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Review

Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions

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Abstract: This review paper provides a summary of methods in which artificial intelligence (AI) techniques have been applied in the management of variable renewable energy (VRE) systems, and an outlook to future directions of research in the field. The VRE types included are namely solar, wind and marine varieties. AI techniques, and particularly machine learning (ML), have gained traction as a result of data explosion, and offer a method for integration of multimodal data for more accurate forecasting in energy applications. The VRE management aspects in which AI techniques have been applied include optimized power generation forecasting and integration of VRE into power grids, including the aspects of demand forecasting, energy storage, system optimization, performance monitoring, and cost management. Future directions of research in the applications of AI for VRE management are proposed and discussed, including the issue of data availability, types and quality, in addition to explainable artificial intelligence (XAI), quantum artificial intelligence (QAI), coupling AI with the emerging digital twins technology, and natural language processing.

Keywords: digital technologies; forecast; hybrid system; optimization; renewable energy

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Citation: Yousef, L.A.; Yousef, H.; Rocha-Meneses, L. Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions. *Energies* **2023**, *16*, 8057. https://doi.org/10.3390/en16248057

Academic Editor: Valentina Colla

Received: 12 October 2023
Revised: 21 November 2023
Accepted: 28 November 2023
Published: 14 December 2023

1. Introduction

With increasing global concerns over climate change, the energy sector is one of the major greenhouse gas (GHG) emitters that are being looked at in the push to increase sustainability efforts. Increased GHG levels have led to warmer temperatures globally, with anthropogenic warming reaching 1.25 °C above the 1850–1900 baseline as of June 2022 [1,2] and projections for the future predicting a rise ranging from 1 to 3.7 °C at the end of the century. Such a rise will have drastic impacts on human health, weather patterns, and crop production in addition to numerous other aspects of life on Earth [3].

As a result, renewable energy resources have seen an increase in popularity in recent decades [4]. Energy demand is addressed in traditional electricity grids through conventional resources, primarily fossil fuels. The location of power plants is typically constrained by proximity to these resources, which increases their complexity, ultimately adding to the disadvantages of conventional grids [5]. The increased penetration of renewable resources leads to an increase in the complexity of conventional power systems and makes them more susceptible to reliability concerns with the use of conventional electrical transmission and distribution networks [6,7].

Variable renewable energy (VRE) resources, specifically those governed by weather, are expected to be critical players in the global decarbonization efforts and push towards renewable energy. Renewable energy contributed to 81% of the net capacity energy expansion in 2021, with VRE installed capacity in the forms of solar and wind accounting for 88% of the new renewable capacity and continuing to dominate the renewable capacity expansion [8].

A power system generally includes three kinds of generation: baseload units (which produce the most economical power for the longest period and are only turned off for maintenance), mid-merit units (which operate 30–70% of the time to supply daily peak periods), and peaking units (the most expensive ones which are only operated during peak load periods) [9]. The main source of complexity in the integration of solar and wind energy is due to their power generation being of a stochastic nature, along with seasonal fluctuations, variations over time and space, and the availability of data [10]. One important issue with the rapid spread and penetration of VRE is oversupply, where an excess of power is generated but the consumer demand is not enough to match it. This requires an independent system operator to curtail VRE power to maintain the stability and security of the grid and prevent damage to power production units. Such curtailments result in significant green energy losses [11]. Another issue is low VRE production that can occur from the curtailment on production in addition to weather or hydrometeorological configurations with low resources. Operational flexibility is needed to ensure that supply can match demand requirements, despite both being of uncertain and variable nature. An important consideration is the utilization of large back-up energy sources or energy storage options [12]. The intermittent nature of VRE sources leads to variable patterns in energy generation, which can impact the system performance and reliability, making energy storage solutions necessary to alleviate the imbalance in supply and demand [13]. Therefore, the adoption of hybrid renewable energy systems (incorporating one or more renewable resources), along with energy storage and sometimes diesel generators, has been applied in the integration schemes of VRE [14].

When working with VRE systems, it becomes fundamental to use forecast tools to minimize uncertainty in the energy generation process, as this impacts all phases of decision-making, planning, and funding. Forecasting at varying time scales is important in planning for energy storage schedules and provisions of alternative energy sources in addition to VRE resource installation locations [15]. Such problems have presented a level of complexity that requires advanced solutions, leading to digital technologies now emerging as part of the future for the energy sector [16]. Artificial intelligence (AI) utilizes computer capabilities to simulate the behavior of human intelligence. It is an interdisciplinary science that incorporates logic, thinking, cognition, information, systems, and biology [17]. Implementation of AI techniques has three key advantages: the automation of repetitive and time-consuming processes, the ease of finding insights that would otherwise be lost in unstructured data, and the integration of numerous resources for tackling complex problems [18]. Figure 1 illustrates how AI and data science methodology can be applied to energy forecasting for a data-driven decision-making process. AI has found uses in the conventional energy sector, with applications in accelerating and reducing risk in numerous business processes related to the utilization of hydrocarbon resources [19]. AI has additionally played a role in reservoir modeling and simulation, production and drilling optimization, drilling automation, and process control [20]. It has also been studied as a method of monitoring energy consumption in buildings and track anomalies [21].

Despite the promising strides in VRE integration, challenges persist in optimizing their utilization within the existing power systems. The stochastic nature, seasonal fluctuations, and inherent variability of solar, wind, and marine power generation present obstacles in seamlessly incorporating these renewable sources into conventional grids. Furthermore, the management of VRE systems demands advanced solutions for addressing issues related to oversupply, curtailment, and the intermittent nature of energy production. To address these challenges, this paper aims to achieve the following research objectives:

- Background on AI techniques relevant to the paper topics
- Background on the influences of weather elements on VRE generation and planning
- Comprehensive review of AI applications in VRE management
- Exploration of future directions for advancement of AI applications in VRE

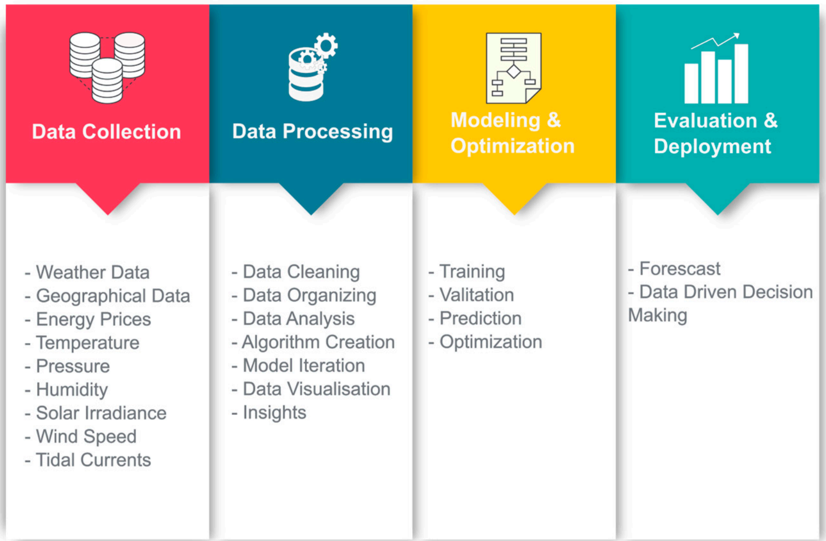

Figure 1. Steps involved in the development of modeling and optimization tools for energy forecasting.

The development directions of AI for VRE are of paramount importance in navigating the challenges and optimizing the utilization of renewable energy sources. As the global energy landscape undergoes a transformative shift towards increased reliance on VRE, AI offers strategic avenues to enhance the efficiency, dependability, and eco-sustainability of these systems. The integration of AI methodologies in VRE management addresses complexities related to data quality, model transparency, and system optimization. The burgeoning digitalization of energy supplies, coupled with the dynamic nature of VRE, necessitates innovative solutions to harness the full potential of renewable sources. AI has the potential to contribute significantly to overcoming inherent challenges, not only paving the way for improved energy forecasting, distribution, and system control but also through fostering a more sustainable and resilient energy paradigm in line with the demands of a rapidly evolving global climate and energy landscape.

Despite the significant role AI currently plays and is projected to play in the management of VRE systems, there is a gap in the literature providing a comprehensive review for this field. The novelty of this review is in its dual contribution. Firstly, it systematically reviews the existing landscape of AI methodologies employed in the context of VRE systems and offers a comprehensive understanding of their current state. Secondly, the manuscript takes the step of outlining distinct future research trajectories. The incorporation of quantum artificial intelligence, Digital twins, explainable AI, natural language processing, and refined data practices collectively enriches the review's novelty. In essence, this work not only consolidates the prevailing knowledge on AI applications in VRE forecasting but also introduces innovative avenues for advancing the optimization and sustainability of VRE systems. This combined contribution positions the manuscript as a timely resource in the intersection of AI and VRE research.

This paper is organized into a number of sections, starting with an overview of AI techniques of interest to VRE applications, explaining their classifications and differences. A review of VRE types and the role and impact of weather variables is then provided. This is followed by the applications of AI in existing literature for the management of VRE systems, namely in the forecasting of power generation and demand, energy storage, integration costs, and system optimization. Future directions of research related to applying AI for VREs are then covered, and the conclusions of the review are then provided. Table 1 provides a list of existing review papers and the topics they cover, highlighting the gaps which this comprehensive review tackles.

Table 1. Comparison between the topics addressed in this study and other studies.

No.	Background on Artificial Intelligence Techniques	Weather and Variable Renewable Energy Types	Artificial Intelligence Applied to Variable Renewable Energy Systems	Future Research Directions	Reference
1	• Traditional machine learning • Metaheuristic optimization algorithms for machine learning • Deep learning • Natural language processing • Fuzzy logic	• Solar energy • Wind energy • Marine energy	• Optimization of power generation forecasting (solar power forecasting; wind power forecasting; marine power forecasting) • Integration of variable renewable energy into power grid (power demand forecasting; energy storage; system design, monitoring, performance and security; cost management)	• Data availability, types, and quality • Explainable artificial intelligence • Quantum artificial intelligence • Digital twins coupled with artificial intelligence • Natural language processing	**This study**
2	Not reported	• Solar energy • Wind energy • Marine energy	• AI in solar energy • AI in wind energy • AI in marine energy	Not reported	[22]
3	• Artificial neural networks • Fuzzy logic control • Particle swarm optimization • Ant colony optimization	Not reported	Not reported	• Operation methods of renewable energy generation • Mitigating intermittency issues • Combined energy storage devices	[23]
4	Not reported	Not reported	• Mitigating balancing costs (generation forecasting; demand forecasting; more efficient market design) • Mitigating profile cost (demand response; storage solutions) • Mitigating grid-related costs (power quality disturbance; predictive maintenance)	Not reported	[24]
5	• Classical ML techniques • Fuzzy logic • Hidden Markov models • Neural networks	• Solar energy • Wind energy • Marine energy	Not reported	• Trade-off between performance and explainability • Cloud computing/deployment • Adversarially robust models • Scarcity of data • Novelty detection • State-of-the-art sensor technologies • Real-time prognostic models	[25]
6	Not reported	Not reported	• Energy generation (power generation; renewable energy) • Power delivery (transmission and delivery; system automation and control) • Electrical distribution networks (energy conversion and distribution; integrated energy systems) • Energy storage (battery energy storage; energy storage technologies and devices); energy applications	Not reported	[26]

2. Artificial Intelligence Techniques

AI encompasses a variety of techniques and domains for solving problems, with the most utilized methods falling under the domain of machine learning (ML). ML has advanced at a significant pace in recent years, allowing intelligent functions for applications using computing and data analysis. ML enables systems to learn and improve through experience without targeted programming and is commonly touted as the most prevalent of modern technologies in the Fourth Industrial Revolution. The efficiency and reliability of ML solutions rely on the data being utilized, and the performance of the learning algorithm. It is important to select the appropriate learning algorithm for the needed application, which can be a challenge. To navigate this, it is critical to comprehend the underlying principles of different ML algorithms and how to apply them for various practical uses [27].

2.1. Traditional Machine Learning

ML is categorized into four main groups: supervised, semi-supervised, unsupervised, and reinforcement learning. These methods handle data that comes in various forms, including structured, semi-structured, and unstructured [28].

Supervised machine learning is the process of fitting a model to data that has been labeled, comprising of classification and regression tasks. Unsupervised learning recognizes patterns in unlabeled data without the need for the provision of predetermined labels, with clustering, dimensionality reduction, and association mining as the primary techniques for this branch of ML [29,30].

Within supervised ML, classification tasks represent the problem of mapping numerous input variables to discrete output variables represented as categories and can be either binary or multiclass classifications [29]. This can essentially be viewed as an optimal separation problem, represented in Figure 2a. Regression tasks, however, map input variables to continuous outputs, representing a data-fitting problem (Figure 2b). Logistic regression and linear regression are the simplest algorithms for classification and regression, respectively [31].

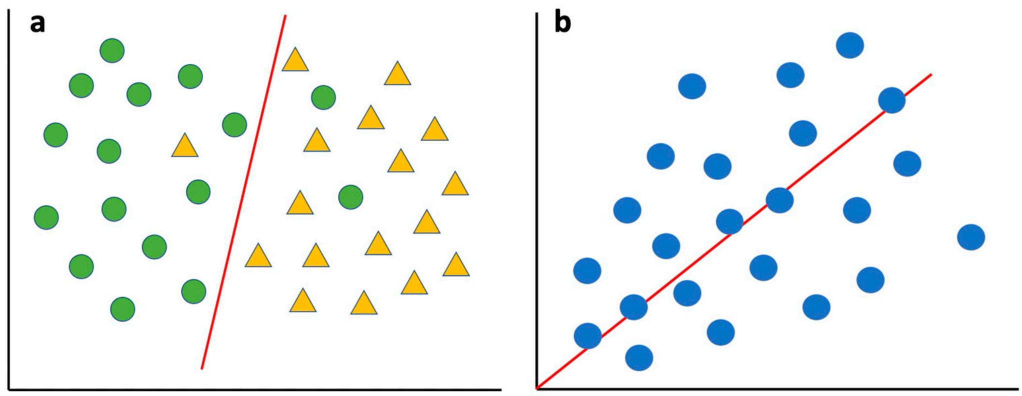

Figure 2. ML tasks including (**a**) classification and (**b**) regression.

The main challenge faced in ML is overfitting, in which the model tends to memorize patterns, including noise, from the data it is trained on, consequentially performing poorly when deployed on unseen data. Limited training data and overly complex models are the primary causes of overfitting, hindering the generalizability of the models. Mitigation of overfitting can be achieved by acquiring more training data through various augmentation methods, reducing the learnable parameters of the model in question, limiting the number of input features via feature selection methods, or reducing their influence by adding penalty terms known as regularization [32].

Decision trees (DT) fall within the supervised learning approaches. They are used to solve classification and regression problems. A DT classifies data through a sequential group of questions regarding features, which form a hierarchy and are encoded as a tree. DTs can offer advantages over other methods in their manner of utilizing simple questions about data in a comprehendible way [33].

K-nearest neighbor (KNN) is another example of a supervised learning technique for both regression and classification tasks. KNN follows the principle of lazy learning, or instance-based learning in which the model is not trained until a query is provided in the form of the test data. Instead of generalizing to the data during training, the training set is simply stored for future predictions. Subsequently, predictions for unlabeled test data are made based on the closest neighbors to the data point, which are determined based on proximity in terms of Euclidean distance. The number of neighbors to take into account, or K, is a hyperparameter which requires tuning according to the specific application [34,35].

Support vector machines (SVM) is a kernel-based ML technique for classification and regression tasks and has been recognized as a powerful supervised learning method. It has become one of the most utilized methods for classification tasks due its strong theoretical foundations and good generalization capabilities, which are achieved through the separation of several classes in the training data with a surface maximizing the margin between them [36] (Figure 3a).

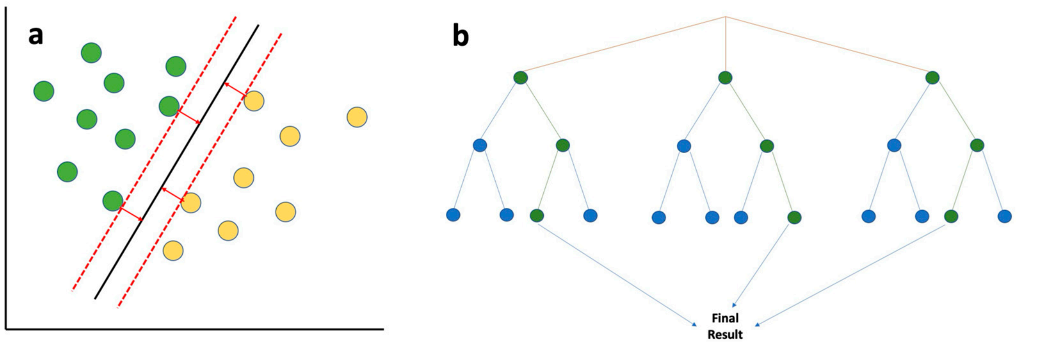

Figure 3. Popular ML models include (**a**) SVM, which finds the optimal hyperplane separating classes, and (**b**) RF, which utilizes an ensemble of decision trees and produces the final output through majority voting/averaging of individual trees.

Ensemble learning is a ML technique that utilizes various baseline models and aggregates them to form a more powerful model that is more diverse, thereby enhancing its generalizability. Random forests (RF) are an ensemble of a predetermined number of DTs. RF algorithms have become more common in recent years because of their interpretability and ability to avert over-fitting. They have three main hyperparameters, which should be determined before training: node size, number of trees, and number of features sampled. Random forest classifiers are then utilized to solve regression or classification problems [37] (Figure 3b).

2.2. Metaheuristic Optimization Algorithms for Machine Learning

When training a ML model, the goal is to find the set of hyperparameters representing the optimal solution to the problem at hand, known as optimization. In the case of simple linear, convex, differentiable and low-dimensional problems, deterministic optimization techniques can be deployed. However, stochastic approaches are necessary when handling high dimensional, non-convex, non-linear, or non-differentiable problems, which rely on random search and empirical testing of the search space. Metaheuristic algorithms (MA) are a class of stochastic optimization utilized in ML [38].

Genetic algorithms (GA) are a form of MA which have been employed to solve complex problems in a variety of scientific fields. GA is inspired by the Darwinian "survival of the fittest" concept. It consists of chromosome representation (which typically takes the binary format), fitness selection, and operators inspired from biology. The chromosomes are considered points in the solution space, with the fitness function assigning values to all chromosomes in the population. The operators are selection, mutation, and crossover. The chromosomes are selected for further processing based on the fitness result [39].

Particle swarm optimization (PSO), another MA, is an optimization algorithm that was inspired by the behavior of bird flocks and fish schools. Optimization problems are solved through the swarm of particles searching the space in specified dimensions and determining the solution that optimizes the problem. The exploration phase is where the space is explored extensively, and the exploitation phase is narrowed down to the most promising subspaces [40].

2.3. Deep Learning

Artificial neural networks (ANNs) are comprised of a group of nodes, or neurons, which incorporate weight parameters and activation functions. ANNs are commonly divided into input, hidden and output layers. The connections between neurons are each a signal that is processed and transmitted to the following layer until an output response is achieved [41]. ANN models do not make assumptions on the distribution of the input variables, or the underlying physical dynamics between input and output variables. The robustness of ANNs therefore is reliant to a large extent on the form of the input and variables, and the method in which they are fed into the model. The quantity of data fed into the models is an important factor, with longer-term datasets being highly recommended in order to capture necessary information and obtain better predictions [42] (Figure 4).

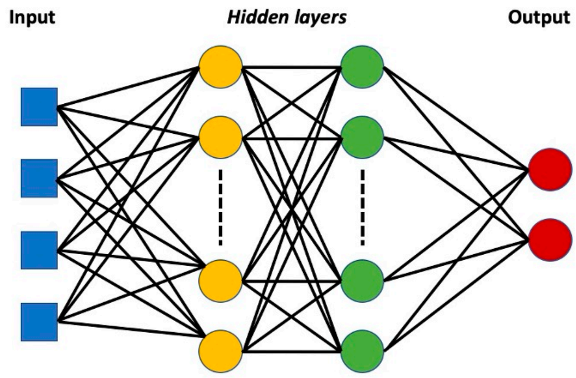

Figure 4. Popular deep learning architectures including ANN, which processes input nonlinearly through hidden layer(s) consisting of artificial neurons to produce predictions.

Multilayer perceptron (MLP) is the most popular ANN model using back-propagation training. It contains one or more hidden layers, with neurons in the same layer not connected and only connecting in the direction of lower to upper layers. Optimization of the number of connections is of great importance to the accuracy of MLP results [43].

One of the most widely utilized DL models is the convolutional neural network (CNN), developed for computer vision tasks. It permits the bypassing of manual feature extraction through mathematical operations known as convolutions, which are specialized for handling grid-type data, such as images. Ultimately, it allows for automated feature extraction and is advantageous, as it is translation-invariant [44] (Figure 5).

In the case of sequence data, such as text or time-series data, recurrent neural networks (RNN) were developed to handle the extraction of temporal features. The basic concept of RNNs is the integration of past state and current state information for network updates. Traditional RNNs, however, suffered in the case of large input data when long-term dependencies were required for accurate predictions [45]. This in turn led to the evolution of RNNs into two new architectures, long short-term memory (LSTM) and gated recurrent units (GRU), which allow the processing of large input data and handling of long-term information integration [46].

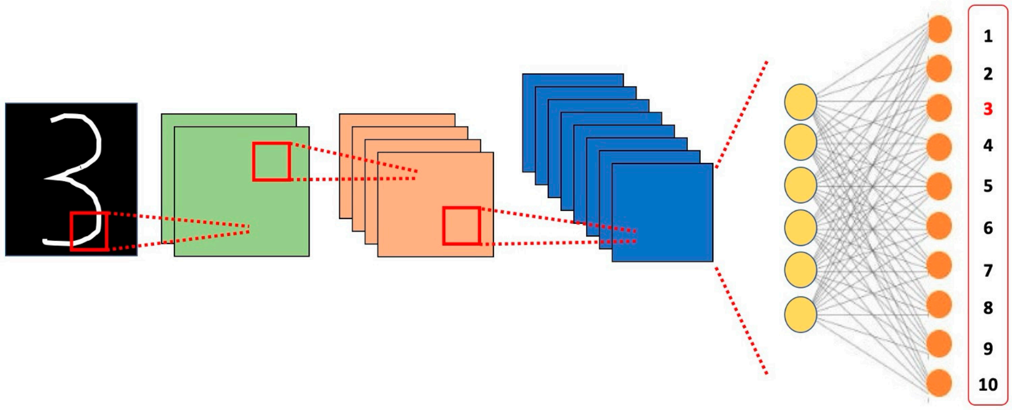

Figure 5. CNN model, which extracts latent features from images through a series of convolutional layers, sequentially reducing the size of images and increasing their depth/channels. Convolutional outputs are then passed to a fully connected layer to produce the final output.

The transformer is the most novel and ubiquitous DL model, consisting of encoder and decoder blocks, which in turn contain self-attention modules that can handle various input sizes and effectively capture long-range dependencies. It currently dominates natural language processing (NLP) but is also utilized in various domains, such as computer vision, audio processing, and generative AI [47–49].

2.4. Other AI Techniques

Other AI techniques with applications in the energy sector include natural language processing (NLP) [50]. The roots of NLP date back to the 1950's as the nexus of AI and linguistics. NLP is the computer science field that deals with the utilization of computational techniques to learn, understand, and generate human language content. Modern day research in this field focuses on the utilization of this tool in real-world applications, where systems can speak, speech can be translated, and information can be mined from social media challenges [51].

Fuzzy logic (FL) is an established tool which develops algorithms integrating structured human knowledge. It enables the representation of a model designed for human interpretation modes that are not precise, but inexact. The process of applying FL includes fuzzification, where the classical data in converted into membership functions; the fuzzy inference process, in which the membership functions are combined with the fuzzy control rules to generate the fuzzy output; and the defuzzification step in which the fuzzy output is converted into crisp results with the accompanying rules [52].

3. Weather and Variable Renewable Energy Types

VRE systems are primarily powered through solar, wind, and marine resources, which tend to be variable and non-dispatchable in nature, unlike renewable energy systems that utilize hydropower from dams, geothermal, and biomass. Solar energy has seen a significant scale-up in use over the past decades. Solar power is generated from two types of plants: solar photovoltaic (PV) and solar thermal systems. PV plants have advanced further due to their conversion being more direct and economically viable, as they enable the direct conversion of global horizontal irradiance (GHI) into electricity using semiconductors. This has resulted in PV being a mature technology from both technical and economical perspectives and has allowed its market to be one of the most quickly expanding in renewable energy alternatives [53]. The amount of energy generated from a solar PV system is dependent on a number of factors, which include the PV type, the setup of the system, and the climate and geographic variables [15]. Concentrated solar power (CSP) is the second mainstream approach to generating solar power. It is based on the concept of redirecting, focusing, and collecting direct normal irradiance (DNI) as heat, utilizing mirrors. This heat is then used to power a thermodynamic cycle that produces electricity [54]. There are numerous options for the solar collector types, materials, structures, and systems for heat transport, storage, and electricity conversion systems [55].

Wind energy has become a competitively priced option in numerous global markets and provides over half the growth in renewables worldwide due to it being cost-effective and sustainable in comparison to other energy sources. Turbines are utilized to convert the kinetic energy of wind movement into rotational energy through the turbine rotor blades. This rotational energy is then used to turn a generator through a drive shaft, producing electricity [56]. The intermittency in wind power generation has been a major obstacle in its adoption as a primary energy source and causes challenges in generation, storage, and transport [57]. Other challenges related to the use of wind turbines are noise pollution, aesthetic impacts, and avian life issues [58].

Marine energy can be generated from ocean tides, waves, and currents, in addition to free-flowing water in rivers, lakes, and streams. It can also be generated from changes in salinity, pressure, and temperature. Marine energy, in all its various forms, has the potential to contribute to the supply of renewable energy and reduction in carbon emissions. With oceans covering more than 70% of the Earth's surface, their utilization for generating energy provides substantial potential. The conversion of energy from the ocean is primarily classified as thermal and electrical conversions. The thermal process integrates a direct sea-source heat exchanger and heat pumps, while the electrical process integrates current turbine/wave energy converters, tidal stream generators, ocean thermoelectric generators, floating PV panels, and off-shore wind turbines [59]. Tidal energy is generated using the periodic horizontal movement of seawater that results from the celestial gravitational force. The kinetic energy from the water flow is converted using tidal turbines into electrical energy [60].

Weather elements are critical controlling factors for VRE resources as is power demand. Studies in Greece [61] and South Africa [62] have shown that the use of climate data could help with increased accuracy of energy demand forecasting models. Studies on the influence of weather regimes on energy demand for Europe show the importance of integrating weather regimes into energy sector analyses and that further advances are required to better understand their link [63]. Variables of interest for VRE applications include solar irradiance (GHI and DNI), aerosols, dust storms, temperature, relative humidity, wind speed and direction, atmospheric pressure, surface albedo, and cloud cover. For example, with regards to PV power generation, environmental and weather elements including cloud cover, ambient temperature, humidity, precipitation, wind speed and direction, and dust influence the output. Dust accumulation is a primary factor in energy losses, as it results in lower power generation and decreased lifespan of PV modules. Humidity, temperature, and wind play an important role in the deposition and removal of dust from modules [64,65]. Clouds play an important role in the energy balance of the planet and are a key player in both directly and indirectly influencing the amount of power output from VRE resources. Cloud cover, and its movement, has a significant effect on sunlight intensity. Geographic location plays a role in the study of cloud cover—for example, desert clouds are sporadic in nature, which enhances the importance of better methods to forecast their movement and integration into modeling efforts [66,67]. Wind patterns impact energy generation from both wind and marine resources. With regards to marine energy, weather elements, primarily wind speed and direction, directly influence the intensity and characteristics of waves and the amount of electricity generated. Tidal energy, in addition to mainly being governed by celestial forces, is impacted by atmospheric pressure systems and wind patterns [68].

Sustainability of energy and climate change are two problems with complex links that are critical to addressed through integrated solutions. Climate change has a significant impact on utilized energy through its impacts on energy demand, generation, and infrastructure [69]. Extreme events, hot or cold, are likely to increase the demand for power [70]. Additionally, climate change projections are important for planning long-term VRE resource allocations, and the need for advanced climate modeling is adamant for planning for uncertainties in VRE systems [71].

The role of local weather conditions is significant on the variability of solar radiation as it passes through the atmosphere, which has a direct impact on the amount of solar energy generated. Variables such as cloud cover movement can lead to upward and downward shifts in generation within a time scale of seconds. Solar resources are unavailable at night, while wind is less intermittent but also less easy to predict, with low wind conditions causing disruptions [72]. Forecasting is therefore of great importance at varying time scales to plan for energy storage schedules and provisions of alternative energy sources in addition to VRE resource installation locations [15]. Accurate weather forecasts give VRE generators the ability to forecast their power generation. Weather forecasting techniques have ranged over the years to include physical models, statistical models, and—in recent decades—artificial-intelligence-based models.

Numerical weather prediction (NWP) data is the most recognized form of weather modeling output. NWP is based on solving a set of partial differential equations that govern movement and developments in the atmosphere. These equations represent basic laws of conservation, including those for momentum, mass, energy, and water vapor. The current (initial) atmospheric conditions are used with the equations to obtain predictions of future atmospheric conditions [73]. NWP is generally employed for day-ahead forecasts as opposed to short or medium-term forecasting, since future meteorological trends improve model forecast accuracy with larger time horizons [74]. NWP forecasting is used as a tool in assisting for planning of short-term future power scenarios. Errors in these forecasts cause direct errors in the power prediction, making studies on current NWP challenges, shortcomings and model enhancements necessary to maintain the stability of power supplies [75].

Advanced weather forecasting is one of the primary applications for AI in the challenges of integrating VRE [76]. Machine learning has found applications in weather data preprocessing, observation operators, and the processing of satellite data. ML methods have been shown to produce reasonable weather forecasts despite no integration of atmospheric physics in their setup, through the utilization of historical observation data for algorithm training [77]. AI forecasting can be used as a standalone approach separate from NWP models and their affiliated physics, with comparable results. The challenge to using this approach is the availability of adequate data for the training phase. For this reason, the current best approach to utilizing DL methods is to combine them with NWP methods. This can be done using available training data in a residual learning approach. ML methods can also be utilized to enhance the parametrization of physical processes that are not explicitly resolved in models [78].

4. Artificial Intelligence Applied to Variable Renewable Energy Systems

The deployment of VRE systems requires optimization methodologies in order to achieve the highest possible efficiency in their use. AI techniques are commonly used in VRE performance forecasting applications to model and control systems and for decision-making applications. A summary of notable studies utilizing AI for VRE is provided in Table 2, with the following sections elaborating on the subfields in which AI is being applied.

Table 2. Selection of studies utilizing AI for power generation forecasting and integration of VRE into power grids.

Application		Model Configuration	Outcome Measure	Performance	Reference
Power generation forecasting	Solar-power forecasting	Multi-objective PSO (MOPSO) paired with ANNs	PIs of point forecasts	MOPSO paired with measures of solar power output significantly reduces the uncertainty of PIs for short forecasting horizon	Aler et al. [79]
	Wind power forecasting	GRU	Regression task for prediction of wind speed	RMSE of 0.3757 when combined with wavelet soft threshold denoising (WSTD)	Peng et al. [80]
	Marine power forecasting	Transformer encoders	Classification of significant wave heights (SWHs)	Accuracies ranging between 0.900 to 0.991 over a prediction period of 24 h	Chen at al. [81]
		LSTM	Regression task for prediction of wave energy power output	RMSE values between 0.42 and 0.56 for different input variables	Mousavi et al. [82]
Integration of VRE into power grids	Power demand forecasting	Hybrid ANN	Energy demand forecasting	RMSE of 3.85% for 6-h and 4.37% for daily energy demand prediction	Al-Musaylh et al. [83]
	Energy storage	Many objective evolutionary algorithms with fuzzy decision making	Hybrid microgrid systems (HMS) sizing optimization	Reduction in costs of 7–21% in comparison to existing optimization models	Cao et al. [84]

4.1. Optimization of Power Generation Forecasting

VRE resource forecasts are critical for minimizing the uncertainty of their generation, as this impacts all phases of decision-making, planning and funding. In the short-term, it helps with system stability through enhancing unit commitment and reducing reliability issues, in addition to being utilized in spot market electricity trading, and reducing the risk of incurring penalties for imbalances. In the long term it plays a role in preparations for extreme weather events through allocation of adequate balancing reserves, planning future expansions and the placement of VRE plants [76].

Forecast horizon is defined as the time period between actual and effective time of prediction. Four categories have emerged in recent literature, namely very-short-term (seconds to 30 min), short-term (30 to 360 min), medium-term (6 to 24 h), and long-term more than 24 h). Nowcasting refers to the process of producing short-range forecasts in the range of 4–6 h in the future. Nowcasting is projected to undergo significant improvements through the use of varied data sources, such as ground-based observations, radar data, remotely sensed observations, etc. These will result in challenges, including the handling of big data, quality control, and assigning weights to the various data sources [78].

Power forecasting is primarily done with three methods: physical, statistical, and hybrid. Physical methods rely on the systems design parameters to simulate the output power. Statistical methods encompass both traditional statistical modeling techniques and ML algorithms. Hybrid approaches are used to refer to the combination of two different methods [85].

Power forecasting generally includes two kinds of approaches: deterministic, which provides a unique value for the variable being forecasted at each future time-step, and probabilistic, which provides the full potential range of events using quantiles, prediction intervals (PIs), or distributions. Deterministic approaches have been explored for several decades, while probabilistic approaches have gained momentum in the past decade [86]. Probabilistic models provide a more comprehensive outlook on the possible scenarios resulting from forecasting processes, in the form of an interval where the point forecasts are expected to be found [87].

Reviews and studies on VRE power forecasting have found that classical ML models, such as linear regression, can be a decent choice for simplicity, but they may fail to capture non-linear relationships, making RF and SVM possible better choices. Hybrid models combining traditional time series forecasting with ML have also been used for VRE power forecasting [71]. The following subsections elaborate on studies conducted for power forecasting within each VRE domain.

4.1.1. Solar Power Forecasting

Numerous reviews on the use of AI for solar power forecasting have been conducted [88–90]. The accurate forecasting of solar irradiance is of utmost importance for the power system designers and grid operators for efficient management of solar energy systems. An interesting observation from literature searches on solar power forecasting with AI is that most studies have been conducted for PV systems. This seems to primarily result from how forecasting methods have been developed largely for GHI, with few studies dedicated to DNI forecasting [54]. Reviews of solar power forecasting from PV systems provide insights into the current methodologies and future directions. The quantity of GHI is a primary influencing factor on the efficiency, in addition to the temperature, of the PV module. The efficient design of a PV forecasting system is also dependent on factors including the incorporation of forecast horizons, the selection of inputs with correlation analysis, pre- and post-processing of data, weather classification, network optimization, and uncertainty quantification [74].

GHI forecasting is performed primarily through two methodologies: the first utilizes cloud imagery with physical models, and the second utilizes ML techniques for statistical models [91]. Physical models utilize atmospheric variables that are directly related to solar power generation, making its process complex due to being affected by the uncertainty of the meteorological variables being used as input. Alternatively, statistical models utilize historical data to determine the relationship between meteorological variables and PV power generation, which is then utilized to build the power forecasting model [92].

Among the physical, statistical, AI, ensemble and hybrid models, extensive literature reviews have found that ANNs, and specifically convolutional neural networks (CNNs), are the most promising for short-term forecast accuracy and are covered most extensively in the literature [88]. A study on ML techniques for solar radiation forecasting envisioned the use of SVM, regression trees, and RF in the coming years due to their promising results, competing with ANN. A recommendation was for the use of ensemble predictors rather than simple ones [91]. Figure 6 shows the process of utilizing AI for solar power forecasting.

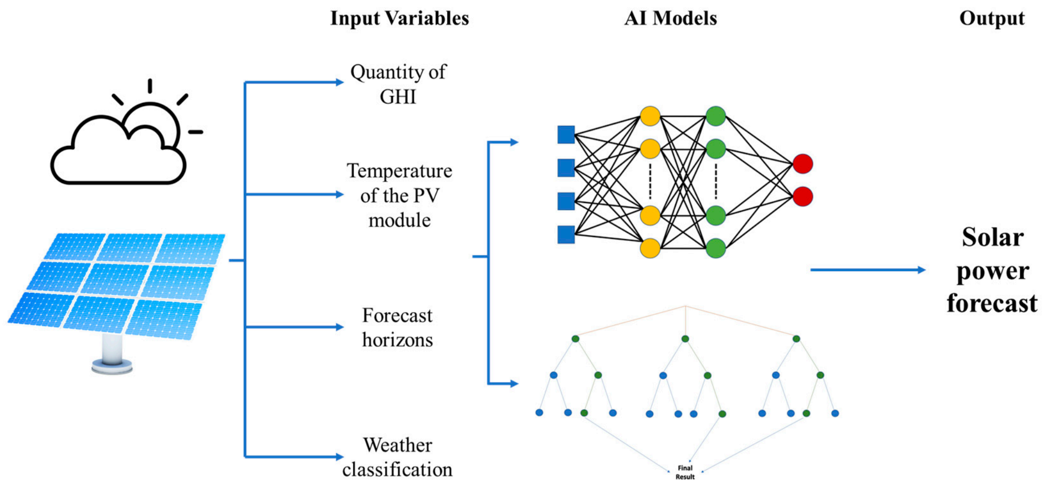

Figure 6. Schematic showing process of input variables feeding into AI models (e.g., neural network, RF) to obtain solar power forecasts.

The estimation of PIs for point forecasts of solar power and their improvement is a topic that has gained interest in recent literature. The use of optimization techniques paired with ANNs can be used to customize PIs to different times of the day rather than have intervals, e.g., the power output during night hours is zero—thus, the interval of PIs during those hours can be narrower than during the day [93]. A study conducted on solar stations in Australia estimated prediction intervals using multi-objective PSO paired with ANNs. The prediction intervals were found to be improved when measured solar output was utilized as input alongside meteorological forecasts for short forecast horizons of 1–2 h, thus reducing uncertainty [79].

An interesting point discussed by Garus et al. [88] was on the models in the existing literature mainly being trained for the conditions of specific locations. The authors suggest that AI tools should be utilized to generalize models over a wider set of conditions with better prediction accuracy through integrating the existing AI approaches with optimization techniques such as GA, PSO, and analysis of variance (ANOVA). A complication to the generalization proposal lies in the impacts of different meteorological conditions in different locations. Climate conditions have been shown to influence the performance of different ML techniques for solar irradiance prediction. One example of this is a study conducted for solar power prediction at the Shagaya Renewable Energy Park in Kuwait, an arid desert region with predominantly sunny and clear sky conditions. The use of a regime-dependent approach, in which k-means clustering was used to independently classify regimes before applying an ANN, led to a degraded performance. The dominance of clear sky conditions in the meteorological conditions of Kuwait makes regime-identification approaches perform worse, due to minimal cases of cloudy sky conditions, and such approaches could be better suited to climate regimes with more diverse cloud conditions [94]. Another example is provided for the Nordic climate, which is characterized by daylight hours that are long in the summer and short in the winter, heavy snow, and highly variable weather conditions due to fast-moving clouds. These cloud movements can cause significant issues for PV plants integrated with low-voltage grids. Additionally, the snow-caused soiling effect during the winter is an important factor to consider. The estimation of the reduction in power generation due to soiling is difficult due to the complex optical characteristics of snow. A review of ML approaches to forecasting concluded that the choice of ML algorithm depended on the weather conditions of the study area. The deterministic component is more dominant than the stochastic component during stable weather conditions, making conventional ML algorithms such as SVM and RF viable choices. In conditions of unstable weather, in which the stochastic component is as important as the deterministic, the conventional algorithms mostly perform poorly, and DL methods are found to better capture the complex nature of the processes [95].

The estimation of behind-the-meter (or what is known as invisible) solar power has drawn attention in recent published literature. Invisible solar power refers primarily to small-scale rooftop solar resources for a single building, which is invisible to system operators due to privacy concerns or the lack of measurement infrastructure. Invisible power can lead to the underestimation of power demand during extreme weather conditions, in addition to impacting the stability of the power system. A review of methods conducted utilizing historical data discusses studies using fuzzy models, ANNs, SVR [96]. The authors note the importance of employing simplified approaches that do not require the historical records of many variables due to the difficulty of their collection for grid operators.

4.1.2. Wind Power Forecasting

The unstable and random nature of wind speed is the primary contributor to the complexity of creating a stable supply of energy from wind resources. Wind speed is impacted by multiple atmospheric elements, including wind direction and atmospheric pressure [80]. Power generation in wind farms fluctuates sharply with changes in wind speed due to the non-linear generation between power generation and wind speed. Enhanced forecasting capabilities for wind energy are therefore critical for wind farm site selection, energy production planning, and grid stability. Literature searches yielded a number of reviews conducted on the use of AI for wind power forecasting, with AI methods creating breakthroughs in the forecasting process [97]. Relevant results from these studies are highlighted in this section.

AI techniques such as ANNs and SVM have been applied for wind speed forecasting, primarily generating point forecasts. The stochastic nature of both wind speed and the conversion of wind to power make uncertainty forecasts with a probabilistic framework a necessary area of research for wind power forecasting. PIs are therefore employed to quantify the uncertainty through upper and lower bounds of the forecasted variable [98]. The use of more than one ANN to forecast wind speed is recommended, and appropriate choices for pre- and post-processing techniques to increase accuracy. Ensemble methods have also shown promise for future use [99].

Big data research is becoming increasingly relevant to wind speed studies due to the increase in data sources that can be utilized, including weather satellites, equipment images, and time series. For example, forecasting using integrated information from wind farms in various geographic locations of a region is recommended to be studied as an alternative to only utilizing on-site data to forecast for a single farm [100]. Wind power forecasting models are generally classified into three categories: physics-based, data-based, and hybrid [101]. Data-based methods include AI approaches that assist in integrating big data to forecast wind energy output. For data-based wind forecasting, the most common approaches applied in studies are those employing AI methods and AI-based hybrid methods [102]. The hybrid approach of coupling NWP with ML methods, such as ANNs, is attracting attention due to its potential to produce more accurate forecasts. [101]. Hybrid applications often lack sufficient interpretability, leading to recommendations for future work to consider explainable AI methods for wind power forecasting [102].

4.1.3. Marine Power Forecasting

ML and DL can be applied to a variety of areas in the field of marine energy, varying from perception in remotely sensed data, forecasting/prediction, optimization of design, and autonomous operations using reinforcement learning. Tidal energy at present is in need of more accurate energy forecasting methods to efficiently design and locate tidal turbines. Traditional forecasting methods do not have the full potential to meet this requirement. Currently, tidal currents are predicted using four method categories: statistical methods, dynamic models, AI, and hybrid models. Reviews of work utilizing AI for tidal energy forecasting discuss the utilization of DL for analyzing and extracting the change rules of tidal currents and using the learned rules for forecasting. DL algorithms are touted as a method that is not constrained by the weaknesses of current statistical methods and numerical models. MLP has been utilized for forecasting tidal height, long short-term memory (LSTM) for tidal water level prediction and meridional and zonal components of tidal current velocity [103]. Forecasting of significant wave height is an important element for wave energy management and requires heavy computational power in conventional numerical simulation methods. ANNs have found applications in this field, with recent advances including empirical mode decomposition techniques and transformer-based encoders [81]. LSTM has been used for the prediction of power generation from wave energy converters and has been shown to be faster and more accurate than the utilization of numerical simulations [82].

4.2. Integration of Variable Renewable Energy into Power Grid

Energy transition initiatives have prompted power planning scenarios to move from traditional versions to integrated ones, to account for the characteristics of VRE. In addition to power generation forecasting, various elements exist which must be considered, including power demand forecasting, energy storage systems, performance of energy systems, and maintenance.

4.2.1. Power Demand Forecasting

Accurate demand forecasting is critical to ensure reliability of power systems and provide an uninterrupted power supply to end users. It is important for grid stability and reliability, enabling grid operators to balance supply and demand in real-time in addition to assisting with efficient allocation of resources to avoid over-generation or under-generation. It also helps with minimizing costs associated with the purchase of power at high prices during peak demand times. Demand forecasting allows for the effective planning of the integration of VRE sources, including the needed infrastructure and charging schedules for energy storage systems [104].

ML methods have undergone improvements due to advancements in data analytics and have become a more standardized method for forecasting projected changes in energy demand. Reviews of ML techniques for demand forecasting have classified the most accurate forms based on a system level: on a microgrid/smart building level, ANNs or hybrid ANNs should be deployed; on a smart grid/smart city level, hybrid ANNs are found to perform best; and on a national/regional level, linear models display the best accuracy [24]. Literature surveys of load forecast model research have shown advancements in ANN to improve their capabilities over traditional methods [105]. A study conducted for Queensland, Australia employed ANN models to forecast 6 h and daily electricity load demand using climate data (e.g., temperature, rainfall, solar radiation) and determined that the best performance was obtained from a hybrid ANN approach with multivariate adaptive regression spline (MARS), multiple linear regression (MLR), and autoregressive integrated moving average (ARIMA) models [83]. kNN is another method that has been utilized for power demand forecasting [106,107]. A study conducted on analysis and short-term forecasting of energy demand for industrial facilities utilized a modeling approach based on clustering and kNN, with an error of 3% [108]. A predictive model for energy consumption applying kNN was utilized in Malaysia and had a minor difference in error compared to SVM while outperforming ANN [109]. KNN was applied in a study on predicting the stability of the grid linked with VRE, which involved conducting supply and demand predictions [110].

4.2.2. Energy Storage

Energy storage options that are commonly deployed include transient variation options such as pumped storage hydro, adiabatic compressed air, lithium-ion and redox-flow batteries, and long-term storage such as hydrogen. Forecasting is important for scenarios in which storage is available and decision-making capabilities are required for when to charge and discharge batteries. The discussions in previous sections on AI techniques for forecasting of power generation and demand are therefore applicable for energy storage scenarios. Cost minimization is the primary planning goal, with the incorporations of flexibility strategies for real-time scheduling and deployment [111]. Optimum battery configuration is determined through the optimization of power matching and energy management algorithms [112]. PSO is widely employed in this framework [113].

For off-grid applications, hybrid VRE systems and microgrids are utilized to compliment energy storage options. AI methods are under study for use in optimization of coupling VRE resources in Saudi Arabia [72] and supplementing physics-based forecasting in Kuwait [114]. Some of the issues that arise with the development of these systems include stability analysis, big data analytics, and optimization of the combined components. Optimal sizing of hybrid microgrid systems is an example of where AI techniques can be implemented, where metaheuristic algorithms including PSO and GA have been utilized with good results. Evolutionary algorithms have been shown to achieve good results when using three or fewer objectives and therefore should be designed based on the number of objectives and constraints in the microgrid sizing problem [84].

4.2.3. System Design, Materials, Monitoring, Performance, and Security

The role of AI is becoming increasingly significant in the space of VRE systems, including the system design and materials, system monitoring and performance assessments, and overall security. The optimized design and sizing of VRE system components is another field in which AI has found applications. An example is ANN-based modelling of solar-grade silicon under wide temperature variations. Electrical parameters of the studied solar-grade silicon vary non-linearly with temperature. The ANN-based models allowed for their prediction using a limited amount of data over a wide temperature range [115]. An extensive list of more applications on AI for VRE design is provided in other reviews [116].

ML methods have found applications in renewable energy material studies, namely in the development of materials and devices for energy harvesting, storage, conversion and power grid optimization. Neural networks have become a recent subject of focus in the field of physical system modeling with the underlying property physics. The most common application in this field is the prediction of properties for material screening, which shortens the time needed. Examples of uses for the developed descriptors include material design for CO_2 capture, battery electrolytes and electrode discovery, and material screening for solar cells [117]. Closed-loop ML methods are being studied for applications in material discovery, as they enable the expansion of explored chemical space without the typical costs of time and effort. This is achieved through pattern detection in material structure–property relationships to create databases for training models, which will then produce predictions for other candidates in the chemical space [118]. Perovskites are a material type for which ML methods are greatly advantageous due to having a large chemical space from which constituents are selected [119].

AI can be of great assistance in applications for managing the performance and maintenance of VRE systems. An example of performance management is the use of an ANN to predict the temperature of the water outlet in a solar collector, through ingesting seven input variables. The ANN serves to better understand the behavior of the heating fluid, which can facilitate better use of mathematical models [120]. Another example is the application of ANNs to enhance the performance of a hybrid distributed generation VRE systems, in which the ANN was applied as a controller to enhance the quality of the power network [121].

Predictive maintenance is the augmentation of the system's current operation states with the forecasting of future failure states. Predictive maintenance, along with condition-based monitoring, assists in lowering system maintenance costs, minimizing downtime, and increasing their useful life. AI methods have been incorporated for studies on developing prognostic maintenance systems, such as SVM and RF, for reliability assessment and maintenance optimization [25]. AI techniques allow for monitoring and anomaly detection of solar energy systems in real time through constant evaluation of performance data. Variations from the predicted working behavior can be detected swiftly, such as PV module failures, shading issues, and inverter malfunctions. This allows for increased reliability of energy systems through minimizing downtime and reducing losses [122]. Wind turbine maintenance is an application of AI which utilizes ANNs, GA, PSO, and fuzzy logic most frequently. ANNs are employed for monitoring, optimization, forecasting and decision-making, resulting in them being the most adaptable method. Optimization and decision-making are mostly performed utilizing GA and PSO, while risk mitigation employs fuzzy logic [41]. For smart grids, fault detection and classification are a critical component of self-healing and mitigating system failures. ANNs have been studied for intelligent fault detection, classification, and localization, with results indicating high success rates, and they have the potential to significantly improve power system reliability [123].

With regards to performance prediction, literature reviews have found that ANN and FL have been used more extensively than other approaches for solar energy performance prediction. The number of studies conducted on hybrid approaches, such as adaptive neuro-fuzzy interface system (ANFIS), are few despite their higher prediction accuracy due to their significant costs and computational time requirements, in addition to the complexity they add to the prediction process [88]. Another area for applications of AI is in system optimization incorporating batteries. Optimum configurations for batteries and ultra-capacitors have been done with PSO, artificial bee colony optimization, and harmony search algorithms [124].

Weather variations, in addition to playing a governing role in power generation forecasting, also impact the resilience and performance of energy systems in addition to the demand on them. Extreme weather conditions have been the main focus in modelling weather impacts on power distribution systems, and weather causing specific faults. ML methods employed in the integration of these conditions for system resilience include DL, ANNs, and probabilistic modelling. Despite weather variables playing a prominent role in the degraded reliability of VRE systems, they are often overlooked in reliability analysis. A lack of modelling of the collective effects of weather conditions for forecasting total system disruptions has been noted in the literature [125].

With the increased popularity of adopting smart grids along with VRE systems, attention has been brought to several critical issues, including individual privacy, security, and reliability in terms of communication and performance [126]. The cyber-physical system of a smart grid integrating VRE can be made more secure using AI. Example studies have looked into utilizing neural networks to identify the point of attack and impact of cyber attacks, with the breach of consumer data privacy being identified as a significant threat [127].

4.2.4. Cost Management

The costs involved in integrating VRE into power systems are not taken into account for the levelized cost of electricity (LCOE), which can result in them negatively impacting the economic feasibility of VRE. Several cost components control the integration of VRE systems based on their characteristics, including uncertainty and variability. The uncertainty stems from the differences between VRE forecasted output and actual generation, and the need to balance the differences in a short time period. The variability relates to power being generated in specific weather conditions, which does not always match demand, making the frequent ramping up and down of backup generators necessary additional profile costs [128]. As discussed in previous sections, AI can assist in more accurate VRE power generation and demand forecasting, thus assisting in the mitigation of uncertainty and variability costs. With increased availability of data on energy demand and supply, AI will assist in optimized scheduling based on weather conditions and consumer patterns, enabling further cost reductions [129].

5. Future Research Directions

With the increased penetration of VRE in the provision of energy supplies, challenges have been identified in optimizing their utilization. This section delineates prospective research trajectories in the realm of AI applied to VRE systems, elucidating strategic avenues to optimizing their efficacy. Against the backdrop of a transformative global energy paradigm increasingly reliant on renewable sources, the challenges inherent in maximizing VRE potential necessitate nuanced and innovative AI-driven solutions. The exploration in this section covers five pivotal trajectories, each addressing angles within the convergence of AI methodologies and VRE management. From confronting intricacies associated with data quality to augmenting transparency in AI models, and from probing the quantum landscape to conjoining digital twins with AI, this segment establishes a comprehensive foundation for leading-edge advancements. Further enrichment is garnered through the inclusion of natural language processing (NLP), emphasizing the vital role of linguistics in human–machine interactions and data comprehension. These prospective research trajectories aspire to improve VRE by increasing their efficiency, dependability, and eco-sustainability. Figure 7 summarizes the main gaps and challenges identified in this paper and the future research directions proposed to overcome them.

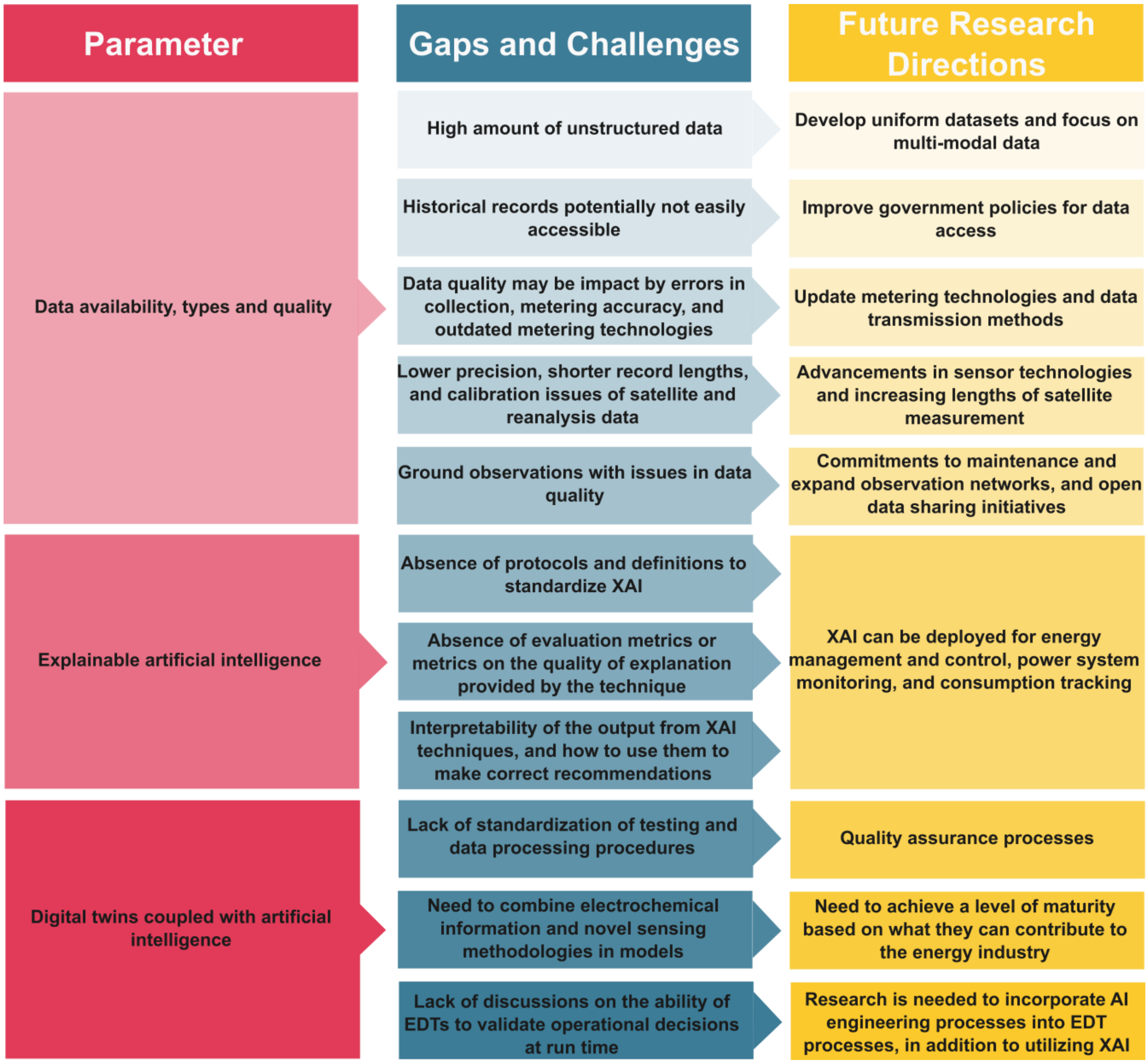

Figure 7. Summary of the main gaps and challenges identified in this paper and the future research directions proposed to overcome them.

5.1. Data Availability, Types, and Quality

With the digitalization of energy, the need for data availability, processing, and interpretation is becoming increasingly significant. ML is being employed for energy distribution optimization and provides data-based services for VRE, which include supply, marketing, storage, and usage, making it an integral part of the transition to smart grids [130]. Big data research is primarily focused on working with structured data. Numerous forms of unstructured data exist, which could contribute to the betterment of VRE operations, such as remote sensing records and metrics of plant operations. Working with multi-modal data would provide opportunities for potential betterment of forecasts and is an area being looked into for research applications [102].

The collection of data on user consumption allows for time series analysis to infer valuable data characteristics, which can be used for forecasting. Residential and commercial buildings are increasingly being monitored in real-time, allowing the development of historical records on consumption [131]. Current historical records are impacted by numerous challenges, including potential limited access by utility providers due to data protection regulations and privacy concerns [132]. Another issue is the fragmentation of data across different utility providers and regions. Data quality may be impacted by errors in collection and metering accuracy in addition to outdated metering technologies being employed in older buildings [133]. Future efforts are needed to construct uniform datasets through updating metering technologies and data transmission methods and overcoming the challenges of data access and fragmentation through government policies.

Availability and quality of historical climate observations is a necessary component in the utilization of AI methods for energy forecasting generation. The lower precision, shorter record lengths, and calibration issues are fundamental problems with the utilization of satellite and reanalysis data, making ground observation availability of great importance. Ground observations can be plagued with issues in data quality resulting from poor configuration and/or maintenance of stations, inaccurate instrument readings, and issues with post processing [134,135]. Advancements in sensor technologies and increasing lengths of satellite measurement records can help combat this issue, as can commitments to the maintenance and expansion of observation networks and open data-sharing initiatives supported by governments and research institutions.

5.2. Explainable Artificial Intelligence

AI models are generally categorized through three classifications: white, grey, and black-box models. White models are utilized for systems with parameters that are known and well-defined in terms of parameters. Grey models are utilized when the system formulas and equations are known, but their parameters are not. Metaheuristic and evolutionary methods are generally employed in this category. One of the main current challenges being faced in the use of AI for forecasting is the model being a black box, in which the mathematical formulations of the relationship between input and output are not fully revealed [136]. Black-box models are usually utilized when the system is completely unknown, and the majority of current ML models work as black boxes [116].

To effectively understand and manage AI systems, it is important to incorporate explainability to understand how the output is produced. Explainability has therefore been determined as a critical factor in the wider adoption of AI applications in various sectors [137]. The increased use of ML, and specifically DL models, has led to the field of explainable artificial intelligence (XAI) undergoing significant growth. In the fields of energy and power, accountability in decision-making is critical. Therefore, XAI has the potential to solve the issues stakeholders have in trusting ML outputs. One main limitation in the application of XAI is the absence of protocols and definitions to standardize it. Another is the absence of evaluation metrics or metrics on the quality of explanation provided by the technique. An important challenge presents itself in the interpretability of the output from XAI techniques, and how to use them to make correct recommendations. Overcoming these challenges and limitations would present opportunities for XAI to be deployed for energy management and control, power system monitoring, and consumption tracking among other potential applications [138].

5.3. Quantum Artificial Intelligence

Traditional approaches for renewable energy systems rely on classical computing methods, which may soon hinder progress with the growing size and complexity of applications in the field. Quantum computers utilize quantum bits or qubits as units of fundamental information. Quantum hardware and algorithm advancements have made quantum computing an attractive option for future research directions in energy [139].

Quantum artificial intelligence (QAI) presents itself as an attractive option for future large-scale VRE developments. QAI has found applications in various areas of renewable energy, including power distribution networks, energy scheduling, network supply optimization, power forecasting, system fault diagnosis, and system control [140]. For ML tasks that are computationally challenging, quantum algorithms can help with faster completion and reduce the time constraints. This utilization of quantum subroutines for

ML techniques is called quantum ML (QML) [141]. QLM allows for the training of larger and more complex models in a more efficient manner through the analysis of big data containing multitudes of variables. Such capabilities can contribute to multiple aspects of energy system management, such as more efficient tracking and prediction of meteorological variables, allowing for more efficient and optimized use of resources and preparedness for VRE systems with changing weather conditions [142].

5.4. Digital Twins Coupled with Artificial Intelligence

Digital twins are virtual representations of physical systems created through the use of various data sources. The purpose of a digital twin is to mirror the attributes and behavior of the real-world physical counterpart. It allows for real-time data integration, two-way communication of information between the digital and physical systems, simulation of scenarios, performance prediction, and lifecycle management.

Digital twin technology shows promise at assisting in the optimization of energy plant operations and assets to further the goals of decarbonizing the energy sector. The use of energy digital twins (EDT) to digitalize processes can contribute to better efficiency and optimization of energy systems. It can contribute to better energy management, maintenance, design, existing site extensions, and VRE integration. Battery digital twins are predicted to have a significant future role in the development of battery technologies, allowing for the development of longer life battery systems. Challenges identified for widespread application include the lack of standardization of testing and data processing procedures as well as the need to combine electrochemical information and novel sensing methodologies in models for estimation of system lifetime [143]. Additionally, EDTs have found applications in the chemical energy and power system fields. One challenge identified was the lack of discussions around the ability of EDTs to validate operational decisions at run time before application at power plants. Quality assurance processes must be included in order to promote wider EDT adoption with minimal risks [144].

AI techniques can contribute to EDT developments in multiple ways, such as optimization for the reduction of intractable search-spaces, generating models for complex systems, and time series forecasting for modeling extreme events [145]. In order for AI and ML algorithms to be applied in this field, they must achieve a level of maturity based on a concrete understanding of what they can contribute to the energy industry. Research is needed to incorporate AI engineering processes into EDT processes in addition to utilizing XAI [144]. Through simulation of behavioral characteristics of VRE sources using EDT, system operators can better optimize grid performance, resulting in increased energy efficiency and cost savings [146].

5.5. Natural Language Processing

Natural language processing (NLP) is an area under the domain of AI which explores how to utilize natural language text and speech for the development of tools and methods that enable computer systems to perform tasks in response [147]. NLP has found uses in a number of applications related to renewable energy. One such application is in the forecast of stocks using a NLP technique to investigate the sentiment of investors on social media, combined with deep learning and benchmark models, with study outcomes showing that the sentiment variables provide valuable information that is not incorporated through traditional financial market analysis, and enhance the forecasts of renewable energy stocks [148]. NLP is also being utilized as an assistant and advisor on decisions for policymakers and energy producers [149].

For future applications, NLP could be used to analyze weather forecasts and historical data in order to make predictions about renewable energy resource availability, helping to optimize energy production and storage. NLP can also help utilize unstructured data included in reports, emails, etc., in addition to making human–machine communication easier [150].

6. Conclusions

This paper undertakes a thorough review and examination of the landscape of integrating artificial intelligence (AI) with variable renewable energy (VRE) systems, laying a foundation for optimizing their utilization in the dynamic context of the global energy paradigm. The initial section meticulously assesses the current state of VRE technologies, emphasizing their pivotal role in achieving sustainability objectives. It elucidates the challenges inherent in VRE, ranging from intermittency to grid integration complexities, and proposes AI-driven solutions to enhance reliability and efficiency. A critical facet highlighted throughout is the substantial impact of weather variations on VRE system performance, bringing attention to the need for robust forecasting solutions. The extensive exploration of these applications contributes to a deeper understanding of the transformative potential of AI in steering VRE systems towards heightened efficiency and reliability.

Transitioning to the next section, the paper delves into the application of ML techniques for VRE forecasting and management. By dissecting various ML models and algorithms, it underscores their versatility in addressing the intricate nature of VRE systems. The importance of diverse, high-quality data in training robust models is underscored, while the inclusion of ensemble methods and hybrid models showcases innovative approaches to bolster the predictive capabilities of AI. The weather-focused discussions within this context underscore the influence of meteorological conditions on the performance of VRE systems, emphasizing the pivotal role of accurate weather forecasting in optimizing energy production.

The identified future research directions provide strategic insights to further harness the capabilities of AI for VRE. Addressing the challenges posed by diverse data types and qualities emerges as a crucial focal point, necessitating concerted efforts in data handling and accessibility for AI training and testing. The imperative of XAI has been highlighted as pivotal in fostering trust among end-users, countering the prevailing opacity of "black box" ML models. QAI stands out as a promising frontier with the capacity to expedite and empower complex AI models in the VRE domain. Moreover, the envisioned convergence of EDTs with AI, once matured, promises advancements in optimization and time series forecasting for VRE systems. This coupling holds the potential to elevate the efficiency and resilience of energy grids. Furthermore, the incorporation of NLP introduces a new dimension, offering avenues for improved human–machine communication, diverse data format utilization, and enhanced forecasting of VRE-related variables.

In summary, this paper asserts the transformative potential of AI in mitigating challenges associated with VRE, extending from improving forecasting accuracy to optimizing energy distribution and grid integration. By encompassing an in-depth analysis of the present state, application of ML techniques, and prospective research trajectories, the paper provides valuable insights for researchers, policymakers, and industry stakeholders. Policy interventions are recommended to incentivize research and development in AI applications for VRE, fostering collaboration between industry stakeholders and research institutions. Practical applications should prioritize the integration of XAI models, ensuring transparency and accountability in decision-making processes. Additionally, investments in QAI research and the convergence of EDTs with AI warrant strategic consideration to capitalize on their transformative potential. Ultimately, the adoption of these recommendations can pave the way for a more sustainable and efficient future in the realm of VRE systems.

Author Contributions: Conceptualization, L.A.Y.; methodology, L.A.Y.; software, L.A.Y.; validation, L.A.Y.; formal analysis, L.A.Y.; investigation, L.A.Y., L.R.M. and H.Y.; resources, L.A.Y.; data curation, L.A.Y.; writing—original draft preparation, L.A.Y., L.R.M., and H.Y.; writing—review and editing, L.A.Y., L.R.M., and H.Y.; visualization, L.A.Y., L.R.M., and H.Y.; supervision, L.A.Y.; project administration, L.A.Y.; funding acquisition, L.A.Y. 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: The authors would like to acknowledge Phil Hart for the administrative support and guidance in preparing the manuscript.

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

Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Interface System
ANOVA	Analysis of Variance
ARIMA	Autoregressive Integrated Moving Average
CNN	Convolutional Neural Network
DL	Deep Learning
EDT	Energy Digital Twins
GA	Genetic Algorithm
GHI	Global Horizontal Irradiance
LCOE	Levelized Cost of Electricity
LSTM	Long Short-Term Memory
MARS	Multivariate Adaptive Regression Spline
MA	Metaheuristic Algorithm
ML	Machine Learning
NLP	Natural Language Processing
PI	Prediction Interval
PSO	Particle Swarm Optimization
PV	Photovoltaic
QAI	Quantum Artificial Intelligence
QML	Quantum Machine Learning
RF	Random Forest
RMSE	Root Mean Square Error
SVM	Support Vector Machine
SWH	Significant Wave Height
VRE	Variable Renewable Energy
WSTD	Wavelet Soft Threshold Denoising

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