<i>Approximation</i>					
2020	16	125	0.03	1334	1788
2022	16	117	0.03	1323	1780
2023	8	116	0.03	1073	1441
2020_–8GW	16	108	0.03	1132	1783
2022_–8GW	16	103	0.03	1140	1799
2023_–8GW	8	90	0.03	960	1446

gives enough information to solve such a system. A graphical representation of this design for three dimensions is shown in Fig. 8, where each simulation is indicated as a red dot. As one can see, the information is concentrated in the corners of the design space.

4.2. Combining artificial neural network and Latin Hypercube design

If a non-linear relationship is considered, ANNs are frequently applied, as they are known to provide very powerful universal approximations (see. e.g. Rao and Srinivas (2003)). ANNs consist of so-called neurons (in analogy to the human brain) that process the received inputs (here: p_i) by calculating weighted sums and transforming the result using so-called activation functions, usually a sigmoid-function. Those neurons are arranged in layers between the inputs and the outputs, so-called hidden-layers. ANNs for regression-type problems only require one neuron for the output-layer which uses the identity activation function and thus only performs the weighted sum. In our work, we use ANNs to estimate the curve parameters $\hat{\zeta}_k$ as introduced in Equation (6) and thus combine this tool with the energy system model as introduced in Section 3.

A simplified schematic of an ANN with two inputs, one hidden-layer with two neurons and one output layer with one neuron is depicted in Fig. 7: This illustration does not depict the actual ANN design used in this research (cf. Table 5). However, it links the simplified schematic with an energy system model. Therefore, probabilities for non-availability of power plant units p_i are assigned to input neurons and a curve parameter $\hat{\zeta}_k$ to estimate LoLP values is assigned to the output neuron.

The weights that are eventually used to process the inputs and thereby allow to predict the output, are calculated by performing *supervised learning*: training data, consisting of known input-output pairs, is processed by the ANN. The ANN tries to predict the output with initially randomly chosen weights. After this *forward pass*, the weights are adapted as to minimize a certain error function. This process is consequently named *backward pass*. The procedure of forward and backward pass is repeated until a certain stop criterion is fulfilled (e.g. number of iterations, so-called *epochs*). To adapt the weights, many different approaches are used. In this paper, we use the *Levenberg-Marquardt* algorithm combined with *Bayesian regularization* as described originally in Foresee and Hagan (1997), due to its good generalization ability, which allows all sampled information to be used to adjust the weights. To find the best network structure (number of layers and number of neurons per layer), a heuristic search algorithm is utilized which limits the maximum number of hyperparameters (weights and bias values) to the number of training data and evaluates the networks performance using the mean squared error.

The information, or more specifically the input-output pairs, are sampled using a so-called *Latin Hypercube Design* (LHD) as originally described by Ye (1998). Due to its stochastic nature, 30,000 LHDs are constructed and evaluated in terms of a metric criterion. For additional information at the extreme values of the design space, we also sample a so-called two-level factorial design. In this context, the number of levels represents the number of different settings (here: minimal and maximal values, i.e. two settings) and the term *factorial* indicates that every possible combination of those two levels is selected. The design that is used to generate information for fitting the linear regression as well as training the ANN is illustrated in Fig. 8 in three dimensions, where each dimension represents the normalized probability p_i for non-availability of block i as introduced in Equation (1). The LHD is represented by the green rectangles, the two-level factorial design by the red circles.

5. Description of relevant data and scenarios

To demonstrate realistic model results, it is necessary to reflect realistic conditions as closely as possible. Therefore, only scientifically reliable input data from well-established sources that can be claimed to

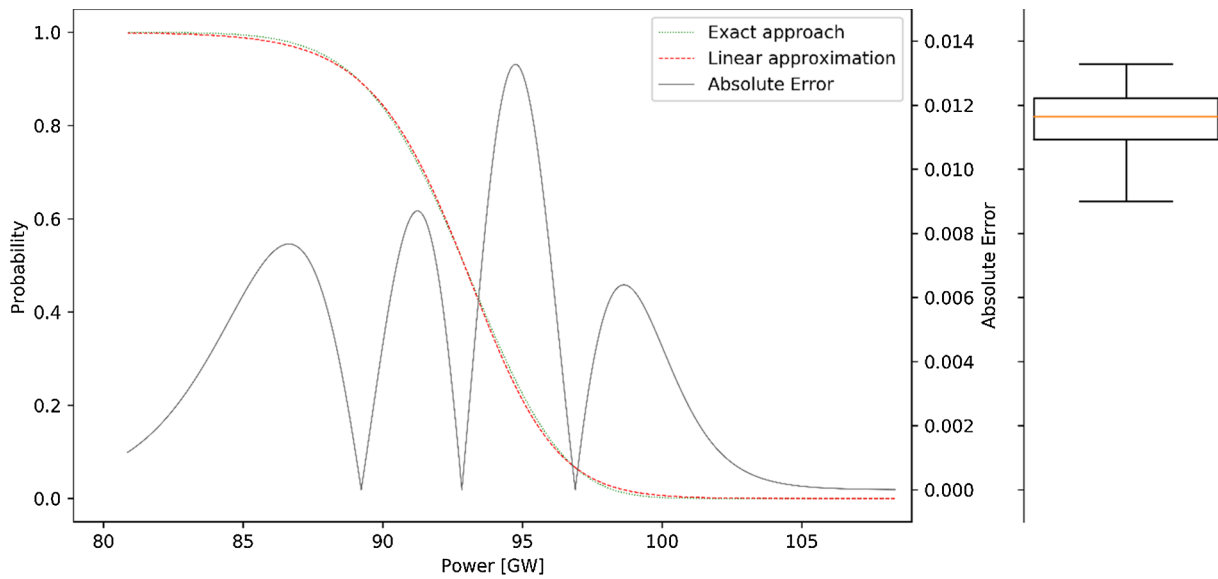


Fig. 9. Exact calculation and linear approximation of the probability distribution and course of absolute error over capacity for scenario 2020 in the hour with the least fit (left) combined with a boxplot of the maximum errors for each hour of the year (right).

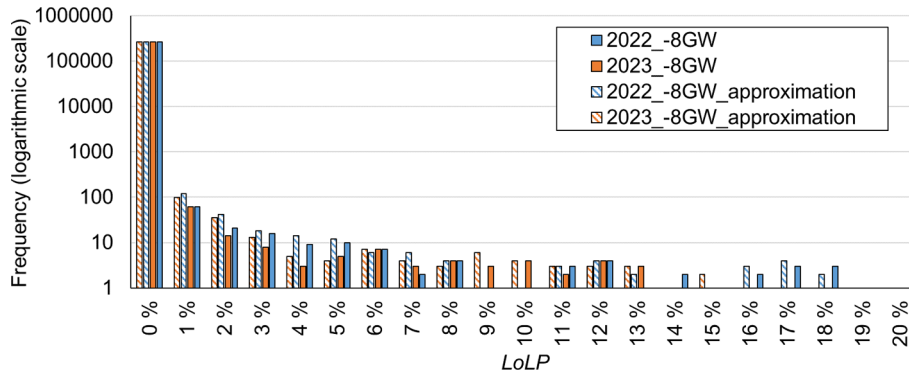


Fig. 10. Frequency distribution of *LoLP* values for scenarios with capacity shortage.

Table 3
Accuracy of linear approximation - *LoLP*.

	2020	2020_-8GW	2022	2022_-8GW	2023	2023_-8GW
RSS	0	4	26	12,454	26	6,360
RMSE	0.0	0.2	0.5	11.1	0.5	7.9

be free of bias were used within our analyses. Further, all following assessments are based on a real-life case for Germany. We use currently available data and highly relevant future scenarios to assess security of electricity supply in central Europe for the years 2020, 2022, and 2023.

Necessary data-inputs comprise the following: (1) installed controllable and renewable power plant capacities in Germany, (2) installed capacities in neighboring countries, and (3) net transfer capacities (NTCs) between Germany and its neighbors.

For currently installed capacities of controllable power plants in Germany, the list of power plants published by BNetzA (2018b): Kraftwerksliste (Power plant list) was used. Future commissioning and decommissioning was implemented according to BNetzA (2018c): Kraftwerksstilllegungsanzeigenliste (KWSAL) (List of power plant closure notifications). Regarding renewable energies in Germany, data published by entso-e (2017) was used. Here, the datasets provided for years 2020 and 2025 were interpolated to reflect conditions in the scenario-years under investigation. For the installed capacities in neighboring countries, the same source of data, entso-e (2017), was

used to guarantee consistency. Necessary NTC values to assess the import potential were taken from entso-e (2016) and interpolated accordingly.

In addition to the installed capacities as given in the above-mentioned sources, further details such as system stability measures, switchable loads, and network stability units need to be accounted for. For reasons of brevity, we however refrain from a closer description of the according input data, here.

Having described necessary input-data, we introduce the scenarios under investigation. Based on the phase-out of nuclear power plants, we chose the scenario-years 2020 (8 GW of nuclear power plants installed in Germany), 2022 (4 GW of nuclear power plants), and 2023 (no nuclear power plants) as reference years. To reflect ongoing political debate on a possible phase-out of coal-fired power plants, we investigated scenarios with an additional shut-down of 8 GW of coal-fired power stations. Overall, we used six different scenarios for the validation of our metamodels, as can be seen in Table 1.

6. Results and discussion

The results section of this paper is divided into two parts. First, we give results that were achieved based on a linear approximation approach. Second, we show results produced by an ANN-based approximation.

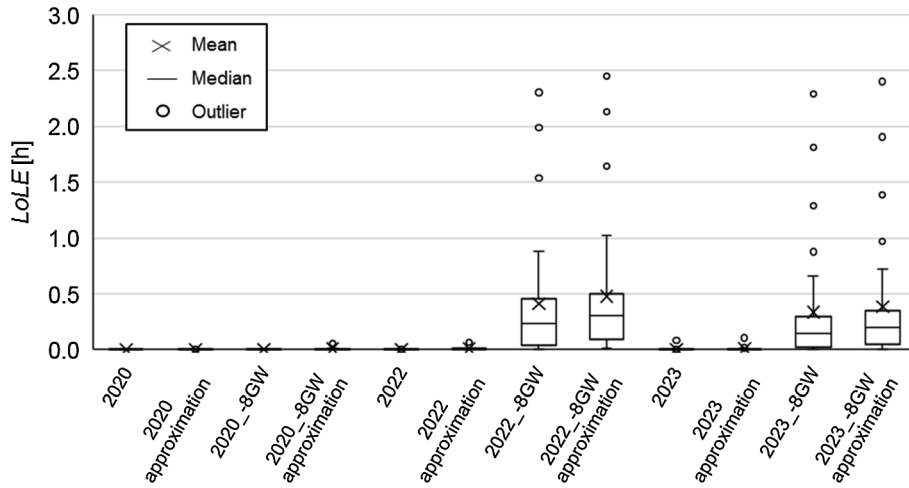


Fig. 11. LoLEs for each scenario using exact probability distribution curves and linear approximations.

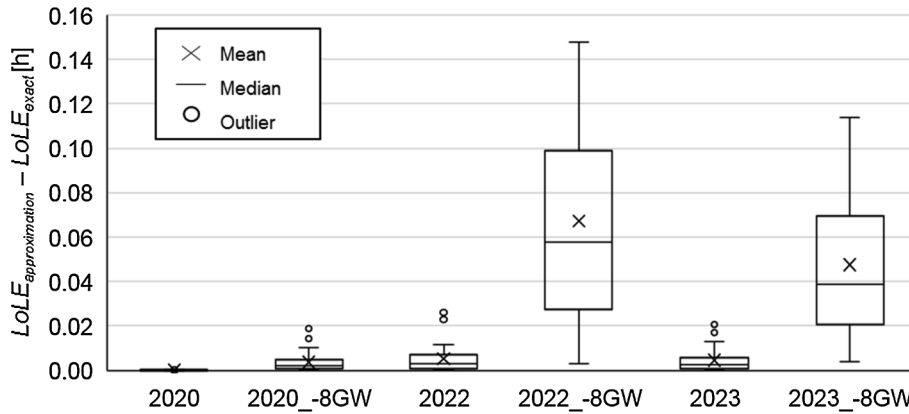


Fig. 12. Deviations of LoLEs using linear approximation methods.

Table 4
Accuracy of linear approximation - LoLEs.

	2020	2020_-8GW	2022	2022_-8GW	2023	2023_-8GW
Mean absolute error [h]	0.00	0.00	0.01	0.07	0.00	0.05
Median absolute error [h]	0.00	0.00	0.00	0.06	0.00	0.04
Maximum absolute error [h]	0.00	0.02	0.03	0.15	0.02	0.11

Table 5
Hyperparameters and boundary conditions of the ANN.

Hyperparameter/Boundary condition	Value
Maximum Number of Epochs	200
Hidden Layers	1
Maximum Number of Neurons	7
Normalized Input and Outputs	Yes
Activation Function Hidden Neurons	Tangens hyperbolicus
Activation Function Output Neuron	Linear
Training Algorithms	Levenberg-Marquardt and Bayesian Regularization

Table 6
Runtime and memory evaluation using different methods (scenario 2022_-8GW).

	Number of simulations [/]	Total Runtime [sec]	Total Runtime [h]	Average Memory [MB]	Max Memory [MB]
Exact approach	8760	30,602	8.50	6593	8367
Linear approximation	16	103	0.03	1140	1799
ANN	49	179	0.05	2308	2967

6.1. Linear approximation

Performing the methodology as described in Section 3, one can see that the relationship $\zeta_k(p_i(t))$ can be approximated by a linear function when we perform only 16 simulations for years 2020 and 2022 and only eight simulations for year 2023, instead of originally 8,760 simulation runs (i.e. exact calculation), thus reducing computational effort by up to 99.7%. Table 2 shows the significant reduction of runtime and memory requirements for the calculation of the necessary probability distribution curves.

Besides the evaluation of runtime gains, it is of high importance to analyze the fit of the approximated curves. Using the linear

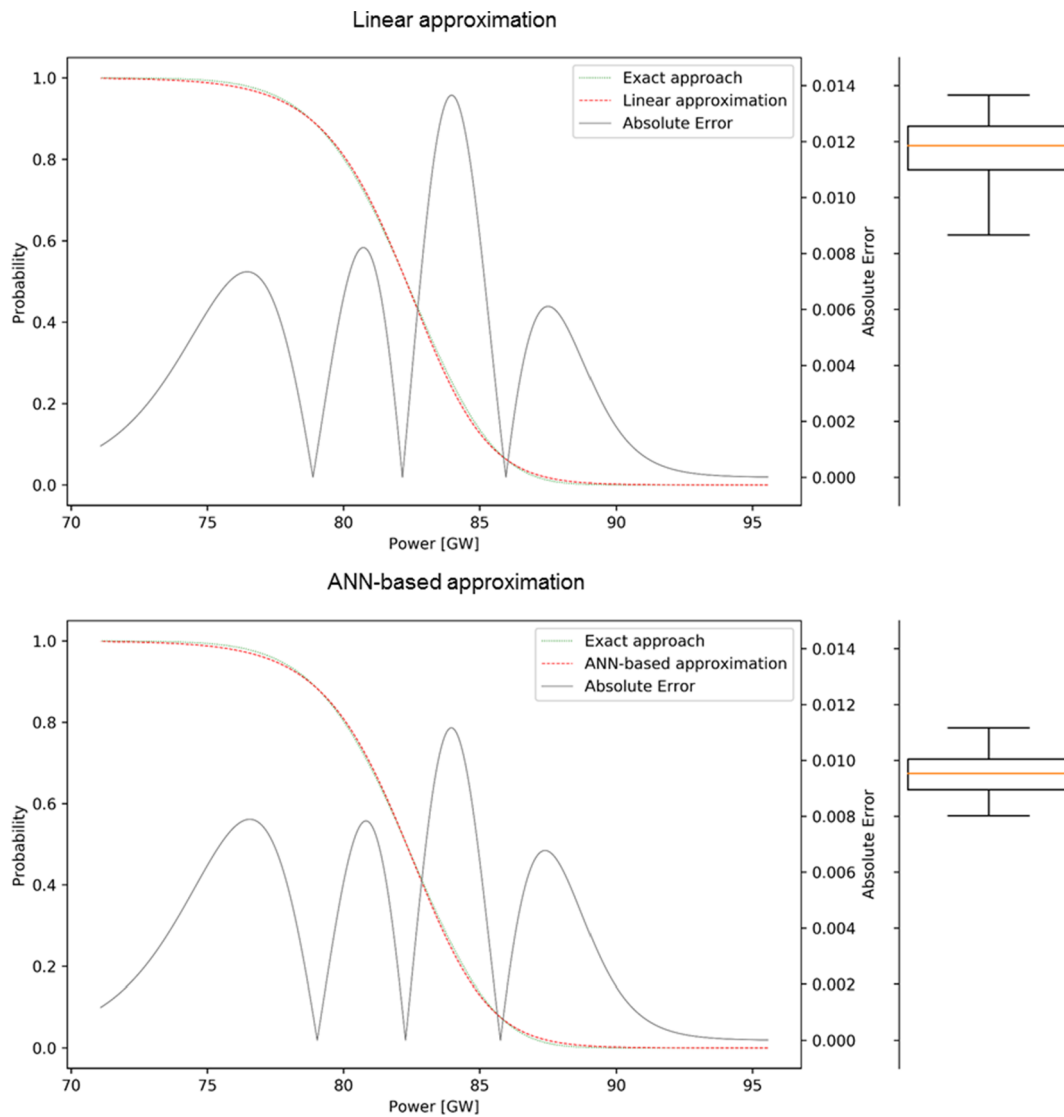


Fig. 13. Comparison of exact calculation, linear approximation, and ANN-based approximation of the probability distribution and course of absolute error over capacity for scenario 2022_8GW in the hour with the least fit (left) combined with a boxplot of the maximum errors for each hour of the year (right).

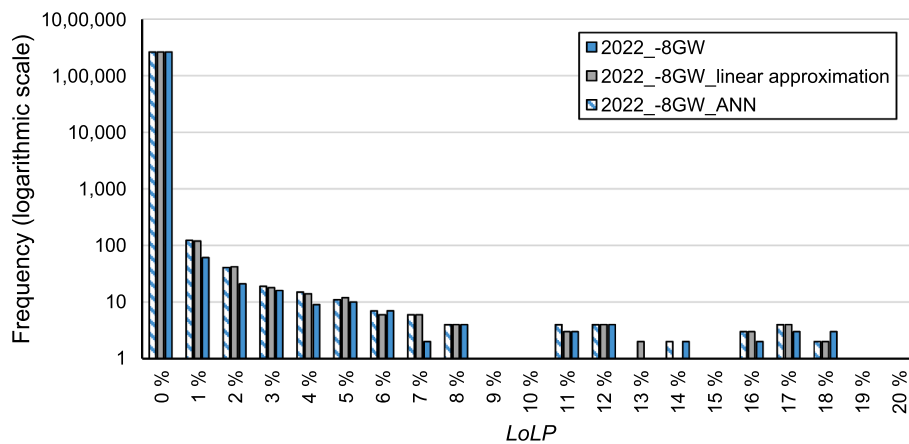


Fig. 14. Frequency distribution of LoLP values exact calculation and approximation based on ANN.

relationship, a sigmoid function can be fitted in the whole design space. To visualize the accuracy, Fig. 9 shows the example of the hour with the least fit of the distribution for the year 2020 (left) combined with a boxplot of the maximum errors for each hour of the year (right). The

diagram indicates that the distribution functions during the year are fitted closely. Here, the maximum error turns out to be less than 1.4%.

As introduced in Section 3.3.3, the probability distribution functions built the basis for the calculation of scientific key indicators to assess

Table 7
Comparison of accuracy based on LoLP frequencies (scenario 2022_–8GW).

	Linear approximation	ANN-based approximation
RSS	12,454	13,858
RMSE	11.1	11.7

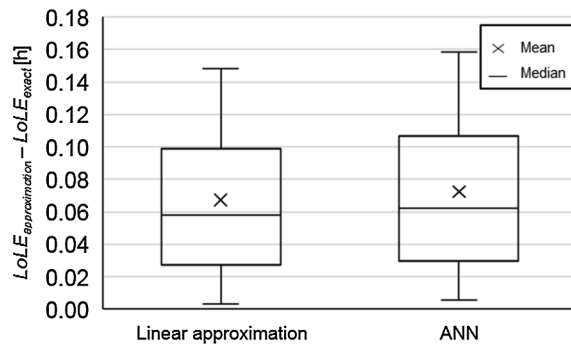


Fig. 15. Deviation of *LoLEs* – comparison of approaches.

Table 8
Comparison of accuracy.

	Linear approximation	ANN-based approximation
Mean absolute error [h]	0.07	0.07
Median absolute error [h]	0.06	0.06
Maximum absolute error [h]	0.15	0.16

security of electricity supply. Therefore, we investigated whether the approximated probability functions provide *LoLP* and *LoLE* values with sufficient accuracy. Our results using the exact probability distribution curves indicate that for scenarios with no additional coal-reductions, almost no hours with capacity shortage occur, independent of the weather year. However, the situation changes for scenarios 2022_–8 GW and 2023_–8 GW. The resulting frequency distributions are shown in Fig. 10 below. It should be noted here that the total number of hours under considerations evolves to $30 \cdot 8760h = 262,800h$ based on the consideration of 30 different weather years.

In Fig. 10, it can be seen that the frequency distributions are approximated very closely. However, the results also reveal a tendency of the approximation to slightly overestimate the loss of load probability. To quantify the deviations from the exact frequency distribution, the residual sum of squares (RSS) and the root mean square error (RMSE) are listed in Table 3.

Even more clearly than based on the distribution of *LoLP* frequencies, the accuracy of our approximation approach can be shown and proven statistically when *LoLE* values are considered. Fig. 11 demonstrates the emerging *LoLEs* for each scenario considering 30 weather years. Both sets of results, using the exact approach and the approximation based on metamodels, are depicted.

One can draw the conclusion from the boxplots depicted in Fig. 11 that the results vary only slightly when simplifications are applied. Fig. 12 explicitly shows the deviations between the original results and those based on approximations.

Further evidence for the sufficient fit of the approximated probability distributions to reflect realistic results is provided in Table 4. Here, mean absolute errors, median absolute errors, and maximum absolute errors are reported for each scenario under investigation.

One can see that the deviations between the *LoLE* values calculated on the basis of the exact convolution curves and those based on the approximated curves are insignificant. As *LoLE* values are interpreted in absolute terms, usually in the unit of hours, even the maximal deviation

of 0.15 h (i.e. 9 Minutes) does not comprise the interpretation of the results. Further, approximated curves only overestimate *LoLEs* in the scenarios under investigation, which can be seen as estimation on the safe side.

6.2. Artificial neural networks

Even though the linear regression already allows for an acceptable approximation as shown above, we applied a more advanced method based on ANNs to improve accuracy of the second stage approximation even further and implement possible non-linear effects. Thus, a *Latin Hypercube Design* with 33 factor level combinations was added to the already existing two-level factorial design. The hyperparameters and boundary conditions for the ANNs training are depicted in Table 5.

As deviations between exact calculations and the linear approach are highest for scenario 2022_–8GW (see Table 3 and Table 4), this scenario was chosen as the starting point for the assessment of possible further accuracy improvements. First, an evaluation of runtime and memory effects is summarized in Table 6.

One can conclude that the more advanced approach based on ANNs requires more simulations and thus leads to slightly increasing runtimes and memory requirements. However, the reductions are still highly significant in comparison to the exact approach. To demonstrate the fit of the approximated curve in comparison to the linear model, both approximations are depicted for scenario 2022_–8GW in Fig. 13.

Fig. 13 demonstrates that both the median absolute error and the maximum absolute error decrease, when ANN-based approximation is used. For further analysis of the accuracy of the approximations, both the distribution of *LoLP* frequencies and the corresponding *LoLE* values are calculated and depicted in accordance with Section 6.1. First, the *LoLP* frequencies are depicted in Fig. 14.

This shows that the distribution is estimated very closely. Again, RSS and RMSE are provided so as to quantify the fit, see Table 7.

One can see that the ANN-based approximation has higher RSS and RMSE values in comparison to the linear metamodel, indicating a higher deviation from the exact results. At first glance, this seems to be in contradiction to the overall better fit of the approximated curve using ANN as shown in Fig. 13. However, a closer analysis reveals that nonconformity to the original curve is higher for the ANN approximation for small residual loads. This turns out to be the most important part of the distribution curve for the assessment of security of electricity supply, as residual load mostly ranges in this area. Using the linear approximation method, the maximum absolute error in this part of the curve is 0.86%. The corresponding error for ANN-based approximation is 0.91%. The same picture emerges, when *LoLE* values are computed, as demonstrated in Fig. 15 in the Appendix A.

No additional gains in accuracy can be reached by the application of ANN. This is shown in further detail in Table 8.

In summary, we can state that the application of ANN-based approximation methods does improve the overall-fit of the probability distribution function, but at the cost of a decreasing fit in a part of the curve with high importance for the resulting scientific key indicators. Furthermore, the ANN training demands more computation than the linear regression resulting in higher runtimes for the two-stage metamodel with ANN. For these reasons, an application of ANN-based approximation methods does not provide any further gains in the use-case as demonstrated within this paper.

7. Conclusion & outlook

Probabilistic assessments of security of electricity supply are of high importance, as policy makers require a scientifically sound base for decisions. However, up until to now, the computation time per scenario often proved to be a barrier for more in-depth analyses of a variety of possible scenarios. This is mainly caused by the computationally intense calculation of probability distribution functions for available capacities.

Therefore, we implemented two-stage metamodels to approximate the distribution curve, and thus decreased the required computational effort. To perform the approximations, we used both, linear methods and approaches based on artificial neural networks.

Our results indicate that the application of linear regression methods significantly reduces the computational effort by up to 99.7% without noticeably comprising the resulting scientific key indicators. The observed deviations ranged well below 10 min concerning the calculated loss of load expectation values for all scenarios under investigation (see Table 4). However, using an approach based on artificial neural networks did not achieve further improvements in the approximations. Despite a better overall fit of the approximated curves, higher approximation errors in important parts of the distribution curve prevented gains in accuracy.

Therefore, our key findings are as follows:

- In general, our results indicate that the linear approximation methods allow for analyses with a greater variety of scenarios, thus providing more profound insights for the assessment of security of electricity supply.
- Additionally, our approach proves that well-chosen approximation tools can assist in handling modeling complexity while keeping the results sufficiently accurate. Our results indicate that well-chosen and tailor-made approximation methods resting on rather simple mathematical approaches can outperform highly elaborated tools that are less suitable for the specific use-case.
- Thus, we conclude that by chaining a selection of rather straightforward approximations challenging problems (as often faced in the field of energy system modeling) can be efficiently solved.

We hypothesize that our results could be transferred to further applications in energy system modeling: whenever computationally complex problems occur within the field of computational engineering or managerial decision making, appropriate tools to circumvent complexity by using metamodels can help to reduce complexity and achieve results with high accuracy.

For future research, we propose to investigate the applicability of approximations based on artificial networks for more complex and non-linear interrelations within energy system modeling. These could for example serve to directly model weather effects and the impact of changing power plant portfolios on the expected outage durations. This would allow robust optimizations of power plant park portfolios without the need to conduct computationally intense convolutions. Also, sensitivity analyses can be performed to evaluate the impact of those diverse factors on the expected outage duration. For this purpose, design and performance spaces need to be expanded resulting in more complex and non-linear interrelations. The model complexity and the high model performance that are being strived for require the tailor-made utilization of design of experiment methods, ANN-based approximations and machine learning techniques.

Appendix A

See Fig. 15.

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