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Artificial Intelligence and Mathematical Models of Power Grids Driven by Renewable Energy Sources: A Survey

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Abstract: To face the impact of climate change in all dimensions of our society in the near future, the European Union (EU) has established an ambitious target. Until 2050, the share of renewable power shall increase up to 75% of all power injected into nowadays' power grids. While being clean and having become significantly cheaper, renewable energy sources (RES) still present an important disadvantage compared to conventional sources. They show strong fluctuations, which introduce significant uncertainties when predicting the global power outcome and confound the causes and mechanisms underlying the phenomena in the grid, such as blackouts, extreme events, and amplitude death. To properly understand the nature of these fluctuations and model them is one of the key challenges in future energy research worldwide. This review collects some of the most important and recent approaches to model and assess the behavior of power grids driven by renewable energy sources. The goal of this survey is to draw a map to facilitate the different stakeholders and power grid researchers to navigate through some of the most recent advances in this field. We present some of the main research questions underlying power grid functioning and monitoring, as well as the main modeling approaches. These models can be classified as AI- or mathematically inspired models and include dynamical systems, Bayesian inference, stochastic differential equations, machine learning methods, deep learning, reinforcement learning, and reservoir computing. The content is aimed at the broad audience potentially interested in this topic, including academic researchers, engineers, public policy, and decision-makers. Additionally, we also provide an overview of the main repositories and open sources of power grid data and related data sets, including wind speed measurements and other geophysical data.

Keywords: power grids; renewable energy; systems monitoring; energy forecasting; complex networks; machine learning; deep learning; reinforcement learning; Bayesian inference; dynamical systems; stochastic data modeling

Citation: Srinivasan, S.; Kumarasamy, S.; Andreadakis, Z.E.; Lind, P.G. Artificial Intelligence and Mathematical Models of Power Grids Driven by Renewable Energy Sources: A Survey. *Energies* **2023**, *16*, 5383. https://doi.org/10.3390/en16145383

Academic Editor: Abu-Siada Ahmed

Received: 5 May 2023
Revised: 27 June 2023
Accepted: 6 July 2023
Published: 14 July 2023

1. Introduction and Overview

The power grid is probably the largest man-made system ever, spanning from small communities to vast continents, and showing a macroscopic behavior that often is not the simple composition of the behavior of its parts, something that so-called complex systems share. At the heart of the need for such a large and highly complex infrastructure lies the paramount importance of energy production and management in nowadays' world, with an ever-growing population and more ambitious technology demands. Energy sources are generally classified into two types [1], conventional energy sources (CES) and renewable energy sources (RES) [2], and to share it, large grids have been built, which connect the production points and the locations where energy is needed, from cities to industries. Figure 1 illustrates the different types of complexity shown by power grids, including the different sizes of nodes where power production and consumption occur, the different energy sources, and the different weights of its lines.

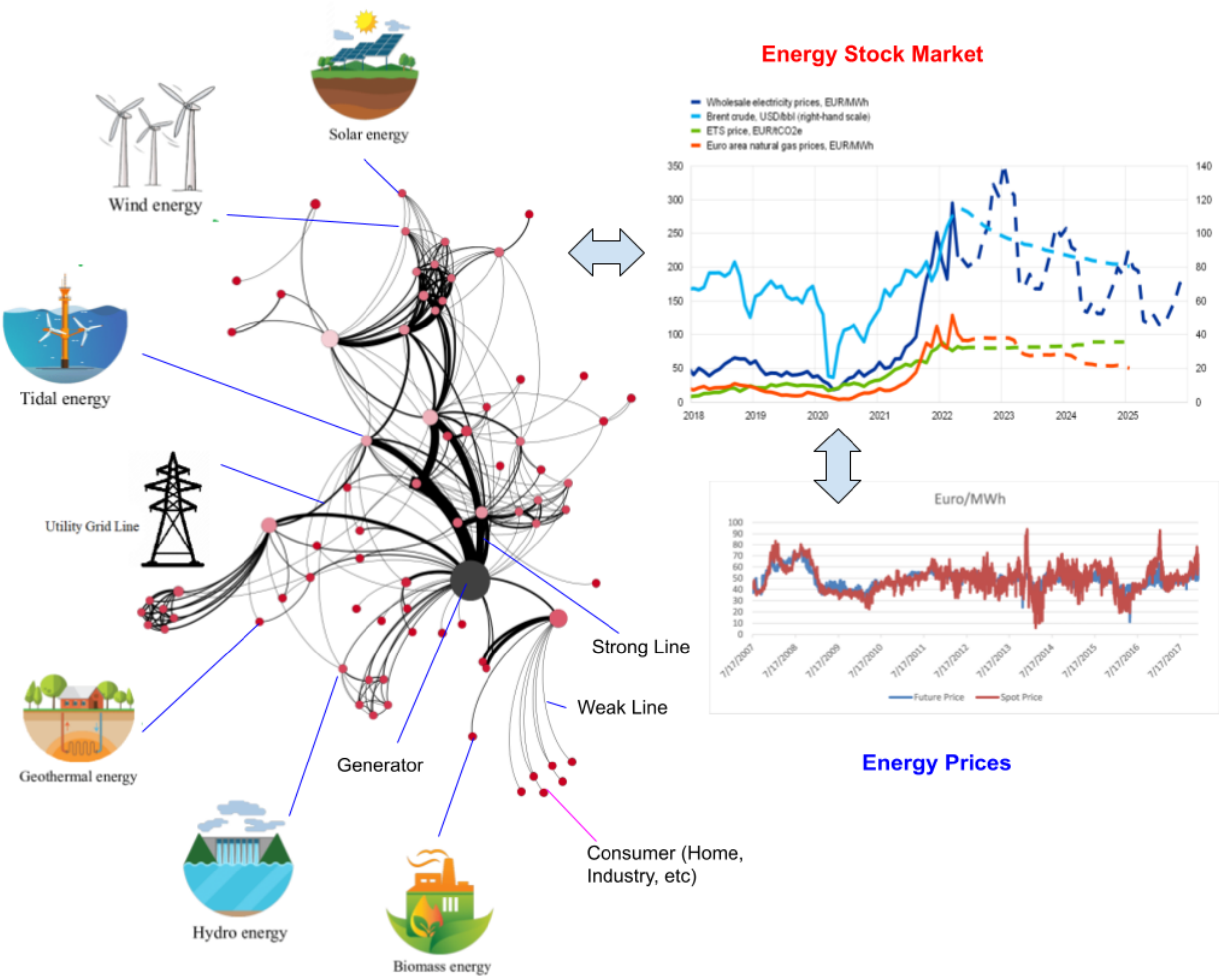

Figure 1. Overview of the different levels of complexity of a power grid, represented as a complex network. Nodes represent the sources and sinks of power and can vary in size and nature, with different energy sources and different consumption spots, including cities and industries. Edges vary also in size and nature, depending on which nodes they connect, e.g., transmission and distribution lines. Simultaneously, power grids are coupled to external systems, namely the energy stock markets, which are influenced by, and influence, the functioning of power grids.

CES have been the dominant energy sources until the recent two decades. Typically, CES comprehend fossil fuels and nuclear resources. Fossil fuels are basically compounds of hydrocarbons comprising coal, natural gas, and oil, whereas nuclear resources are typically radioactive isotopes, such as uranium or plutonium, which can provide energy through their fission in a reactor, heating water into steam, which is used to turn a turbine and generate electricity [3]. Fossil fuels are not sustainable and contribute to the increase in the global temperature due to the resulting CO_2 emissions that are produced during consumption [4]. This global warming effect promotes the occurrence of abnormal floods and rains, affecting agricultural and urban regions. The bitter truth is that the majority of industries around the world still strongly depend on fossil fuels for electricity production since they are very effective and controllable to comply with the fluctuating energy demand in different regions of the globe and during different seasonal conditions [3]. In recent decades, however, different industries and governments have aimed to switch their strategies of energy production and consumption towards more sustainable and clean solutions, opening the stage for RES as a central source of energy for future societies [5].

RES are obtained from sources [6] such as the sun, wind, and the natural flow of moving water, leading to several types of RES, namely solar, wind, hydro and tidal sources, thermal sources, biomass, and fuel cells [7].

Recent papers have introduced a neural-network-based boost converter for fuel cell systems; evaluated the techno-economic aspects of photovoltaic–hydrogen refueling stations in Tunisia and solar/wind energy systems for hydrogen production in Salalah, Oman; and explored optimal sizing for photovoltaic systems in green hydrogen refueling stations in Oman. A neural-network-based four-phase interleaved boost converter for fuel cell systems is introduced [8] to reduce current fluctuations and enhance fuel cell lifespan. A robust and straightforward neural network controller is developed using Simulink in MATLAB to regulate the output voltage under varying fuel flow rates, supply pressures, and temperatures. Reference [9] evaluates the techno-economic aspects of a photovoltaic–hydrogen refueling station in Tunisia, demonstrating the potential of green hydrogen production in the country. Furthermore, analysis and optimization of solar and wind energy systems for hydrogen production have been conducted, focusing on Salalah, Oman [10]. The findings highlight the economic viability and suitability of a hybrid energy system comprising photovoltaic, wind turbine, fuel cell, and hydrogen tank systems to meet both electrical and hydrogen production needs. Reference [11] explores the optimal sizing of photovoltaic systems for green hydrogen refueling stations in Oman, examining different approaches and providing insights into cost reduction and mitigation of carbon dioxide emissions. These energy sources are typically limitless, nonpollutant, and clean. Therefore, RES are taken as the best candidates for energy sources to cope simultaneously with the increasing need for energy in modern societies and the necessary mitigation of environmental impacts caused by anthropogenic factors, which we now know underlie the present climate change situation.

European power supply systems, for example, have slightly more than 20% of the electricity demand covered by RES, such as wind and solar power [12] and biomass [13], and Europe's plan is to increase this share of RES [14] of the total electricity produced and distributed up to 75% [15]. In the USA, renewable energy technology investments [16] have grown significantly in the past decade [17], from USD 11.4 billion in 2005 to about USD 46.5 billion in 2018, boosting the renewable energy market with a "green" direction in all sectors of the country [18]. There are recent developments in the US that we need to mention, such as the inflection reduction act [19], which also is heavy-handed on clean energy [20,21].

As for China, it is the largest energy consumer country worldwide since 2015, being also the country with the highest CO_2 emissions. Therefore, strategies based on renewable energy are highly necessary to protect the environment without compromising economic and social development [22]. The Chinese government announced official plans to increase the share of renewable energy from 8% in 2006 to 15% in 2020 [23].

Similarly, India, also a significant player in global energy consumption, is determined to establish itself as a leading producer of clean energy [24]. The Government of India has already implemented several measures [25] and established specialized agencies to facilitate the realization of this objective [26]. Currently, renewable energy sources, excluding large hydro projects, account for 9% of the total installed energy capacity, equivalent to 12,610 MW. When combined with large hydro-power plants, the contribution rises to over 34% of the total capacity, exceeding 48,643 MW out of a total of 144,980 MW. It is noteworthy that numerous developed and developing countries are also committed to increasing their renewable energy capacity from 7% to 30% of their total energy capacity by 2025 [27]. For further information, refer to [28–32].

For these countries, a significant portion of renewable energy investments is allocated towards the procurement of materials and personnel required for constructing and maintaining the infrastructure, rather than relying on expensive energy imports. As projected by the International Energy Agency (IEA), global electricity demand is expected to rise by 70% by 2040, with its share in final energy use increasing from 18% to 24% during the same period. Various renewable energy scenarios for the period up to 2040 have been explored in [13], and an overview is presented in Table 1. For researchers and stakeholders, it is crucial to make informed choices regarding the selection of renewable energy sources (RES) and the reasons behind those choices. Factors such as cost, stability, efficiency, and environmental impact must be carefully considered to determine the optimal utilization of RES. Differently from their conventional "cousins", these sources present several challenges still to be solved in order to guarantee achieving these goals. The main disadvantages of using RES resources relate to their "nontunable", desultory character. The strong fluctuations of the available renewable power from different RES make them difficult to monitor, predict, and adjust to the cycles and patterns of energy demand both in the short- [33] and long-time horizons [34]. Injecting unbalanced power supplies in a power grid [35], may lead to the malfunctioning or even failure of extensive regions of the power grid, and therefore, power grids are a research area of utmost importance [36].

Table 1. Scenario of RES in 2001, 2010, and 2022, and estimates for 2030 and 2040. Data taken from [13].

Year	2001	2010	2020	2030	2040
Total consumption (million tons oil equivalent)	10,038	10,549	11,425	12,352	13,310
Biomass	1080	1313	1791	2483	3271
Large hydro	22.7	266	309	341	358
Geothermal	43.2	86	186	333	493
Small hydro	9.5	19	49	106	189
Wind	4.7	44	266	542	688
Solar thermal	4.1	15	66	244	480
Photo-voltaic	0.1	2	24	221	784
Solar thermal electricity	0.1	0.4	3	16	68
Marine (tidal/wave/ocean)	0.05	0.1	0.4	3	20
Total RES	1365.5	1745.5	2964.4	4289	6351
Renewable energy source contribution (in %)	13.6	16.6	23.6	34.7	47.7

Research on RES commenced several decades ago. In 1977, Landsberg proposed a simplistic model that allowed for the determination of economic viability conditions for solar thermal or solar photovoltaic energy conversion [37]. In the early 1990s, Marchetti and colleagues [38] presented a statistical hybrid model for solar and wind power, considering factors such as annual energy cost, battery autonomy function, sizing criteria, and ecological constraints. Concurrently, optimization schemes were introduced to determine optimal outcomes for hybrid renewable energy systems (HRES) such as solar–wind systems. Hybrid RES systems are defined as systems that incorporate two or more energy sources, with at least one of them being a renewable energy source.

In 1995, Consoli and colleagues [39] devised a solar–wind hybrid model that employed long-term simulations to assess a system integrating diesel-generating sets with the two RES. Bonanno et al. [40] introduced a logistical model for HRES to evaluate fuel and energy savings. They highlighted challenges associated with the utilization of combined renewable and conventional energy sources.

Research and discussion around the main challenges of power grids injected with a large share of RES has now become a hot topic in different contexts and for different audiences, ranging from basic science researchers in physics, mathematics, and artificial intelligence, to engineering and applied sciences, public sector, and governance [41]. There are several review articles on RES power grids, covering important related topics such as complex networks [42], renewable energy forecasting [43], grid intelligence [44], demand response [45], wind energy [46–48], energy conversion systems [49], data mining methods [50], biofuel research [51], energy economics [52], energy market [53], stochastic models of power grid [54], dynamical systems approaches on complex networks [55], energy storage and conversion [56], and energy management [57].

In this review, we present an updated sketch of the state of the art concerning modeling and analyzing the different aspects of power grid dynamics and structure. More than detailing each aspect of power grid research, we aim to provide a good "road map" to researchers and stakeholders of a broad audience, intending to learn and investigate particular aspects of power grid dynamics. Still, we hope to provide the main contributions of the extensive literature that has been published in the different related fields, such as engineering, natural science, and computer science. We start in Section 2 by introducing the main research questions underlying power grid research with the injection of RES. In Section 3, we present the details of power grid data, providing a list of the most used open data sources available. In Section 4, we describe the main models and results related to power grids for each research question and the different RES and power grid dynamics aspects. Figure 2 presents an overview of the entire paper, including the main research questions, data types, and modeling approaches. Finally, in Section 5, we discuss future perspectives and challenges, giving some attention to those questions and methods that, up to now, have not been investigated or developed as much.

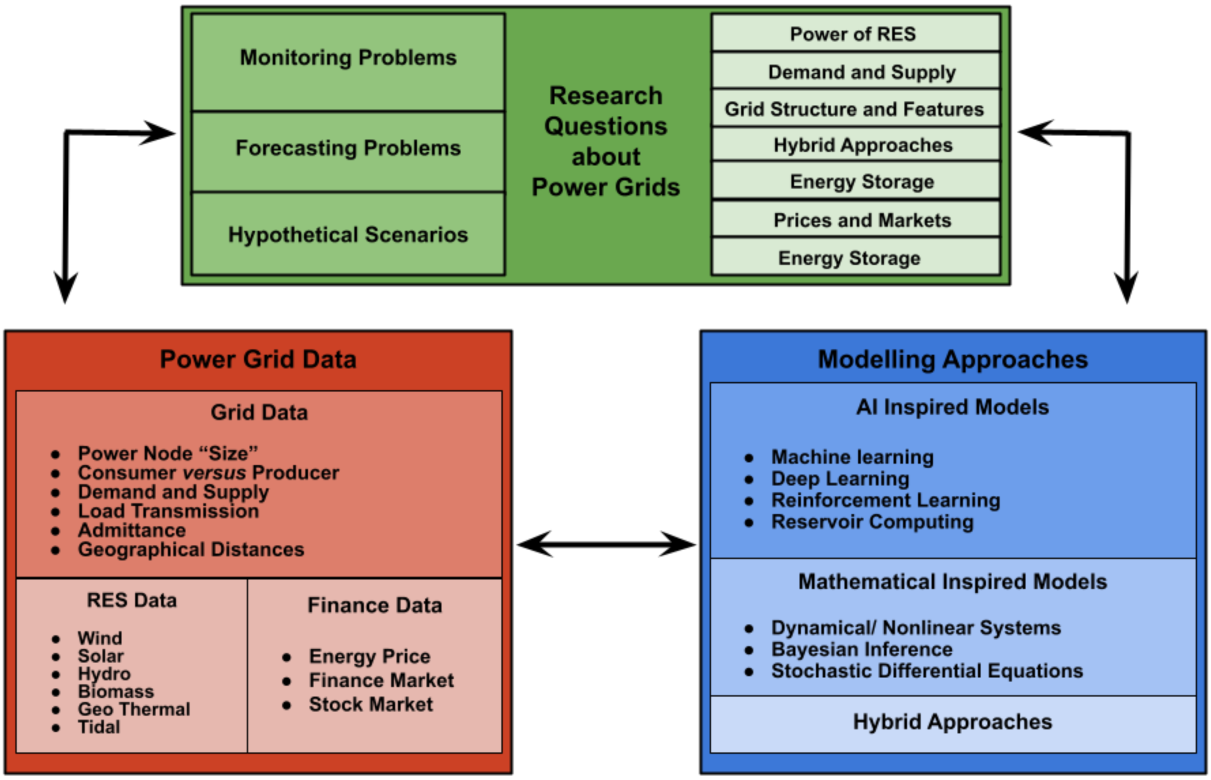

Figure 2. Overview of the review covering the main research question about power grids, as well as the different types of data involved in power grid analysis, and the main types of modeling approaches to simulate the functioning and perform monitoring of power grids.

From a methodological perspective, the search for articles and data sources was carried out on scientific repositories, namely *Scopus*, *arXiv*, *PubMed*, *Mendeley*, and *GitHub*, as well as known research article search platforms such as *Google Scholar*, *Web of Science*, and *Baidu*. The articles were selected according to two major criteria: (i) number of citations and

(ii) year of publication. Articles that are not included in *SCI* nor in *Scopus* were excluded. We also excluded articles older than 15 years.

We hope this review can assist both academia and industry, facilitating the literature and data sources on power grid research activity.

2. The Research Questions Underlying Power Grid Research

When subjected to the injection of RES, the monitoring of power grids and the understanding of their functioning present many challenges. Important examples are the detection and forecasting of frequency and voltage anomalies under changes in power injection of grid topology, the forecasting and simulation of overloaded distribution lines, or the demand and supply mismatch in specific geographic regions, subject to external factors, such as migration tendencies and transitions in the economic sector.

The research questions addressing these challenges can be grouped into three distinct types of questions:

- Questions related to the functioning of power grids;
- Questions related to the forecasting of the different properties, variables, and features characterizing the power grids;
- Questions addressed through the exploration of hypothetical scenarios, which are typically implemented in digital representations of the power grid.

Some of these questions are related to the main pros and cons of RES, summarized below and in Table 2.

Table 2. Advantages and disadvantages of each one of the main RES, namely sun, wind, water, biomass, and natural heat (see also Section 3.2).

Source	Advantages	Disadvantages
Sun	Unlimited energy source during periods of sunlight. Low level of pollution, at least during energy production.	Produces energy only during sunlight periods, with no energy generation during the night or cloudy weather. More expensive than other RES. Large geographical footprint, in particular for massive energy production.
Wind	Wind turbines function with no need for fuel. No-fuel functioning reduces overall costs for massive energy production in large-scale wind farms compared to other RES. One of the cleanest forms of energy. Last turbine generations are already extremely efficient.	Poses danger to some wildlife. Usually, wind turbines are quite noisy, so one has to install them where no people live and also where the wind is good. Produces no energy when wind is not blowing. Construction of massive structures are often hundreds of feet tall and require substantial upfront investment.
Water	A clean and abundant RES, at least close to large bodies of water.	Requires construction of dams, which has some environmental impact. In regions or situations that lack water, it has natural limitations.
Biomass	Clean, abundant, and can be used without interruption. Energy generation can be almost as controllable as conventional energy sources. Enables an efficient use of waste and reduces methane emissions for biogas.	Generates air pollution. Not very efficient. Can be seasonable and competes with food production activity. Requires large areas of landfill for biogas, at least when compared to conventional power plants, and also generates considerable amounts of pollution.
Geothermal Energy	Environmentally very safe and friendly. Lifetime of the source is very large (until earth life) and has huge potential for energy. Very sustainable, nonfluctuating, and reliable compared to other RES.	Implemented geothermal plan has accessible energy. During digging, some gases stored under the earth's surface may be exploited. Long time investment and very costly. Maintaining sustainability is very tough enough.

2.1. Monitoring the Functioning of Power Grids

In all the regions of the grid where power is generated and distributed, monitoring the functioning of the grid is fundamental. Control protocols were established, aiming to monitor the local power dynamics, focusing on the two main parameters of the electric power system, namely the voltage and the frequency. Since the electrical devices we use operate at a given voltage, the voltage provided by the grids must be kept within a short range of admissible values, typically covering variations not larger than 6% of a mean voltage value.

Otherwise, the devices will be subjected to operation errors, malfunctioning, and damage. One of the main protocols concerns keeping the so-called nominal frequency at 50 Hz or 60 Hz, depending if we are in Europe, Asia, or North America. These choices are based on technical compromises that happened during the building of the respective electrical power systems (see, e.g., [58]). Deviations from the nominal frequency occur due to imbalances between power (in this context also called load), generation, and consumption.

The admissible ranges of fluctuations should be preferably within 0.1 Hz, although this range can vary from country to country. Beyond this range of fluctuations, one considers the power system to enter emergency conditions, with ranges typically between 47.5 Hz and 51.5 Hz for a nominal frequency of 50 Hz. In such cases, control strategies take place. There are three levels of frequency control strategies [59], particularly important when injecting highly fluctuating energy sources, such as several of the renewable sources.

The first level, the primary control, takes place in an automatic way within a response time between 15 and 30 s, and aims to stabilize the frequency value, enabling the system to generate the required additional power. In other words, primary control is implemented to guarantee the stable condition of the electrical power operating system, clearing the unbalance between generation and consumption. Moreover, this control protocol will remain for approximately 15 min, depending on the specific requirements of the transmission system implemented.

Primary control is fundamental for all high-voltage power systems and presents serious challenges to the so-called fluctuating energy sources, which are typically the renewable ones. Indeed, when injecting RES into the grid, power generators must be coupled to storage systems in order to compensate for the power, depending on the frequency deviations from nominal frequency. In case over-frequency fluctuations occur, the system can simply store or release the exceeding power, but under-frequency events can be very difficult to handle since they imply a power increase, which is necessarily bounded by the capacity of storage systems.

Shortly after primary control is triggered, the frequency value is still different from the nominal one, and the power exchange between the different nodes in the grid is not the predefined one. Therefore, a secondary control strategy is needed to restore the nominal frequency and the predefined inter-nodal power exchange. Secondary control occurs after 200 s and lasts for two hours approximately using generators. If the frequency value is less than the nominal one, generation capacity is started; otherwise, it is stopped unless a corresponding load increase is observed.

The last level of control, the tertiary control, aims to restore the power reserve of the generators used by the secondary control. It runs under the control of the grid operator, typically after primary control stops, after approximately 15 min and during the time needed until stabilization.

The main questions related to the monitoring of grid functioning, is directly related to the implementation of these control strategies:

- What are the best properties to measure that can function as good precursors of the system's condition and operating status?
- What is the impact of fluctuating injected power on these properties?
- What are the best control protocols to stabilize the operating status at each control level?
- How can data be stored in an accessible format and best provide documentation with a detailed description of the data?

Due to the remote nature of power plants, particularly those situated in offshore areas, the implementation of reliable condition monitoring and control systems has become imperative. These systems are essential for effectively managing valuable assets located over long distances. Currently, there is a lack of established tools and techniques for real-time grid monitoring and control, which are crucial for assessing the status of renewable energy sources and making informed asset management decisions. The absence of such tools increases the risk of unexpected faults leading to complete or partial blackouts. While a few articles in the literature have proposed methods to enhance the effectiveness of renewable energy sources and monitoring systems [60], there is ongoing research on nonintrusive load monitoring strategies, particularly in the context of NILM systems [61]. For an up-to-date review of frequency control and forecast models, refer to [55]. Furthermore, an important aspect of grid monitoring is maintaining a balance between power demand and supply in specific regions [62–64].

2.2. Forecasting Dynamical Features of Power Grids

For the planning and operation of a power grid, the understanding of the dynamical features of all properties involved is fundamental. Understanding the dynamical features of these properties is relevant in three different contexts:

- When assessing the evolution of (fluctuating) geophysical properties that drive one specific RES. One example is the wind speed in front of wind turbines, whose statistical properties are reflected in the highly fluctuating wind power production at wind farms. Another example is the solar irradiance on the earth's surface.
- When assessing directly the evolution of power and frequency at specific nodes of the grid. Here, the dynamical features are of importance for the monitoring of the overall stability of the grid (see previous subsection).
- When assessing the evolution of external factors that eventually influence the power grid. One important example is the intrinsic demand for energy in cities, following daily, weekly, and seasonal cycles, as well as industry demands in specific locations. Other important examples are demographic and economic transitions, triggered by sudden events, such as climate catastrophes and wars, which change abruptly established patterns of production and consumption.

In each one of these contexts, one needs to define the time scale within which the dynamical evolution of such properties should be analyzed. In particular, while averages within windows of 10 or 15 min are standard in the wind energy industry, several properties such as cumulative loads and extreme fluctuations are known to occur within short-term intervals of a few seconds [65]. Short-term wind forecasts have been improving, but there are still noticeable challenges, particularly in shoulder months when wind penetration is higher. In this review, we briefly discuss several articles approaching these problems, e.g., in forecasting problems reported in short-term load forecasting [66], multiple power type prediction [67], renewable energy forecasting methods [43], hybrid energy forecasting model [68,69], and forecasting of natural gas demand [70].

Short-term wind speed can be classified depending on time horizons, methods and models, input data and forecasting data, and predicting objects. There are four types classified based on these factors,:(i) long-term (more than one week ahead years), (ii) medium-term (48 h to one week ahead), (iii) short-term (30 min to 48 h), and (iv) very short-term forecasting (seconds to 30 min ahead). In the literature, there are several articles devoted to short-term wind speed models and forecasting. For specific target stations, using historical data without considering factors such as the wind speed, wind direction, temperature, pressure, and air density of the neighboring stations on the performance of the forecasting model of the target station, many forecasting models have been reported [71–73]. Other meteorological factors in forecasting models for short-term wind speed can be found in [74–77].

As mentioned above (cf. Figure 1), dynamical and structural features of power grids are related to each other. Therefore, to forecast the evolution of dynamical properties, it is also important to assess the topological structure of the grid. Here, even the most simple characteristics of the grid, such as the distribution of nearest neighbors among the nodes, raise controversy. For instance, there are different studies about the specific grids, namely the transmission system in the Western U.S [78–82], with some authors claiming that a power-law distribution of the number of nearest neighbors is the best model, while some studies support a pure exponential fit.

2.3. Assessing Hypothetical Scenarios with Simulated Topological or Dynamical Features

Being probably the largest man-made system on earth makes the investigation of grid behavior in extreme situations highly challenging. While there is no empirical knowledge of how a grid would respond if such a scenario occurs, investigating grid behavior in such situations enables the exploration of possible measures and improvements to prevent, or at least mitigate, the critical impact on society.

To this end, researchers and engineers use a *digital twin* of a power grid [83,84], i.e., a digital reconstruction of a power grid incorporating all features, ranging from the topological structure, as well as the properties characterizing each node and edge. Feeding in empirical data from different series of measurements of geophysical data, RES, and demographic data, they can then "calibrate" this twin of the real power grid and investigate its behavior when specific features are switched from their normal patterns to critical ones.

The main questions that are addressed with power grid digital twins aim to understand and uncover what changes in the grid functioning when the grid structure and dynamics change, i.e., when nodes and/or edges are removed or new ones are added, or when the features characterizing such nodes and edges are changed in terms of their size and nature or type (see above). As known [85,86], the consequences of such changes, even when very localized and of small proportions, such as the removal of one single distribution line, can lead to broad outages, as in Germany in 2003 [87] and in India [88,89].

These changes have several possible causes, such as demographic migration [90,91], new power plants [92,93], maintenance of distribution lines [92,94], and wars and energy transition policies [95–97], particularly with the tendency of a renewable share increase.

3. What Data Are Power Grid Data?

The accuracy and applicability of energy systems modeling strongly depend on the nature and quality of the input data available. Power grid data requirements strongly differ from model to model and depend on the question being addressed. For example, in a single-node power grid model, active power data of generation and demand are needed. For the grid topology information, electric parameters are avoided for this kind of single-node modeling. Differently from this simple model, trans-shipment models [98] require active power of demand and generation over extensive areas, to distinguish between nodes and power lines. Figure 2 shows an overview of the main types of data within power grid data analysis and modeling, which can be grouped into three different categories: grid data, including demographic data related to energy production and consumption; data series of RES; and finance data related to the energy market. Figure 3 illustrates these different types of power grid data.

3.1. Grid Data: Topological and Electrical Features Underlying the Grid

At a low level, grid data deal with what is usually known as the power grid topology, including geographic positions of generators and loads, also called buses, and the lengths of their corresponding lines or transformers. Figure 3 (first row, left) shows the IEEE-300 bus grid structure from [99] with 300 buses (red bullets) and 409 lines (blue edges). Representing as α the set of buses composing a power grid and as β the corresponding lines or transformers, which are defined through the respective pair of joint buses, the power grid can be represented as a mathematical object called a graph, $G \sim [\alpha, \beta]$ [100–102]. This graph representation underlies the main mathematical object that enables the treatment of the structure and dynamics of a power grid, which is its adjacency matrix. The adjacency matrix $\mathbf{A}$ of a power grid has elements a_{ij}, which can take only the value 1 if buses i and j are connected or 0 if they are not.

In case we only address how buses (nodes) are connected, the adjacency matrix can be considered symmetric, i.e., $a_{ij} = a_{ji}$. If, for instance, the flow of power from power plants (generators) to cities (loads) needs to be assessed, the underlying graph is directed, and consequently, the adjacency matrix is not symmetric. Using this graph representation of a power grid, one can assess some of their structural properties, such as the distribution of the number of nearest neighbors, also called the degree of a node i: $k_i = \sum_{j=1}^{N} a_{ij}$, where N is the total number of nodes (generators and loads together) in the grid. In the literature, there are a few ways to predict the graph structures. The most useful are degree distribution [103], characteristic path length [104], graph diameter [105], clustering coefficient [105], and degree assortativity [103]. For a general overview of how to compute such properties from the adjacency matrix, see also [106–108].

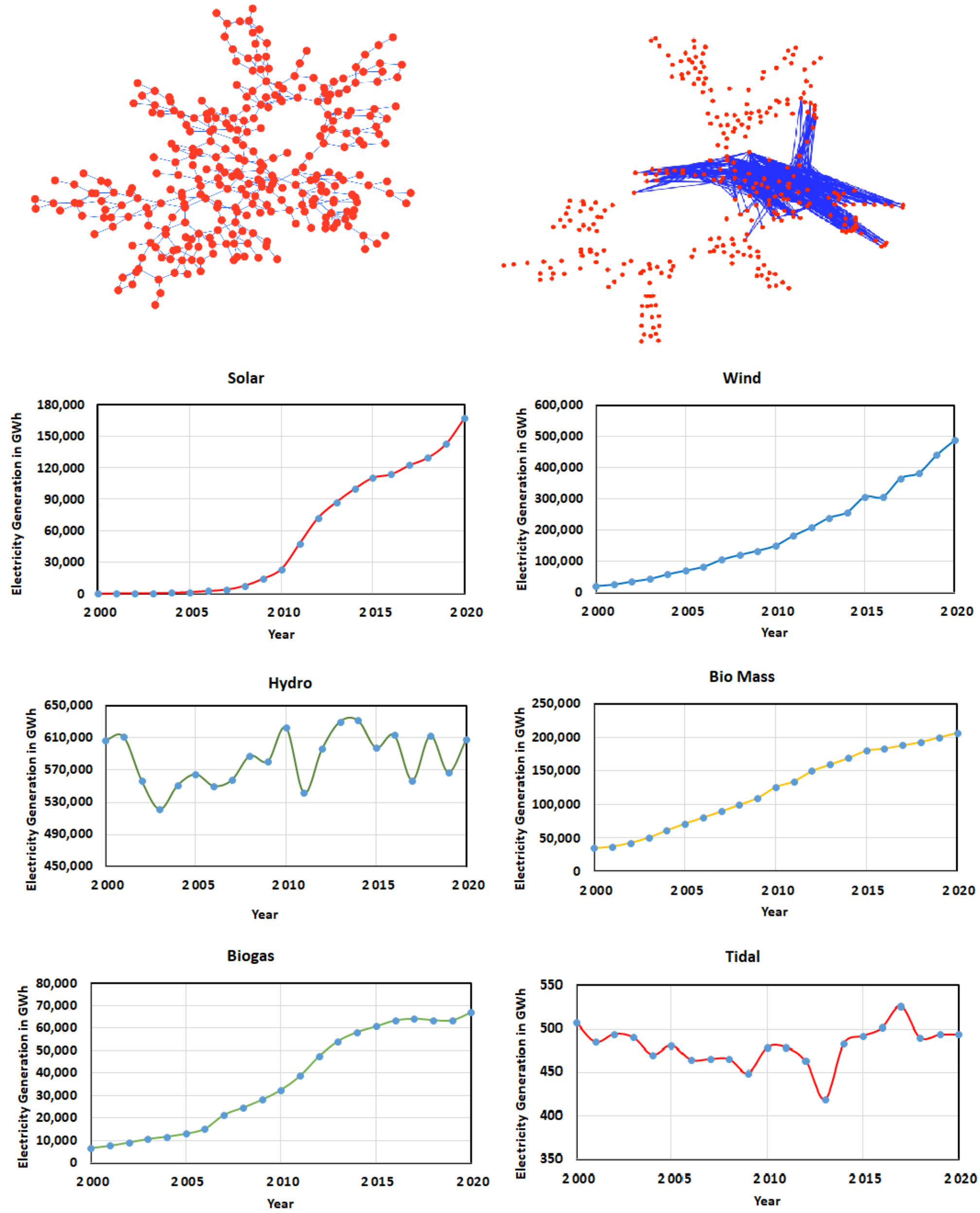

Figure 3. Illustrative example of the different types of data involved in power grid analysis (see text).

While the adjacency matrix provides the skeleton of a power grid, encoding its topological features, a proper description is only possible if one considers the adjacency matrix together with the specific properties that make the grid a *power* grid. Therefore, at a higher level, grid data also provide information about the type of nodes, i.e., generators or consumers (loads), in the grid, as well as the type of edges, i.e., distribution lines or transformers. Moreover, it is also typical to consider a *weighted* graph representation of the power grid, where nodes and edges have different sizes. In particular, one indicates the amount of power produced (if generator) or consumed (if a load) and distinguishes between them through a negative sign for loads, whereas distribution lines are characterized by their admittances, which are a measure of the electrical distance between buses connected by this corresponding line [99].

Demographic data are also fundamental to simulate power grids. The growth of the world population is directly reflected in the overall energy demand. Energy demands are increasing proportionally to population growth [109]. The situation is even more pronounced since 2006 and the advent of what scientifically is termed "the fourth industrial revolution". By the projections of this scenario, the energy demand will exponentially increase depending on the population in the future. This situation will produce a tremendous impact on energy demand, which is predicted to reach as high as 71,961 ZW in 2030. Moreover, detailed demographic data are useful to understand the heterogeneous patterns in consumption and production of energy from country to country or even between different regions in each country.

Countries classified as high income or "developed" by the United Nations are assumed to have achieved a 100% electrification rate from the year they entered that category. Therefore, the global increase in electrification rates has primarily been driven by improved access in low- and middle-income economies. This trend is particularly noteworthy in several countries. For instance, in India, access to electricity has risen from 43% to almost 85%. Indonesia is also nearing total electrification, with an access rate of nearly 98%, up from 62% in 1990. In countries with significant population growth, these advancements in expanding access to electricity are even more remarkable.

3.2. Renewable Energy Data: Geophysical and Energy Time-Series

Conventional sources of energy can be represented as nonrenewable sources of energy and have been used for many years. Examples of these conventional sources are coal, petroleum, and natural gas (fossil fuels) and data about the amount available of each of these sources can be represented as a time series associated with the specific location of the plant converting the source into injected power to the grid. In what concerns renewable energy, the main sources are the sun, wind, water, biomass, and natural heat. The electricity generation of each one of these sources from 2000 to 2020 is shown in Figure 3. The main advantages and disadvantages of each of these RES are summarized in Table 2 above. Next, we address the data describing each one of these sources.

Sunlight stands as one of the most abundant and readily accessible energy resources on our planet. In just one hour, the solar energy that reaches the earth's surface exceeds the total energy needs of the entire planet for a full year. While this makes solar energy seem like an ideal renewable energy source, its availability varies based on factors such as the time of day, the season of the year, and the geographical location.

Wind is one of the most important and unlimited sources of clean energy on the earth. Wind farms are progressively increasing in many countries. For example, one may cite the UK, where wind energy production shows an ever-increasing contribution to its National Grid. The UK installed over 11,000 wind turbines and produces 28 gigawatts (GW) on average from on/off shores and will lead in the production of wind energy around the world by 2023 [110]. Electricity is usually acquired from wind energy by utilizing turbines to drive power generators, which again deliver the electricity to the grid. There are many domestic wind energy generation systems available; however, not every land is able to have a domestic wind instrument [111,112].

Hydropower is one of the RES with the largest commercial growth. Hydropower generation systems can be established by setting up a barrier to make a large reservoir that can be used to control the flow of water. The controlled flow of water will drive turbines to generate electricity. Compared to other sources, hydropower energy sources are more reliable than solar or wind power since they do not fluctuate so much. Hydropower can be produced either in rivers, by constructing dams, or on the sea using tidal waves as a source. Particularly in dams, one can control the amount of water flowing downriver and, consequently, drive the amount of electricity produced adjusting it to the demand and supply needs of the grid.

Biomass, derived from the organic matter of plants and animals, is a renewable energy source. It remains a significant fuel source in many countries, particularly for co-oking and heating purposes in developing nations. Developed countries are increasingly using biomass fuels for transportation and electricity generation to reduce carbon dioxide emissions associated with fossil fuel use [113–115]. It is important to note that while biomass energy has a relatively low environmental impact, its characteristics resemble those of conventional energy sources. In essence, biomass energy involves converting plant-based materials into electricity through combustion. However, modern biomass energy production processes are cleaner and more energy-efficient.

In the context of biomass energy, there are two distinct sources of electricity. One is acquired from forests and fields, including harvested wood and grass, which is burned in industrial steam producers to feed turbines driving generators of electric energy. The other is natural gas acquired by the controlled process of fermenting agricultural and/or domestic waste. The end product is a biogas consisting mostly of methane and carbon dioxide. Concerning this latter source, by converting agricultural, industrial, and domestic waste into solid, liquid, and gas fuels, biomass power generation offers a more economically and environmentally favorable option. As a result, we will exclude biomass energy from this review.

Biogas energy is another RES source that typically yields methane from wastes such as food waste, agricultural waste, green waste, etc. From this methane, electricity is produced via biogas energy pyrolysis technology. Additional products are obtained such as RNG fuels, hydrogen fuel, and CO_2. Note that other wastes, i.e., wood waste, plastics, and biosolids, cannot be employed in this method. Biogas is energy-efficient and replaces fossil fuels, preventing the release of greenhouse gases.

Tidal power operates twice daily through tidal currents to run turbine generators. The strong movement of ocean waters produces this tidal energy during the rise and fall of tides. In most tidal energy generators, the turbines are placed in tidal streams. The tidal stream is nothing but a fast-flowing body of water that is caused by tides. The turbine machine converts the energy from the flow of fluid. Compared with the wind, water is more dense, hence tidal energy is more powerful than wind energy. More importantly, the tides are more predictable and stable than the wind or the sun. Although, from an engineering perspective, tidal energy production is still in its inception, it is an important renewable source of energy. More research on this field will facilitate the better use of tidal power generation in the near future [116–118].

Finally, by utilizing the natural heat below the earth's surface, geothermal energy can be used to heat homes directly or to generate electricity. As per the report of the International Geothermal Association [119], geothermal resources have been identified in around 90 countries, and 79 of those have witnessed records of geothermal utilization. Apart from electricity production, geothermal energy can be used in a wide variety of applications, ranging from agriculture and aquaculture to the production of consumer goods. Due to data protection, we did not present the electricity production plot in Figure 3.

3.3. Finance Data: The Energy Market

In recent times, the spending/investment to put countries on RES is increasing at an unprecedented rate, with the main goal of achieving efficient pathways to zero emissions. Developing countries are witnessing an emerging investment scenario in clean energy, although their economies spent less than 8% (less than USD 150 B) in 2020. However, a slight rebound was anticipated in 2021. To achieve the goal of achieving net-zero emissions by 2050, these economies must increase their annual capital expenditure on clean energy by more than seven-fold, surpassing USD 1 trillion by the end of the 2020s. This significant surge in investment can bring substantial economic and societal benefits. However, achieving this target will require comprehensive efforts to enhance the domestic environment for clean energy investment within these countries, in conjunction with international endeavors to accelerate capital inflows.

The transformation of the power sector and increased investment in the efficient utilization of clean electricity are crucial components of sustainable development. The growth of renewable energy investment varies significantly from country to country, encompassing a wide spectrum ranging from the least developed nations to middle-income economies and influential energy-producing nations such as India, Indonesia, and other major global demand centers. These countries generally exhibit low per-capita energy consumption, but their expanding economies and rising incomes offer substantial potential for future growth. The challenge lies in identifying development models that fulfill the aspirations of their populations while avoiding the carbon-intensive choices made by previous economies. The declining costs of key clean energy technologies present an extraordinary opportunity to pave a new path towards growth and prosperity with reduced emissions. Failing to seize this opportunity and encountering obstacles in clean energy transitions within these countries could become a significant obstacle in global efforts to combat climate change and achieve sustainable development goals.

Figure 4 illustrates the investment trends in renewable energy sources (RES) worldwide. In 2019, global financing for renewable capacity amounted to USD 282 billion, with onshore and offshore wind leading the way at USD 138 billion, followed by solar at USD 131 billion. This achievement can be attributed to the advancement of technologies and the declining costs associated with renewables. The chart above vividly portrays the remarkable progress made. Renewable energy investments have already surpassed the estimated USD 100 billion allocated to new coal and gas power projects in 2019. According to research conducted by BNEF, by the end of 2020, the global installed capacity of solar, wind, hydro, and geothermal power was projected to exceed 2600 GW, accounting for 38% of the total global capacity. Continued investments are expected to drive this number to over 55% by 2030 and 74% by 2050. These statistics are based on data obtained from the Global Landscape of Renewable Energy Finance 2020 report, jointly developed by the International Renewable Energy Agency (IRENA) and the Climate Policy Initiative (CPI). The report provides a comprehensive overview of global renewable energy investment trends, including a breakdown of financial flows by region, sector, and technology. For further information on the methodology used to track global renewable energy investment, please refer to [120].

While energy prices can also be considered outside the scope of power grid research, closer for instance to finance engineering and models of mathematical finance, they are here taken as a type of power grid data. The main reason for such is that energy prices are driven not only by economic and social factors, but also by the amount of energy consumed and produced throughout a power grid. Particularly under scenarios where RES are not negligible, the fluctuating nature of such renewable sources is reflected in the fluctuations and uncertainty of the energy injected in the grid as well as in all variables down the chain of energy consumption and production, including the energy market.

3.4. Where to Find Power Grid Data?

For the monitoring and evaluation of renewable energy policies, one needs accurate and properly processed data. The different sources of data described above help analysts and policymakers to make informed decisions and the academic community to conduct research on renewable energy scenarios. Power grid data are available either as private (payable) data sets or as open-source data sets. The open-source categories are commonly used by researchers for the analysis and modeling and several initiatives have recently made different databases available, providing data from specific RES. In this section, we list some of the main openly available power grid data sets.

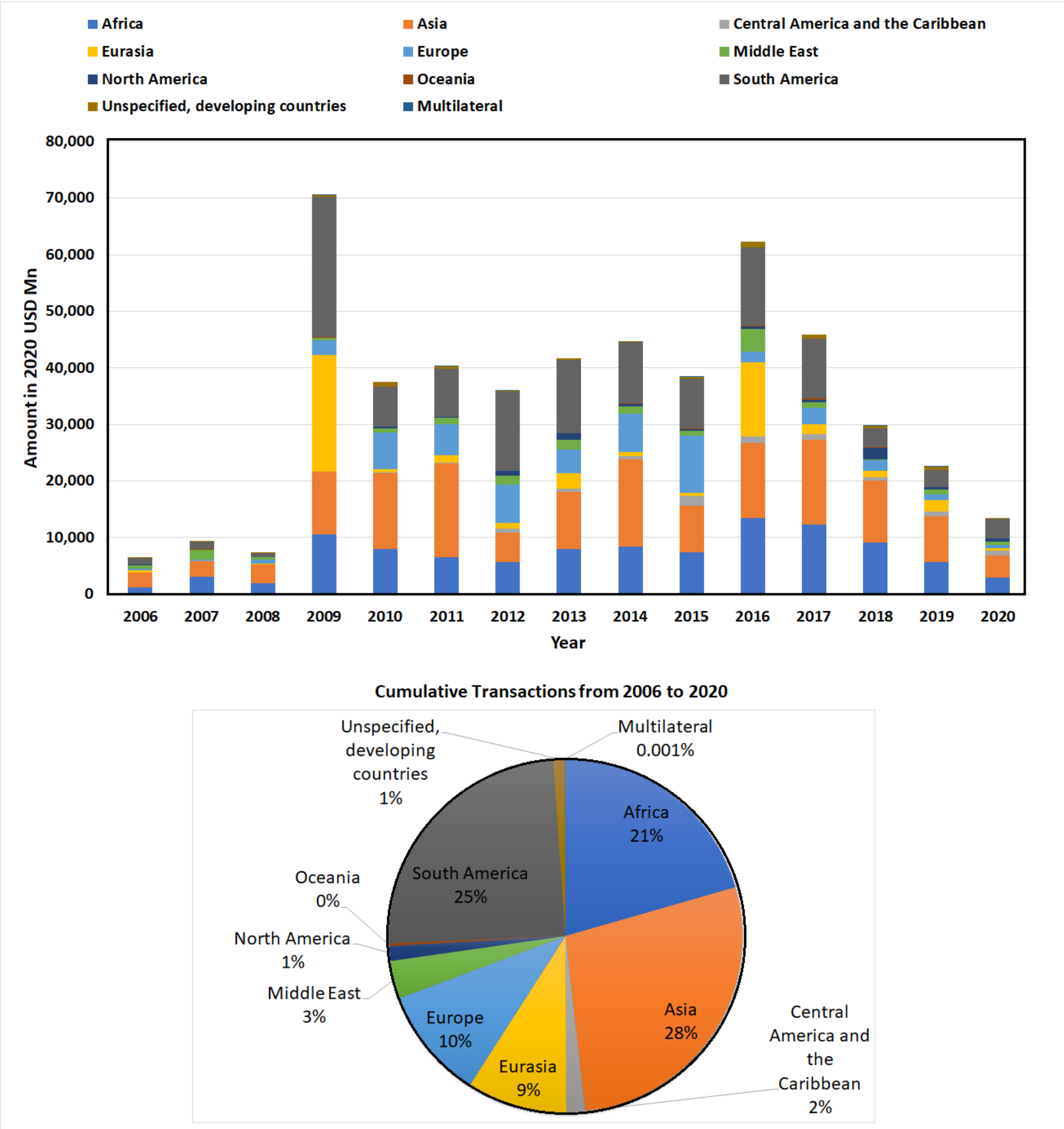

Figure 4. Investment trends in renewable energy worldwide. Plot shows finance flow in renewable energy sources. Information is available in the IRENA database and includes equity investment, green bonds, investment funds, and project commitment. Source: IRENA portal [120].

`Open Power System Data:`

This platform aims to provide free and open data of European power systems, provided by single individuals and researchers, but also under the scope of research projects, associations or companies. The data are openly available (see [121]), but may be of restricted use to noncommercial applications.

`IRENA:`

The platform in question provides comprehensive information regarding renewable energy capacity, power generation, and renewable energy balances. The data presented are gathered directly from participants through the IRENA Renewable Energy Statistics questionnaire, with additional research conducted when official statistics are unavailable. The statistics pertaining to renewable power generation capacity are released on an annual basis in March. Furthermore, datasets containing information on renewable power generation and renewable energy balances are made available in July (see the web page in [120]).

`Energy Map.info`:

A database with all renewable-based power generators in Germany. The data are available at [122].

`Enipedia`:

Collection of global power plant data sets, maintained by TU Delft University. Available at [123].

`Global Power Plant Database`:

The World Resources Institute (WRI) leads a collaborative effort to maintain an extensive, open-source database of power plants worldwide. This database includes detailed information on each power plant, such as its geographical location, capacity, generation, ownership, and fuel type. As of April 2018, the database encompasses approximately 25,000 power plants from 162 countries. Available at [124].

`OpenGridMap`:

The platform utilizes crowd-sourcing techniques to collect comprehensive data on electricity network components. By employing statistical methods and graph theory, these data are used to infer a realistic network structure. You can access this platform at [125].

`Paul-Frederik Bach`:

Paul-Frederik Bach has made available a compilation of time-series data, which can be accessed in [126]. This collection includes time-series data on wind, solar, load, energy price, and cross-border flow for 11 countries. Some of the data in this collection date back to 2006.

`Power grid frequency database`:

A series of recordings of power grid frequency data collected from the power grids in Europe, the USA, and South Africa. Available at [127].

`Renewables.ninja`:

Stefan Pfenninger and Iain Staffell oversee a platform that generates wind and solar profiles using MERRA weather data from various locations worldwide. This platform employs *R*-codes to calculate wind power production based on MERRA-2 wind speeds using the COPA model. It includes illustrative examples that guide readers through the entire process of deriving wind power production from spatially distributed wind data, along with an extensive collection of functions for vertical and horizontal interpolation of wind speed and bias correction. Available at [128].

`SciGRID`:

This database includes grid topology data and is openly available. It was developed by *Next Energy* and is derived from `OpenStreetMap`, published under `ODbL`. Available at [129].

`FINO` (I, II, and III):

The acronym FINO stands for *Forschungsplattformen In Nord-und Ostsee*, which translates to "Research Platforms in the North and Baltic Seas". The primary purpose of these platforms is to investigate and study the environmental conditions at their respective sites, specifically focusing on the potential effects of offshore wind farms on the marine ecosystem. The underlying data collected from these platforms are available upon request through their individual websites, as listed below. There are three distinct platforms located in the sea. FINO 1 is situated in close proximity to areas where wind farms are either under construction or already operational. Detailed information about FINO 1 can be found at [130]. The research funding provided by the Federal Ministry for Economic Affairs and Energy aims to reduce wind energy costs, achieve economies of scale, and enhance the reliability of wind turbines. The measurement data collected at FINO 1 play a vital role in optimizing the efficiency and effectiveness of offshore wind farms. The research platform FINO 2 was established in the southwestern Baltic Sea in 2007 and is accessible at [131]. FINO 3 serves as a valuable resource for obtaining meteorological, oceanographic, and ecological data, contributing to numerous research projects. This platform plays a crucial role in optimizing the construction of offshore structures, such as wind turbines and substations, while also minimizing associated risks. More information about FINO 3 can be found at [132].

`ENTSO-E`:

The European Network of Transmission System Operators (ENTSO) is composed of 39 electricity transmission system operators from 35 European countries. Available at [133].

`Open-eGo`:

This project aims at developing a grid planning tool, including inter-grid-level operation. It enables the investigation of different scenarios of grid expansion, with different storage and redispatch options to assess their economic viability. Available at [134].

`React Energy Lab`:

This source provides visualization showcases of locations of renewable power plants primarily based on Germany, with a specific emphasis on the renewable power plants. In the initial view, the visualization displays the aggregated renewable capacity organized by TSO. As users zoom in, subsequent levels reveal aggregated data based on DSO, and further zoom levels provide information on individual plants. For more details, please refer to the visualization available at [135].

`Agorameter`:

Agora Energiewende operates close-to-real-time charts that depict German power generation and prices. These charts provide up-to-date information on the current state of power generation and prices in Germany. Agora Energiewende also offers a comprehensive documentation of the charts. For scientific purposes, the underlying data can be obtained upon request through the provided link at [136].

`Energy Charts`:

This database includes time charts of German power generation and the respective prices. It is operated by Fraunhofer ISE. Available at [137].

`EU ETS Dashboard`:

This interactive tool enables the user to analyze data from the European Union Emission Trading System. Available at [138].

`SMARD`:

This is another tool for time visualization of electricity market data, collected in Germany and some other regions in Europe. It is operated by Bundesnetzagentur. Available at [139].

`Tmrow Electricity Map`:

Data of CO_2 emissions from electricity generation collected by several countries all around the world. Available at [140].

`WattTime Explorer`:

Another data source of CO_2 emissions from electricity generation, focusing in the United States, collected by its balancing authorities. Available at [141].

`IAEE EDL:`

Comprehends a list of energy data links of power grid data. It was compiled by the International Association for Energy Economics. Available at [142].

`Open Energy Modeling Initiative:`

This a Wiki-based interface, listing different open energy data sources. Available at [143].

`Yahoo Finance:`

This database includes financial data, stock price quotes and international market data of energy. It also lists other source pages. Available at [144].

From the different RES listed above, there is a focus on wind and sun due to the highly fluctuating nature of these sources, which may reflect in a stronger impact in the grid functioning and triggering extensive blackouts.

4. Modeling Power Grid Functioning and Dynamics

In this section, we cover the core of our literature survey, covering the main types of models chosen to address the research questions mentioned in Section 2 and using the data types described in Section 3. The synopsis of the various models is presented in Figure 5 (top panel), giving brief statistics of the power grid models in general and for each one of the main topics.

As per our earlier discussion, we classify the models into two categories: mathematically inspired models and artificial intelligence (AI)-inspired models. For mathematically inspired models, we group the articles into three different topics, namely

- Models based on dynamical systems and equations, as well as nonlinear methods;
- Models based on stochastic differential equations;
- Models based on Bayesian inference.

Dynamical system approaches assume that the system being considered is in a state represented by a set of variables, which are functions of time and fulfill a time-evolution (differential) equation [145,146]. When this equation includes stochastic terms describing probabilistic features of variables' time evolution, we have a stochastic differential equation such as model [147,148]. As for Bayesian inference, the focus is less on the time evolution of the relevant variables and more on the statistical properties of the different data sets extracted from the power grid system, which can be inferred [149,150]. Mathematical models of power grids address their modeling, using optimization schemes, performance analysis, and stability (synchronization) regimes.

As for AI-inspired algorithms, we divide them into

- Machine learning algorithms;
- Deep learning algorithms;
- Reinforcement learning algorithms;
- Reservoir computing algorithms.

Machine learning (ML) [151–153] is a field focused on developing computational, data-driven methods that *learn* from data sampling how a certain system functions, and is therefore able to model or predict its behavior. Deep learning (DL) [154,155] has become a field independent of ML, focused on extending the complexity of such learning architectures to a level beyond human understanding, which sometimes raises new scientific challenges, namely the ability to explain the underlying mechanisms justifying or explaining the outcome of a specific prediction. It is mainly based on what is called *neural network architectures* [156], in which computations are performed throughout a sequence of layers of nodes and connections, evaluating specific functions and combinations of the different input values used to train the model. Its internal structure is inspired by biological brain systems composed of neurons (nodes) and synapses (connections among nodes). Reinforcement learning (RL) [157] comprehends the family of approaches, merging the learning algorithms from ML and DL with optimization schemes that maximize the reward when "good" results are obtained. Finally, reservoir computing (RC) [158] is a sort of generalization of neural networks found in DL architectures that solves some of the drawbacks of the neural networks, namely their computational cost. The paradigm behind RC is based on a reservoir of a huge but fixed number of output units, each one producing one possible result, which is then submitted to a selection criterion. In this way, RC avoids computational costs associated with the optimization of parameters defining the model or the structure of the learning architecture, e.g., NN-based.

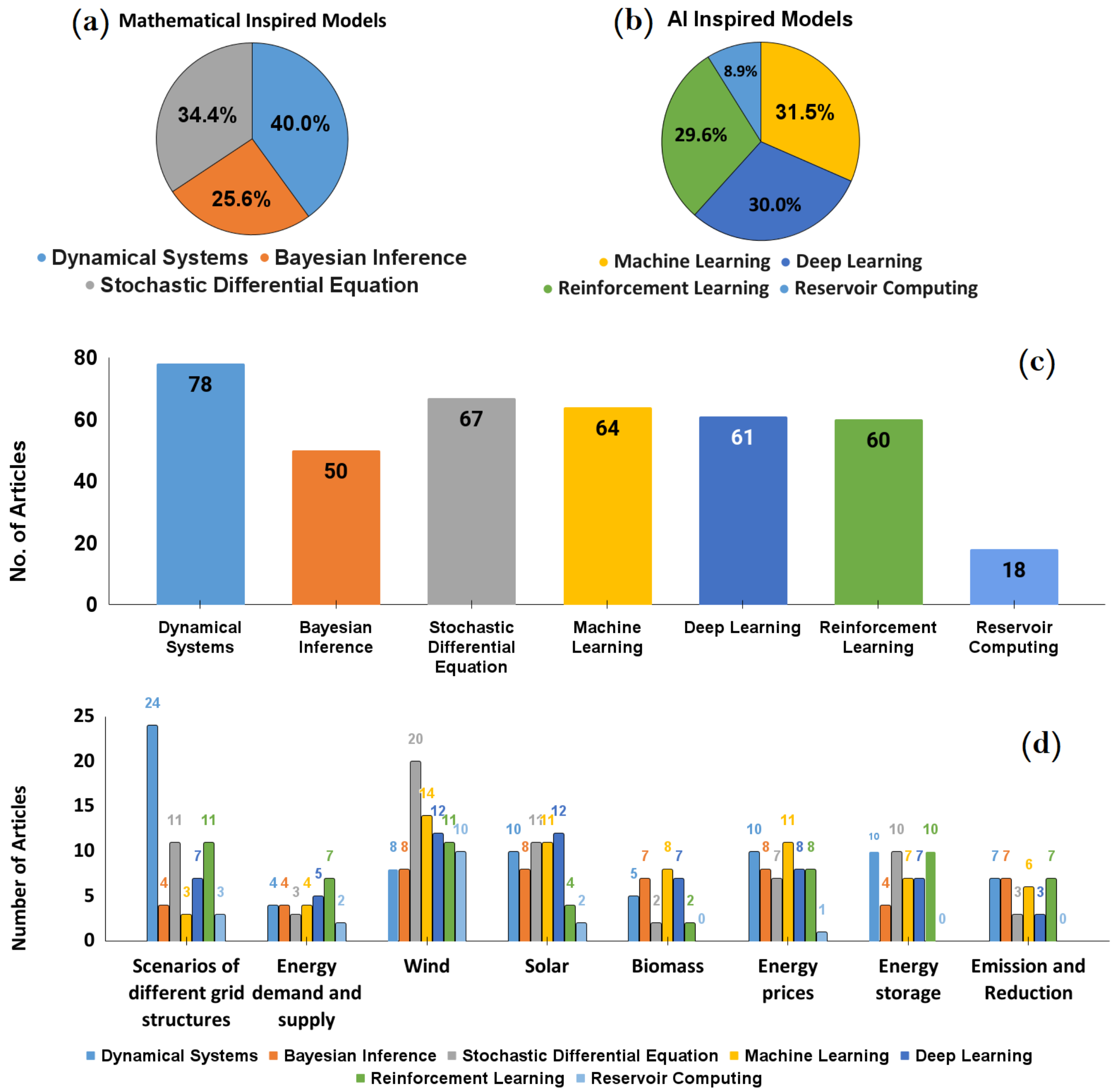

Figure 5. Statistics of the literature survey in this paper with respect to the modeling approaches, namely (**a**) mathematically-inspired models and (**b**) AI-inspired models. In (**c**) we plot the statistics for each of the modeling approaches, and in (**d**) the statistics of each modeling approach with respect to the different topics related to power grid research.

As shown in Figure 5 (top panel), all these approaches are evenly addressed in the literature, with a dominance of dynamical system models, most probably due to its direct connection to single-node dynamics, based on the balance between mechanical and electrical power, described through the so-called *swing equation* [159,160]. We note that modern AI approaches within reservoir computing seem to be not so ubiquitous in the context of power grid research, showing one possible avenue to be more intensely investigated in future research (see also the absolute number of articles in our bibliography shown in Figure 5 covering each type of modeling approach).

AI-inspired approaches are typically bottom-up methods, while mathematical modeling tools follow from top-down approaches. In the middle ground between AI- and mathematically inspired models, we also find approaches mixing algorithms from both these groups. Such hybrid approaches aim at merging the pros of different algorithms, avoiding their cons. In particular, there are two main features that usually lead to trade-off decisions when selecting a model: accuracy *versus* explainability. High accuracy is often obtained through the increase in complexity, something obtained using, e.g., DL architectures. However, such complexity also leads to the loss of tangibleness of the mechanisms leading to such outcomes. Mathematically inspired models, such as differential equations of a dynamical system, are constructed in a way that enables grasping the mechanisms driving the evolution of the properties being modeled.

As an example, we can think of a wind turbine, converting wind energy into electrical power, which is then fed into the power grid. Modeled with, e.g., a stochastic differential equation, one typically decomposes the time evolution of wind power into two parts [161,162]: one deterministic and another stochastic. The deterministic term describes the functioning of the wind turbine itself, while the stochastic term describes the interaction between the turbine and the (stochastic/turbulent) atmosphere. With such an approach, it is possible, e.g., to inspect changes in the functional dependencies of the deterministic term, which can indicate some malfunctioning of the wind turbine or characterize the statistical fluctuations of the stochastic term to evaluate the long-term power production or life expectancy of the turbine. However, in what concerns short-term predictive power, e.g., power production in the next hour, such mathematical models would be of little use. For that, the high-dimensional neural networks and other DL architectures achieve quite reasonable results at the expense of losing the understanding of the different processes underlying the series of power output, either within the engineering devices of the turbine or its underlying interaction with the atmosphere. Hybrid approaches are therefore possible avenues to explore how to better balance both the accuracy and the explainability of the models used in power grid research.

Because of this apparent tension between these two schools of thought, one AI-driven and the other mathematics-driven, in this section, we present our survey reflecting both these sides. In the next section, we will come back to discuss more about these two schools of thought and how they can work together to produce new "hybrid" approaches in power grid research. Moreover, we present these modeling approaches within the following topics:

- Modeling of grid structures;
- Modeling of energy demand and supply;
- Modeling RES, namely wind power, solar power, and biomass power.
- Modeling the energy market, particularly in connection with the power grid functioning and monitoring approaches.

Towards the end of this survey, we will also examine literature covering some of the present challenges in power grid research, namely in what concerns futuristic scenarios:

- Exploring scenarios of energy storage;
- Exploring scenarios of emission reduction.

Figure 5 (bottom) shows the statistical distribution of the number of works classed according to subject and approach. Finally, there are several libraries already available in different programming languages, namely

- In *Python*, there is the library `PyPi` [163];
- In *R*, there is the library `renpow` [164];
- In *Julia*, there are the libraries `NetworkDynamics` [165] and `PowerDynamics` [166].

4.1. Modeling Different Grid Structures

Due to the increasing growth of RES around the world, electricity grid structures and their operation are facing new challenges, namely related to grid saturation [167,168].

In the realm of mathematically inspired models, dynamical systems approaches are frequently employed to explore hypothetical scenarios. In [169], the authors proposed a hybrid approach that utilizes complex networks for structural vulnerability analysis of power transmission networks. Yun and colleagues presented a small signal dynamical model for grid-interfacing power quality compensation [170]. Barthelemy [42] discussed how spatial constraints impact the structure and properties of networks, providing an overview of recent empirical observations and significant models of spatial networks. Lee introduced a method for identifying relevant buses in reduced models of power grid networks described by a system of differential–algebraic equations [171]. Nishikawa and co-workers employed dynamical systems to investigate inherent frequencies and coupling structures in various models of power grid synchronization [172]. Battista et al. addressed the dynamical variable structure involved in output power regulation of fixed-pitch variable-speed wind energy conversion systems [173].

Suzuki and Mezic presented a data-based approach for stability assessment of power systems without parametric models, utilizing Koopman mode analysis for nonlinear dynamical systems [174]. Huang et al. focused on understanding the structure of smart power grids, studying their underlying network model, interactions, relationships, and cascading failures in the system [175], proposing a model for smart power grids based on interdependent complex network topologies. Van der Schaft and his team performed modeling and analysis of power networks using the swing equation as an approximate model for the power generator [176]. Cuadra et al. described an approach that optimizes the structure of a smart grid with renewable energy generation by combining complex network and evolutionary algorithm concepts [177]. Faza and colleagues modeled the reliability of power grids, investigating the interdependencies between cyber and physical failures and examining their effects on physical power flow in the grid [178]. The swing equation has been extended and studied by other groups for scenarios involving decentralized monitoring procedures [179] and control [180]. Other applications include the prediction of cascading failures in electrical transmission networks [181], where a framework accounting for network dynamics can identify critical lines and components of the grid. The identification of critical lines and hidden units is also addressed in [182,183]. For a comprehensive review of these topics, refer to [55].

Using a linearized version of the power flow equations, Schiel et al. [184] found that overload probabilities vary strongly between different pairs of nodes in the grid and, in particular, are affected by the spatial correlations of wind power fluctuations. Interestingly, such standard approaches in electrical engineering are able to uncover paradoxical behavior of power grids under RES injection, namely that increasing wind power injection at one node can increase the power threshold at another node.

Several other works are worth noting. In [185], the authors presented what they call a hybrid generation system of power control strategies of a grid-connected hybrid generation system. Guan and co-workers presented a generalized mathematical model for balanced and unbalanced grid conditions [186]. Ropp and co-workers introduced a full gradient-based maximum power point tracking model, i.e., a single-phase grid-connected model [187], and in [188], the authors reported a systematic investigation of microgrid systems, using signal modeling.

The literature on approaches using stochastic differential equations is not as abundant as for deterministic dynamical systems. Anghel and colleagues described the quasi-static dynamics of an electric transmission network on a power grid under perturbations [189]. Wang and co-authors investigated the feasibility of a "green" power grid, addressing the integration of solar photovoltaic panels and wind turbines into the grid for power supply reliability with different renewable energy configurations [190]. Carrillo and co-workers analyzed a family of stochastic differential systems modeling grid cell networks [191].

Chau and colleagues applied the so-called stochastic grid bundling method to numerically solve backward stochastic differential equations governing the local dynamics of the nodes composing the grid [192]. Huifeng and co-authors proposed an adaptive grid based on multiobjective Cauchy differential evolution for solving the so-called stochastic dynamic economic emission dispatch (DEED) with wind power uncertainty [193]. DEED can be formulated as an optimization problem aiming at minimizing the operating costs of a power system, including environmental impacts (e.g., emissions), constrained to some operational requirements, namely the balance between power supply and demand, distribution lines' maximum capacities, and maximal power generation of the sources involved. Ren and colleagues defined the load increment in the short-term time horizon, and introduced the conditional risk value to help the distribution system operator in the incremental distribution network [194]. Wang examined the fluctuations in power supply and demand and applied stochastic network calculus to different configurations of renewable energy [195]. Alnowibet [196] presented a stochastic programming approach to address the so-called wind power investment problem, i.e., the problem referring to the challenge of making decisions about investments in wind power projects, namely the place to build wind power converters, the type of converters, and the optimal time to do it, in order to maximize the final profit, constrained to risk factors, which involve, e.g., meteorological patterns and regulatory requirements. The author presented a bi-level framework that considers the impact of grid strength on wind power investment decisions, using a stochastic programming approach to model uncertainty and optimize investment strategies. More related to frequency stability analysis, some stochastic modeling was done, using statistical approaches beyond the assumptions of the central limit theorem, namely in the context of Lévy stable statistics [197]. In this context, Wolff et al. uncovered the role of grid heterogeneities, namely the amount of production and consumption, in the enhancing of non-Gaussian features of power grids dynamics. Using linear response theory, Haehne et al. derived the grid frequency measurements with non-Gaussian fluctuations, showing how they depend on the wind power generation in the grid [198].

Approaches based on Bayesian inference are even less used when investigating hypothetical scenarios than the other mathematical modeling approaches. Joshi and co-authors introduced a new approach using Bayesian inference for stochastic differential equation models in the grid-based incremental distribution network [199]. Chen and co-authors proposed an adaptive construction and inference that is based on the genetic algorithm [200]. Ma and co-workers derived the frequency dynamics in a power grid, using Bayesian statistics from real frequency measurements [201].

In the context of AI research, exploring energy scenarios with ML approaches is becoming a hot topic since recent times, though it is still in its beginning. Rudin et al. introduced a general process for transforming historical electrical grid data into models that aim to predict the risk of failures for components and systems [202], using standard ML models based on ranking algorithms. Anderson, in his patent, explained in detail about the machine learning in power grid dynamics [203]. Vasseur et al. obtained a patent for a machine learning algorithm in a network structure [204].

DL architectures have been utilized in various applications related to smart grids. Rong et al. identified fundamental challenges in data communications for smart grids [205], while Li et al. proposed a DL-based framework for detecting false data injection attacks [206]. Runze et al. developed a stacked autoencoder neural-network-based DL method for improving the accuracy of short-term load forecasting [66]. Wei et al. investigated DL-based approaches to predict multiple power types [67], and Wang et al. provided a comprehensive review of renewable energy forecasting methods using DL [43]. Additionally, Huang reviewed the history of deep learning and introduced the basic network structure and characteristics of deep neural networks in the context of grid intelligence [44]. More recently, graph neural networks have been used to predict the ranges of parameter values for which power grids are stable [207].

For RL-based models, Mukherjee et al. presented a model-free optimal control power system designed for electric power systems by using techniques of RL and adaptive–dynamic programming [208]. Du et al. proposed an intelligent multimicro-grid energy management based on deep neural network and model-free RL techniques [209]. Rivera et al. demonstrated the standard RL models into smart grid devices to understand the dynamics of smart grid devices, and characterized their behavior [210]. Sharma et al. emphasized RL algorithms to simplify medium-level power grid problems [211]. Pu et al. reported a power control framework combining edge computing and RL into power flow adjustment for smart microgrid [212].

Ghasemkhani et al. proposed a robust deep RL algorithm to design a recommended system (DeepGrid) [213]. Li reported recent exciting achievements of deep RL [214]. Liu proposed a novel multiagent RL method for job scheduling problems, especially for realizing load balancing in grids [215]. Galstyan et al. studied a minimalist decentralized algorithm for resource allocation in a simplified grid-like environment [216]. Peters et al. showed how feature selection and regularization can be leveraged to smart electricity markets using real-world energy market data [217]. Kuznetsova et al. reported a microgrid for energy distribution and proposed a two-steps-ahead RL algorithm that plays a key role in the achievement of consumer goals [218].

As for RC, Markovic et al. discussed how the cloud computing model can be used for developing smart grid solutions [219]. Lukoševičius et al. proposed a brief introduction and highlight some applications of RC on the power grid structure [220]. Zhou et al. introduced the ResGrid of overview, architecture, and implementation status of the power grid structures [221]. In general, we find a lack of literature exploring the potential pros and cons of RC methods to simulate power grid scenarios.

4.2. Modeling of Energy Demand and Supply

The literature on modeling the supply and demand of RES is in general limited. Verwiebe et al. conducted a systematic review of recent literature covering different aspects of energy demand models, such as techniques, prediction accuracy, inputs, energy carriers, sectors, temporal horizons, and spatial granularity [222].

In the dynamical system approach, Ochoa and van Ackere analyzed the capacity expansion dynamics in the Swiss electricity market and the impact of policies such as nuclear withdrawal and management of electricity exchanges [223]. Fu established a new supply–demand system for energy resources in two regions of China [224], while Mei et al. used nonlinear empirical research to identify the parameters of Shanghai's energy demand-supply system based on statistical data from 1999 to 2005 [225]. Matsypura's dissertation focuses on solutions for electric power supply chains, including power generators, suppliers, transmission service providers, and consumer demands [226].

The use of stochastic differential equations in the context of demand and supply is also limited. Song et al. developed a fuzzy stochastic model to predict such prices under the effect of demand-related policy [227]. Ouyang et al. proposed the single-vendor and single-buyer-integrated production inventory models [228]. Long et al. reported on a stochastic inventory model based on the partial derivative equation for the supply–demand problem [229].

Finally, using Bayesian inference models, Poole et al. proposed a sampling importance resampling (SIR) algorithm initially for invertible models, and then extended it to the more difficult, and more typical, case of noninvertible models [230]. Gupta et al. estimated spatial Bayesian vector autoregressive models for six metropolitan areas of South Africa [231], based on the first-order spatial contiguity and the random walk averaging priors. More details on these methods and concepts from Bayesian statistics can be found in [232].

The price of electricity in the spot market is influenced by various factors related to supply and demand, such as profits, energy security, and risk management. In addition to the cost of energy production, the price of electricity is determined by the dynamic interplay between supply characteristics and consumer demand. To address these complex dynamics, AI-based models have become more prevalent compared to traditional mathematically inspired models.

The maintenance of energy consumption is an important task to obtain a sustainable environment and can be automated with the help of machine learning services and solutions. Khan et al. presented a hybrid energy forecasting model based on machine learning techniques [68]. Jia et al. proposed a piecewise linear stochastic approximation algorithm showing that the achieved growth rate cannot be reduced by any piecewise linear policy [233]. Macdougall et al. proposed a black box approach for investigating the longevity of aggregated response of a virtual power plant using historic bidding and aggregated behavior with machine learning techniques [69]. Sharma et al. examines techniques for the accurate forecasting of natural gas demand [70].

With respect to the DL approaches, Paterakis et al. delved into the realm of deep learning methodologies to effectively predict the aggregated energy consumption in their research [234]. Coelho et al. devised a novel mechanism employing evolutionary computing and GPU parallel function evaluation for forecasting household electricity demand using low-frequency data [235]. In their study, Polson et al. proposed the utilization of deep spatiotemporal models and extreme value theory to capture the influence of load spikes, particularly focusing on the tail behavior [236]. Paudel et al. presented an innovative approach through a context-aware architecture aimed at energy-saving techniques [237]. Petkovic et al. put forth a deep learning model based on spatiotemporal convolutional neural networks to address the challenges related to gas flow forecasting in a complex high-pressure transmission network [238].

In the RL approaches, Lu et al. proposed a dynamic pricing deep reinforcement algorithm for energy management in a hierarchical electricity market that considers both service provider's profit and customers' costs [239]. Similar approaches can be found in [240]. Bao et al. proposed a deep transfer RL algorithm for large-scale power systems [241]. Wen et al. studied RL utilized to explore the optimal incentive rates at each hour, which can maximize the profits of both energy service providers [242]. Munir et al. studied a risk-aware energy scheduling problem for a micro-grid-powered MEC network [243]. Vazquez-Canteli et al. used RL for demand response applications in the smart grid [45] and a similar study in [244].

Finally, in the context of reservoir computing, Colla et al. presented a novel application of the modeling of industrial processes in energy management [245]. Orang et al., in their paper, reported a time-series forecasting technique composed of a group of randomized high-order FCM models labeled R-HFCM using an RL algorithm [246].

4.3. Modeling Wind Power

Several reports and tools are available that provide modeling, mapping, and optimization for wind energy, evenly distributed among the different modeling approaches. Mathematical approaches in this context are already widely used. They mainly focus on wind integration into power systems, analyzing and forecasting the effects on grid stability and reliability.

With dynamical system approaches, Song et al. reported an overview of the latest developments in modeling and control of wind power generation systems [247]. Hilbert et al. reviewed the wind resources assessment models, site selection models, and aerodynamic models including wake effect [46]. Pulgar-Painemal et al. presented a dynamic model appropriate for power system analysis [248]. Akhmatov presented a PhD thesis carried out within the areas of electric power engineering and grid connection of wind power [249]. Muljadi et al. illustrated the process of a dynamic model for validations of wind turbine generators and wind power plants with the available data [250]. Guo et al. proposed a nonlinear control design technique for wind generation systems based on a high-order nonlinear dynamical system [251]. Li et al. dealt with the stochastic characteristic of the wind speed and provided an autoregressive moving-average (ARMA) model for wind speed subjected to particular power spectral density [252]. In order to consider high-order statistical moments, such as heavy tails, other authors have tried coupled integrated ARMA (ARIMA) processes to model the wind speed fluctuations [253].

Stochastic differential equation-based approaches have shown significant advancements in predicting temporal wind speed patterns that exhibit statistical properties resembling real-world observations. Moller et al. introduced an innovative methodology for wind power forecasting by employing logistic-type stochastic differential equations [254]. Iversen et al. proposed a modeling framework for short-term probabilistic wind speed forecasting [255]. Wang et al. incorporated variable wind power into a dynamic model to analyze the long-term stability of power systems [256]. Olsson et al. presented probabilistic models to assess the potential impact of large-scale integration of wind power [257]. Sauhatas et al. utilized historical electricity price data to evaluate the viability of constructing wind energy farms in a specific region [258]. Zarate et al. proposed two general procedures for developing wind speed models based on stochastic differential equations [259]. Verdejo et al. discussed uncertainties in electrical power system analysis and presented a systematic methodology using stochastic equations [260]. Su et al. developed a stochastic equation-based model to maximize the utilization of wind turbine gearboxes [261]. Loukatou et al. proposed a continuous-time model incorporating the longer-term daily cycle of wind speed [262]. Jiang et al. presented a novel approach for modeling power systems with integrated wind power using stochastic differential equations [263].

Inspired by concepts from statistical physics out of equilibrium involving evolution equations of distributions of stochastic variables—so-called Fokker–Planck equations—Peinke and Friedrich [264,265] introduced a framework to derive deterministic and stochastic contributions of stochastic processes. This framework was then extensively applied to different stochastic processes, beyond the scope of wind power [266]. Specific applications of this framework in the context of wind data include the assessment of power performance of wind turbines [267,268], modeling of short-time fluctuations of wind and solar power [269] as well as 10-min averages wind power curves [270], the torque of wind turbines [271], fatigue loads on wind turbines [272] and wind turbine vibrations [273].

The deterministic and stochastic contributions of such equations may describe, respectively, the dynamics of the wind turbine functioning and its interaction with the turbulent atmosphere.

However, measurements and records of wind speed, wind power, and other power grid data may be subjected to so-called measurement noise. This measurement noise, also known as observational noise, spoils the data series by hiding the underlying stochastic process. Several approaches have been published to overcome this challenge, with results that are of interest to other research communities, e.g., in signal processing. Böttcher et al. [274] and Lind et al. [275] introduced a method that allows the estimation of the different terms in SDEs to model wind stochastic processes in the presence of strong, delta-correlated Gaussian measurement noise. An alternative approach was presented by Lehle [276,277], which enables one to deal with large amplitude of exponentially correlated Gaussian noise, and in [278], the method was extended to a nonparameterized form of the different terms in the SDE, in order to distinguish between two superposed signals in the series of measurements.

The main framework to derive both deterministic and stochastic contributions were already implemented in open-source routines in *R* [279], with extensions to more general stochastic processes such as jump-diffusion processes (in *Python*) [280] and with the derivation of entropy-based measures (in *MATLAB*) [281]. Reviews of these frameworks and methods in stochastic differential equations can be found in [266] and more recently in [282].

Chen et al. proposed a discrete Markov model for wind speed and power time series using Bayesian inference models [283]. Li et al. provided a comprehensive review of Bayesian methods applied in wind energy conversion systems, summarizing the basic theories and examining the literature on their applications [49]. Xie et al. proposed a short-term wind power probabilistic forecast that captures the dynamic behavior of the underlying physical wind power stochastic process under various meteorological conditions using nonparametric methods [284]. Haslett et al. focused on estimating the long-term average power output from a wind turbine generator [285]. Chiodo et al. investigated the characterization of destructive wind forces, particularly extreme winds, also using a Bayesian model [286]. Ning et al. proposed a data-driven adaptive robust optimization framework for integrating wind power into smart grids [287]. Pesch et al. presented a novel statistical approach based on Markov chains that can reproduce wind power time series by incorporating a variable second lag [288]. Mbuvha explored the application of Bayesian neural networks for one-hour and day-ahead forecasting of wind power generation in his thesis [289].

From the AI side, the modeling of wind energy is more related to (high) accuracy of weather forecasts, as well as with the support plant monitoring and maintenance procedures. By leveraging artificial intelligence, the major players in the energy market aim to optimize the strengths of wind power generation while minimizing its limitations.

ML models give better results/predictions than classical statistical models, especially in the form of feature extraction and model generalization. Demolli et al. studied long-term wind power forecasting based on daily wind speed data using ML [290]. Negnevitsky et al. reviewed the main forecasting techniques used for power system applications, focusing on loads, energy prices, and wind power prediction [47]. Heinermann et al. investigated the use of machine learning ensembles for wind power prediction [291], and similar studies are presented in [291–294]. Other authors proposed novel algorithmic solutions using various forms of machine learning techniques in multistep ahead wind power generation (see, e.g., [48,295–297]). A stochastic-based machine learning model is proposed for short- and midterm forecasting of solar and wind power [298,299]. Singh et al. proposed to improve the forecasting accuracy of short-term wind energy generation in Turkish wind farms, using gradient descendent schemes of tree-based methods trained with wind speed and direction [300].

For wind time series, DL approaches focus mainly on the long short-term memory (LSTM) network and the convolutional neural network (CNN), with outstanding performance. Mishra et al. conducted short- and long-term multivariate predictions using five deep learning models [301] and Wang et al. proposed a method to advance point of probabilistic wind power [71,302]. However, some comparative studies [273] have shown that ANN implementations in general are not as effective in grasping the statistical features of wind data sets as other mathematically-based models such as SDEs described in some of the previous paragraphs of this section.

A new lower upper bound estimation (LUBE) model based on gradient descent optimization method for short-term interval prediction of wind is proposed by Li et al. [303]. Tao et al. reported the hidden rules of wind power patterns based on deep belief networks, extracted from historical data collected at wind farms [304]. Hossain et al. reported very short-term forecasting of wind power generation by using DL architectures [305] and similar works are found in [306,307]. Wang in his article reviewed the various DL technologies being used in wind speed and wind power forecasting [308], and similar works are presented in [309,310].

Articles on RL approaches to model wind power and wind data deal mainly with forecasting models of energy production at wind power plants from single wind turbines and also with wind farm control. Zhang et al. studied the control performance of automatic generation control for wind power ramping using deep RL [311]. Moreover, they also proposed a two-step wind power prediction method for long-time-scale coarse prediction and short-time-scale fine correction [312]. Yin et al. proposed a wind power prediction model based on ensemble reinforcement learning [313]. Dong et al. provided a comprehensive review of the development and most recent advances in wind farm control technologies [314]. Malik et al. proposed an adaptive self-learning wind speed predicting model using fuzzy reinforcement learning [315]. Wei et al. presented a self-dispatch model for wind speed based on deep RL [316]. Zhong et al. studied dynamic pricing demand using Weber–Fechner law and clustering algorithms [317]. Kuznetsova et al. use reinforcement learning algorithms [218] to propose a battery scheduling, which plays a key role in the achievement of the consumer goals. Li et al. adopted an agent-based simulation approach to investigate the bidding optimization of a wind generation company in the deregulated day-ahead electricity wholesale markets [318], and a similar study is presented in [319].

Finally, with respect to the reservoir computing models in the wind power prediction, Moreno et al. investigated wind power ramp events, aiming at predicting them, based on reservoir computing methodology [320]. Similar approaches can be found in [321–324]. Wang et al. introduced a novel forecasting system that can perform deterministic and probabilistic forecasting of wind power [325], using dynamic reservoir RNN, which the authors show to outperform standard gradient descent algorithms. Hu et al. proposed a new forecasting approach to estimate the wind power prediction intervals to quantify the prediction uncertainty [326]. Mammedov et al. proposed a weather prediction RC method divided into two models for wind speed and atmospheric system forecasting [327]. Ferreira et al. introduced what they call the reservoir computing and design training, which simultaneously optimizes reservoir parameters, topology, and weights, avoiding some of the drawbacks of RC implementation, namely spectral radius rescaling [328]. A new method for attack detection of smart grids with wind power generators using reservoir computing was introduced by Hamedani et al. [329].

4.4. Modeling Solar Power

Solar power is an RES that has been developed for longer than wind power. Modeling, forecasting, simulating, and analyzing solar power are, however, as challenging as wind power due to its strong fluctuations, mainly driven by cloud cover and wind speed patterns.

In the field of dynamical systems, Chaabene et al. proposed a dynamic model that predicts the thermal performance of low-temperature solar power plants [330]. Similar research has been reported in other studies such as [331–335]. Bessa et al. introduce a spatial–temporal forecasting method based on the vector autoregression (VAR) framework that utilizes data from smart measurement devices and distribution transformer controllers to predict solar generation patterns [336]. A similar study can be found in [337]. Farrokhfal et al. concentrated on the integration of solar energy generators into the electrical grid through the use of energy storage systems (ESS) [338]. Chong et al. discussed the validation process of dynamic real-time monitoring system (RMS) models by comparing simulations with actual plant responses and assessing the accuracy requirements set by the Australian Energy Market Operator (AEMO) [339].

Bayesian inference models have also been utilized in solar power modeling. Panamtash et al. proposed a Bayesian approach based on copulas to enhance solar power forecasting, using the joint distribution between solar power and ambient temperature [340]. Similar works can be found in [341–343]. Short-term predictions of photovoltaic (PV) power in solar power technologies were reported by Buwei et al. in [344], and a review of data mining methods for solar power data is presented in [50]. Sheng et al. proposed a weighted Gaussian process regression approach as an innovative method for solar power prediction, where data samples with higher outlier potential have a lower weight in the modeling process [345]. Oluwafemi et al. presented a nonlinear autoregressive exogenous neural network (NARX) model to predict solar power in Nigeria [346]. Gondalia et al. reviewed the work published in the field of solar power forecasting, highlighting the best tools and techniques to better predict the plant load factor [347].

In the realm of SDE-based models, much of the existing literature focuses on gaining empirical insights into generating and assessing stability and reliability within the energy grid. Iversen et al. proposed an SDE model of the uncertainty associated with solar irradiance [348]. Badosa et al. derived forecast frameworks, based on SDE, of the daily solar irradiance [349]. Similar studies can be found in [254,255,350,351].

Zhang et al. in their paper focused on the prediction of PV output power in different seasons and overcomes the uncertainty of PV power generation [352] using SDE.

Qui et al. proposed an ultra-short-term stochastic generation control method for cascaded hydropower to mitigate solar power volatility [353]. Zhang et al. reviewed concentrated on solar power plants technologies and solar tower collectors, addressing the pros and cons of each one and describing the use of the predictions in simulating the required plant configuration of an optimum STC [354]. Moreover, Peinke and Friedrich [264,266], described the modeling of wind power to solar power, e.g., in [269], to quantitatively assess the power fluctuations of RES.

AI-based approaches have been investigated as a means of learning key information about solar power in the multidimensional information domain, rather than relying on complex rules and classical models. For classical models, long time-series data such as solar radiation, temperature, or wind data are required to better simulate the design, control, and operation of solar energy systems. However, such long-term measurements are often not available for most locations or, where available, may suffer from various shortcomings such as poor data quality or insufficient length. AI techniques offer a promising solution to overcome these challenges.

In the domain of ML approaches, Munawar et al. presented a framework for quantitatively evaluating various models and feature selection methods for short-term solar power forecasting [355]. Amarasinghe et al. applied several ML algorithms for solar power forecasting in the Buruthakanda solar park in Hambantota, Sri Lanka [356], and similar studies have been conducted for other locations worldwide [357,358]. Jawaid et al. performed a comparative analysis of ANNs and standard regression algorithms for forecasting [359]. Sharma et al. explored site-specific prediction ML models automatically created from a framework for solar power generation using weather service forecasts. Similar works can be found in [337,360]. Ramadhan et al. compared the accuracy of physical and ML models for solar power generation at different stages [361]. Guher et al. estimated solar power based on hourly meteorological data from a specific location using various ML algorithms [362]. Ibrahim et al. evaluated the performance of different ML schemes for anomaly detection in photovoltaic components [363]. An overview of ML-based forecasting methods for solar irradiation can be found in [364].

Complementary to ML, DL approaches are used, particularly in situations where big data sets exist. Torres et al. introduced a DL approach based on feed-forward NN for big data series of solar energy [365]. Similar works can be found in [366–369] from long- to short-term solar power forecast [370,371]. Wen et al. presented an investigation of the residential power load and PV power output, which are forecasted using the input of the microgrid optimization model. The adoption of EVs and ESS in microgrids contributes to 8.97% cost reduction [372]. Chang et al. introduced weather forecasts using DL techniques [373]. Torres et al. proposed a new approach based on deep learning for the task of solar PV power forecasting [374]. Zaouali et al. applied an autoconfigurable middleware based on an LSTM model for several forecasting time dimensions to choose the significant time scale for the learning scheme [375]. Poudel et al. also presented an LSTM network to predict solar power output. The results obtained from the comparison of LSTM NNs and moving averages (MAs) indicate that the LSTM approach is reasonable for short-term solar power prediction [376].

In the realm of RL approaches, Leo et al. utilized RL to derive an optimal management strategy for a grid-connected solar microgrid system, considering a consumer, a solar photovoltaic system, and a battery [377]. Raju et al. also focused on a grid-connected solar microgrid system comprising a local consumer, a solar photovoltaic system, and a battery [378]. Singh et al. introduced deep RL with a fuzzy reward mechanism to track the maximum power point and improve the translation of continuous space into different levels of abstraction [379]. Heidari et al. proposed a control framework based on RL that considers the water usage behaviors, solar power generation, and weather conditions, aiming to strike a balance between energy use, occupant comfort, and water hygiene in a solar-assisted space heating and hot water production system [380].

Finally, approaches using RC have been also proposed. Hu et al. proposed a new forecasting approach to estimate the wind power prediction intervals to quantify the prediction uncertainty [326]. Basterrech used the so-called echo state networks model to predict solar power output [381]. This model is a variant of RNN often used for solving temporal learning problems. In their work, the authors base their implementation on a generalization of swarm optimization named geometrical particle swarm optimization. These methods of reservoir computing, and particularly the echo state network model, show the potential to significantly improve the accuracy of power grid monitoring and veer towards allowing real-time decisions for avoiding disruptions in the power grid. However, both ML and RC models are not very ubiquitous yet in the research literature of solar power modeling.

4.5. Modeling Biomass Power

Biomass power is produced based on the huge amount of waste produced, whose calorific value is what can be used as a part of formed fuels. However, while it can mitigate the impact of fossil fuels on the environment, it also leads to significant environmental impact due to its combustion generating greenhouse gasses.

In the domain of mathematically inspired models, Macek et al. developed long-term optimal maintenance strategies that leverage the dynamics of boiler efficiency and anticipated heating demand, derived from empirical data, for improved performance [382]. Moraes et al. investigated the impact of biomass burning in the Amazonian forest on absorbed solar radiation and net radiation fluxes at the surface, highlighting the effects of this perturbation [383]. The transient basin stability is examined through deterministic quantities such as the escape probability and the mean first exit time, providing insights into system dynamics [384]. Ludovici et al. focused on simulating the dynamic behavior of biomass power plants, specifically considering the utilization of an externally fired micro-gas turbine for electricity generation [385]. Jadhav et al. proposed the application of fractional calculus theory to derive a compact model of a gas turbine used in the conversion of biomass into electrical power, aiming to enhance the understanding and analysis of the system [386].

As for Bayesian inference models, Spinti et al. proposed the implementation of a digital twin for analyzing biomass energy systems [387]. Nicoulaud-Gouin et al. addressed biomass dynamic models of evergreen forests in order to improve biomass growth dynamic assessment at the regional scale [388]. Hou et al. [389] illustrated the procedures of Bayesian inference calibration of the so-called building energy models. Xie et al. proposed a Bayesian approach applied to develop two additive biomass model systems [390]. Hilborn et al. considered Bayesian methods for decision-making procedures using uncertainty measures associated with biomass data [391]. Khorri et al. developed a probabilistic risk assessment model for an empty fruit bunch boiler using a Bayesian network approach [392]. Chiu et al. used a Bayesian model to examine the effects of extreme weather and the invertebrate grazer community on epilithic algal biomass dynamics over 10 years [393].

Stochastic differential equation models are more limited in the literature on biomass modeling than the other mathematical approaches. Shabani et al. developed a two-stage stochastic optimization model to estimate the uncertainty of biomass supply [394], and Titi et al. provided a general framework for analyzing the optimal harvest of a renewable resource [395].

Our survey shows that, for the large-scale assessment of biomass energy, mathematical modeling approaches are limited due to stock variability, conversion economics, and supply chain reliability. In recent decades, AI-based models have been applied to bioenergy systems to address these challenges.

With ML approaches, Elmaz et al. employed regression techniques to predict different compound outputs, such as CO, CO_2, CH_4, H_2, and HHV, which result from the biomass gasification process [396]. Umenweke et al. also reported advances in the application of ML to biomass prediction and management [397]. Zuocai Dai et al. appleid feed-forward

ANNs to estimate biomass efficiency [387,398]. Xing et al. proposed three ML approaches estimating specifically the biomass compound HHV [399]. Tao et al. proposed a method based on infrared spectroscopy and ML models [400]. Han et al. used structural and spectral information, provided by remote sensing from aerial vehicles, in combination with ML methods to predict maize biomass [401].

In what concerns DL models, Zhang et al. developed an approach to estimate biomass by integrating LiDAR and Landsat-8 data through a DL framework, including autoencoders [402]. Li et al. presented a methodology for predicting NO_x emissions, which is based on the combustion process of biomass [403,404]. Kartal et al. introduced a circulating fluidized bed gasifier model as a tool to create a huge amount of data sets for the training of a DL model to predict the lower heating value of the biogas [405]. Nam et al. in their report analyzed DL model forecast electricity demand and renewable energy generation [406]. Here, the authors suggest that renewable energy scenarios guide the energy policy for Jeju Island. Ardabili et al. reviewed different DL techniques applied to biofuel production and consumption, as well as their environmental impacts [51]. Ferrag et al. proposed a novel DL framework for smart grids, entitled DeepCoin. The proposed approach is composed of an intrusion detection system, using RNNs for detecting network attacks and fraudulent transactions in the blockchain-based energy network [407].

Finally, with respect to RL models, less literature is available. Kozlov et al. dealt with the control and optimization problems combining solar and specific biomass sources, namely diesel power plants [408]. Obafemi et al. reviewed the different ANN models for predicting biomass thermal value, identifying some research gaps in this topic [409]. It seems that reservoir computing approaches were still not applied to biomass power modeling, and SDE- and ML-based approaches also still lack to a significant extent.

4.6. Modeling the Energy Market: from Power Grid Data to Energy Prices

Mathematically inspired models for energy market forecasts mainly focus on electricity markets and carbon emission factors that drive energy prices. Several reports are available in the literature and some important articles are presented here.

Through the application of dynamical systems approaches, researchers have made significant contributions to understanding energy markets and related dynamics. Wang et al. introduced a nonlinear system model that incorporates energy prices, supply, and economic growth, allowing for the analysis of the dynamic behavior of the overall system and its subsystems [410]. Similarly, Duan et al. investigated a dynamic grey time delay model for energy price prediction, focusing on the detailed examination of the effects of time delay [411]. In the realm of risk assessment, Cao et al. proposed a method that considers the uncertainty and dynamic correlation of energy prices, providing insights into effective risk management [412]. Zhou et al. delved into the stability conditions of wholesale electricity markets by analyzing real-time retail pricing and incorporating realistic consumption models with memory [413]. Other studies have explored various aspects of energy price dynamics, such as volatility in power grids [414], empirical analysis of electricity consumption in commercial and industrial sectors [415], nonlinearities and stochasticity in asset price dynamics [416], real-time retail pricing models [417], and the influence of carbon emission factors [418]. Additionally, within the framework of stochastic modeling of wind data, a stochastic analysis of power output in wind farms has been conducted to identify the principal wind turbines that characterize the overall output of these farms [419].

Muller et al. presented a novel Bayesian estimation method for modeling electricity prices [420]. Dehghanpour et al. proposed an agent-based model to address short-term strategic bidding in conventional energy generation.

SDE models have also proven valuable in valuing derivative contracts and conducting financial simulations for energy risk management. In this regard, Lewis provided an overview of commonly used stochastic processes in these applications, emphasizing their relevance in evaluating derivative contracts and simulating energy-related risks [421]. For Brazilian energy prices, a novel SDE model was applied in [422] to identify the optimal

SDE representation. Simon et al. introduced a nonlinear stochastic continuous-time model that effectively captures the key characteristics of price dynamics [423]. Garrido et al. focused on numerically evaluating swing options in electricity markets using a two-factor model [424]. Ecclesia et al. presented models describing the dynamics of spot prices for energy commodities and their associated forward curves [425]. Yin et al. utilized a stochastic differential method to provide long-term price guidance for flexible energy service providers, addressing the challenges posed by long-term market imbalances [426]. Benth et al. modeled spot prices in energy markets using exponential non-Gaussian Ornstein–Uhlenbeck processes, discussing the pricing of forwards and options, as well as the determination of the market price of risk in incomplete markets [427].

AI-based methods are capable of uncovering hidden relationships within data, although they may have certain limitations. In the field of price forecasting, machine learning (ML) techniques have experienced rapid development. Ghoddusi et al. provided a review of ML techniques in energy economics and highlighted the potential for improved crude oil and electricity price predictions using different datasets [52]. Herrera et al. described datasets spanning nearly four decades, containing monthly prices of six major energy commodities [428]. Sheha et al. presented various models for the proactive prediction of energy demand in entire cities [429]. Castelli et al. focused on improving the accuracy of electricity price forecasting by employing machine learning techniques that combine standard regression techniques with genetic algorithms [430]. Additional studies on this topic can be found in [406,431–434]. Mosavi et al. provided a comprehensive overview of ML models utilized in energy systems, along with a novel taxonomy of models and applications [435]. Antonopoulos et al. offered an overview of AI methods applied to demand–response decisions [436].

In the realm of deep learning (DL) approaches, Lago et al. proposed a novel modeling framework for electricity price forecasting [437], with similar work being presented in [438,439]. Alameer et al. introduced a DL-based method for forecasting coal prices [440,441]. Brusaferri et al. proposed a novel methodology utilizing Bayesian DL techniques for probabilistic energy price forecasting [442]. Mari et al. discussed a DL-based approach to model the complex dynamics of commodity prices observed in real markets [443]. Scholz et al. presented and analyzed a novel approach for predicting the energy price in the continuous intra-day market at the European power exchange spot [444].

RL-based algorithms have been developed and applied to diverse energy price datasets, offering valuable insights. Xu et al. addressed the challenge of determining both energy bids submitted to the electricity market and energy prices charged in the retail electricity market using RL techniques [445]. Nanduri et al. presented a solution framework based on RL and nonzero sum stochastic game theory, enabling the assessment of market power in day-ahead markets [446]. Kim et al. investigated dynamic pricing and energy consumption in the context of microgrids, employing RL methods to tackle these problems [317,447]. Mocanu et al. pioneered the utilization of deep RL approaches in the context of smart grids, exploring their benefits [448]. Lu et al. proposed a dynamic pricing RL algorithm for effective energy management in hierarchical electricity markets [449]. Jogunola et al. provided a comprehensive review of consensus algorithms combining blockchain and deep RL for energy trading decision-making [53]. Jiang et al. applied RL techniques to optimize the performance of heating, ventilation, and air-conditioning systems in building construction, highlighting potential control strategies [450].

Finally, there are only a few papers on RC. One of them is [451], where the authors propose the unscented reservoir smoother, a model that unifies both the deep sequential model and the state-space model to achieve both frameworks´ superiority.

5. Future Perspectives

This section extends some of the topics from the previous section and closes the paper by putting in perspective the state of the art of the different modeling approaches covered in our survey. In particular, we will first extend the survey to recent research on topics of energy sustainability, namely covering exploratory approaches to more futuristic scenarios. We will focus on the modeling of the different strategies for energy storage and emission reduction. In the end, we will come back to the tension between the two schools of thought on which this survey is based.

5.1. Exploring Scenarios of Energy Storage

Exploring different energy storage scenarios includes the modeling of grid operation, planning, and resource adequacy of different storage strategies, as well as their challenges with respect to physical and financial constraints of energy storage and the range of services that those strategies can provide. Energy storage systems give high stability and flexibility in the variations of supply and demand of microgrids, especially in RES-based grids. The variety of energy storage systems and their contribution to the power grid performances are tabulated in Table 3.

In the realm of storage scenarios, mathematically inspired models cover various aspects such as planning, optimization, maintenance, and control. Within the context of dynamical system approaches, Ortega et al. proposed a generalized model for energy storage systems to analyze voltage and angle stability [452]. Sidorov et al. provided a comprehensive review of battery energy storage methods and offer an example of battery modeling for renewable energy applications, focusing on an adaptive approach to solve the load-leveling problem [453]. Calero et al. developed a dynamical system model for battery energy storage [454], and a similar work can be found in [455]. Gallo et al. proposed a procedure to determine battery model parameters by fitting experimental data and integrating it into a real-time smart grid management system alongside energy source and load models [456]. Berrada et al. introduced a modeling framework for the operation of hybrid renewable energy systems [457], while Raccanello et al. analyzed the behavior of single-tank configurations of thermal storage involving mass transfer [458]. Yu et al. utilized the lumped parameter method to develop models for different thermal energy storage systems [459]. Maton et al. explored dynamic models for compressed air and hydrogen energy storage systems [460], and Bird et al. presented a reduced-order dynamic model of a power system incorporating sensible thermal energy storage in the form of a stratified hot water tank [461].

In the context of Bayesian inference, Chiodo et al. reported the application of multicriteria analysis to design batteries energy storage systems [462]. Jacob et al. used such approaches to identify the parameters of a fractional order battery system [463]. Suharto introduced Bayesian causal maps to predict wind power generation and assess storage strategies [464]. Khan et al. developed a hierarchical Bayesian network to estimate residential energy storage degradation, which is trained using experimental results of lithium iron phosphate batteries [465].

With mathematically inspired models based on SDEs, Ortega et al. described a variety of deterministic techniques to model energy storage devices [466], and Barreiro-Gomez et al. presented simulations of a microgrid, exploring different energy storage strategies [467]. Johnson et al. reported a method based on partial differential equations, using the stochastic differential equation for stochastic electricity selling price [468]. Ortega et al. offered a comprehensive stochastic analysis of the influence of energy storage systems on the transient stability of transmission grids, shedding light on this topic [469,470]. Bayram et al. introduced a sharing-based architecture for energy storage systems, where the stochastic nature of customer demands is taken into account. This architecture enables the accommodation of aggregate demand by utilizing a combination of power drawn from the grid and the storage unit when the demand surpasses the grid capacity [471].

Durante et al. introduced a new model that has some hidden complexity, defining henceforth a partially observable Markov decision process [472]. Emereuwa models energy storage systems using integrated mathematical homogenization theory and stochastic models [54]. Chaychizadeh et al. introduced a stochastic dynamic simulation of a hybrid system, combining a thermal-compressed carbon dioxide storage system with RES, namely wind power, reporting that it is capable of smoothing RES output even in a scenario of random production [473]. Finally, a combination of dynamical systems approaches and SDEs has been used to explore different scenarios of integrated electrical storage units [474].

Table 3. The different energy storage systems and their effect on the power grid performances.

Energy Storage Systems	Effect on Power Grid Performances
Supercapacitors (store electrical energy directly and thus do not need to convert to other energy forms)	Supercapacitors, an alternative form of battery, find application in power grids, particularly microgrids, to stabilize voltages during periods of power peaks. They are well suited for addressing short and medium transient events due to their high specific power. By dampening peaks and ripples in both loads and sources, supercapacitors contribute to voltage stability. Moreover, they enhance the flexibility of microgrids as they enable better adaptation to varying sources and demands across a wider current range, provided effective management is in place.
Hydrogen tanks	Hydrogen storage is considered a viable option for mitigating production plant outages and managing demand fluctuations. It serves as an effective energy storage approach and contributes to the balancing of power grids. The utilization of hydrogen presents a promising solution for distributing generated renewable energy. Introducing hydrogen into microgrids can significantly impact their behavior, particularly in terms of the peak electrical energy transfer between the microgrid and utility grid. As the level of hydrogen penetration increases within the microgrid, the peak of electrical energy transfer decreases, indicating the potential for reduced dependency on the utility grid.
Flywheels (store energy in the form of mechanical energy)	Stabilizes the frequency and degree of power grids and serves as short-term compensation storage. Flywheel storage power plants are available in the ranges of KWh to tens of MWh, similar to battery storage power plants.
Thermal energy storage systems (convert electrical into thermal energy; the storage medium can be solid or liquid)	Thermal energy storage systems find utility in both small-scale applications for heating purposes and large-scale applications for electrical energy generation. In large-scale applications, these systems utilize stored heat energy to generate electricity during periods of high power demand. They exhibit a rapid response capability, making them suitable for meeting short-term high-load demands. Furthermore, thermal energy storage systems offer the advantage of low initial investment and maintenance costs. However, it is important to note that these systems need to be specifically designed according to the intended application area to ensure optimal performance and efficiency.
Pumped hydroelectric storage (PHES; makes use of gravitational potential energy to store energy, managing upper and lower reservoirs)	Due to its gravitational potential energy of flow, whenever the power peak demands the elevation reservoirs open the turbines. For low power demand/cheap power, the operations are reversible, i.e., the water is pumped up. PHES allows more electricity sold for peak demand and increases revenue. The applications of PHEs are low operational cost, immediate operations, handling large load variations, high-pressure operations, and compact storage volume.
Compressed air energy storage (CAES; electromechanical device that produces electrical energy converted from mechanical energy)	CAES is a technology that involves storing high-pressure air in a tank and then expanding it through a turbine connected to a generator to produce electricity. It serves as an alternative to pumped hydroelectric storage for medium-term energy storage. During the compression process, the air temperature increases, while during the expansion, the pressurized air removes heat from the system. Storing the heat generated during the compression phase significantly enhances the efficiency of the energy storage process. There are two main types of CAES systems: diabatic and adiabatic. Each type employs different approaches to manage the heat produced during compression. Additionally, there is a third type called isothermal CAES that aims to maintain a constant temperature throughout the process.
Batteries	The batteries stabilize the microgrid voltage (DC bus) to store large amounts of energy during the narrow voltage operation. It is increasing the cost reduction, improvement in performance, and specific energy in mobile and stationary energy applications.

AI approaches have shown promise in improving the accuracy and performance of energy storage systems. Rangel-Martinez et al. presented an extensive overview of the current state of ML applications in the manufacturing sectors that impact sustainability and renewable energy systems [475]. Similar works focusing on storage strategies can be found in [429]. Chen et al. utilized ML approaches to introduce basic procedures for energy storage strategies, covering areas such as catalysis, batteries, solar cells, and gas capture [476]. Artrith reported on the recent progress of ML approaches in computational modeling of material interfaces [56]. Gao et al. provided a comprehensive review of recent advancements, concepts, approaches, and applications of ML implementations in various energy storage systems, including battery energy storage, hybrid energy storage, grid and microgrid systems, pumped-storage systems, and thermal energy storage systems [477]. Zitnick et al. introduced the challenges in finding suitable electrocatalysts and utilized the Open Catalyst Project (OC20) dataset for model training [478]. Henri et al. presented a supervised ML approach for predicting and operating residential PV battery systems [479]. These studies highlight the potential of AI and ML techniques in optimizing energy storage systems and improving their operational efficiency.

In the realm of deep learning (DL) approaches, Zsembinszki et al. presented a DRL architecture capable of handling the complexity of an innovative hybrid energy storage system to achieve optimal efficiency in terms of energy consumption [480]. Hafiz et al. introduced a framework for energy management, combining optimization and control schemes [481]. Jang et al. proposed a DL-based energy storage system management method for energy-efficient private residencies [482]. Miao et al. introduced a control strategy for battery energy storage systems using a DL adaptive–dynamic algorithm for optimization [483]. Chuttar et al. developed ANN-based prediction tools [484], and Kim et al. proposed an energy storage algorithm based on the optimization of water filling followed by a load forecasting based on LSTM neural networks [485]. These studies demonstrate the application of DL techniques in optimizing the operation and management of energy storage systems, leading to improved efficiency, cost-effectiveness, and prediction capabilities.

In the realm of RL models, Wang et al. introduced a novel temporal arbitrage policy for energy storage that maximizes its efficiency [486]. Henze et al. evaluated the operation of electrically driven co-ol thermal energy storage systems in large commercial buildings using a model-free RL control algorithm [487]. Cao et al. proposed a model-free deep RL method that optimizes battery energy arbitrage while considering accurate battery degradation models [488]. Oh et al. investigated an RL-based energy storage system operation strategy that effectively manages the uncertainty associated with wind power generation [489]. Gorostiza et al. proposed a deep RL-based approach for multielectrical energy storage systems, enabling them to provide frequency response services to the power grid [490]. Shang et al. developed an RL solution that combines Monte-Carlo tree search with domain knowledge expressed as dispatching rules [491]. Sun et al. proposed a sparse neural-network-based RL scheme to optimize the control system structure for enhancing the transient stability of power grids with energy storage systems [492]. Nyong-Bassey et al. proposed RL-based hybrid energy storage systems aimed at mitigating load demand and addressing the stochastic variability of renewable energy sources (RES) [493]. Yang et al. proposed a deep RL-based energy management strategy specifically for supercapacitor energy storage systems in urban rail transits [494]. Additionally, Zhou et al. proposed an adaptive and lightweight algorithm to obtain the optimal scheduling strategy for energy storage systems [495].

Finally, reservoir computing approaches are also being explored for energy storage scenario exploration, although further research is required to fully understand their potential in this domain.

5.2. Exploring Scenarios of Emission Reduction

The modeling of emissions and reductions can be based on various conditions, which need to be assumed or established when conducting simulations. These conditions include the power consumption of the whole society, wind power, PV and other technologies, as well as energy storage capacity, emission factors of the power industry, carbon sink quota of the power industry, and the carbon sink which is provided by various sink repositories, such as the so-called LULUCF (Land Use, Land-Use Change and Forestry) and the CCUS (Carbon Capture, Utilisation and Storage).

Mathematically inspired models have been employed in various domains, with dynamical systems serving as a valuable tool. Fang et al. applied a dynamical systems approach to explore the dynamic evolution of energy-saving and emission reduction patterns in response to energy construction adjustments. They developed a three-dimensional spatial energy-saving model to analyze these patterns [496,497]. Xu et al. utilized a dynamic simulation model to forecast China's CO_2 emissions and gross domestic product development under different energy structure adjustment plans and carbon intensity constraints from 2008 to 2020 [498]. Song et al. developed a dynamic optimization model based on a dynamic input-output approach, enabling the examination of regional economic, energy, and environmental impacts [499]. In the context of a low-carbon environment, Zhou et al. formulated a differential game involving a manufacturer and a retailer in a dual-channel supply chain [500]. Barros et al. discussed greenhouse gas emission targets in Argentina and proposed an emission target formulation considering macroeconomic and sectoral projections, along with potential mitigation options [501]. Wang et al. introduced a complex system model that integrates multiagent-based models and system dynamics models to address carbon dioxide emission reduction policies [502]. These mathematically inspired models provide valuable insights into the dynamic behavior and interactions of energy systems in various contexts.

With respect to Bayesian inference models, Nadimi et al. used an econometrics approach to forecast the energy consumption of Japan until 2030 [503]. The current issues existing in model predictive control power management strategies are identified and analyzed by Huang et al. [504]. In the field of nonintrusive load monitoring, Zhuang et al. conducted a comprehensive survey of effective systems in this area. Their survey covers various aspects, including algorithms, load signature models, datasets, performance metrics, and commercial applications such as demand response. They also discuss the challenges and future research directions in nonintrusive load monitoring [61]. Qader et al. focused on forecasting CO_2 emissions in Bahrain and applied several forecasting methods to address this task [505]. Brun et al. employed remote sensing maps of land use to analyze changes in deforestation patterns in Indonesia between 2000 and 2010. They compared the performance of different Bayesian computational models and assessed the effectiveness of protected areas in mitigating deforestation [506]. Zhang et al. explored the applications of big data analytics in smart grids, highlighting the potential benefits and opportunities in this area [507]. Heo et al. proposed a probabilistic approach for supporting large-scale investments in energy retrofit of buildings. Their methodology is based on Bayesian calibration of normative energy models, taking into account uncertainties associated with energy retrofit projects [508]. These studies contribute to the advancement of nonintrusive load monitoring, CO_2 emission forecasting, analysis of deforestation patterns, utilization of big data analytics in smart grids, and probabilistic approaches for energy retrofit investments, respectively.

SDEs are not so used for investigations on emission reduction scenarios. Cai et al. apply regression theory to European CO_2 emissions prices and obtain the point and interval estimations for the parameters of their SDEs [509]. Carmona et al. introduced forward–backward SDE models to explain the evaluation of CO_2 emission allowances [510]. Yu et al. proposed co-operative and non-co-operative stochastic differential game models to describe greenhouse gas emissions for decision-making in both developed and developing countries [511].

Since AI-based algorithms are useful for predicting and providing insight for making recommendations and decisions, they are natural candidates for modeling and assessing emission reduction scenarios. In the context of ML models, researchers deal mostly with the reduction of greenhouse gases and carbon emissions as well as other pollutants. Tan et al. addressed the reduction of NO_x by using ML and reported a high-quality and stable solution for optimizing operational parameters [512]. Lacoste et al. presented a tool for our community to better understand the environmental impact of training ML models [513]. Mardani et al. proposed an efficient multistage methodology that utilizes clustering techniques to predict carbon dioxide emissions. Their approach is based on energy consumption and economic growth, and aims to provide accurate predictions of CO_2 emissions [514,515]. Pallonetto et al. conducted an assessment of control algorithms for the implementation of demand response strategies in the residential sector. Their study focuses on evaluating the performance and effectiveness of these algorithms in enabling demand response actions [516]. Akhshik et al. focused on modeling greenhouse gas emissions and utilized machine learning techniques to derive optimal values for hyperparameters. Their research aimed to improve the accuracy of greenhouse gas emission predictions by optimizing the model's hyperparameters using machine learning methods [517]. These studies contribute to the development of methodologies for predicting carbon dioxide emissions, assessing control algorithms for demand response strategies, and utilizing machine learning techniques for modeling greenhouse gas emissions.

Interestingly, DL models are limited in the literature of this topic. For forecasting the emission and reduction model, Nam et al. used DL-based forecasts of electricity demand and renewable energy generation and analyzed scenarios with 100% renewable energy, evaluating their associated economic and environmental costs [406]. As for NO_x emission models from biomass power production, Li et al. presented a methodology for predicting such emissions, using DL architectures [403]. Bakay et al. forecasted greenhouse gas emissions using different DL implementations, and observed an increment of 3% for such emissions and of 6% for electricity production per annum in Turkey [518].

Finally, Yu et al. conducted a comprehensive review of smart building energy management using reinforcement learning (RL) models. They discussed unresolved issues and identified potential future research directions in energy emission reduction, highlighting the importance of RL in optimizing energy management systems [57]. Adams et al. proposed a deep RL optimization framework for determining the optimal operating conditions of a commercial circulating fluidized bed power plant. Their approach aimed to strike a balance between performance and environmental concerns, optimizing the plant's operations for improved efficiency and reduced environmental impact [519]. Cheng et al. presented a combustion optimization system for coal-fired boilers. Their system incorporated a trade-off between emissions control and boiler efficiency, aiming to achieve optimal combustion performance while minimizing emissions [520,521]. Qi et al. utilized deep RL, specifically the deep Q-network, to design a management system for hybrid electric vehicles. Their system autonomously learned the optimal fuel/electricity splits based on interactions between the vehicle and the traffic environment, contributing to efficient energy usage in hybrid electric vehicles [522]. Zhong et al. investigated the uses of the Weber–Fechner law and a clustering algorithm to construct quantitative response characteristics models. Their research focused on developing models that capture the relationship between stimuli and responses, enabling better understanding and prediction of system behaviors [317]. Zhang et al. studied a real-time pricing strategy for a multienergy generation system. Their research aimed to optimize the pricing strategy to achieve a balance between supply and demand, considering various energy sources and generation technologies [523]. These studies highlight the application of RL models in various domains, such as smart building energy management, power plant optimization, combustion control, hybrid electric vehicle management, and pricing strategies for multienergy systems.

5.3. Final Remarks and Conclusions

In this review, we offered a comprehensive survey of previous research work on renewable energy sources models, covering a broad panoply of different approaches. The main goal was to highlight the importance of articles and data sources around the topic of power grids with RES, covering the main modeling approaches of its different aspects, ranging from its structure to specific dynamics of renewable energy production, energy market, and futuristic sustainable scenarios of reduced emissions and optimized storage strategies. The survey can therefore be of use to researchers, policymakers, and stakeholders dealing with RES developments. While it is not exhaustive, we presented an extensive survey on the main developments of mathematical models as well as AI-based approaches to address different RES, different grid structures, the energy market, and hypothetical scenarios of emission reduction and energy storage. An overview of the survey is given in Figure 5.

In what concerns the most and least used approaches in the field of AI, we observed that in all topics covered above, reservoir computing (RC) approaches are the least selected by the research community, especially for modeling biomass power and energy prices and investigating energy storage and emission reduction scenarios. This lack of interest might, in part, be related to RC's infancy stage, compared to the other approaches, particularly in what concerns available open-source routines for different programming languages. However, we believe this lack of attention will be filled up with new investigations. It is known that one major advantage of RC compared to its "cousins" in the family of AI-based models concerns a remarkable combination of fast learning rate together with a low training cost with respect to the amount of data. It is therefore a promising source of models for future power grid research in particular when addressing monitoring protocols and control of power grid functioning. If the research and stakeholder community around power grids becomes more aware of the recent advances RC is making in physical systems, more advances in some of the present challenges might be observed in the near future. For a review on RC approaches to physical systems, see [524].

As for mathematically inspired models, the majority of studies are available within topics in dynamical and nonlinear systems, followed by stochastic differential equations. This preference is not surprising. On the one hand, standard equations borrowed from electrical engineering on power grids, such as swing equations, can be easily handled with techniques from dynamical systems theory. On the other hand, one of the most typical features of RES is their stochasticity, something that underlies the main reasons why they are so challenging to forecast and why they introduce additional risks to the stability of power grids. Both these aspects were already covered above with several examples from the literature, cf., e.g., Sections 4.1, 4.3 and 4.4. The lack of attention to Bayesian inference may be due to its limitations when dealing with dynamical aspects, something that approaches based on differential equations provide in a straightforward way. However, Bayesian inference may be of importance in topics where measures of uncertainty are necessary, namely when assessing the risk of overloaded lines or extreme events in the stability of the grid.

Another important aspect not directly related to the models being applied deals with the availability of data. As one knows, several of the data addressed in Section 3 are data subjected to confidentiality and protected by energy companies and stakeholders due to finance and political interests. With the aim of developing AI-based models, not depending on the availability of specific data sets, AI developers have been developing frameworks in what is now called transfer learning: the model is implemented and trained using other data sets, available to the developers, to make a first tuning of model parameters before using the target data. Given their considerable importance in power grid research, transfer learning strategies become particularly relevant when addressing rare or extreme events. In such cases, there are strategies to arrange large amounts of labeled data, for instance, complex DL architectures. A review of transfer learning techniques in AI approaches, discussing also its advantages and limitations in recent years, can be found in [525].

Also related to the availability of data, it is important to notice the needed co-ordination of different stakeholders holding different data sources, each one committed to confidentiality protocols, and simultaneously needing to share knowledge to properly explore future scenarios of a complex system such as a power grid. To attend to this challenge, AI researchers have developed in recent years approaches, which enable the training of their models—ML, DL, RC, etc.—in a *decentralized* way. In other words, while different stakeholders can train the *same* model for the power grid they all are using, each one trains with its own data sets, without sharing that information with the other stakeholders. Federated learning has gained broad popularity in the research community, in particular with the possibilities for data collection using smartphones and IoT devices. Moreover, the development of federated learning techniques has promoted the enhancement of trustworthiness in AI-based approaches in general [526]. A review of the applications and techniques in federated learning can be found in [527].

Finally, a last word on the structure we have followed throughout this survey, namely in what concerns considering the two schools of thought, one, perhaps more traditional, focused on mathematical frameworks, such as differential equations, and another more AI-based oriented. We agree that such structuring of a survey can introduce some biased assumptions, and as can be seen from Section 4, several articles and studies cover more than one approach, and often from both these schools of thought. It is not difficult to pick good and bad examples from each school of thought for each topic related to power grid functioning. However, it is also true that, probably not without some merit, AI-based models have gained dominant attention and easily are taken as benchmarks in which researchers tend to take for granted its superior performance compared with other (perhaps older) approaches. This is indeed a tendency that should be avoided. We have provided examples, e.g., when reproducing statistical features of wind power where simple stochastic modeling approaches surpass the performance of neural networks [273]. More recently, investigations in other domains have proven that century-old mathematical approaches, such as Markov chains, can still outperform very sophisticated DL implementations such as generative adversarial networks [528].

All in all, particularly for a system as complex as a power grid, two important directions should be considered in parallel. On the one hand, it is necessary to extend such comparative analysis of different approaches in a more systematic way, to better expose the pros and cons typical of each one. By gaining a deeper understanding of the strengths and limitations inherent in each approach, the power grid stands to reap significant benefits in the near future through the exploration of hybrid approaches. These innovative solutions, which harmoniously blend the finest elements of mathematical models with the power of AI, have the potential to revolutionize the way we optimize and manage the power grid. We hope that with such a survey we have pointed the reader in that direction.

Author Contributions: Conceptualization, S.S. and P.G.L.; methodology, S.S. and P.G.L.; bibliographic research, S.S., S.K. and Z.E.A.; text writing, S.S., S.K. and P.G.L.; coordination of content structure, Z.E.A. and P.G.L.; overall supervision, P.G.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable

Acknowledgments: S.S. acknowledges fellowship support to the Basic Research Program of the National Research University, Higher School of Economics, Moscow.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following table lists abbreviations and acronyms used throughout the review manuscript.

AI	Artificial Intelligence
AEMO	Australian Energy Market Operator
ANN	Artificial Neural Network
ARMA	Auto Regressive Moving Average
ARIMA	Autoregressive Integrated Moving Average
CES	Conventional Energy Sources
CKLS	Chan–Karolyi–Longstaff–Sanders
CNN	Convolutional Neural Network
CPI	Climate Policy Initiative
DAE	Denoising Autoencoders
DL	Deep Learning
DEED	Dynamic Economic Emission Dispatch
DeepCoin	Deep Learning and Block chain-based Energy Framework for Smart Grids
DR	Demand Response
ELM	Elaboration Likelihood Model

EPEX	European Power Exchange
ESS	Energy Storage System
EUs	European Unions
FCMs	Fuzzy Cognitive Maps
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GPU	Graphics Processing Unit
HVDC	High-Voltage DC Transmission
HEVs	Hybrid Electric Vehicles
IEA	International Energy Agency
IRENA	International Renewable Energy Agency
LUBE	Lower-Upper-Bound-Estimation
LSTM	Long Short-Term Memory
LiDAR	Light Detection and Ranging
MA	Moving Averages
MMC	Modular Multilevel Converters
ML	Machine Learning
MLP	Multilayer Perceptron
MPC	Model Predictive Control
MPPT	Maximum Power Point Tracking
NARX	Nonlinear Autoregressive Model that has eXogenous inputs
NILM	Nonintrusive Load Monitoring
PV	Photo Voltaic
RES	Renewable Energy Sources
RL	Reinforcement Learning
RMS	Root Mean Square
RC	Reservoir Computing
R-HFCM	Randomized High-Order Fuzzy Cognitive Maps
SIR	Sampling Importance Re-Sampling
SCADA	Supervisory Control and Data Acquisition
SDAE	Stacked Denoising Autoencoders
STC	Star Tracker
SVM	Support Vector Machine
VAR	Vector Auto-Regression
WPP	Wind Power Plant
WTG	Wind Turbine Generator

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