



Artificial intelligence and design of experiments for resource adequacy assessment in power systems

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ABSTRACT

Assessing the effects of the energy transition and liberalization of energy markets on resource adequacy is an increasingly important and demanding task. The rising complexity of energy systems requires adequate methods for energy system modeling leading to increased computational requirements. Furthermore, with complexity, uncertainty increases likewise calling for probabilistic assessments and scenario analyses. To adequately and efficiently address these various requirements, new methods from the field of data science are needed to accelerate current modeling approaches. With our systematic literature review, we want to close the gap between the three disciplines (1) resource adequacy assessments, (2) artificial intelligence (AI), and (3) design of experiments. For this, we conduct a large-scale systematic review of selected fields of application and methods and make a synthesis that relates the different disciplines to each other. Among other findings, we identify meta-modeling of complex probabilistic resource adequacy assessment models using AI methods and applications of AI-based methods for forecasts of storage dispatch and (non-)availabilities as promising fields of application that have not yet been sufficiently covered. Eventually, we define a new methodological pipeline for adequately and efficiently addressing the present and upcoming challenges in the assessment of resource adequacy accounting for modeling the complexity and uncertainties of future developments.

1. Introduction

Assessing the security of electricity supply is an increasingly important and demanding task. In particular, depicting the effects of the energy transition and liberalization of energy markets on resource adequacy accompanied by required long-term planning horizons is becoming more relevant and challenging. The rising complexity in energy systems [1] calls for efficient and adequate methods for energy system modeling (see e.g. Ref. [2] for the case of optimization models). This has been addressed by the *European Agency for the Cooperation of Energy Regulators* (ACER) with a comprehensive set of requirements that assessments of resource adequacy in the European context should fulfill: the so-called *Methodology for the European resource adequacy assessment* (ERAA methodology [3]). Following the ERAA methodology, we define resource adequacy in the context of this work as the overall adequacy of the electricity system to supply current and projected electricity demand levels. While the document formulates high standards for assessments of

security of electricity supply, their implementation in practice comes with several challenges, especially in terms of input data, the methodology itself, and the computational complexity of the proposed modeling approaches.

We identify requirements from different stakeholder perspectives such as regulators, practitioners, e.g. transmission system operators (TSOs), as well as the scientific community and derive four main challenges for assessing the security of electricity supply: (1) Improving the availability and the quality of input data, (2) improving forecasts for future scenarios based on the input data, (3) implementing a realistic representation of the interrelationships of the real energy system by fulfilling certain methodological requirements and (4) reducing the computational complexity of models to allow incorporating an adequate representation of additional uncertainties into the probabilistic assessment models. To address the above challenges, we develop a methodological toolchain for resource adequacy assessments that incorporates machine learning-based methods applied, e.g., in the areas of data consolidation, data forecasting as well as metamodeling and design of

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Nomenclature	
<i>Abbreviations</i>	
ACER	Agency for the Cooperation of Energy Regulators
AI	Artificial intelligence
ANN	Artificial neural network
API	Application programming interface
CNN	Convolutional neural network
DOE	Design of experiments
ERAA	European resource adequacy assessment
FFNN	Feed-forward neural network
LDA	Linear Discriminant Analysis
LSTM	Long short-term memory network
MARS	Multivariate adaptive regression splines
PCA	Principal Component Analysis
PLEF	Pentalateral Energy Forum
RAM	Random access memory
RES	Renewable energy sources
RNN	Recurrent neural network
SVM	Support vector machine
TSO	Transmission system operator
ENTSO-E	European association for the cooperation of transmission system operators

experiments (DOE) (Fig. 1).

The improvement of data availability and quality is a critical aspect of energy system modeling and can be achieved through various methods, including data consolidation techniques [4]. Moreover, data reduction through aggregation is a valuable strategy in energy system modeling. This approach effectively reduces the volume of data input into the model, thereby enhancing its manageability and efficiency. Given that assessments of electricity supply security often inform strategic decision-making, the underlying models must be based on reliable forecasts. A range of forecasting methods can be applied to diverse types of input data [5,6]. This technique finds its application in various areas, notably in forecasting models for electricity load [7] and in models for predicting renewable energy feed-in time series [8].

Probabilistic models for the assessment of supply security that tackle the aforementioned challenges turn out to be computationally complex (i.e., requiring a high amount of computational resources such as core-hours or random access memory (RAM)). The detailed analysis of different future scenarios is therefore limited by the necessary hardware

availability and computing time. Hence, only a few scenarios can be evaluated adequately. For reducing the model complexity, the reduction of input data [9], the reduction of depicted systemic complexity [10], and metamodeling approaches can be applied. For the case of metamodeling, Nolting et al. [11] showed that in particular approaches from the fields of AI and DOE seem to be promising for mapping the relationships between model input variables and model results without encountering limitations in terms of available computing resources.

Although the literature provides a variety of reviews on the application of AI in the energy domain, there is a critical research gap in the field of security of electricity supply assessment. As a result, this review literature underrepresents or even neglects key assessment steps such as the forecasting of unavailabilities of energy infrastructure or adequately representing uncertainties in probabilistic assessments.

First, there are several studies that provide a broad overview of the integration of AI into energy research. Early on, Schulte et al. [12] identified a variety of potential application areas for AI. Kalogirou [6] focuses on artificial neural networks and presents a large variety of application fields such as heating systems, forecasting of loads, and renewable feed-in followed by an extension to other methodological approaches [13]. The application of AI methods for different renewable energy sources from wind to bioenergy is presented by Jha et al. [14]. In Ref. [15], the authors unfold a comprehensive range of application areas for AI both for the energy industry and energy research. Nishant et al. [16] elaborate on the challenges posed by integrating AI into the energy domain and identify ways to address them and Ahmad et al. [17] analyze the relevance of AI for the current and future energy industry. Finally, Dellosa and Palconit [18] focus on the variety of specific AI techniques that are applied in different fields of application within the energy domain.

Second, studies for individual research areas in the energy field provide deeper insights into the application of specific AI methods to particular research questions:

- Forecasting renewable energy power feed-in [8,19,20].
- Forecasting load and consumption data [21,22].
- Flexible energy demand and demand side management [23].
- Building energy management [4,24,25].

The overall potential of AI-based methods in the context of the assessment of security of electricity supply in systems with high shares of renewable energy sources (RES) has not yet been systematically evaluated. Hence, the goals of this review are to (1) identify relevant methods and algorithms from the field of AI and DOE, (2) to associate potential fields of application, and (3) to synthesize the findings and provide a

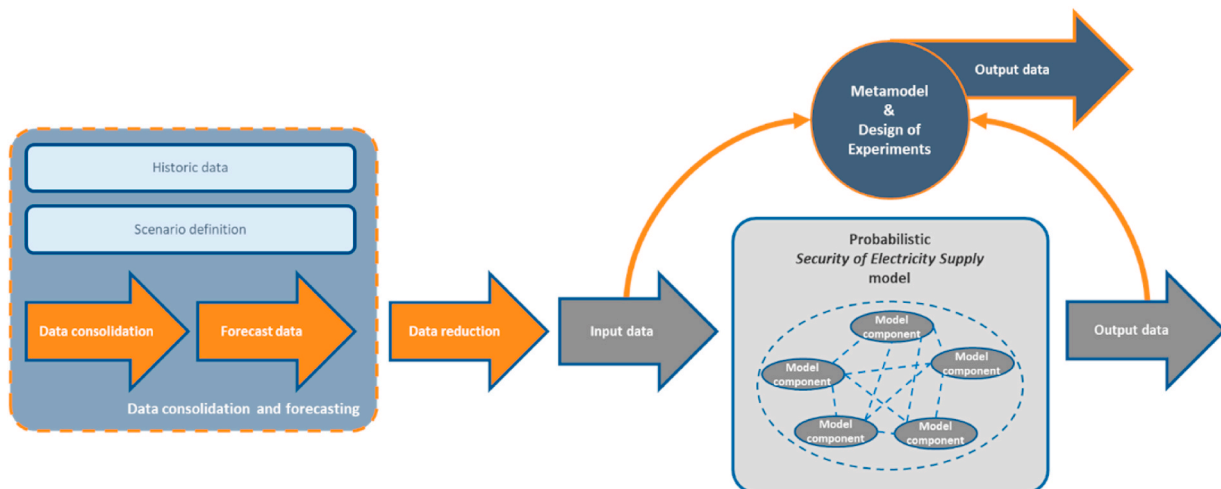


Fig. 1. Pipeline for the assessment of security of electricity supply incorporating metamodeling and design of experiment.

strategic outlook on how to beneficially embed AI-based methods within the assessment of security of electricity supply. By conducting a review of existing approaches and providing an outlook on their potential to enhance resource adequacy assessments, we substantially contribute to the existing body of literature. The procedure for carrying out the systematic review is based on [26–28]. Fig. 2 shows our process applied for conducting the systematic review.

We start with the conceptualization of the review by defining and filling in the two dimensions (1) fields of application and (2) AI-based methods. These two dimensions are based on previous works such as [11,29]. We then conduct a first qualitative literature review to identify keywords and assign the keywords to the categories defined in the first step. The 88 keywords identified through this process are grouped into clusters for evaluation (see Tables 8–16 in the Appendix section). Using these keywords, we conduct a large-scale literature review for the period 2010 to 2022 using the *Scopus* database, the provided application programming interface (API), and the package *pybliometrics* [30]. After generating our article database, we conduct a second qualitative literature review and identify patterns in model specifications and trends in the use of AI-based methods. Finally, we summarize our findings across all application domains and AI-based methods and present their evolution over time following the literature review and presentation in Ref. [31].

With this paper, we want to give researchers and practitioners in the field of resource adequacy assessment a comprehensive overview and a guideline on how to integrate artificial intelligence (AI) into their methodological pipelines. We believe that the need for such a guide arises from the increasing complexity of investigations and the simultaneous increase in their relevance, both of which can be addressed to a certain degree by using machine learning-based methods.

The manuscript is structured to methodically explore the domain of resource adequacy assessments and the integration of AI-based methods. Beginning with Section 2, we review recent studies and outline current methodological challenges, laying the groundwork for the subsequent sections. Section 3 introduces the concept of metamodeling and Design of Experiments (DOE), essential for comprehending the complexities in this field. Section 4 gives an overview of Artificial Intelligence (AI) in fields related to resource adequacy assessments. Section 5 builds on the previous chapters by identifying relevant application fields and presenting results from a systematic literature review covering data processing, forecasting, metamodeling, and DOE. The interconnection of these components is further examined in Section 6, which discusses the potential and challenges of AI-based methods in resource adequacy assessments. The manuscript concludes in Section 7 by summarizing our key findings.

2. Assessing the security of electricity supply

While security of electricity supply covers multiple dimensions and there is a broad range of definitions (see Ref. [32]), we will focus on resource adequacy in the sense of the *ex-ante* evaluation of the ability of the electricity system's resources to meet the demand for electricity at a point in time. The term *resources* comprises primary energy sources, electricity generation assets including energy storages, demand side flexibility potentials, as well as electrical grids.

2.1. Review of resource adequacy assessment studies

While in the past rather straightforward deterministic capacity balances between secured feed-in power and electricity load during the hour of peak load have been used to assess the security of electricity supply, today, mostly complex probabilistic simulations in hourly resolution are applied. With such simulations, key figures of supply security are determined considering stochastic influences on (1) the availability of fossil power plant blocks, (2) the fluctuating feed-in of renewables, and (3) electricity load. The two approaches – deterministic and

probabilistic assessments – differ in terms of required input data, modeling approaches, and key figures calculated for the level of supply security. This will lead to different approaches from the field of AI being suitable for integration into the respective modeling pipeline.

Before we compare different modeling approaches, we start by examining the fundamental process and analysis involved in mathematical modeling for resource adequacy assessment. A mathematical model is a simplified representation of a real system (such as energy systems) that is used to avoid field or laboratory experiments that often cannot be applied. Modelers encounter an interplay between model complexity and practical utility. Following the adage of George Box and Norman Draper, ‘all models are wrong, but some are useful’ (cited by Ref. [33]), modelers must navigate the balance between model simplicity and the required accuracy of the analysis. The process begins with the formulation of a specific research question, guiding the selection of an appropriate conceptual model. This initial step is crucial as it sets the direction for the entire modeling process. Subsequently, the model's components and level of detail are carefully chosen (such as the technological, temporal, or spatial resolutions). This systematic approach ensures that the resulting methodological approach while acknowledging its inherent limitations as a simplified representation of reality, remains sufficiently detailed and accurate to provide valuable insights for resource adequacy.

Deterministic capacity balances represent rather straightforward, top-down models with low complexity to derive non-probabilistic key figures such as capacity margins. They are usually conducted for 1 h per year (i.e., the hour with the highest electricity load) and consider only one (often worst-case) weather situation. The key figure calculated is the remaining capacity (RC) which is the difference between the available capacity and the peak electricity load. The RC can then be considered as a buffer for covering unexpected loads or power plant outages that have not been accounted for.

On the other hand, probabilistic simulation models represent rather complex, bottom-up models that are used to calculate stochastic key figures such as the loss of load probability (LOLP), the annual loss of load expectation (LOLE) for interruption hours or the annual expected energy not served (EENS, sometimes referred to as expected unserved energy – EUE). Such analyses are commonly performed in hourly resolution and reflect different weather situations (so-called historic weather years¹) and other stochastic influences such as power plant outages. The generalized formulaic relations built on [3,34] are as follows:

$$LOLE = 1 \frac{h}{a} * \frac{1}{\sum \alpha_w} \sum_w \left(\alpha_w * \sum_t LOLP_{w,t} \right), \text{ and} \quad (1)$$

$$\text{with } LOLP_{w,t} = P(C < L_{w,t}) \quad (2)$$

$$EENS = 1 \frac{h}{a} * \frac{1}{\sum \alpha_w} \sum_w \left(\alpha_w * \sum_t ENS_{w,t} \right), \quad (3)$$

where $w \in W$ is the number of different weather years, $t \in T$ the number of hours per year, α_w the weighing factor for weather year w (often, weather years are equally weighted), $P(C < L_{w,t})$ the probability of a loss of load during hour t in weather year w where capacity C is smaller than load $L_{w,t}$, and $ENS_{w,t}$ the energy not served due to insufficient capacity resources during hour t in weather year w . The calculation of $P(C < L_{w,t})$ and $ENS_{w,t}$ depends on the applied probabilistic methodology, for which two common examples are (1) approximation of the uncertainty space by combining Monte Carlo simulations with economic dispatch (in some cases unit commitment) problems or (2) superposition of probability

¹ A weather year represents the meteorological conditions in an area and is used to calculate weather dependent electricity load and feed-in profiles. See e. g. Ref. [7].

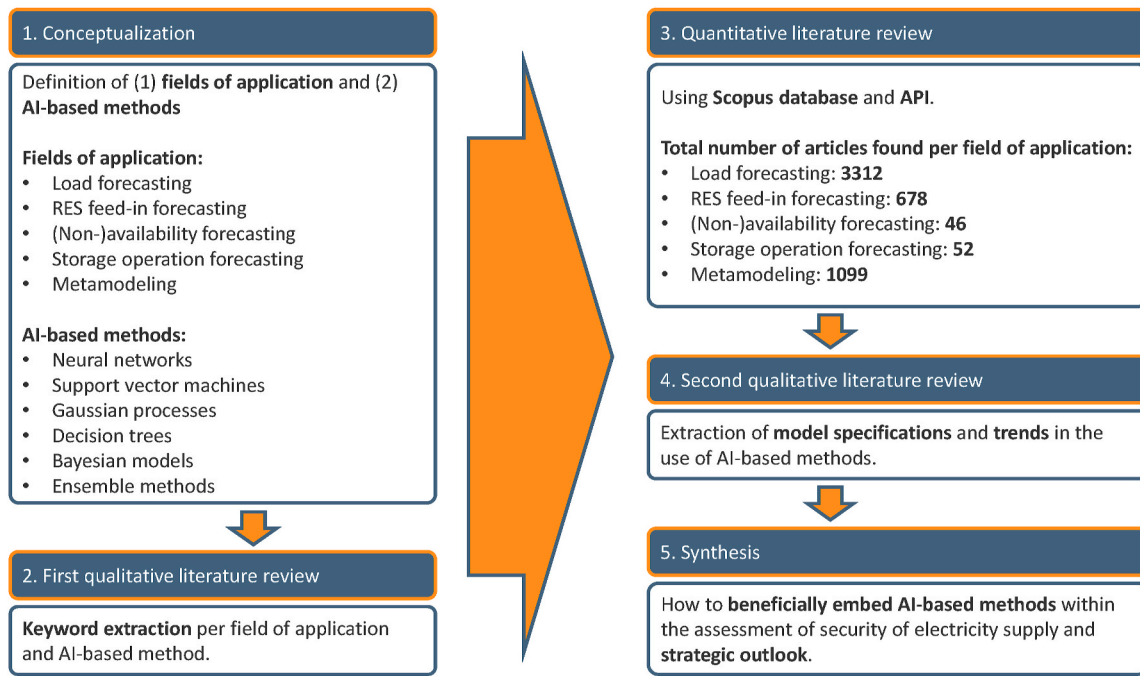


Fig. 2. Overview of systematic review design.

distributions using convolution algorithms. For case (1), a simplified objective function to be minimized can be formulated as:

$$\min_{g,t} \sum_{g,t} x_{g,t} * \Delta t * \left(\frac{c_{g,t}^{fuel} + e_g * c_t^{CO_2}}{\eta_g} + c_g^{other} \right) + \sum_t y_t^{import} - y_t^{export} + ENS_t * VOLL_t. \quad (4)$$

Here, $g \in G$ represents the generation assets (including discharging storage and renewable energies) and $t \in T$ the hours per year. The generation of assets g at hour t is the decision variable $x_{g,t}$. Other decision variables are y_t^{import} for the electricity import costs, y_t^{export} for the electricity export revenues and ENS_t for the unserved energy. The cost parameters for electricity generation are $c_{g,t}^{fuel}$ for the fuel cost, $c_t^{CO_2}$ for the CO₂ cost, and c_g^{other} for other operating costs. The assets' specific emission factors are resembled by e_g and the efficiency factor by η_g (here assuming constant efficiencies). The unserved energy ENS_t is multiplied by an estimation of its value, the so-called Value of Lost Load (VOLL), see [193, 194]. By running optimizations for different weather years and outage scenarios using a Monto Carlo approach, the resulting ENS values form the basis for the subsequent calculation of resource adequacy metrics.

Various approaches have been applied in studies by consulting companies, research institutions, and TSOs in different contexts. Currently, resource adequacy assessments are mainly done in Europe, North America, and Australia. However, other countries such as India are preparing for such assessments by setting up guidelines [35]. Table 1 provides an overview of existing studies, methods used, and core results achieved.

Recently, the methodological approaches have streamlined following national and international initiatives to make resource adequacy assessments more comparable. This can be seen exemplarily in Europe with the unified methodological requirements given out by ACER. However, certain challenges to the current state-of-the-art methodological pipelines remain that either could not yet be solved or were caused by the new requirements in the first place.

2.2. Challenges in the assessment of resource adequacy

ACER introduced the ERAA methodology as a legal mandate for the European association for the cooperation of transmission system operators (ENTSO-E) to ensure a transparent and consistent pan-European assessment of security of electricity supply by providing a standardized methodological basis for assessing resource adequacy. However, its implementation comes with major challenges, in particular regarding the input data, the methodology itself, and the computational complexity of the proposed modeling approaches. These challenges include among others the following (see Refs. [3,43–45]):

- conducting prognoses of electricity demand for all countries that are part of the European interconnected grid in future scenarios,
- simulating market mechanisms that cause incentives for (des-)investments in electricity assets (*economic viability assessment*),
- depicting storage dispatch and demand side response potential,
- forecasting unavailabilities of power plant units accounting for maintenance optimization, *common-mode/common-cause events*², and temporal linkages,³
- simulating international power flows based on Flow-Based market coupling,
- modeling balancing reserves and real network development,
- accounting for climate change in weather models,
- identifying the reasons for potential adequacy concerns,
- applying probabilistic analysis and accounting for extreme events, and
- appropriately representing uncertainties in the aforementioned areas.

To ensure reliable and realistic results, resource adequacy assessments should incorporate the (des-)investment in and dispatch of all resources that potentially contribute to resource adequacy including future power system developments with regard to generation capacities,

² These are events that cause the joint unavailability of various assets, like cold spells.

³ These are events that are caused by preceding failures.

Table 1
Selection of recent studies in the field of assessing the security of electricity supply.

Reference	Methodology	Geographical scope	Time horizon	Reliability criteria	Key findings
Studies published by individual or groups of transmission system operators					
ENTSO-E, MAF 2020 (2021) [36]	Probabilistic simulation (Monte Carlo)	European synchronous grid area	2025, 2030	LOLP, LOLE, EENS, others	In a baseline scenario, loss of load is only to be expected in Malta, Sardinia, Iceland, and Turkey. COVID-19 has only minor impact on resource adequacy.
ENTSO-E, ERAA 2022 (2022) [37]	Probabilistic simulation (Monte Carlo)	European synchronous grid area	2025 to 2030	LOLP, LOLE, EENS, others	Widespread adequacy risks identified, with Ireland and Malta facing the highest risks in 2025, and a shift of scarcity concerns towards central regions by 2030.
AEMO EAAP 2022 (2022) [38]	Probabilistic simulation (Monte Carlo)	Australia	2023, 2024	EENS	Security of supply is anticipated to remain within reliability standards, albeit with potential load-shedding risks, while resource limitations from fuel and energy sources are emerging as significant reliability concerns.
NERC ProbA 2022 (2023) [39]	Probabilistic simulation (Monte Carlo and convolution)	North America	2024, 2026	LOLP, LOLE, EENS	Varying shifts across regions in reliability metrics, largely driven by factors like seasonal outages, hydroelectric unit shutdowns, transmission constraints, and load scenarios, prompting adaptations and mitigation strategies for reliable resource adequacy.
National Grid ESO (2022) [40]	Probabilistic simulation (Monte Carlo)	United Kingdom	2025 to 2040	LOLP, LOLE, EENS	A fully decarbonized power system can be achieved with substantial investments in reliable technologies like new nuclear, CCS, and hydrogen generation, although uncertainty in new tech adoption and potential for prolonged tight periods due to weather patterns pose challenges.
Journal Publications					
Turner et al. (2019) [41]	Probabilistic simulation (Monte Carlo)	U.S. Pacific Northwest	2035	LOLP, others	Climate change alters power shortfall risks in the U.S. Northwest, intensifying summer shortages and reducing winter deficits, emphasizing compound events.
Kockel et al. (2022) [192]	Probabilistic simulation (Monte Carlo)	Germany	2025	LOLE, EENS	Reduction of natural gas consumption in the power sector of up to 30% with only minor impacts on resource adequacy.
Nolting & Praktijnjo (2020) [29]	Probabilistic simulation (Convolution)	Germany	2020, 2022, 2023	LOLP, LOLE, EENS	Security of supply may decrease, potential implications for identifying efficient security thresholds and increased reliance on energy imports.
Yu et al. (2019) [42]	Probabilistic simulation (Monte Carlo)	Taiwan	2025	LOLE	Level of security of supply depends on limitations put on coal power plants and increases in gas power plant capacities.

network infrastructure, energy storage, as well as demand patterns [3]. Thus, resource adequacy assessment models need to appropriately reflect the economic viability of electricity assets. This assessment of economic viability is highly complex and poses challenges, in particular regarding the maximum price cap, which affects the decisions of (dis-) investing in market capacity, and a specific representation of demand side response potential. While future maximum price caps determine the potential remuneration of dispatchable generation capacities during hours of scarcity, the cost of demand side response determines the provision of demand flexibility in those hours and also affects the magnitude and frequency of scarcity prices [46]. The modelling parameters of the respective sub-models in the ERAA framework, *Economic Viability Assessment* and *Adequacy Assessment*, ought to be consistent and coherent, to ensure reliable results [47,48]. In addition, the modeling of Flow-Based market coupling and the incorporation of future network developments enables an adequate estimation of cross-zonal capacities [44,47,49], while the modeling of balancing reserves enables an accurate assessment of the interaction between short-term operating reserves and resource adequacy [46,50]. As many input parameters are weather-dependent, long-term resource adequacy assessments should reliably incorporate the effects of climate change [51,52]. Moreover, to address potential resource adequacy concerns and to ensure a secure power system, not only the adequacy concerns themselves, but also the causes for potential inadequacies and scarcity events should be identified [45,53]. To account for the highly stochastic nature of resource adequacy, the assessment should be based on state-of-the-art probabilistic analyses. Finally, methodologies for analyzing the resilience of the power system with regard to extreme events such as rare and extreme natural hazards as well as consequences of malicious attacks and fuel shortages should be incorporated [54,55].

The implementation of resource adequacy assessments that incorporate the aforementioned challenges requires the development of models with very high computational complexity. Further, the band of uncertainty of the results that comes with the different input data calls

for assessing a larger variety of scenarios to depict possible future developments. We hence transfer methods from the fields of AI and DOE to contribute to more sound assessments of security of electricity supply reducing the computational complexity of models to allow incorporating the additional requirements listed above into the probabilistic assessment models, while including an appropriate representation of future scenarios.

3. Metamodeling and design of experiments

Metamodeling and DOE are promising tools to address the aforementioned challenges of the computational complexity of the assessment models and associated limited coverage of uncertainty margins. To create a metamodel, information about the system behavior of the given simulation model is needed. In this section, metamodeling and a very effective method for minimizing the simulation effort to generate the required information about the system behavior, the so-called design of experiments (DOE), are presented in more detail.

3.1. Metamodeling of simulation models

The direct use of complex simulation models for in-depth analyses is only possible to a limited extent due to long simulation durations. Metamodels are capable of achieving predictions with high quality in a few milliseconds. The term metamodel and the concept goes back to the works of Blanning [56–58]. This method became more popular with the work of Kleijnen who extended it with some statistical tools [59]. These metamodels represent the system behavior of the simulation model by mapping a relationship between the input and output variables. This is realized by a mathematical approximation. Metamodels are also called approximation models, surrogate models, and response surface models [60]. Fig. 3 schematically shows the procedure of metamodeling for the case of security of electricity supply assessment.

Metamodels are generated from real simulation data and are valid

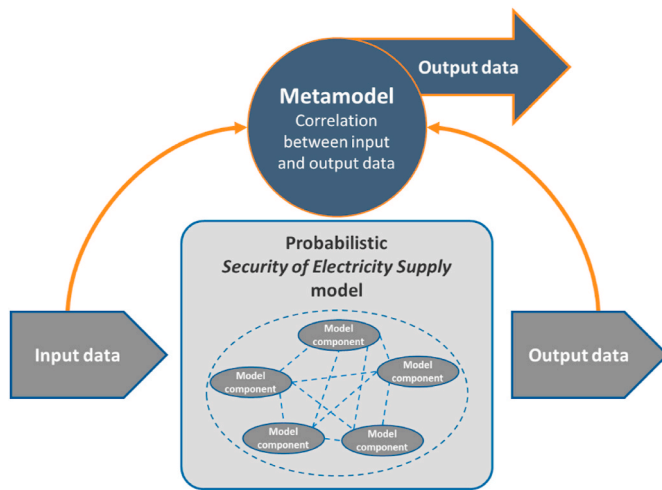


Fig. 3. Schematic representation of the basic principle of metamodeling for the case of security of electricity supply assessment.

for a predefined design space. The design space represents a multidimensional structure spanned by the input data of the simulation model and that comprises the complete range of all input data combinations. The boundaries of the design space are thus defined by the minima and maxima of the input data of the simulation model. A subset of this input data is selected as the feature set and the corresponding output data (that is calculated via the simulation model) serves as the label set. Together, these selected features and calculated labels constitute the sample to which metamodel is fitted. An illustration of a design space and selected features for a metamodel is given in Fig. 4.

Once the metamodel has been created, the label (i.e., the output data) of any feature combination of the input data within the design space can be predicted. When selecting the feature sample from the input data, it should be ensured the amount of information gained is sufficient to represent the system behavior. At the same time, the effort to generate the information must be minimized. The most effective way to implement this is to use methods from DOE.

For metamodels, a variety of methods from the portfolio of regression models can be applied which achieve varying degrees of accuracy depending on the problem at hand. Several classical statistical methods can be used. Among them are for example linear or polynomial regression. In many use cases, simulations have a more complex nature. This

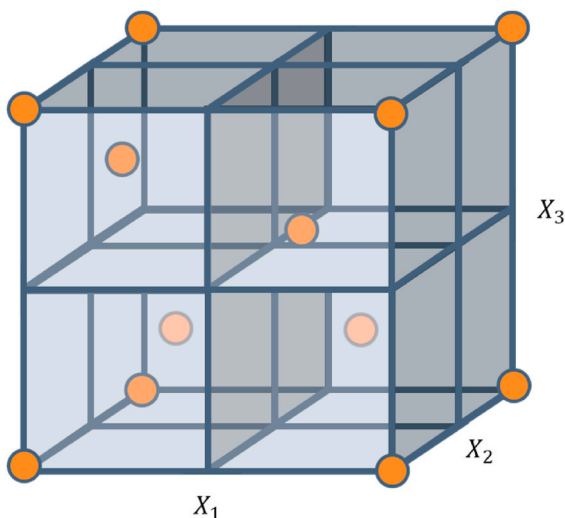


Fig. 4. Design space with selected input data combinations that serve as features for a metamodel.

often leads to nonlinear relations between the input and output data which cannot be sufficiently approximated by classical statistical methods. For these cases, machine learning methods can be applied (see section 4.4 for details on a selection of methods).

The choices of the approximation method and the design depend on the problem at hand and the optimal choice, in most cases, cannot be determined *a priori* (see section 5.6). For this reason, testing and validating different approaches is a very important part of metamodeling. Decisive for the testing of different metamodels is the quality of the validation data. These samples must be independent of the training data, which were used for the metamodeling itself. Furthermore, test data must be evenly distributed over the design space, so that the evaluation of the predictive quality is representative of the entire design space [61].

3.2. Design of experiments for effective scanning of the design space

DOE is a method for efficient planning and designing experiments. Experiments can be costly and lengthy. Due to limited budget or time, it is rarely feasible and probably never reasonable to carry out a series of experiments in an unplanned manner. This is particularly the case for models that are intended to depict complex relationships in the energy system. To get the most information out of the system under different limiting circumstances, DOE can be applied.

DOE was developed in the early 20th century and was originally developed for real-world experiments [62]. The methodology was then later adapted for the statistical DOE [63,64]. In the following, we will give a short overview of the concept of DOE for the case of metamodeling simulation models. For an extensive overview of the DOE methodology and a variety of designs, see Montgomery [65] and Siebertz et al. [61].

3.2.1. Methods for setting up designs

The most important part of the DOE is the selection of an appropriate design. In this subsection, a short overview of a selection of designs will be given. For reasons of brevity, we focus on describing the basic features of the respective methodologies. In addition to these designs, there are several other important designs. Among them are screening designs, Box-Behnken designs, and the quasi-Monte Carlo method.

3.2.1.1. Full-factorial and fractional factorial designs. According to the Yates standard [66], the most important designs for problems with linear relationships are full-factorial and fractional factorial designs. The term factor is used synonymously with the term feature in the context of DOE because of its original application to real experiments. Full-factorial and fractional factorial designs contain extreme value combinations on the vertices of the factor space (see Fig. 5). The number of factor combinations results from the number of variable factors k . A full-factorial design results in 2^k combinations and 2^{k-p} for fractional factorial designs where p is the number of commingling. In the case of fractional factorial designs, information is lost due to the commingling of (supposedly) negligible interactions. These designs are only used if it is evident that the commingling variables are negligible or if the number of experiments should be reduced for efficiency purposes.

3.2.1.2. Central composite designs. If a nonlinear relationship is suspected, the above designs are no longer sufficient. It becomes necessary to extend the ability of the metamodel to also consider the quadratic terms of the main effects. A design often successfully used is the so-called central composite design (CCD). The CCD can be thought of as an extension of the formerly described designs: A (fractional) factorial design is extended by so-called “star” points (see Fig. 6) as well as center points. The additional points added to the design allow for evaluating potential quadratic effects. The star points extend the (fractional) factorial design space in most cases and are then called circumscribed. Choosing the distance of the star points to the (fractional) factorial

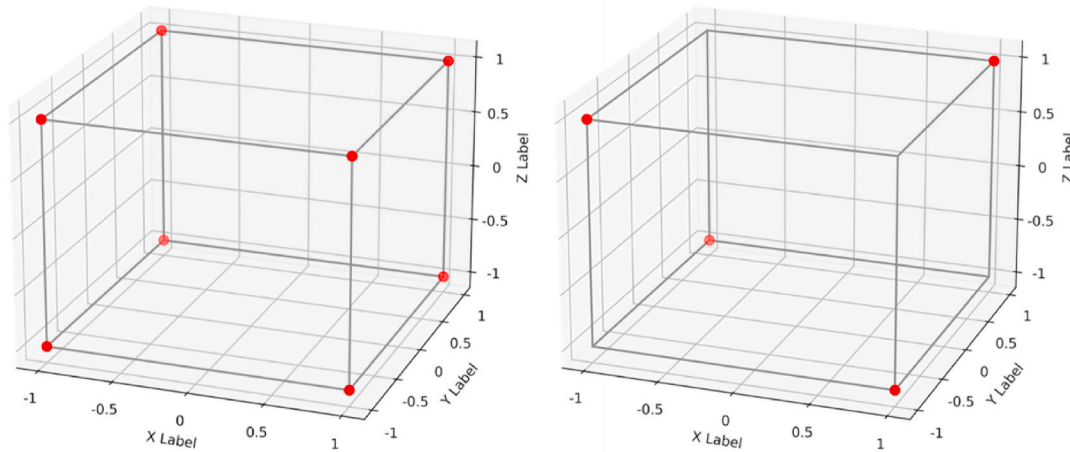


Fig. 5. Full-factorial (left) and fractional factorial (right) design ($k = 3$).

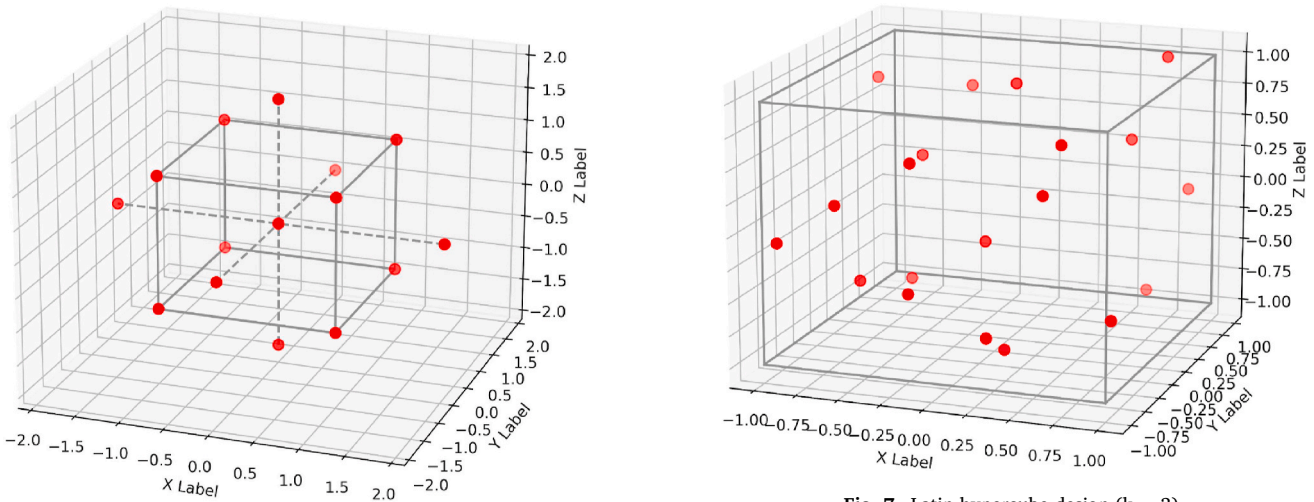


Fig. 6. Central composite design (CCD) ($k = 3$).

Fig. 7. Latin-hypercube design ($k = 3$).

design space is given by choosing a desired statistical property the final design should have.

There is also a subtype of this design, the so-called face-centered-central-composite design. In this design, the factor combinations of the “star-shaped” design lie on the plane spanned by the corner points of the full/partial factorial design. However, this worsens the representation of nonlinear behavior. Therefore, it is only used if a factor can only be varied as an integer.

3.2.1.3. Latin-hypercube design. Another class of designs that are increasingly used in nonlinear contexts, especially when dealing with computer-aided experiments (CAE), are the space-filling designs. One example of those designs is the so-called Latin-hypercube design (LHD) [67,68].

For the LHD, the factor combinations are determined using some sort of stochastic procedure, for example by using a randomly permuted array to construct the full design by a given logic [69]. This method resembles the Monte Carlo method, where the factor combinations are also determined randomly. In contrast to this, the Latin Hypercube uses a methodology to ensure uniform coverage of the entire multidimensional design space (see Fig. 7 for an exemplary LHD). If an LHD is well constructed, the variance of the global mean will be significantly lower than when using a random Monte Carlo field with the same number of

test points.

Basically, in an LHD the design space is first divided into zones. From this zoned design space, a random factor combination is then determined in each zone. A uniform and correlation-free coverage of the factor space is not automatically ensured. For this, further methods such as orthogonal designs or rather space-filling designs would have to be applied [69]. There are a variety of possible methods for constructing an LHD. The selection is strongly dependent on the problem at hand. Recommended approaches are described for example by Moon [70] and Dash et al. [71]. A good overview of space-filling methods and publications is provided by van Dam et al. [72].

3.2.2. Current developments in design of experiments

A large potential for improvement and further development in the field of DOE lies in a subarea of machine learning, the so-called area of active learning also known as query learning [73,74]. In the statistical literature, this application area is also called optimal or adaptive DOE.

Settle describes the basic idea of active learning as follows: “[...] that a machine learning algorithm can achieve greater accuracy with fewer training labels if it is allowed to choose the data from which it learns”. The goal is to minimize the number of factor combinations while achieving a certain forecast quality in combination with metamodeling. Settle defines the term active learning in his work as follows: “Active learning systems attempt to overcome the labeling bottleneck by asking queries in the form of unlabeled instances to be labeled by an oracle (e.

g., a human annotator). In this way, the active learner aims to achieve high accuracy using as few labeled instances as possible, thereby minimizing the cost of obtaining labeled data". For the case of the assessment of security of electricity supply, this oracle is the probabilistic simulation model. Settles divides active learning into three main scenarios membership query synthesis [75], stream-based selection sampling [76,77], and pool-based sampling [78]. Fig. 8 shows an illustration of these concepts.

According to Settles [73], there are a variety of different approaches to active learning. For example, one approach to metamodeling a simulation model using active learning is to add iterative factor combinations to a baseline design. In each iteration, metamodeling and validation are repeated until the desired prediction quality is achieved. The difficulty is to scan the experimental space as effectively as possible and to select the factor combination that provides the greatest possible additional information benefit about the system behavior. For the selection of these factor combinations, there are different basic strategies on which more current approaches are based. Among others are *uncertainty sampling* [78], *query by committee* also known as *ensemble-based strategy* [79], and *expected error reduction* [80].

Current work is focused on the further development of approaches for different application areas and optimization for different metamodeling methods. For example, neural networks with active learning still have a lot of potential. In particular, with the increased use of deep learning methods in recent years, a large research field of deep active learning has emerged. The combination of active learning and deep learning poses some challenges. In contrast to statistical approximation methods, the strengths of deep learning methods do not lie in showing where the uncertainty in the prediction is large. Also, iterative approaches are very computationally intensive since the network must be retrained in each iteration. A very first general overview of this very broad field is given by Ren et al. [81] and Liu et al. [82].

3.3. Combine metamodeling with design of experiments

A possible methodical approach to metamodeling simulation models is demonstrated in the work of Reich et al. [83]. This approach is done using a model for the simulation of an energy supply system but can also be applied to other simulation models. The authors conclude that using an LHD to sample the information to train an artificial neural network is the best approach for approximating the response of the analyzed energy supply system. Furthermore, LHDs and artificial neural networks can be used more flexibly and can thus be better adapted to the problem at hand.

For the presented approach, six steps are defined by the authors: Problem definition, defining the design space, developing designs, developing approximation models, comparison and validation as well as system analysis (see Fig. 9). To illustrate the methodical approach, an exemplary application from Ref. [84] is presented along the individual steps.

3.3.1. Problem definition

Depending on the problem, factors are determined that could have a decisive influence on the system behavior of the simulation model.

In the aforementioned example, the authors present a two-stage metamodeling of a computationally intensive partial calculation of a probabilistic simulation model of security of supply assessments. In the first step, the probability distribution of the available capacities is approximated using a sigmoid function. In the second step, the regression coefficients of the sigmoid function are approximated. The probabilities for non-availability of power plant units are used as features and the target values of the metamodeling are the parameters of the sigmoid function.

3.3.2. Defining design space

In the second step, the design space is defined for which the later

metamodel is valid. For this purpose, the boundaries of the features or independent factors, respectively, selected in step one are set depending on the problem.

Metamodeling aims to reduce the computational effort so that the metamodel must be valid within the boundaries of the scenarios under observation. The boundaries of the design space are defined by the required minima and maxima of the features. In the example, these are the minima and maxima of the probabilities for the non-availability of power plant units extracted from available databases.

3.3.3. Developing designs

Since sampling the simulation and extracting information is often the most time-consuming step, the effort lies in sampling as little as possible while maintaining high informational value.

In their work, the authors compare two regression methods and create a separate design for each to sample the input-output pairs. To represent linear relationships, only the extreme value combinations are required (the corners of the design space), resulting in the design space being sampled using a full factorial two-level design. For the ANN, the input-output pairs are sampled using an LHD. To create the final LHD that is used, 30,000 LHDs are constructed due to their stochastic nature and evaluated using a metric and a correlation criterion.

3.3.4. Developing approximation models

Once the simulation model has been used to generate the system information for the factor combinations of the design, approximation methods can be used to create a metamodel.

In the example work, the authors build an ANN as well as a linear regression for comparative purposes. Both models are built using the non-availability of the power plant units as input data and the curve parameters of the sigmoid function as output data. While the linear regression is built using least square methods, the ANN needs more sophisticated methods. For their work, the authors implement the stochastic nature of the ANN training process (minimizing an error function by finding optimal weight and bias values using a backpropagation algorithm supervised by a validation process) in a meta-heuristic search of the optimal structure (=number of layers and neurons in each respective layer).

3.3.5. Comparison and validation

To evaluate how well the metamodel can approximate the response of the system, the prediction quality must be evaluated. The meaningfulness of the prediction quality depends decisively on the quality of the test points. High-quality test points have two characteristics. Firstly, the test points have uniform distribution in the design space and, secondly, they were not used to create the metamodel.

3.3.6. System analysis

With a metamodel capable of representing system behavior, a variety of possible analysis options are possible. These are among others, the evaluation of the effects of individual input variables on the output variables, sensitivity analysis, large-scale scenario analysis, and multi-criteria optimization.

We will provide more examples of the application of metamodeling and DOE in the field of security of supply assessments in section 5.6.

4. Artificial intelligence for resource adequacy assessment

The advances in the applicability of AI-based methods can be beneficial to several of the aforementioned challenges for the assessment of resource adequacy. In the following, some approaches are presented.

Although there is no commonly agreed-upon definition of the term "artificial intelligence", it is typically used to describe behavior exhibited by computers that were initially thought to require (human) intelligence [85]. There is, however, a consensus on the distinction between strong or general AI, which mirrors the capabilities of intelligence as a

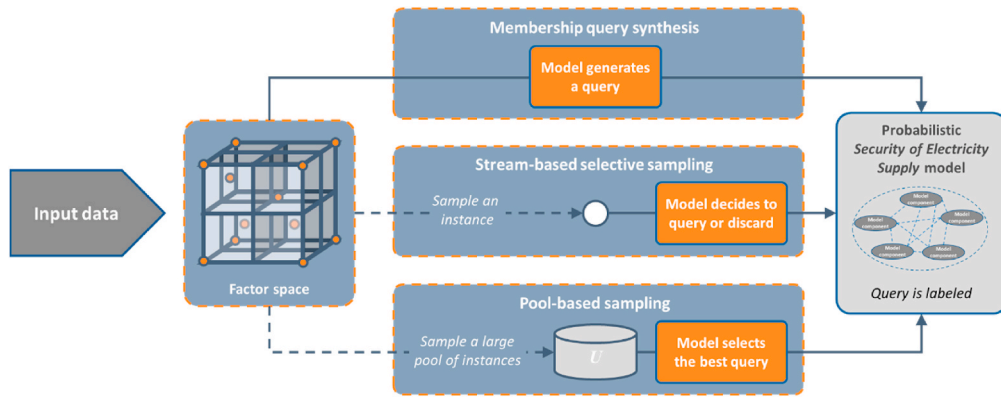


Fig. 8. Schematic representation of the three main scenarios of active learning in the context of the assessment of security of supply. Own representation based on Settles [73].

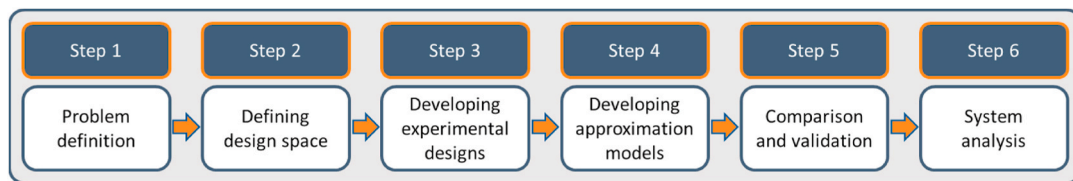


Fig. 9. Methodical approach to the metamodeling of a computer simulation based on Reich et al. [83].

whole on the one side and weak or narrow AI, which is developed to solve specific problems on the other side [86].

The methods explained in this paper are problem-specific approaches that fit under the term narrow AI. Moreover, they are also part of the realm of machine learning, a subfield of AI concerned with learning statistical relationships. Machine learning can thus also be regarded as a subfield of statistics. Contrary to other statistical measures, the exact nature of the statistical relationship (e.g., a functional relationship) between the input data and the output data is not explicitly defined but rather implicitly inferred by the machine learning model itself.

Data is typically structured as multivariate samples or observations [87]. If the data is in table structure, the columns typically denote the features, while the rows are the observations. Often, the term “feature space” is used when talking about data in a machine-learning context. This stems from regarding N features as the axis of an N -dimensional space where every observation is one point in this feature space. Data can be structured as time series data, image data, text data, geodata, or others, leading to different machine learning approaches being suitable to identify patterns within them.

In general, three forms of machine learning can be distinguished in terms of how the model receives feedback during its learning process: Supervised learning, unsupervised learning, and reinforcement learning [88]. In supervised learning, the training data itself contains a set of variables to be explained, the so-called *labels*, and data that is used as explanatory input, the so-called *features*. The input data and labels are fed into the model which then learns the relationship between the two [89]. Supervised learning can be used for regression and classification models. The most prominent examples are artificial neural networks (ANNs) (see exemplary Fig. 10).

An ANN consists of several layers, each layer, in turn, comprising one or multiple neurons [90]. All ANNs have an input layer, which receives the inputs fed into the model, and an output layer, which contains the model’s output. In addition, more layers may be added between the input and the output layer. These layers are called hidden layers and a model including hidden layers is called a deep learning model [91]. In a so-called densely connected ANN, all neurons within one layer are

connected to all neurons in the previous and the next layer. These networks constitute the basic form of neural networks and are called feed-forward neural networks (FFNNs) or multilayer perceptrons [92].

Other network architectures are convolutional neural networks (CNNs) that are particularly suited for dealing with data that is inherently structured in a grid-like fashion [93] (most known for having been used with great success in image recognition and image classification [90]) and recurrent neural networks (RNNs) that are particularly suited for dealing with sequence-like data, such as time series and written or spoken language. Long short-term memory networks (LSTMs) are one of multiple subtypes of RNNs that are characterized by their ability to learn and store long dependencies and patterns in sequences using special circuit elements that regulate forgetting and long-term memory of information. There are many more learning models in the field of supervised learning such as gaussian process regression [94], decision trees [95], or hybrid ensemble methods [96].

In unsupervised learning, data is not labeled and, therefore, problem-specific measures are used to evaluate the model’s quality. For example, clustering is the unsupervised counterpart to classification: In clustering, no classes are known *a priori* and the model creates its own classes or clusters based on pre-defined distance metrics. Clustering unveils the structure inherent in the data by allocating the observations to distinct groups. Generally, the aim is to find clusters of observations that are as dissimilar to each other as possible while the objects (or observations) within the clusters are as similar to each other as possible [97]. Usually, these similarities are measured by a (dis)similarity or distance measure [98]. Two popular clustering approaches are k-means clustering and hierarchical clustering. There is a considerable body of literature on clustering (e.g. Refs. [97,98], or [99]), which the reader may consult for a more comprehensive overview.

For data in high-dimensional spaces, clustering may lose meaning since the data becomes naturally sparse [100]. For such cases, dimensionality reduction can be performed. The most well-known approach is principal Component Analysis (PCA) which forms linear combinations of existing features by maximizing the data’s variance [101]. Other approaches for dimensionality reduction are linear discriminant analysis (LDA) [102], t-Distributed Stochastic Neighbor Embedding (T-SNE)

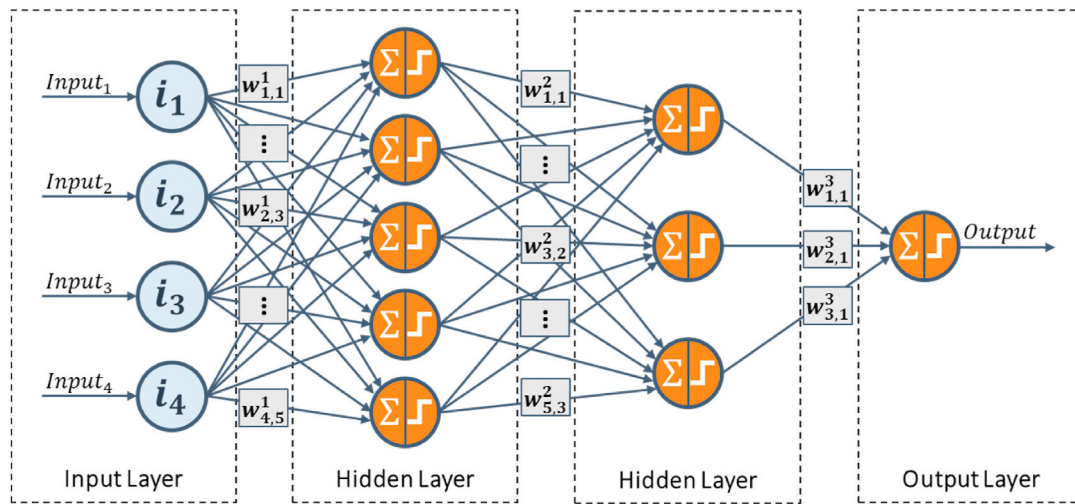


Fig. 10. A basic feedforward neural network consisting of several layers of connected neurons. Here, connections between two neurons have a weight that is determined during training and neurons in the hidden and output layers are equipped with an activation function.

[103], or autoencoders [104,105].

Finally, reinforcement learning applies a cost function that defines rewards and penalties during the training procedure. This approach is particularly useful when it is impossible to cover all possible system states during training, such as when teaching machines to play games or in autonomous driving [89].

With regard to the assessment of resource adequacy, AI methods can be used broadly in three fashions: Preprocessing of relevant input data, forecasting of input data, and metamodeling energy system models. In the first case, an AI method (or model) prepares data for other models while in the second case, an AI method is used to forecast relevant data that might be fed into further energy system models or directly analyzed. The third case refers to using a conventional energy system model in order to generate data for training the AI model. That is, the AI model is used to model the behavior of the conventional model and to explore a broader range of scenarios (see Ref. [11]).

The following sections provide an overview of AI-based methods used for data processing (consolidation and aggregation), feature selection, forecasting, and metamodeling. The subsections are to be understood as an overview of models and methods that are of particular interest in the context of resource adequacy assessments. In section 4.5, methods for evaluating the accuracy of AI-based models are presented.

4.1. Data consolidation

Data consolidation is the process of integrating and merging data from multiple sources into a unified data format while performing data cleaning procedures. In this context, statistical methods, especially those based on AI, are becoming increasingly important. By using machine learning-based algorithms such as clustering, regression, and dimensionality reduction, AI is capable of analyzing both structured and unstructured data, identifying patterns, and shaping them into a coherent whole.

The input data for complex probabilistic models is high-dimensional spanning among others the dimensions of time, space, and technologies. Ready-made data bases do not exist, and data needs to be collected and consolidated from various sources, often with different data formats, resolutions, and underlying methodologies. An adequate data basis is the foundation of any solid resource adequacy assessment. Therefore, researchers and practitioners collect data from as many sources as possible and merge them in order to generate a sound foundation for the input data of their models. This merging process can be supported with AI-based methods such as clustering or dimensionality reduction, i.e. methods from the field of unsupervised learning (for an overview, see

Ref. [106]).

With data imputation methods, missing data in data sets can be filled based on patterns identified in the available data points. Jadvar et al. [107] give an overview of various machine learning models that can be applied to such problems.

4.2. Data aggregation

Data aggregation is useful in energy system modeling as a tool for reducing the amount of data fed into the energy system model. Data aggregation is often performed using clustering algorithms whereby cluster centers are typically expressed through the mean, centroid, or medoid of the observation's features. In energy system analysis, it often finds use as a data reduction method for time series data. Clustering time series (i.e., time series or temporal aggregation) allows representing the data through a considerably lower number of data points, which can reduce model runtimes while also impacting model accuracy. Hoffmann et al. [9] present a comprehensive review of time-series aggregation methods and compare various approaches, including clustering. Other reviews include the ones conducted by Teichgraeber et al. [108] and Kotzur et al. [109].

Besides temporal aggregation, also other dimensions of the input data space can be aggregated such as the spatial or the technological dimension [110,111] as well as the demand side dimension in terms of energy consumers (e.g. Ref. [112]).

4.3. Feature selection

Energy system modeling usually involves handling time series data. Time series are in turn often the result of several effects superimposed over each other. Thus, decomposing a time series into its components (e.g. constant, cyclical, and trend components) can help interpret and model time series data [113]. Recently, there has been promising research on the combination of decomposition and feature selection as preparation for a forecasting model (see e.g. Refs. [114,115]).

Fig. 11 shows an exemplary seasonal decomposition of an electricity load time series. The original time series (orange line) is decomposed into three components: a trend component, a seasonal component, and a residual. In this example, multiplicative decomposition is performed. The multiplication of all components results in the original time series.

Feature selection refers to deciding on which features to feed into the model [116]. This is particularly potent in combination with time series decomposition methods, as it can allow keeping only those components of a time series that are both meaningful and predictable. This can

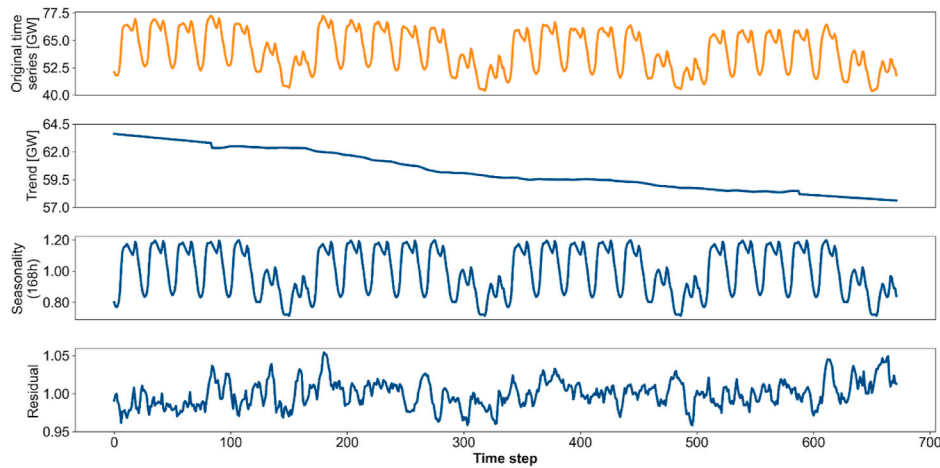


Fig. 11. Trend, seasonality (168 h), and residual series of a decomposition of a four-week electricity load time series (orange line). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

increase the quality of the prediction while avoiding adding unnecessary dimensions to the input data. Typically, feature selection approaches are classified as filters, wrappers, or embedded methods [116]. A filter is independent of the subsequent model, while a wrapper “wraps around” a predictive algorithm, thereby accounting for its design [117]. Embedded methods are predictive methods that inherently include some sort of learning that can be used for feature selection [87].

4.4. Forecasting and metamodeling

Forecasting refers to extrapolating historical information (e.g. on electricity load or renewable feed-in) into the future or prediction an outcome of one feature based on the knowledge about other features. Therefore, forecasting methods can be applied to a multitude of data sets such as time-series data or input-output model relations as required for metamodeling. In terms of AI-based models, supervised learning is applied which requires labeled input data. A general distinction in the structure of forecasting models can be seen in Fig. 12. The information provided is a simplified representation of model structures and does not account for feedback or other more complex variants.

A univariate forecasting model is based entirely on historic information on the output feature. In contrast, multivariate models use additional information as input features that correlate with the output feature. Multivariate models can be further distinguished between using information predictions for the future values of input features or not. In addition, a hybrid model that uses both, historic information and future predictions of input features can be constructed. In this case, further prediction models are used for forecasting input feature values.

In energy system modeling, AI-based forecasting models are applied for example as tools to forecast weather-dependent renewable feed-in (e.g. Refs. [118,119]), electricity loads (e.g. Refs. [120–123]), or detecting anomalies and malfunctioning (e.g. Refs. [124–126]).

4.5. Selecting and evaluating machine learning methods

Having introduced a variety of machine learning methods, the question that is yet to be answered remains which method to apply under which circumstances. This also includes evaluation of the model’s quality or “goodness of fit”. Unfortunately, there is no straightforward answer to these questions. Machine learning methods are highly problem-specific and as has been mentioned already, often deep knowledge of the data is necessary in order to decide which method to apply. Thus, there are guidelines for choosing models (such as in Ref. [127]), but these are to be understood as recommendations rather than objective rules.

Similarly, evaluating the quality of a particular model being applied to data is also a problem-specific and even an algorithm-specific matter. For supervised learning methods, model quality is ensured by separating a part of the data from the rest of the dataset and not using it when training the model. After the model has been trained on the rest of the dataset (the training set), this so-called test set is used to compare the model’s prediction against the correct label [128]. Common metrics used to do this are, among others, the Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the Root Mean Square Error (RMSE) [129] (see Fig. 13 for the calculation of the different error measures). This allows for comparing the performance of different machine-learning approaches for the same task.

Ensuring the quality of an unsupervised learning approach, such as clustering or PCA, is less straightforward since these algorithms are designed for tasks where there is no correct label. For example, in clustering, a variety of generic (so-called external) evaluation metrics have been proposed, which allow the comparison of the results of different clustering algorithms. However, these metrics rely on external data (i.e. correct labels), which is often not available [131,132]. So-called internal metrics rely only on the information inherent in the input data and are often based on the metric the algorithm tries to optimize [131], making them algorithm-specific. This makes different clustering results difficult to compare.

Both supervised and unsupervised machine learning methods, however, share the necessity to perform so-called *hyperparameter tuning*. The various methods introduced in this paper typically require the user to set several parameters such as the number of neurons and layers in an ANN, or the number of clusters in k-means clustering [133]. The optimal set of hyperparameters often depends not only on the task at hand but also on the concrete dataset and the choice of hyperparameters can influence the model performance to a great extent [134]. Thus, careful choice of hyperparameters is important in order to achieve satisfactory results. Typically, hyperparameter tuning is performed manually or through heuristics, although automated approaches for this procedure are being investigated [133].

5. Results of the quantitative literature review

In this section, we present the development of the adoption of selected AI approaches related to resource adequacy assessment from 2010 to 2022. We do not claim this selection to be exhaustive but rather want to give a broad overview of the latest developments in relevant fields. For each field of application, we conducted a separate systematic literature research.

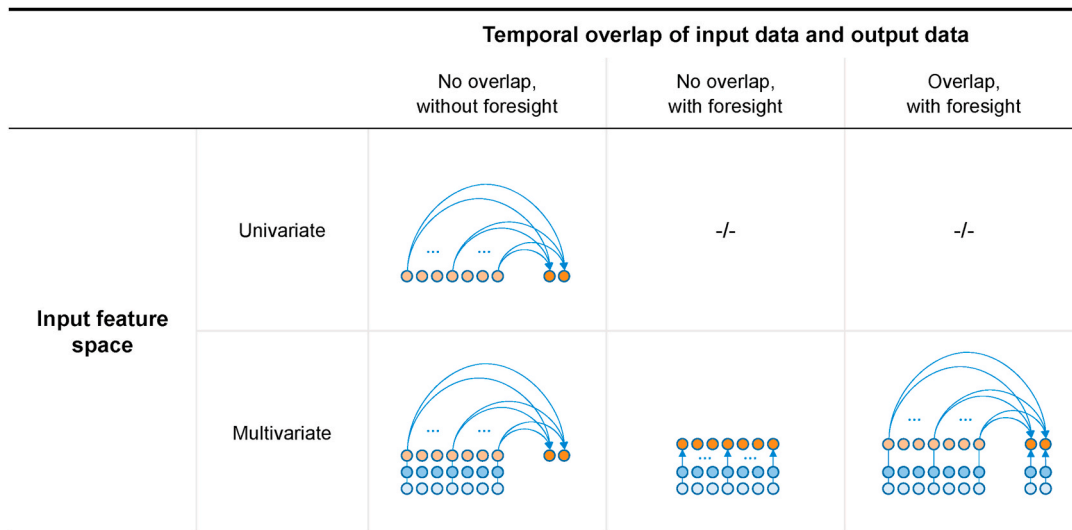


Fig. 12. Categorization of the general structure of forecasting models.

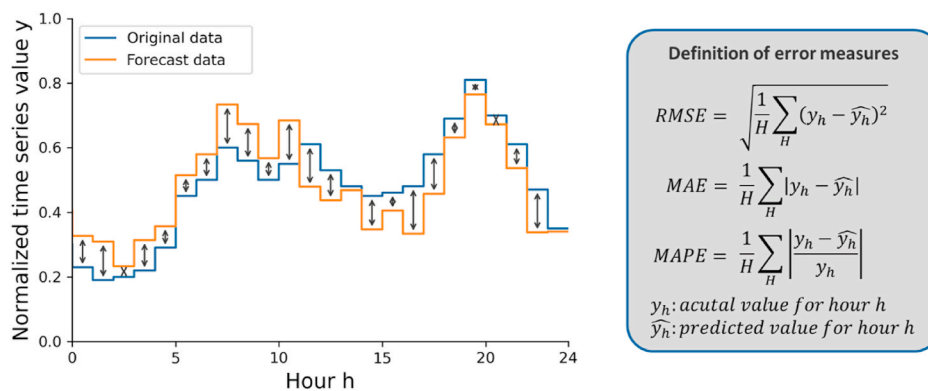


Fig. 13. Exemplary illustration of the deviation between actual and predicted electricity loads based on Hoffmann et al. [130].

5.1. Data consolidation and aggregation

Unsupervised learning in the form of clustering and dimensionality reduction algorithms are generally the tools of choice when it comes to data consolidation and aggregation. A general increase in the application of methods from this field to energy data can be observed from our literature review.

Fig. 14 shows the number of articles on some of the most popular clustering algorithms in the field of energy system modeling since 2010.⁴ A variety of clustering algorithms exists and choosing a well-suited algorithm is a highly data- and problem-specific task.

The k-means algorithm is the predominant clustering algorithm used in the energy-context. From the list of publications, it can be seen that clustering is usually one part of a processing pipeline that serves to structure data while at the same time reducing the amount of data points for subsequent analysis such as forecasting.

Fig. 15 shows the number of articles on some of the most popular methods for dimensionality reduction in the field of energy system analysis since 2010.⁵ Again, the selection of an appropriate algorithm to achieve a well-balanced reduction of dimensionality while maintaining or even increasing the informative value of the data depends on the underlying data and the modeler's objective.

While for most of the time since 2010, PCA approaches have been preferred by researchers to reduce dimensionality in energy data, autoencoders have become increasingly popular from 2018 onwards. This shift underscores the evolving nature of energy system analysis, where dimensionality reduction not only consolidates datasets but also serves as a preliminary step for downstream tasks such as forecasting. Crucially, these methods enhance the efficiency of subsequent models by reducing input data volume and eliminating correlations between features, representing key innovative approaches in the field of energy data analysis.

5.2. Forecasting electricity load profiles

Forecasting electricity load profiles can be categorized into four different time horizons shown in Table 2:

Electricity load forecasts are used in different fields of application [135]. For assessing the security of electricity supply, long-term forecasts are used to plan and build infrastructure for a secure provision of electricity. Electricity load profiles are affected by a multitude of factors, such as weather, economic factors, or the portfolio of end-user technologies [29].

5.2.1. Forecasting data

Electricity load profiles are given as time series with varying temporal resolutions. Electricity loads can be provided as aggregated information, usually from minute to hourly averages [136]. Average

⁴ For details on the search term specification, see Table 8 in the appendix.

⁵ For details on the search term specification, see Table 9 in the appendix.

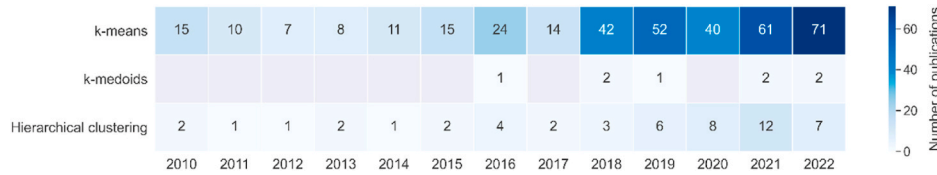


Fig. 14. Number of scientific articles found on the application of popular clustering algorithms in energy system analysis published in energy-related journals in the Scopus database from 2010 to 2022.

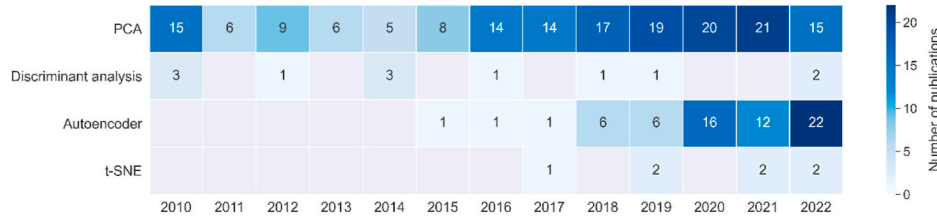


Fig. 15. Number of scientific articles found on the application of popular dimensionality reduction methods in energy system analysis and published in energy-related journals in the Scopus database from 2010 to 2022.

Table 2
Definition of four different time horizons for load profile forecasting [7].

Abbreviation	Forecasting duration	Time interval
VSTLF	Very short-term load forecast	Less than 30 min.
STLF	Short-term load forecast	30 min to 1 day
MTLF	Medium-term load forecast	1 day to 1 year
LTLF	Long-term load forecast	>1 year

values have the advantage that, aggregated, they represent total annual consumption. However, due to the aggregation, peak loads are usually neglected that would be better represented by maximum instead of average values. In turn, using the maximum function for aggregating temporal data would overestimate the total annual consumption. Hybrid solutions using averaging as an aggregation method and adding peak load values are used to compensate for the individual disadvantages of the aggregation methods. Electricity loads can be subject to different aggregation levels [137]:

- Sectoral aggregation: Total load profiles vs. sectoral load profiles
- Regional aggregation: No regional differentiation vs. including regional identifiers
- Temporal aggregation: Time series data in sub-hourly, hourly, daily, or weekly resolution

In principle, the less aggregated the data, the more accurate the representation of the real system. However, this principle does not apply if the quality of the data sample is low. The level of aggregation of the data should, therefore, be chosen so that the accuracy of the data at the chosen resolution meets the requirements. This means that data may need to be aggregated.

5.2.2. Feature selection

The main features influencing electricity loads are calendrical information, meteorological (temperature and weather) data, and economic factors (such as future prices or prices of other energy carriers) [138]. Features, as well as the forecasting data, can vary in terms of sectoral, regional, and temporal aggregation. Table 3 shows a selection of studies on medium- and long-term forecasting and the features used in the forecasting models.

5.2.3. Prediction models

Fig. 16 shows the results of the systematic literature review on the

development of electricity load forecasting models within the Scopus database.⁶

Neural Networks are the most widely used AI methodology for predicting electricity load time series. Studies using FFNN are published at numbers between ~80 and ~200 per year. Studies using CNNs and RNNs have become increasingly popular since 2018, with RNNs being used even more frequently than FFNNs from 2020 onwards. In the field of RNN, LSTM neural networks dominate and are used in the majority of studies. Support vector machines are constantly used in ~40–100 studies per year, making them a popular alternative to neural network approaches. Finally, the number of studies based on decision trees and ensemble methods has recently increased significantly since 2018.

5.3. Forecasting renewable feed-in profiles

In addition to the demand side, there is also uncertainty on the supply side, driven in particular by the expansion of renewable energies. This is the most critical scheduling input, as both situations of oversupply and undersupply are possible. In the context of assessing the security of electricity supply, undersupply is of particular relevance [29]. However, the inclusion of situations of oversupply in the analysis becomes more important the more storage facilities in the system can absorb this energy and make it available again at times of undersupply [144]. Similar to forecasting electricity load profiles, the time horizon of the forecast can be used as an initial distinction of the fields of application (see Table 4).

For the field of application portrait in this paper, i.e., *ex-ante* assessments of security of electricity supply, long-term forecasting is again the relevant time horizon. Renewable feed-in profiles combine the availability of the power plant with a capacity credit that is based on weather forecasts [144]. We will address the forecasting of non-availabilities in section 5.4 in more detail. Forecasts of renewable feed-in profiles can now focus on the solely weather-dependent aspects or a combination of the two.

5.3.1. Forecasting data

Renewable feed-in profiles are given as time series with varying temporal resolutions. Similar to electricity load profiles, they are given as aggregated information providing, e.g., minute or hourly averages [147]. In addition to average values and in contrast to electricity load profiles, it is not maximum but minimum values that are of interest for

⁶ For details on the search term specification, see Table 10 in the appendix.

Table 3
Comparison of features used for predicting electricity loads based on selected studies.

Study	Melodi et al. [139]	Sangrody et al. [140]	Yasin et al. [141]	Matsuo and Oyama [142]	Behm et al. [7]	Dai and Zhao [143]
Feature						
Historic load	X	X	X	X		
Calendrical information		X		X	X	X
Air temperature			X	X	X	
Wind speed			X		X	
Irradiation					X	
Relative humidity			X			
Weather classification				X		
Heating day information		X				
Cooling day information		X				
Price data						X
Gross domestic product	X					
Population	X					

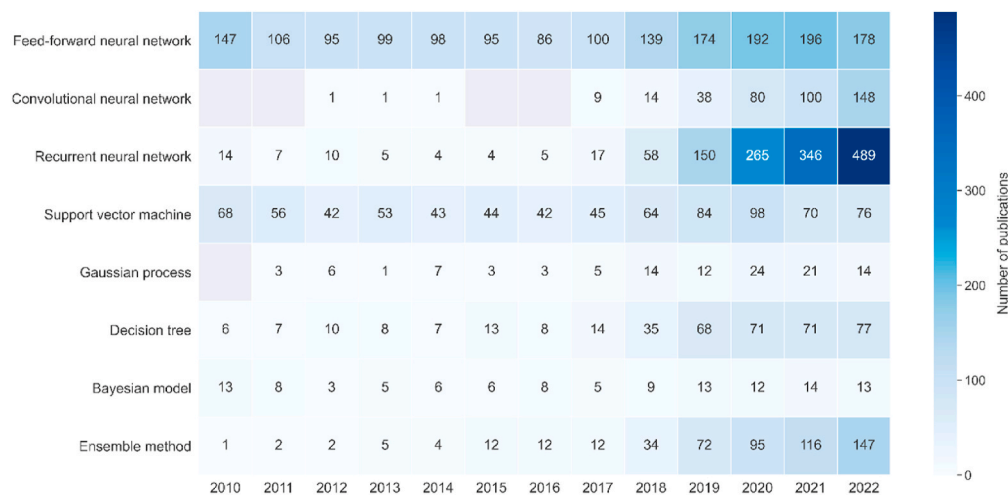


Fig. 16. Number of scientific articles found on load forecasting in energy-related journals in the Scopus database from 2010 to 2022, categorized by AI-based methodology.

Table 4
Generation forecast methods and applications [145,146].

Time horizon	Methods	Key applications
5–60 min ahead	Very short-term forecast	Regulation, real-time dispatch, trading, market-clearing
1–6 h ahead	Short-term forecast	Scheduling, load following, congestion management
Day(s) ahead	Medium-term forecast	Scheduling, reserve requirement, trading, congestion management
Weeks or more ahead	Long-term forecast	Resource investment planning (generation, network), contingency analysis, maintenance planning, operation management

assessing the security of electricity supply in order to perform a robust analysis that can also map extreme events. Renewable feed-in profiles can be subject to different aggregation levels:

- Technological aggregation: E.g., aggregating or disaggregating rooftop PV and ground-mounted PV
- Regional aggregation: No regional differentiation, including regional identifiers, or per unit
- Temporal aggregation: Time series data in sub-hourly, hourly, daily, or weekly resolution

5.3.2. Feature selection

The main features influencing (aggregated) renewable feed-in profiles are historical meteorological data, numerical weather predictions

(NWP), and information about the surroundings to estimate the effects of shadows and wind shadows [148]. Table 5 shows a selection of studies on wind power feed-in forecasting and the features used in the forecasting models.

5.3.3. Prediction models

Fig. 17 shows the results of the systematic literature review on renewable feed-in forecasting.⁷

Similar to studies on predicting electricity load profiles, FFNNs used to be the most widely used AI methodology for predicting renewable feed-in time series. Since 2021, studies based on RNNs have suddenly exceeded FFNNs. CNNs as well have drastically increased in popularity since 2018. While support vector machines have a constant number of publications of ~20, the number of publications with ensemble methods has exceeded 30 per year in 2021. Other methods such as decision trees, Bayesian models, or gaussian processes are not yet used as frequently for predicting renewable feed-in time series.

5.4. Forecasting (non-)availabilities

A major uncertainty in assessing security of electricity supply is the availability of generation capacities and network components. As our review concentrates on generation adequacy, network components are not the focus of this section. Generation capacities in the energy system

⁷ For details on the search term specification, see Table 11 in the appendix.

Table 5
Comparison of features used for predicting wind power feed-in based on selected studies.

Study	Chen and Folly [149]	Xiaoyun et al. [150]	Pelletier et al. [151]	Bilal et al. [152]	Shahid et al. [153]	Nazaré et al. [154]
Feature						
Wind speed (at different hub heights)	X	X	X	X	X	X
Wind direction	X	X	X	X	X	
Air temperature	X	X		X		X
Zonal and meridional flows					X	
Air density		X	X			
Air pressure	X	X				X
Relative humidity	X			X		X
Turbulence intensity			X			
Wind shear			X			
Yaw error			X			
Solar irradiation				X		

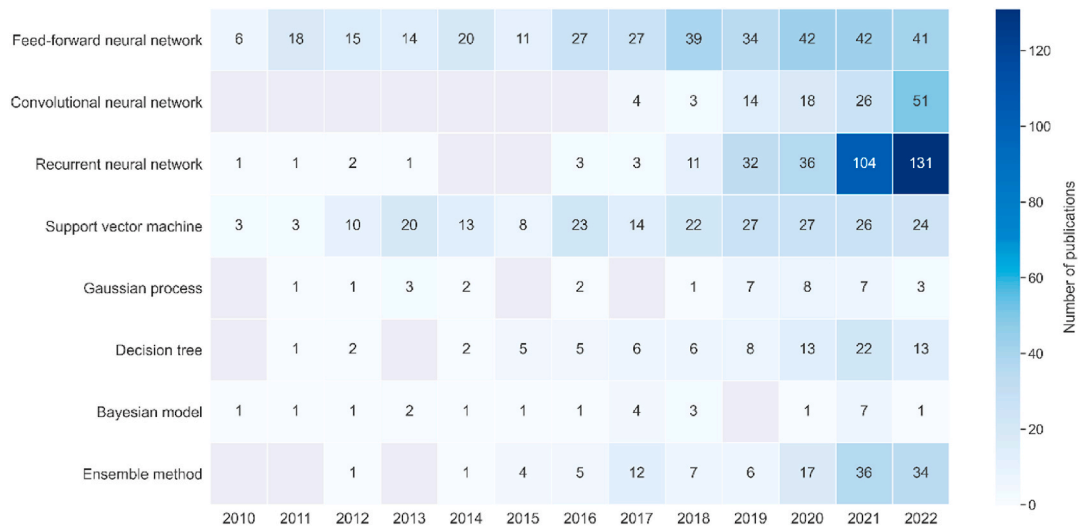


Fig. 17. Scientific journal articles on renewable feed-in forecasting in energy-related journals in the Scopus database from 2010 to 2022, categorized by AI-based methodology.

can be non-available due to planned and unplanned outages [29]. Planned non-availabilities are known in advance and are usually due to scheduled (e.g., annual) maintenance. Unplanned non-availabilities are not known in advance, are subject to a much more random distribution than planned non-availabilities, and can be due to malfunctioning or uncontrollable external factors such as extreme weather conditions. Both types of events have a major impact on supply security [155]. Due to the differences in their distribution and influencing factors, they are usually modeled and predicted separately [156].

The application field of the availability of power plants for machine learning-based methods is therefore twofold. For planned unavailability, scheduled maintenance cycles need to be predicted [29]. Insights from predictive maintenance can be transferred to improve predictions on maintenance schedules [157]. In contrast, in the case of unplanned unavailability, factors such as complex thermodynamics and the security of supply of fuels need to be modeled [158]. This imposes fundamentally different requirements on predictive models.

Another challenge stemming from the systemic perspective in the assessment of security of electricity supply is that no further operational data from specific sites are available. This is because the entirety of power plants must be depicted, with various operators and at various locations. Forecasting models, therefore, have to rely solely on external factors such as weather conditions that can be monitored and predicted.

Finally, a distinction needs to be made between modeling the non-availability of components independently or (1) considering common-mode (or common-cause) situations and (2) considering time-dependence [159–161].

5.4.1. Forecasting data

Component unavailability can be available as binary information, multiple discrete states, or continuous availability levels [156,159]. Binary data indicates whether the component is available or not while discrete and continuous data additionally show the share of non-available capacity. Data on non-availability are subject to different aggregation levels:

- Technological aggregation: Total capacity, capacity per generation technology, or capacity per generation unit
- Regional aggregation: No regional differentiation or including regional identifiers
- Temporal aggregation: Annual data (availability factor), data for certain points in time (e.g. during annual peak load), or time series data (e.g., hourly resolved)

5.4.2. Feature selection

We assume the main features influencing the availability of generation capacities to be calendrical information, technology-specific data, weather and further environmental data, price data, and load data. Table 6 shows a selection of studies on (non-)availability forecasting for thermal power plants and the features used in the forecasting models. The studies listed do not exclusively apply machine learning-based methods as the number of such studies found in the literature research was too low at the time the search was conducted. We assume that independent of the methodological approach, the listed features can serve as a good starting point for constructing machine learning-based models.

Table 6

Comparison of features used for predicting (non-)availabilities of thermal power plants based on selected studies. Additional information on the methodological approach and the dependencies mapped in the model is provided.

Study	Koch and Vögele [162]	Gils et al. [156]	Yuyama et al. [163]	Murphy et al. [160]	Nolting et al. [29]	Hundi and Shamsavari [158]	Malladi et al. [159]
Method applied	Analytical model	Mean-reversion Jump-diffusion model	Lognormal and Weibull hazard models	Non-homogeneous Markov and Logistic regression model	Sliding window technique	Linear regression, SVM, random forests, ANN	Continuous-time Markov chain with dependence sets
Non-availability category	Un-planned	Planned, unplanned	Unplanned	Unplanned	Planned	Unplanned	Unplanned
Number of plants modeled	Single	Multiple	Multiple	Multiple	Multiple	Single	Multiple
Time dependence				X	X		X
Common-mode failures				X			X
Asset type	X	X	X	X	X	X	X
Asset age			X	X			
Asset size	X		X	X	X		
Calendrical information		X	X				
Air temperature	X			X		X	
Air pressure						X	
Relative humidity	X					X	
Stream temperatures or levels	X						
Environmental regulations	X						
System load				X			
Other	X					X	X

Interestingly, price data (forward or spot prices) are not found as explanatory variables in the literature.

5.4.3. Prediction models

Fig. 18 shows the results of the systematic literature review on the non-availability of generation capacities.⁸

The field of prediction models for the (non-)availability of power plants using machine learning is not yet established on a large scale. Neural networks with a focus on RNNs are the most relevant method applied and numbers have been rising over the last years. Support vector machines and Bayesian models are used in a few works. Looking into the few available studies, the most cited works rely on sensor data [164–166]. As sensor data is usually used for forecasting individual plant outages, we conclude that on a system level, the application of machine learning-based methods for forecasting the (non-)availability of power plants is a major research gap.

5.5. Forecasting storage operation

In traditional energy systems, storage systems were mainly large-scale central units such as pumped hydro storage power plants. Decentralization of the energy supply increases the number and variety of storage facilities considerably [167]. Also, new central storage technologies may be deployed in the future such as compressed air electric storage (CAES) [168]. Small and large storage units will operate differently in energy markets as large units may have an impact on the market price (price makers) while small ones do not (price takers) [169]. The increasing number and capacity of energy storage systems together with their different operating strategies, the decline in controllable power plants, and the expansion of volatile renewables increase the importance of storage systems for security of electricity supply [170]. As a result, forecasting the operation of storage is becoming increasingly important.

Unlike thermal and renewable power plants, storage systems do not

necessarily operate in line with overall system goals such as security of supply. Storage operators may withhold stored energy or create additional electricity demand for self-interested reasons. Rationales for this include arbitrage opportunities, extending the life of their assets, or maximizing self-consumption [171]. Large energy system models that incorporate storage alongside power plants and minimize total system costs have difficulty representing these behaviors endogenously [172]. To overcome this problem, model coupling approaches can be applied. Submodels that take the perspective of the storage operators can then represent the storage operation, which is, for example, iteratively fed into a larger system model. Such submodels could again apply cost-minimization methods or depict storage operation by applying machine learning-based methods that learn such behavior from historical data.

5.5.1. Forecasting data

Storage operation will ultimately be needed in the same temporal resolution as other temporal input data that is used for the assessment of the security of electricity supply. Data on storage operation is subject to different aggregation levels:

- Technological aggregation: Total storage dispatch and state of charge (SoC), per storage technology, or per storage unit
- Storage-specific information: Storage dispatch and/or SoC
- Regional aggregation: No regional differentiation or including regional identifiers
- Temporal aggregation: Time series data in sub-hourly, hourly, daily, or weekly resolution

Information on storage operation can be based on historical data or simulations. Scapino et al. [173] use a physics-based model to simulate a storage system and generate the forecasting data for the prediction model (this approach belongs to the field of metamodeling, see sections 4 and 6).

5.5.2. Feature selection

The main features influencing storage operation besides technical

⁸ For details on the search term specification, see Table 12 in the appendix.

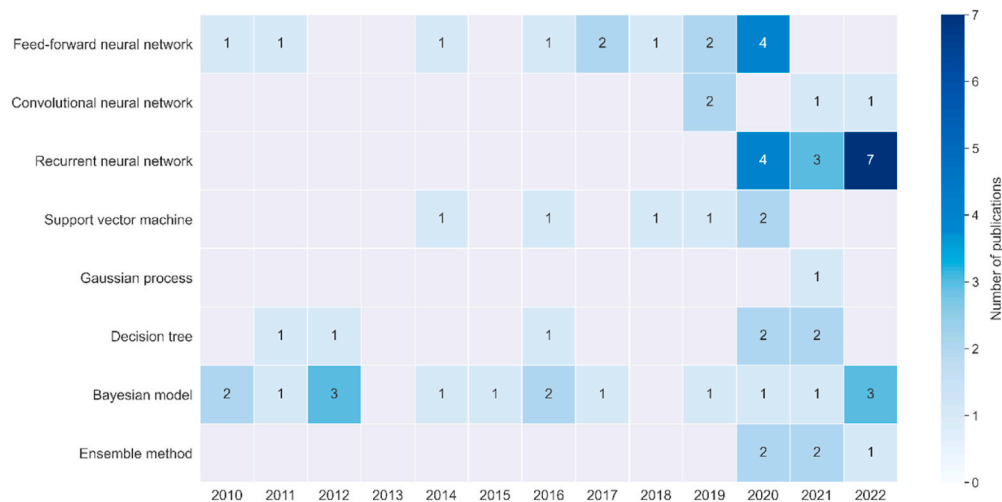


Fig. 18. Scientific journal articles on predicting (non)-availability of power plants in energy-related journals in the Scopus database from 2010 to 2022, categorized by AI-based methodology.

characteristics price and other market information are weather data, and load and generation data (see Table 7). The studies listed do not exclusively apply machine learning-based methods as the number of such studies found in the literature research was too low at the time the search was conducted. We assume that independent of the methodological approach, the listed features can serve as a good starting point for constructing machine learning-based models.

5.5.3. Prediction models

Fig. 19 shows the results of the systematic literature review on predicting storage operation.⁹

The field of prediction models for storage operation using machine learning is not yet established on a large scale though has made a significant jump in recent years. Neural networks are the most frequently applied method but also support vector machines, Gaussian process regression, and decision trees are used. In the field of neural networks, a trend toward RNNs is emerging. Wang et al. [178] developed a prediction model for distributed electric heating storage systems. They find that their correlation-based LSTM model outperforms support vector machines and regular RNN models. Xiao et al. [179] come to a similar conclusion when comparing multiple methods for behavior learning in microgrids. They find LSTM models most suitable for microgrids that include storage systems.

5.6. Metamodeling and design of experiments for boosting the scenario scope

The basic design method has been successfully used in combination with metamodeling in many publications. In the following, a possible approach is presented, as well as the benefits of metamodeling based on exemplary publications. Further, modeling recommendations for the combination of metamodeling and DOE are provided.

Unlike in real-world experiments, the input variables in computer-based experiments can be varied continuously with less effort. This allows the design space to be sampled at a higher resolution. However, in many use cases, simulations have a rather complex nature with nonlinear behavior. Metamodeling using a full factorial design (full-FD) and linear or polynomial regression is not possible in these cases. In these cases, more complex designs and more complex methods for metamodeling, e.g., from the field of machine learning must be used.

Fig. 20 shows the results of the systematic literature review on the

application of AI-based methods for metamodeling in energy-related publications.¹⁰

Since 2010, primarily models based on FFNN and GPR have been used for metamodeling in publications in energy-related journals. Other methods of deep learning such as CNNs and RNNs have only been used from 2017 onwards. In addition to these methods, the number of publications per year applying SVMs and Bayesian models for metamodeling is relatively constant. A trend can be seen in the application of decision trees and ensemble methods that have become more popular since 2017.

Fig. 21 shows the results of the systematic literature review on metamodeling applications in combination with DOE in energy-related publications.¹¹

Metamodeling and DOE have been combined since 2010 with numbers between ~35 and ~60 publications per year. AI-based methods only make up for a small share of these publications and the numbers are only slowly increasing. In 2022, ~20 % of all publications we found on metamodeling and DOE in energy-related journals included the application of AI-based methods.

Nolting et al. [11] show that linear regression and full factorial designs should not be excluded in advance from computer simulations. In this comparative study, the prediction performance of linear regression (with full-FD) and artificial neural networks (with LHD) for the approximation of a probabilistic simulation model for assessing the security of electricity supply in Germany were investigated. The investigation showed that linear regression has better prediction quality for the present use case with fewer trial points and thus reduced associated simulation time. The results also show that analogous to the selection of a suitable approximation method, a suitable method must be selected from the DOE on an application-specific basis.

Metamodeling can also be applied to the second most common method for resource adequacy assessments, i.e., optimization models. Hirvonen et al. [180] apply a metamodeling approach for the optimization of energy communities. To avoid a large number of optimization runs, the authors initialize a small training with the optimization model, train a neural network as a metamodel, and then iteratively add further training data as required to achieve sufficient accuracy of the metamodel. This can only be implemented with metamodeling, otherwise, the results have to be generated with many time-consuming simulations.

A comprehensive comparison of metamodeling methods is presented

¹⁰ For details on the search term specification, see Table 14 in the appendix.

¹¹ For details on the search term specification, see Table 15 and Table 16 in the appendix.

⁹ For details on the search term specification, see Table 13 in the appendix.

Table 7
Comparison of features used in studies for predicting storage operation.

Study	Nojavan et al. [174]	Zhour et al. [175]	Henri and Lu [176]	Mousavi et al. [177]
Method applied	Optimization	Optimization	Neural networks, random forest	Optimization and neural network (metamodeling)
Storage technology	Compressed air storage	Generic storage system	Combined PV and battery storage system	Pumped hydro storage (in an island system)
Technical characteristics	X	X	X	X
Calendrical information			X	
Precipitation				X
Air temperature			X	X
Relative humidity				X
Wind speed				X
Radiation				X
Electricity price	X	X	X	
Gas price	X			
Electricity load		X	X	
Renewable feed-in		X	X	
State of charge	X	X	X	X

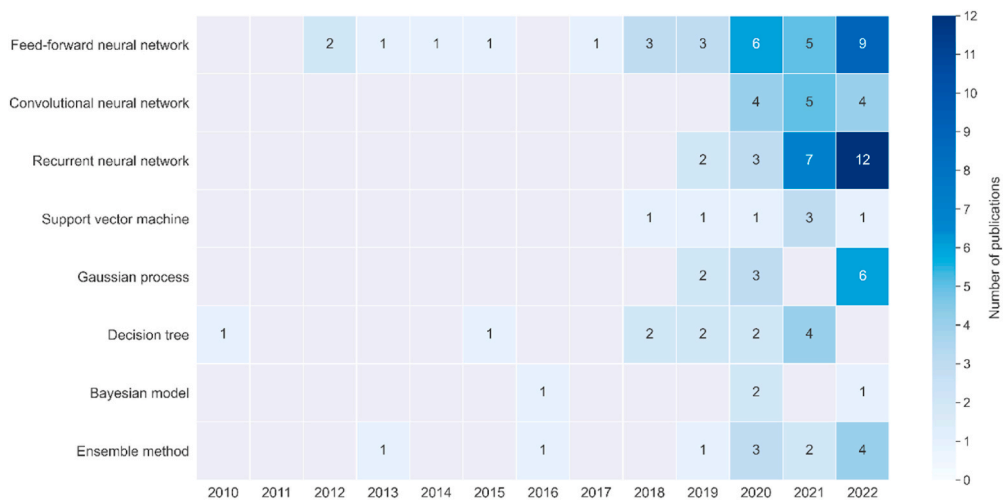


Fig. 19. Scientific journal articles on predicting storage behavior in energy-related journals in the Scopus database from 2010 to 2022, categorized by AI-based methodology.

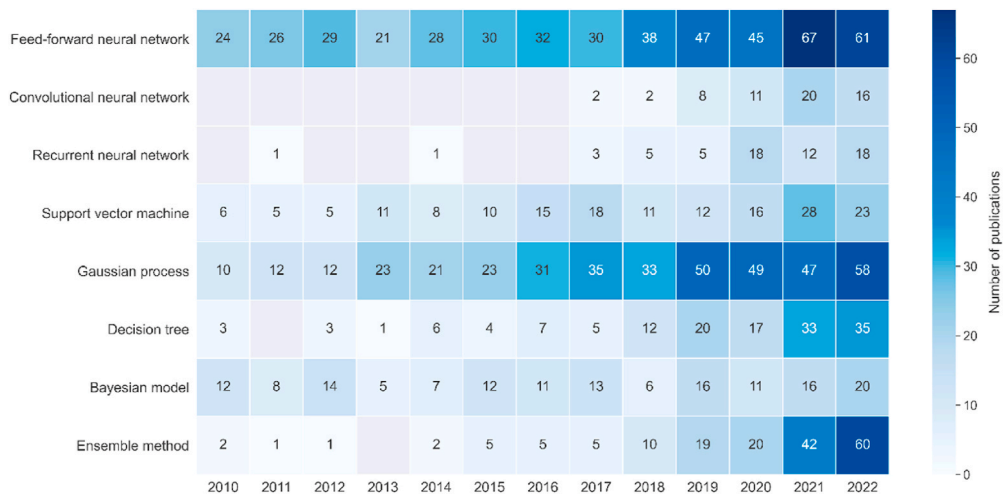


Fig. 20. Scientific journal articles on metamodeling in energy-related journals in the Scopus database from 2010 to 2022, categorized by metamodeling methodology.

by Østergård et al. [181]. In this study, the six most used methods for metamodeling are applied to 13 application cases in building performance simulations with different dimensionality and complexity. The authors conclude that the choice of method depends largely on the

problem and that the literature cannot provide a general preference for the method. From their results, the authors draw the following general conclusions, among others:

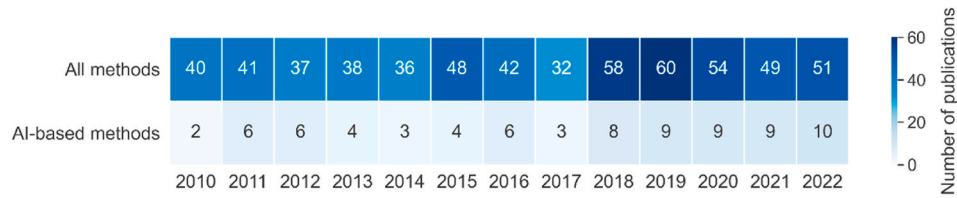


Fig. 21. Scientific journal articles on metamodeling in combination with design of experiment in energy-related journals in the Scopus database from 2010 to 2022, categorized by metamodeling methodology.

- Standard settings generally provide poor or mediocre accuracies, so optimization of the hyperparameters is necessary,
- hyperparameters must be adapted to the respective problem,
- in general, the best results were achieved with GPR followed by ANNs, and multivariate adaptive regression splines (MARS),
- linear regression models achieved the worst accuracy due to the nonlinearity of the problems considered,
- for large datasets, ANNs performed most effectively, while GPR was slow and less robust, and
- dimensionality has only a small influence on accuracy.

The authors demonstrate the possible prediction quality of meta-modeling methods. A coefficient of determination of up to $R^2 > 0.99$ was obtained for the eight mathematical benchmarks. For the building performance simulation problems, an $R^2 > 0.90$ for CO₂-emissions and $R^2 > 0.99$ for the remaining output parameters could be achieved.

6. Discussion of the potential and limitations of AI to address current challenges in assessing resource adequacy

Having motivated our review with increasingly complex energy systems and the need for adequate assessments of security of electricity supply, our extensive review demonstrated substantial potential for a large variety of AI-based methods to contribute to more effective and efficient assessments of resource adequacy. The fields of applications as shown in section 5 demonstrate the transferability to relevant use cases.

Nolting and Praktiknjo [182] argue that in situations where increasingly sophisticated research questions lead to increasingly complex and, therefore, computationally resource-intensive models, the

accuracy of those models then becomes more and more dependent on the quality of the input data. At the same time, the more comprehensive these input data are and the further ahead into the future assumptions have to be made for them, the more they are subject to uncertainties [183]. The authors define this as a “complexity dilemma” where more complex models allow for more complex analyses but at the same time lead to increased data uncertainty.

Besides data uncertainty, working with highly complex simulation models leads to another drawback: The limitation of scenario scope due to time and hardware restrictions. ACER formulates requirements for resource adequacy assessments to be a probabilistic analysis in terms of stochastic influences such as weather conditions [3]. Also, an optimization-based assessment is required, leading to very high computational requirements per analyzed scenario. Therefore, the requirements by ACER to deal with further uncertainties such as the progress in capacity expansion of renewable energies need to be considered only to a very limited extent.

AI-based methods can mitigate these dilemmas and provide solution strategies. In Fig. 22 we present a solution approach by integrating machine learning into the resource adequacy assessment toolchain. The identified application areas in the methodological pipeline that address the challenges derived in Section 2.2 for assessing resource adequacy in terms of input data, the methodology itself, and the computational complexity are:

- Processing various types of input data in terms of data consolidation, data imputation, and data aggregation as well as feature selection to handle uncertainty in input data and to reduce model complexity;

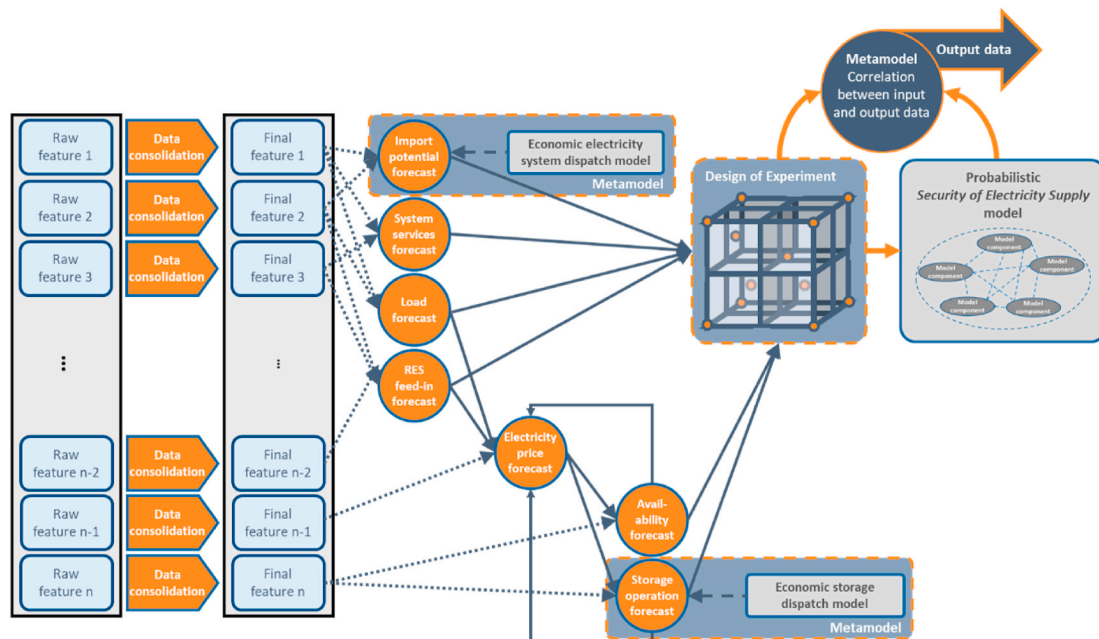


Fig. 22. Link of the different fields of application of machine learning and design of experiment methods in the context of the assessment of security of supply.

- Forecasting of (1) electricity demand, (2) RES feed-in, (3) unavailabilities of power plant units, (4) balancing reserve requirements, (5) import potentials, (6) electricity prices, and (7) storage operation (accounting for uncertainties and stochastic influence by using such variables as input features);
- Metamodeling (preferably in combination with DOE) for the approximation of complex economic viability assessment models while depicting storage dispatch and demand side response potentials;
- Metamodeling (preferably in combination with DOE) for the approximation of complex power system adequacy models applying probabilistic analyses and accounting for extreme events as well as climate change in weather models while appropriately representing uncertainties in the aforementioned areas.

Starting with raw data from multiple sources, the data needs to be consolidated, and missing and incorrect data needs to be imputed and corrected. Such tasks can be performed with the help of machine learning [106,107]. Based on a single input data set of historical, ideally measured or reported data, data forecasting may be required when analyzing a future scenario. For this, machine learning-based models can outperform traditional statistical modeling approaches, especially if a large set of explanatory variables are being processed (see for example [184] for load forecasting [185], for renewable feed-in forecasting [158], for power plant availability forecasting, or [173] for a forecast of storage operation). Lastly, DOE can be combined with metamodeling to efficiently increase the scope of energy system analyses (as done by e.g. Ref. [186]). Thus, metamodeling has the potential to address many of the current challenges in assessing resource adequacy by accelerating computations to adequately incorporate uncertainties in scenarios and sensitivity analyses.

However, there are limitations in using machine learning-based methods for metamodeling resource adequacy assessment models regarding the transparency of the analyses, especially regarding ANNs. Since ANNs are so-called implicit metamodels or black-box models, the potential for identifying the reasons for adequacy concerns is limited. The investigation of the extent to which explicit metamodels (cf. Explainable AI) can be used to assess the relevance of individual model input variables for possible tipping points in supply security is still a research gap. Increasing the transparency of the analysis could become a crucial factor for the future dissemination of metamodeling in combination with DOE to approximate energy system models. Further potentials for the application of metamodeling may lie in forecasting Flow-Based market coupling parameters such as power transfer distribution factors, the remaining available margins, or critical branches.

While according to our literature study methods for metamodeling complex nonlinear simulations and time series forecasting models have been increasingly applied in scientific publications over the last twelve years, it is difficult to assess the current level of dissemination outside academia. In addition to the fact that metamodeling is still a rather new topic in research, another reason for a potentially low degree of dissemination may be its interdisciplinary nature. Expertise in the respective engineering domain as well as in mathematics and computer science are required for implementation. Furthermore, there is no general approach for metamodeling problems and the selection of an adequate model and sampling method for the design space are elaborate problem-specific tasks. Active learning offers the possibility of automation but comes with additional challenges in terms of implementation.

Despite the great potential of AI methods, there is a possibility that future research, development, and applicability of AI methods will be affected by legal regulation. Regarding the EU, ‘The briefing Artificial Intelligence Act’ (see Ref. [187]) provides information on a proposal by the European Commission dated April 21, 2021 for an EU-wide legal framework on AI. While it is considered to be a positive initial step to regulate AI, it is also criticized for its lack of specific guidelines for

limiting automation and enhancing security [188]. The regulation requires a risk-based approach with an application-specific risk classification. This classification is carried out in the following categories: unacceptable risk, high risk, limited risk, and low and minimal risk. While it can be assumed that a large proportion of applications that use AI will be assessed as low risk and will, therefore, be subject to little or no legal regulation, resource adequacy may fall under the high-risk assessment as it concerns critical infrastructure. AI applications assessed as high risk will be allowed but will be subject to regulations that involve EU database registration, risk management requirements, testing, technical robustness, data training, transparency, human oversight, and cybersecurity.

Further, there are potential risks associated with differing international regulations, particularly in terms of international cooperation and investment [189] as the EU, the US, and China currently vary in their stringency in regulating AI [190].

Additionally, the significant computational demands of AI, particularly in tasks such as data consolidation and aggregation, as well as in the training and validation of metamodels and machine learning-based forecasting models, can result in substantial energy consumption. Conversely, when AI is applied to approximate highly complex simulation models in the context of resource adequacy assessments, it has the potential to decrease the overall computational resource needs [191]. This duality highlights the importance of carefully considering the environmental impact of AI applications in energy systems, while also recognizing its efficiency-enhancing capabilities.

7. Conclusion: strategic benefits of AI and DoE for the assessment of resource adequacy

Our review enables researchers and experts from the energy industry to a comprehensive overview of the application of AI-based methods in resource adequacy assessments. To further support the dissemination of methods by researchers and practitioners, we developed a comprehensive modeling chain bringing together the worlds of AI, design of experiments, and security of supply assessment.

Having demonstrated a broad variety of methods from the field of artificial intelligence that can be applied to energy system modeling in general and assessing security of electricity supply in particular, our key findings are as follows:

- **AI-based metamodeling in resource adequacy assessments:** We discovered that AI-based metamodeling could significantly supplement the prevailing resource adequacy assessment requirements, such as those defined by ACER for EU member states. This approach effectively addresses uncertainties in the future development of necessary input data while maintaining a high level of detail in the model. These methods are applicable to both resource adequacy assessment models and upstream models, like storage dispatch.
- **Combining metamodeling with design of experiments:** As the need and complexity of resource adequacy assessments increase, integrating metamodeling with design of experiments emerges as a promising strategy. This enables efficient metamodeling of complex energy system models, facilitating the investigation of a broad variety of scenarios while efficiently circumventing runtime and hardware limitations and maintaining high accuracy levels.
- **Trade-offs in metamodeling:** The advantages of metamodeling must be balanced against the efforts and potential accuracy losses involved. It is particularly suitable for scenarios where simulation times are extensive and numerous parameter variations are required, such as in multi-criteria optimization.
- **Prevalent metamodeling methods:** Feed-forward neural networks (FFNNs), Gaussian process regression, and ensemble methods are the most widely applied methods for metamodeling in energy-related publications. However, when combined with design of experiments, AI-based applications currently represent only a small

fraction (1:5) of the publications compared to non-AI-based statistical methods.

- Potential applications of AI in the energy modeling toolchain:** We identified several potential application areas for AI-based methods within different steps of the model toolchain, including data preprocessing, data consolidation, and forecasting of relevant input data such as electricity loads, renewable energy feed-ins, electricity prices, power plant availabilities, import potentials, and storage operations.
- Gaps in the literature on forecasting in energy systems:** There is a substantial body of literature on forecasting electricity loads and renewable energy feed-ins. However, studies focusing on forecasting storage operation and the (non-)availability of individual power plants are scarce.
- Predominance of RNNs in forecasting:** Recurrent neural networks (RNNs) have become the predominant AI models for forecasting applications in energy systems.
- Data consolidation and aggregation tools:** In the realm of data consolidation and aggregation, k-means clustering, principal component analysis, and autoencoders are the most commonly used tools.

Overall, our conclusion emphasizes the need for future research in two key areas: (1) efficient metamodeling of complex models to assess security of electricity supply using AI-based methods and (2)

applications of AI-based methods for forecasting storage dispatch and (non-)availabilities, as these are promising yet underexplored fields of application.

The methods summarized in this review will gain further relevance when analyzing energy systems with growing shares of renewables: As the complex interplay of renewable sources, energy consumers, and networks drives complexity, the pipeline that we have carved out in our review might support researchers to tackle important questions regarding the future security of electricity supply.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

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Appendix

Table 8

Search term specification for the application of clustering in energy research (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method		
energy	–	k-means	Ener	2010
		k-medoids		2011
		hierarchical clustering		2012
				2013
				2014
				2015
				2016
				2017
				2018
				2019
				2020
				2021
				2022

Table 9

Search term specification for the application of dimensionality reduction in energy research (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
energy	–	principle component analysis (PCA)	Ener	2010
		principal component regression (PCA)		2011
		partial least squares regression (PCA)		2012
		PCA (PCA)		2013
		discriminant analysis (discriminant analysis)		2014
		autoencoder (autoencoder)		2015
		t-distributed stochastic neighbor embedding (t-SNE)		2016
		t-SNE (t-SNE)		2017
				2018
				2019
				2020
				2021
				2022

Table 10
Search term specification for use case “Forecasting electricity load profiles” (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
load forecasting	–	artificial neural network (Feed-forward neural network)	Ener	2010
load prediction		feed-forward neural network (Feed-forward neural network)		2011
		back propagation neural network (Feed-forward neural network)		2012
		multilayer perceptron (Feed-forward neural network)		2013
		ANN (Feed-forward neural network)		2014
		convolutional neural network (Convolutional neural network)		2015
		CNN (Convolutional neural network)		2016
		recurrent neural network (Recurrent neural network)		2017
		RNN (Recurrent neural network)		2018
		long short term memory (Recurrent neural network)		2019
		LSTM (Recurrent neural network)		2020
		gated recurrent unit (Recurrent neural network)		2021
		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

Table 11
Search term specification for use case “Forecasting renewable feed-in profiles” (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
renewable feed-in	–	artificial neural network (Feed-forward neural network)	Ener	2010
wind feed-in		feed-forward neural network (Feed-forward neural network)		2011
solar feed-in		back propagation neural network (Feed-forward neural network)		2012
pv feed-in		multilayer perceptron (Feed-forward neural network)		2013
hydro feed-in		ANN (Feed-forward neural network)		2014
wind power forecast		convolutional neural network (Convolutional neural network)		2015
solar power forecast		CNN (Convolutional neural network)		2016
pv power forecast		recurrent neural network (Recurrent neural network)		2017
hydro power forecast		RNN (Recurrent neural network)		2018
wind power prediction		long short term memory (Recurrent neural network)		2019
solar power prediction		LSTM (Recurrent neural network)		2020
pv power prediction		gated recurrent unit (Recurrent neural network)		2021
hydro power prediction		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

Table 12
Search term specification for use case “(non-)availabilities” (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
power plant"W/2"reliability	–	artificial neural network (Feed-forward neural network)	Ener	2010
power plant"W/2"outage		feed-forward neural network (Feed-forward neural network)		2011
power plant"W/2"maintenance		back propagation neural network (Feed-forward neural network)		2012
power plant"W/2"availability		multilayer perceptron (Feed-forward neural network)		2013
power plant"W/2" unavailability		ANN (Feed-forward neural network)		2014
power plant"W/2" non-availability		convolutional neural network (Convolutional neural network)		2015
		CNN (Convolutional neural network)		2016
		recurrent neural network (Recurrent neural network)		2017
		RNN (Recurrent neural network)		2018
		long short term memory (Recurrent neural network)		2019
		LSTM (Recurrent neural network)		2020
		gated recurrent unit (Recurrent neural network)		2021
		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

Table 13
Search term specification for use case “Forecasting storage operation” (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
storage"W/3"operation	Pumped	artificial neural network (Feed-forward neural network)	Ener	2010
storage"W/3"dispatch	compressed air	feed-forward neural network (Feed-forward neural network)		2011
storage"W/3"behavior	CAES	back propagation neural network (Feed-forward neural network)		2012
storage"W/3"heuristic	Battery	multilayer perceptron (Feed-forward neural network)		2013
storage"W/3"schedule	BES	ANN (Feed-forward neural network)		2014
	BESS	convolutional neural network (Convolutional neural network)		2015
	flywheel	CNN (Convolutional neural network)		2016
	Heat	recurrent neural network (Recurrent neural network)		2017
	Thermal	RNN (Recurrent neural network)		2018
	electricity	long short term memory (Recurrent neural network)		2019
	Energy	LSTM (Recurrent neural network)		2020
	power plant	gated recurrent unit (Recurrent neural network)		2021
		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

Table 14
Search term specification for the application of metamodeling in energy research (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
meta model	–	artificial neural network (Feed-forward neural network)	Ener	2010
metamodel		feed-forward neural network (Feed-forward neural network)		2011
metamodeling		back propagation neural network (Feed-forward neural network)		2012
metamodelling		multilayer perceptron (Feed-forward neural network)		2013
meta modeling		ANN (Feed-forward neural network)		2014
metamodelling		convolutional neural network (Convolutional neural network)		2015
		CNN (Convolutional neural network)		2016
		recurrent neural network (Recurrent neural network)		2017
		RNN (Recurrent neural network)		2018
		long short term memory (Recurrent neural network)		2019
		LSTM (Recurrent neural network)		2020
		gated recurrent unit (Recurrent neural network)		2021
		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

Table 15
Search term specification for the application of any type of metamodel in combination with design of experiments in energy research (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
meta model	design of experiment	–	Ener	2010
Metamodel				2011
Metamodeling				2012
Metamodelling				2013
meta modeling				2014
Metamodelling				2015
				2016
				2017
				2018
				2019
				2020
				2021
				2022

Table 16
Search term specification for the application of AI-based metamodels in combination with design of experiments in energy research (column entries can be arbitrarily combined)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
meta model	design of experiment	artificial neural network (Feed-forward neural network)	Ener	2010
metamodel		feed-forward neural network (Feed-forward neural network)		2011
metamodeling		back propagation neural network (Feed-forward neural network)		2012
metamodelling		multilayer perceptron (Feed-forward neural network)		2013
meta modeling		ANN (Feed-forward neural network)		2014
metamodelling		convolutional neural network (Convolutional neural network)		2015

(continued on next page)

Table 16 (continued)

TITLE-ABS-KEY			SUBJAREA	PUBYEAR
Application field (1)	Application field (2)	Method (Cluster)		
		CNN (Convolutional neural network)		2016
		recurrent neural network (Recurrent neural network)		2017
		RNN (Recurrent neural network)		2018
		long short term memory (Recurrent neural network)		2019
		LSTM (Recurrent neural network)		2020
		gated recurrent unit (Recurrent neural network)		2021
		GRU (Recurrent neural network)		2022
		support vector machine (Support vector machine)		
		gaussian process (Gaussian process)		
		decision tree (Decision tree)		
		classification tree (Decision tree)		
		regression tree (Decision tree)		
		bayesian network (Bayesian model)		
		bayesian net (Bayesian model)		
		naive bayes (Bayesian model)		
		bayesian classification (Bayesian model)		
		bayesian regression (Bayesian model)		
		bayesian belief network (Bayesian model)		
		Bagging (Ensemble method)		
		decision tree (Ensemble method)		
		random forest (Ensemble method)		
		boosting (Ensemble method)		
		xgboost (Ensemble method)		
		catboost (Ensemble method)		
		LightGBM (Ensemble method)		

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