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Review

Wind, Solar, and Photovoltaic Renewable Energy Systems with and without Energy Storage Optimization: A Survey of Advanced Machine Learning and Deep Learning Techniques

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Abstract: Nowadays, learning-based modeling methods are utilized to build a precise forecast model for renewable power sources. Computational Intelligence (CI) techniques have been recognized as effective methods in generating and optimizing renewable tools. The complexity of this variety of energy depends on its coverage of large sizes of data and parameters, which have to be investigated thoroughly. This paper covered the most resent and important researchers in the domain of renewable problems using the learning-based methods. Various types of Deep Learning (DL) and Machine Learning (ML) algorithms employed in Solar and Wind energy supplies are given. The performance of the given methods in the literature is assessed by a new taxonomy. This paper focus on conducting comprehensive state-of-the-art methods heading to performance evaluation of the given techniques and discusses vital difficulties and possibilities for extensive research. Based on the results, variations in efficiency, robustness, accuracy values, and generalization capability are the most obvious difficulties for using the learning techniques. In the case of the big dataset, the effectiveness of the learning techniques is significantly better than the other computational methods. However, applying and producing hybrid learning techniques with other optimization methods to develop and optimize the construction of the techniques is optionally indicated. In all cases, hybrid learning methods have better achievement than a single method due to the fact that hybrid methods gain the benefit of two or more techniques for providing an accurate forecast. Therefore, it is suggested to utilize hybrid learning techniques in the future to deal with energy generation problems.

Keywords: wind energy; solar energy; photovoltaic (PV); renewable energy systems; storage systems; power generation; machine learning; deep learning; optimization; algorithm; Artificial Intelligence (AI); survey

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1. Introduction

Renewable energy systems for electricity generation have been broadly used in several advanced and emerging economies [1,2]. The application of these systems is growing in many regions, inspired by interests in energy instability, environmental change, and air pollution [3]. Energy objectivity, greenhouse gas reduction, and air nature are robust reasons for advancing renewable systems [4,5]. However, policymakers must reflect on the economic consequences of new systems even more widely [6]. Consequently, the job generation potential of modern energy generation has gained considerable awareness from a broad range of experts in current years, including industrial, academia, engineers, government companies, the civil community, and private companies [7–10].

New energy systems (i.e., Wind- and Solar-based energy generation methods) are getting local and global awareness because of the growing damage rate of nuclear and fossil power sources [11–13]. Mainly, operators for Wind and Solar renewable methods are the environmental advantages (loss of carbon emissions because of the value of energy sources and the efficient utilization of fossil energy), decreased expense venture, fuel variegation, and energy independence developed energy performance (less line losses) as well as the possible development of power characteristic and safety and in some instances, possible grid augmentation deferral due to the likelihood of generation close to needing [14]. Some other challenges are worth to mention: fuel-fired power plants may be scaled up and down on the control [15]. Variable renewable energy plant production cannot be forecast with 100% precision. In certain areas, the sun and Wind are greater than elsewhere. Diesel generators provide voltage support and frequency control to the grid. Intermittent renewable energy producers may be able to do so, but it will require more cash [16]. Variable renewable energy sources only run when the sun or Wind align. For instance, in the new report of California Energy, the state's objective is to produce from renewable exporters 33% of the energy demanded by the year 2020, with approximately 70% of that power being generated by Wind and Solar operations [17]. Consequently, finding a proper method to deal with these problems is needed to get better power generation. Normally, the optimization and AI methods are used to determine the problems' parameters, which is the main risen challenge in these problems [18–22]. Other challenges are like availability of power, power quality issues, resource location, cost issue, and others.

In some countries over the world, there is yet no electricity generated, or it is weak [23]. Energy equipment is a major obstacle for all classes in many countries, even developed countries. The smallest power consumption is 208 kWh/capita over the world. Electricity producing volume in 2010 was 5823 MGW, of which 96.05% was thermal, and the rest hydroelectric, at the control positions [24]. The green and growing energy exporters consist of Solar, Photovoltaic (PV), Solar, Wind biomass, and geothermal [25]. As a result, it may be strategically significant to investigate whether a portion of Bangladesh's energy demands can be met affordably using alternative fuels, namely Wind and Solar energy [26].

The power prediction has always been a critical and cost-effective strategy for incorporating renewable resources like renewable power into electrical networks [27]. Solar power forecasting is very new, even though green energy forecasting is standard and frequently used in power grids for middle to high producers. Predicting spread Solar and Photovoltaic (PV) generation is challenging. However, real-time metrics and comprehensive static data can be done quite well (e.g., location, hardware information, panel orientation, etc.) [28].

In this survey paper, the recent studies on Wind and Solar energy renewable storage systems are reviewed concerning Deep Learning and Machine Learning technologies. We intended to show the most critical ideas that attracted the researchers recently. Thus, these studies are summarized to show their main contributions and ideas for future readers. We classified the collected studies into two main parts: Wind and Solar energy systems based on Deep Learning and Machine Learning methods. Conclusions alongside some potential hot directions are also given to assist future research in finding the starting points and where the authors can focus. The main keywords used to find the related works in this paper are Wind, Solar, Photovoltaic, Energy, Machine Learning, and Deep Learning though the Google scholar search engine.

The remaining section of this survey is arranged as follows. The problems definitions and formulations of the Wind and Solar energy systems are presented in Section 2 to give a clear description for the parented problems. The related works that used Deep Learning, and Machine Learning, in the domain of Wind, Solar, and Photovoltaic energy, are given in Section 3. Beneficial discussions and advances in this domain to highlight the most critical points for future readers are presented in Section 4. Conclusion and potential future work directions are shown in Section 5.

2. Wind and Solar and Photovoltaic Systems: Problem Formulations

In this section, the problems' formulations of the Wind, Solar, and Photovoltaic energy systems are presented [29,30]. This section mainly presents Wind speed distribution; problem formulations, Wind power, and energy; problem formulations, and optimizations methods for Photovoltaic based hybrid system: problem formulations. This section will help the new researchers and readers to understand the main mathematical presentation of the given problems. The used abbreviations in this paper are given in Table 1.

Table 1. List of used abbreviations.

Abbreviation	Meaning
PV	Photovoltaic
CI	Computational Intelligence
ML	Machine Learning
DL	Deep Learning
v	Air velocity
A	The rotor cleaned region
AEO	Annual Energy Output
MC	Marginal cost
AVC	Average variable costs
ATC	Average total cost
LCOE	Levelized cost of energy
DPC	Density peak clusterin
PP	Payback period
NPV	Net present value
IRR	Internal rate of return
PI	Profitability index
β	Blade pitchside
R_P	The parallel resistance
R_s	The series resistance
N_{ss}	The number of cells connected in series
k	The pattern of the curve
c	The variation in Wind velocity dispersion
ρ	kilocycle
λ	The rotor tip-speed rate
M_t	The process cost
E_t	The power generated by the Solar and Photovoltaic
C_t	The last cash influx
r	The discount value
Cp	Power coefficient value

2.1. Wind Speed Distribution: Problem Formulations

The Wind speed distribution system, as shown in Figure 1, is presented in this part with its mathematical formulations [31].

Figure 1. Wind Farm [32]. Photograph by INGA SPENCE/ALAMY STOCK PHOTO.

Wind speed changes according to the periods, season (i.e., summer, fall, etc.), even by year [33]. However, more crucially, the Wind is never more constant. The Wind exemplar usually iterates over a long time (i.e., year or longer), so long-term fluctuations are unclear and can not be exactly foreseen [34]. On the opposite, yearly and seasonal fluctuations are much more expected [35]. Consequently, short-term Wind velocity fluctuations may be defined by utilizing a likelihood distribution function. Wind speed is generally identified by the parameters of the Weibull frequency, as shown in Equation (1) [36].

$$f(v) = \frac{k}{c}(\frac{v}{c})^{k-1}e^{-(\frac{v}{c})^k} \tag{1}$$

The rate of k defines the pattern of the curve and is consequently named the shape parameter. For k = 1, it is described the exponential distribution value. For k = 2, it is described the Rayleigh distribution value. For $k > 3$, it resembles the normal distribution value. The value of c defines the variation in Wind velocity dispersion. For example, the trajectory transfers to a higher Wind rate for a higher c value. The c is the scale parameter rate. When the form and measure parameters are identified at one maximum, this methodology determines these parameters' values at different maximum [37].

2.2. Wind Power and Energy: Problem Formulations

The Wind Power and Energy systems are presented in this part with their mathematical formulations [38].

The energy in flowing Wind is the current progress rate of kinetic power per second. The Wind energy changes linearly with the Wind kilocycle (ρ) and the rotor cleaned region (A). However, it changes with the cube of the air velocity (v). The exact power obtained by the rotor knives is the difference between the upstream and downstream air pressures. As shown in Equation (2), the generation power obtained by the rotor blades is represented as a fraction of the upstream airpower, known as the rotor's effectiveness coefficient [39]. The power coefficient value (Cp) has the ideal highest rate of 59% and an efficient maximum rate of 50% or lower. The power degree value is usually represented by the rotor tip-speed rate (λ) and the blade pitchside (β). The tip-speed rate is the degree of the rotor velocity (Ω) to the air velocity. The pitchside is the angle between the string of the blade and the level of the Wind vertigo. The aerodynamic investigation of the Wind moving nearby the moving code with a given pitch purpose sets the association between the vertigo tip rate and the Wind velocity [40].

$$p_T = \frac{1}{2}\rho A v^3 C_p(\lambda, \beta) = \frac{1}{2}\rho \pi R^2 v^3 C_p(\lambda, \beta) \tag{2}$$

$$\lambda = \frac{R \cdot \Omega}{v} \tag{3}$$

The power coefficient value is performed in two modes as given in Equations (4) and (5). The factor value of the power can be achieved by operator data or field inspection of a Wind turbine [41].

$$Cp(\lambda) = \sum_{i=1}^{n} C_{pi}\lambda \tag{4}$$

$$Cp(\lambda, \beta) = C1(\frac{C_2}{\lambda_i} - C_3\beta - C_4\beta^5 - C_6)e^{-\frac{C_7}{\lambda_i}} \tag{5}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + C_8\beta} - \frac{C_9}{\beta^3 + 1} \tag{6}$$

The power generation and performance time calculate the Wind power [42]. It is typically declared as Annual Energy Output (AEO). Remark that the power generation is a function of the power value, which has a non-linear association with the Wind velocity and vertigo speed [42].

The rotating velocity of the turbine remains consistent in repaired operation, whereas the tip-speed rate varies with Wind speed. The stall concept is used to restrict the power output. So when Wind velocity exceeds the rated speed, the power coefficient value decreases. The Wind speed and gear ratio determine the yearly energy generation of a rotor with a fixed velocity. When a low-speed turbine is used, the power output peaks at low Wind speeds [43]. A turbine working at a fast velocity, on the other hand, will achieve its maximum power point at a high Wind speed. A fixed-speed Wind turbine's yearly energy generation may be calculated in both continuous and discrete versions as follows:

$$E_{FS} = 8760\frac{1}{2}\rho\pi R^2 \int_{V_I}^{V0} C_P V^3 f(v)dv \tag{7}$$

$$E_{FS} = 8760\frac{1}{2}\rho\pi R^2 \sum_{V_J=V_I}^{V0} C_P(\Omega, V_j)V_j^3 f(V_j, k, c)\Delta V \tag{8}$$

The control system of a Wind turbine manages the rotor speed to achieve optimal efficiency by continually regulating the rotor speed and power station loading to optimize output and decrease torque loads during the variable-speed performance. To acquire the most excellent power coefficient, the optimal operation is to adjust the turbine speed only with Wind speed. Thus, the tip-speed ratio is continually preserved. The rotation speed is regulated and kept at the power level when Wind speed is much less than the rated Wind speed. The maximum power is lowered by pitching the blades when the current exceeds the reference speed [44]. A various Wind turbine's yearly energy generation is calculated in both continuous and discrete versions as follows:

$$E_{VS} = 8760\frac{1}{2}\rho\pi R^2 \int_{V_I}^{V_R} v_3 f(v)dv + 8760P_R \int_{V_R}^{V_0} f(v)dv \tag{9}$$

$$E_{FS} = 8760\frac{1}{2}\rho\pi R^2 \sum_{V_J=V_I}^{V0} V_j^3\, f(V_j, k, c)\Delta V + 8760\, P_R \sum_{V_J=V_R}^{V0} f(V_j, k, c)\Delta V \tag{10}$$

2.3. Diode Model-Based Solar and Photovoltaic System: Problem Formulations

The Solar and Photovoltaic energy system, as shown in Figure 2, is presented in this part with its mathematical formulations [45].

Figure 2. Solar Panels [46].

Several of the earliest ways for designing simulators is the diode model approximation. Studies have investigated the diode-based approximation approach to imitate Solar and Photovoltaic features since Photovoltaic panels display non-linear behavior [47]. Photovoltaic panels' I-V and P-V properties were duplicated correctly using the most widely used single diode, and double diode-based simulation estimation approaches. Consequently, panels have been utilized in the literature to develop appropriate emulators [48]. Figure 3 illustrate conceptual illustrations of single and double diode designs.

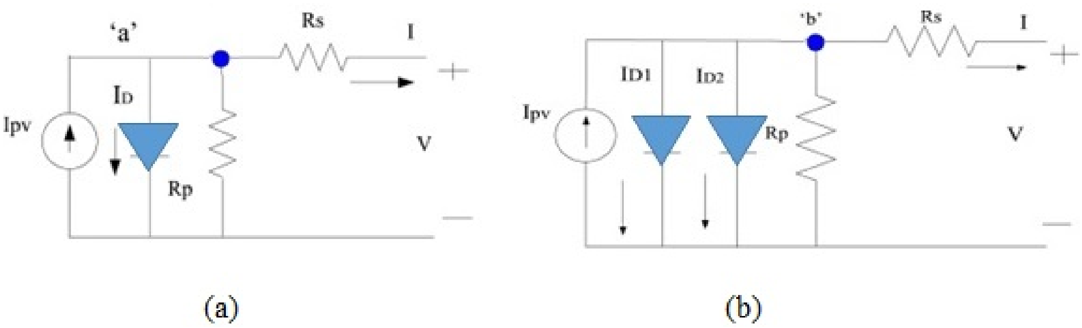

Figure 3. (**a**) Single diode model (**b**) Double diode model.

The output equations of the single diode and double diode models are expressed as in Equation (11), which used Kirchhoff's current source at nodes 'a' and 'b'.

$$I = N_{PP}\left\{I_{PV} - I_0\left[exp\left(\frac{V+IR_s}{\alpha V_t N_{ss}}\right)-1\right]\right\} - \left(\frac{V+IR_s}{R_P}\right) \tag{11}$$

$$I = N_{PP}\left\{I_{PV} - I_{01}\left[exp\left(\frac{V+IR_s}{\alpha_1 V_t N_{ss}}\right)-1\right] - I_{01}\left[exp\left(\frac{V+IR_s}{\alpha_2 V_t N_{ss}}\right)-1\right]\right\} - \left(\frac{V+IR_s}{R_P}\right) \tag{12}$$

where R_s denotes the series resistance and R_P denotes the parallel resistance, I_{PV} is the Photovoltaic voltage, a_1 and a_2 are diode typical factors. N_{ss} is the number of cells connected in series, and N_{PP} is the number of cells connected in parallel [49].

Both models, meanwhile, share some features and account for the realistic losses and recombine effects that occur in real Photovoltaic panels. Table 2 summarizes the importance of each component in diode modeling. It is also worth noting that the precision of these factors has a direct impact on the anticipated Photovoltaic characteristics.

Table 2. Losses in diode modeling.

Sl. No	Component	Representation	Replicated Photovoltaic Characteristics
1	Current source	Optical losses	Current regulation
2	Diode	Recombination losses	Temperature effects
3	Resistance	Ohmic losses	Loading effects

Emulators are often created via realistic modeling of Solar and Photovoltaics, mainly using the well-established single and double diodes-based estimation approaches, as previously mentioned. The architecture of the Solar and Photovoltaic mimic based on a single diode framework to guide is effectively implemented utilizing an operational amplifier-based analog circuit to imitate the change in irradiation levels correctly [50].

In [51], a Photovoltaic emulator was created using curve fitting and a current regulator. Figure 4 shows the methods that were used. Despite using low-cost components, the system fails to anticipate I-V curves accurately under various operating circumstances. Furthermore, the performance of the emulator under partially darkened situations was not examined. The inventor in [52] has suggested and tested a new emulator that includes an ARM controller. However, the same disadvantages described previously apply here as well.

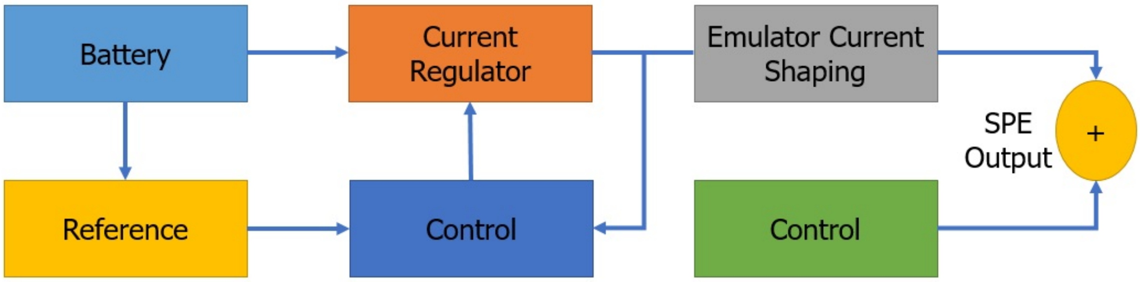

Figure 4. Solar and Photovoltaic emulator design.

2.4. Optimizations Methods for Photovoltaic Based Hybrid System: Problem Formulations

Optimization approaches' flexibility, resilience, and powerful computational intelligence have allowed them to handle complicated challenges in Photovoltaic-based hybrid systems [53]. The optimization goals of Photovoltaic-based hybrid systems were divided into three categories in this survey: economic valuation, energy evaluation, and fusion of economic and energy prediction, which are presented as follows.

Economic Objectives Valuation

From the perspective of the average cost curve in [54], the economic analysis of Solar and Photovoltaic is explained. The statistical value for Solar and Photovoltaic (average) is a line in the chart that represents the per-unit cost from lowest to highest as illustrated in Figure 5, the per-unit price effect for Solar and Photovoltaic includes a marginal cost (MC), average total cost (ATC), average variable costs (AVC), and average fixed cost (AFC). AVC is the cost of producing more elements, AFC is the direct amount divided by the outcome, and ATC is the final product price per output unit. MC is the price of producing one additional unit of outcome [55].

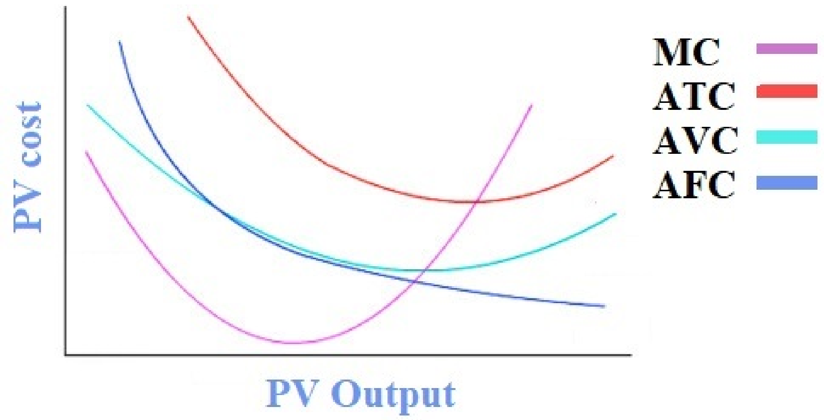

Figure 5. The average cost trajectory of Solar and Photovoltaic.

The performance of the Solar and Photovoltaic system is assessed using a variety of economic matrices, including Levelized cost of energy (LCOE), payback period (PP), net present value (NPV), internal rate of return (IRR), and profitability index (PI) [56]. Here are the mathematical formulae for the metrics mentioned above:

$$\text{LCOE} = \frac{\sum_{t=1}^{T} \frac{C_0+M_t+F_t}{(1+t)^t}}{\sum_{t=1}^{T} \frac{E_t}{(1+t)^t}} \tag{13}$$

$$\text{PP} = \frac{C_0}{C_t} \tag{14}$$

$$\text{NPV} = \sum_{t=1}^{T} \frac{C_t}{(1+r)^t} - C_0 \tag{15}$$

$$0 = \sum_{t=1}^{T} \frac{C_t}{(1+NRR)^t} - C_0 \tag{16}$$

$$\text{PI} = \frac{\text{NPV}}{0} \tag{17}$$

where, C_0 is the overall utilization cost, M_t is the process cost over the time t, F_t is the fuel cost over time t, r is the discount value, E_t is the power generated by the Solar and Photovoltaic over time t, C_t is the last cash influx over the time t, T is foreseen life-span of the Photovoltaic method [57].

3. Wind and Solar Systems-Based Learning Methods

In this section, the related works (Wind and Solar systems-based learning methods) are classified into two main sections based on using Wind and Solar systems-based learning methods; Deep learning techniques and machine learning techniques [58].

3.1. Deep Learning Techniques

In this section, the Wind and Solar systems-based deep learning methods are presented in detail [59], as follows.

Deep learning is a machine learning method that trains computers to naturally to humans: learn by example. Deep learning is a crucial technology after driverless cars, allowing them to identify a stop sign or recognize a pedestrian from a lamppost.

To solve the Wind power problem, this research suggested a solution based on deep learning [60]. According to the method, a statistics controller is prepared that straight maps the input findings, such as forecasted Wind lifetime and energy price, to the Wind farm's control actions, such as the fees schedule of the functional energy storage unit and the reserve buying schedule. Computational results show that the suggested strategy can successfully deal with risks while also bringing high income.

Because bidding is so widespread, several efforts have been conducted to use deep reinforcement learning techniques to produce good bidding policies to optimize profitability. These methods, on the other hand, are based on a model-free technique. The goal of this research is to create a dynamic model for Wind energy acquire specific [61]. Both in energy and reserve markets, the optimum bidding strategy established in this study may be used to maximize profits and overcome uncertainty.

Operators face a hurdle in developing energy management control systems for such a system due to the unpredictability of renewable energy supply and load demand [62]. The goal of this research is to develop a real-time dynamic power management method that considers the system's risks. In order to do this, the power control of a hybrid energy system has been presented as an optimum control goal, with multi-targets and restrictions taken into account [63]. In comparison to other ways, simulation findings show that the sound agent may better control and save up to 14.17 percent in expenses.

Due to the complicated building shading impacts and varying rooftop resource availability, this work presented a unique 3D-GIS and deep learning integrated solution to tackle the difficulty [64]. A 3D-GIS-based daily Solar analyzer was built to forecast dynamic Solar energy irradiance while accounting for the shading impacts of neighboring structures. According to the findings, adding the corresponding Solar energy potential decreases caused by shade and rooftop accessibility tends to overstate the overall reduction by 26 percent.

A thorough understanding of future renewable power resources is essential for siting and development analyses of Wind farms. This work examines potential offshore Wind energy resources in China using simulation data from the Coupled Model Small datasets Project Phase 6 and a new suggested new downscaling approach based on the bidirectional deep neural unit [65]. Under two illustrative scenarios, multi-model composite findings show minor drops in offshore long-term Wind energy output over the East China Sea and a rise in the same parameters over the South China Sea during the middle part of the twenty-first century.

Ordinary power distribution stabilizers calibrated based on the generalized linear simulation model at one operating state may be unable to successfully damp low-frequency oscillations in this setting, posing significant problems to the system's stability. To do this, this work presented a new sequence adaptive control mechanism for online self-tuning of PSS system parameters [66]. In contrast to existing techniques, simulation results show that the suggested method can help the PSS achieve superior damping fluctuation and resilience over changes in Wind power.

Deep learning's relative success in a variety of applications has piqued the interest of academics, as seen by the breadth of suggested approaches and the growing number of papers. This paper presents a review of deep learning-based Solar and Wind energy predicting research published in journals last years, describing widely the data and datasets used during the reviewed works, condition characterized methods, stochastic and deterministic methods, and analyzation and information available in terms of facilitating further studies and advancements in the field [67].

The correct prediction of essential features is critical for the efficient and productive design of industrial materials and systems. For the forecast of conversion efficiency of organic Solar cells, a deep-learning design incorporating an again be short-term memory system, an attention method, and a back-propagation neural network is proposed in this study [68]. The suggested approach is responsible for identifying critical molecular elements, which may be used to reverse-engineer organic Solar cells.

Wind power providers have difficulty in the electricity sector: how to optimize their revenue while dealing with the unreliability of Wind energy. This work presented an integrated planning model that combines Wind power prediction with battery storage decision-making, preventing renewable power prediction from losing decision-making knowledge [69]. Second, an evolutionary programming technique called deep Q-network is used to build the end-to-end controller. Wind energy unpredictability is taken into account immediately throughout optimization, with no assumptions made. Finally, the suggested method's efficiency is demonstrated by an examination of a hypothetical Wind generator.

This research proposes numerous deep learning methods to use high-resolution prediction data and explore various time and geographical connectivities to capture cloud movement patterns and their impact on Solar energy generation forecasts for Solar farms [70]. The authors were able to lower the failure rate from around 21 percent in the persistent model to 15.1 percent in the SVR model and 11.8 percent in the deep neural networks compared to the state-of-the-art prediction error rate. These enhancements have a substantial influence on the renewable power industry's positive growth. In addition, they saved US companies billions of dollars.

A ResNet-inspired system is presented to forecast Solar and Wind energy output using weather photos in search of a unique forecasting technique for the energy market. The model was created to capture high-frequency features while generating genuinely smooth electricity-generating profiles [71]. The significance of adding several weather photographs is demonstrated by showing how the model outperforms classic deep learning approaches and other state-of-the-art computer vision algorithms at periods prior to the estimation time. Finally, some subjects related to motivation are suggested for future research.

Micro-scale Solar cells are available from a variety of producers and systems integrators. As a result, choosing the right panel is a complex undertaking and a risky investment. This paper proposes and analyzes a novel method in [72] based on combining observational testing procedures with short-term facts and artificial neural to measure the effectiveness of micro-scale Photovoltaics and their competency for a particular application in a dynamic context to face this and assist producers. Compared to conventional data, the neural network output has a standard deviation of 23 percent. The coefficient values with prior work are between 87.3 and 91.9 percent.

A hybrid deep learning system is proposed by integrating clustering algorithms, convolution neural networks, long short-term memory, and attention mechanisms with a wireless sensor network to tackle the current PV electrical generation estimation problems. Clustering, training, and forecasting are the three steps of the overall suggested strategy [73]. In contrast to previous methods, such as computational models, long-short attention span deep learning, and an algorithm combining a long defeatist mentality neural network and an attention mechanism, the experimental results indicated massively better prediction test accuracy for all frequency ranges.

This study proposes a model for energy generation from Wind termed multi-objectives renewable electricity [74]. In particular, this framework has five different primary stages: the first process collects and prepares data in order to make it suitable for the outcome; the second process focuses on building restrictions for each dataset and develops one of the optimizers called cuckoo, which is based on horizontal mixture and non-linear and non-optimization; and the third phase focuses on developing constraints on every dataset and improves one of the evolutionary algorithms called cuckoo, which is based on horizontal mixture and multi-objective optimization. The suggested strategy is distinguished by substantial cost savings and expanding the ministry of electricity's mandate.

The utilization of Deep Learning approaches for Photovoltaic forecasting, namely Recurrent Neural Networks, Long Short-Term Memory, and Gated Recurrent Units, was investigated in this article [75]. The suggested prediction algorithms are based on accurate Errachidia provincial meteorological data from 2016 to 2018. RNN and LSTM beat GRU by a bit of margin due to their ability to preserve long-term relationships in time series.

By putting dozens of sensors within the Wind generator, this study utilizes deep learning to anticipate energy consumption and locate the areas that have the most influence on energy expenditure to minimize energy usage and enhance producing efficiency [76]. As a result, while developing a future prediction model for internal energy consumption of Wind turbines, the label data should account for 15–20 percent of the overall data, according to this study. Therefore, this is not only the most accurate technique to train a model but also the most cost-effective way to decide the quantity of revision data.

This research provides a unique Wind speed forecast method for Wind farms by adopting some insight from machine learning approaches [77]. First, density peak clustering (DPC) divides the massive number of distributed Wind farms into a considerably smaller number of groups, which are considered single entities. The preprocessed with various weightings based on the decision making of each indication in a grouping. An in-service Wind farm in China is used to demonstrate the usefulness of the suggested method.

Renewable power forecasting is critical for efficient functioning and reliability. Physical rules are used to calculate the path of the sun's beams and the amount of energy [78]. In the realm of AI, the computer evaluation of Solar energy generation is particularly difficult. According to previous research, there is a 21 percent mistake rate. The 10 percent reduction in mistake rate has a favorable impact on the growth of the Solar energy industry in a more sustainable way, lowering costs (in USD) and reducing dependence on carbon emissions.

This study uses a Mixed-Integer Nonlinear Regression technique to reduce the daily generation expenses of a power system while boosting its resilience, which includes a Wind turbine, storage, and traditional grid [79]. Supervised learning and mathematical analysis and a unique hybrid model were built and utilized to anticipate load requirement and renewable power generation for the next three days. This research helped guide practical and rational judgments for urban micro-grids and improved the integration and usage of renewable energies in cities.

A supervised neural strategy based on a Long Short-Term Memory deep net was introduced in this study [80]. The system sought to anticipate electrical energy output from a Solar-PV power plant with a capacity of 1.15 MW one hour in advance. Two separate data-driven approaches, adaptive ANFIS with fuzzy c-means and ANFIS with grid partition, were combined with the suggested deep net. Measured data were used to validate the data produced from the models. The comparative findings indicated that the presented method produces the best outcomes.

Total transfer capability is calculated using a physical model, which takes a long time. This research presents a rapid data-driven TTC predictor based on deep belief networks for accurate and timely knowledge of transfer restrictions to address this shortfall [81]. In the first step, a network sample creation approach is used to simulate many operating scenario samples for deep belief training of the network utilizing yearly load demand power data. After that, the well-trained leaner is used to anticipate overall transfer capability for the critical transmission channel. Finally, the suggested technique is validated using standard systems.

The mathematical modeling of a hybrid power system is presented in this research, and the controller design is realized using a new deep learning technique. The variable-speed power generator torque is governed using a PID controller within the proposed method [82]. The PID controller's gains are fine-tuned using a deep learning model. In terms of the simulated results produced, the efficacy of the proposed machine learning prototype controllers for the control system in Wind energy conversion is proven and seen to be superior to the other approaches presented in earlier literary works.

This research presents a multi-stage model for power lines, energy storage systems, and Wind station development co-planning that takes extreme weather occurrences into account [83]. A deep learning solution based on Two Long Selective Memory systems is described to estimate yearly peak loads. The suggested model's Mixed-Integer Linear Programming formulation is solved using the Wielders Transform. The suggested model's efficacy is assessed using a modified IEEE RTS experimental setup.

With the advent of the Urban Regional Electricity Internet, clean energy plays a significant role in the future energy system [84]. However, because renewable energy, such as Wind energy, is intermittent and volatile, its primary role in energy supply has been limited. As a result, precisely anticipating Wind output is critical for the safe running of the power system. To solve the above issues, this work proposes a BiLSTM-based time series framework for Wind power. It analyzes accurate Wind data from the Urban Region Energy Network. Several other techniques can be used to predict the power values [85–87]. An overview of applying deep learning techniques to renewable energy is presented in Table 3.

Table 3. An overview of applying deep learning techniques to renewable energy.

NO.	Literature	Years	Sources of Energy	Method
1	[70]	2018	Solar energy	A forecast method for Solar energy using a deep learning approach.
2	[59]	2019	Wind and Solar energy	A new survey for the deep learning methods used in applications of Wind and Solar energy resources.
3	[69]	2019	Wind energy	Incorporating forecasting and management in a deep reinforcement learning based battery energy storage control strategy for Wind farms.
4	[82]	2019	Wind energy	Induction generator in Wind farms using an optimized new deep learning model.
5	[60]	2020	Solar energy	A deep learning method for controlling Wind farms for energy storage system controller
6	[68]	2020	Solar energy	QSPR with deep network for Solar cell heat exchange performance forecast.
7	[72]	2020	Photovoltaic Solar energy	A rapid evaluation of micro-scale Photovoltaic Solar energy methods employing empirical methods mixed with deep learning neural networks.
8	[74]	2020	Wind energy	An innovative integration of machine learning architectures for electrical renewable energy from Solar and Wind.
9	[76]	2020	Wind energy	Forecasting a Wind Turbine's institutional energy usage using semi-supervised classification techniques.
10	[77]	2020	Wind energy	Improved cluster and deep training short-term renewable power prediction.
11	[81]	2020	Wind energy	Deep learning-based predictor for power systems with Wind energy
12	[62]	2021	Wind and Solar energy	A review of Wind and Solar energy forecasting systems based on deep learning
13	[65]	2021	Wind energy	A deep learning-based method for projections of offshore Wind energy resources.
14	[66]	2021	Wind energy	A novel deep learning-enabled sparsity developing method for power operations with Wind energy.
15	[67]	2021	Wind and Solar energy	A machine learning-based regression method for Wind power generation.
16	[71]	2021	Wind and Solar energy	Computer vision deep learning on weather images.
17	[73]	2021	Solar energy	Deep learning and Artificial Intelligence method for Solar energy forecasting in IoT
18	[75]	2021	Solar energy	Deep learning-based approach for Solar energy forecast.
19	[78]	2021	Solar energy	Deep learning-based approach for Solar energy forecast.
20	[79]	2021	Wind energy	A deep learning method for electrical charge and Wind power.
21	[80]	2021	Solar energy	Deep learning procedure for energy generation forecasting in a Solar PV.
22	[83]	2021	Wind energy	Deep learning-based method for transmission, battery power areas and Wind energy.
23	[84]	2021	Wind energy	Deep learning method for forecasting output Wind energy based on IoT.
24	[61]	2022	Energy bidding	Deep learning reinforcement method for Wind energy prediction.
25	[88]	2021	Smart microgrids	A review on deep learning techniques for power capacity and energy forecasting.
26	[89]	2021	Photovoltaic energy	Deep learning for pattern identification of PV power generation.
27	[90]	2021	Wind power	Wind power forecast using novel deep learning system.
28	[91]	2021	Wind power	Deep learning structure for short-term Wind power prediction.
29	[64]	2022	Solar energy	Deep learning combined method for high-accuracy Solar energy.

3.2. Machine Learning Techniques

In this section, the Wind and Solar systems-based machine learning methods are presented in detail, as follows.

Machine learning is a data analytics method that trains computers to do naturally to humans and animals: learn from practice. Machine learning algorithms use computational techniques to "learn" information quickly from data without using a predefined equation as a guide.

Based on data given by the National Data Buoy Center, a data mining and machine learning approach was employed to identify the areas in the United States in this study [92]. The goal was to construct an early evaluation tool analysis of the data obtained to facilitate decision-making in the design process for wave-Wind hybrid systems with great flexibility within each location. In addition, each cluster was given complete statistics.

This research provides a simulation-based technique experimentally verified for calculating Wind farm energy output losses due to typical leading edge attrition [93]. Machine neural networks and Wind farm design algorithms that use the blade element momentum theory combine the prediction accuracy of two-dimensional Navier–Stokes numerical simulations with the runtime savings provided by artificial neural networks. The described technique allows for the equivalent volume of power expended to erosion for multi-turbine Wind farms in a matter of minutes. It serves as a critical tool for forecasting.

Based on standard machine learning approaches, this study proposes a method for estimating Solar energy [94]. The models' applicability for real-time and short-term Solar energy prediction was assessed to meet optimal management and security needs in this sector while employing an integrated solution relying on a personal tool and an acceptable classifier. The preliminary results obtained were compared to Pirapora, a tropical climatic location in Brazil, to demonstrate the study's quality and reputability.

The energy firm can plan for these excesses with better and more exciting predictions that give dependable and strategic management insights. This paper offers a Gaussian stochastic-based deep learning process model for simple electricity, renewable power, and Wind power predictions utilizing two different temporal resolutions of data in addition to optimally quantifying uncertainty [95]. The proposed approach was shown to be capable of solving the specified challenges.

Due to the high cost of instrumentation, China's monthly average radiation from the sun has complicated geographical patterns, and monitoring sites are still missing. This research used machine-learning approaches to build a unique estimation strategy with its complicated spatial pattern over a large region in China to address these issues [96]. The suggested unique strategy is intended to be expanded using interpolation techniques, allowing decision-makers to decide the best location, size, and structure for Photovoltaic system implementation.

Two learning algorithms for daily Solar power prediction are described in this study [97]. Once redundant data is deleted from raw data, investigational image is processed into a settled scope, the best features feature selection technique is chosen, four distinct weather characteristics are created depending on different weathers, and the perfect time series machine learning technique is chosen, the Solar power predictive algorithm has become effective and accurate for renewable energy predicting.

In the past few years, evaluating data collected throughout the energy generation process has become a critical concern in the electric power industry to improve the efficiency of the energy generated. Based on the temperature, Wind speed, and direction measurements collected from the Wind generator in 2015, this study calculated the optimum amount using machine learning approaches [98]. A mathematical formulation has been found that correctly forecasts the value of energy generation by 90 percent. Other users can examine the outcomes of this mathematical equation thanks to a computer application.

This research creates better power price prediction models with adaptive data pretreatment, sophisticated algorithms, a kernel-based model, and an optimum model selection procedure. To provide attractive data transformation results, an adaptive parameter-based variational mode decomposition technology is proposed in [99]. Furthermore, a leave-one-out metaheuristic approach that relies on the chaotic sine cosine algorithm is suggested and utilized in economic growth and population kernel-based artificial neural machine models. The proposed model is a promising, practical, and successful power predictive analysis tool in the real electricity market.

This article explores the causal link between Solar and Wind energy output, coal use, economic development, and CO_2 emissions for these three nations [100]. To address this problem, a cutting-edge Machine Learning approach is applied to validate the predicted causal links between variables. As a rising sustainable energy leader, India should increase the use of limited renewable resources in its electrical supply and reduce its reliance on coal.

Seven machine-learning techniques were utilized to anticipate renewable power and capture higher generation combinations to develop analysis and categorization models related to energy metrics, with random forest showing the highest predictive potential [101]. As a result, the random forest can provide a successful international application developer for a high-efficiency technique and incorporate multi-component combination.

This research suggests a novel technique for Solar energy forecasting that combines machine learning with several publicly available data sources to estimate site-specific temperature and sun irradiation [102]. When comparing the novel methodology to the previous approach for estimating Solar energy generation, preliminary data reveal that the new strategy has a lower error rate. As the use of Solar energy grows, so the likelihood of grid outages. These first findings demonstrate the feasibility of aggregating individual site-specific forecasts to the regional level to assess neighborhood renewable power disruptions and progress toward forecasting grid optimization.

Daily Solar energy predictions are produced by utilizing the power of machine learning algorithms to record and evaluate the complex behavior of large characteristics. For this aim [103], a dataset of 98 Solar stations was obtained from the American Meteorological Society's energy competition for estimating daily Solar energy. Compared to all other suggested approaches, the random forest and ridge regressive have been found to enhance accuracy for both grid sizes. The suggested methods' stability and dependability are tested on a Photovoltaic cell station and many independent runs.

Several techniques of assessing renewable are examined in this research, with a particular focus on a Levelized Cost of electricity evaluation of Solar PV as an alternative source of electricity in the CAISO market [104]. This increase in power price predictions would immediately translate to more confidence while deciding to transition to a Solar PV option, particularly for planners.

Solar and Photovoltaic generation's stochastic characteristics can have a substantial influence on power system stability and dependability. As a result, precise forecasting of PV power output is vital. In this study [105], a computational intelligence approach based on the prediction interval approach is provided for short-term Solar energy forecasting. The simulation findings suggest that PI is more credible and correct than deterministic approaches based on the test metrics.

The possibility of machine training approaches for predicting total daily Solar energy output is investigated in this research. The time series is first simulated using a season variant of the well-known traditional auto-regressive integrated daily average [106]. The results are then compared to other famous deep learning methods, support vector classifiers, and artificial neural network performance. Despite the relative effectiveness of support vector machines in predicting Solar generation, the accuracy rate needs to be increased. Therefore, techniques to attain this goal should be investigated in the future.

The current Singapore's entire sky imaging separation database is updated with foggy and cloudy photos taken by a webcam Waggle sensor node to train each of the machine learning techniques with diverse sky circumstances [107]. One of the deep networks that have been used, the U-Net architecture, segregated cloud pixels one of the most correctly. This ground-based technique is a low-cost way to measure sun intensity and predict Photovoltaic Solar facility generation.

In this paper, the Kyushu College kite technology is utilized to show how test results may be used to train computational linear regression [108]. The technique uses an inflated wing with a suspended kite monitoring system tied a fixed ground anchor or to a car moving to create a controlled comparative flow condition. For data collection, a measuring unit was mounted to the kite. Our models' quality measures show promise for correctly forecasting tether force for novel input/feature pairings and guiding new designs for optimal power generation.

Due to worries about climatic change, many nations are striving to reconfigure their energy mix. As a result, the globe is shifting to renewable power as a source of electricity. In this regard [109], Solar energy has emerged among the most promising alternatives for large-scale power generation. As a result, the quest for more relevant, field-specific approaches will be critical in order to increase accuracy and provide the globe with several financial and environmental advantages. This article addresses the underlying concepts of machine training techniques in this context.

Flow simulation is a problem for flow modeling, and elevated extensive eddy studies across small area domains have frequently idealized the rapid undergo. However, the relevance of applying more accurate large-scale forcing and coupling micro-scale and microscale models for Wind generation is becoming more well-recognized [110]. The factor vulnerability of significant output variables is investigated using machine learning approaches while accounting for mixture model reactions and operator relationships.

This setting offers a systematic and complete examination of neural nets, support vector analysis, random trees, and random forest and the advantages and disadvantages of adopting the approaches as mentioned earlier [111]. This study also guided Wind energy practitioners, bridging the gap between academic research and real-world corporate use cases by laying out the particular designs and model parameters. With petroleum products running out, it is more important than ever to focus on renewable energy sources and get the most out of them. In several places of India, air current energy is a major source of electricity [112]. Energy generation, biomass energy, and other renewable energies are examples. The main goal of this research was to forecast Wind direction for the near term in order to assist Wind farms in channeling Wind energy efficiently and obtaining large bandwidth from the Wind turbines.

To integrate the prediction outputs of base classifiers, three stacking strategies have been explored and likened: feed-forward artificial neural network, support vector regressors, and k-nearest neighbor regressors [113]. The majority of the stacking models studied were seen to be capable of predicting Solar radiation. However, those involving the combination of homogeneous models employing neural meta-models performed better. In addition, the performance of mixed models was compared to that of recurrent models. So over a year, the Solar radiation projections of the examined models were reviewed and compared. The benefits of each different ensemble's performance have now been explored.

Between 2017 and 2020, this article looks at the electricity produced by conventional, nuclear, and hydroelectric power plants. Overall, this study looks at the Photovoltaic cell and Photovoltaic power reflection coefficient [114]. Relying on a massive collection of low-altitude and geostationary sensor data, machine learning can now generate virtual ocean surface airflow fields under clouds, recorded by a global positioning system, even when these Winds are not observed [115]. This database may then be used to look into the climatological relevance of air locations. The same approach may be used to monitor the renewable power facility instantaneously by deploying geostationary satellites every few minutes.

This study provides a complete analysis of machine learning in Wind energy systems, examining the most widely used research in various situations and concluding that artificial neural networks might be a more sustainable strategy in many circumstances than traditional approaches [116]. Since 2015, a significant number of research articles on this issue have been published. They may be divided into five categories focused on the application: different Wind forecasts, design optimization, defect detection, optimization techniques, and maintenance planning. For the current and future developments, data is usually of ANN application in various sectors. An overview of applying deep learning techniques to renewable energy is presented in Table 4. More details also can be found in [117–120].

Table 4. An overview of applying machine learning techniques to renewable energy.

NO.	Literature	Years	Sources of Energy	Method
1	[96]	2019	Solar energy	A novel estimation method for the Solar transmission and prediction using machine-learning procedures.
2	[97]	2020	Solar energy	Machine learning technique for Solar power energy prediction.
3	[102]	2020	Solar energy	A novel machine learning method to estimate Solar power grid changes.
4	[103]	2020	Solar energy	Solar energy forecast method based on using a novel machine learning technique.
5	[104]	2020	Solar energy	A novel machine learning method to assess renewable power systems.
6	[105]	2020	Wind and Solar energy	A new machine learning system for Photovoltaics forecasting using prediction intervals.
7	[106]	2020	Solar energy	A comparison of machine learning approaches for forecasting of maximum weekly PV systems.
8	[108]	2020	Wind energy	Power forecast of airborne Wind power operations using a nvew machine learning method.
9	[109]	2020	Solar energy	Solar energy prediction system using a new machine-learning algorithm.
10	[110]	2020	Wind energy	Wind energy utilization using a novel machine learning method.
11	[92]	2021	Wind energy	Unsupervised machine learning planning technique for wave-Wind offshore power tools.
12	[93]	2021	Wind turbine energy	Machine learning-prediction technique of Wind turbine power.
13	[94]	2021	Solar energy	Machine learning is used to predict renewable electricity based on pearson connection.
14	[95]	2021	Wind and Solar energy	A novel machine learning method for monetary and power policy applications.
15	[98]	2021	Wind energy	Evaluation of Wind turbine energy generation by using machine-learning method.
16	[100]	2021	Wind and Solar energy	A new machine learning method for Solar and Wind energy generation.
17	[101]	2021	Solar energy	A new machine learning method for Solar cells specifications and energy adjustment optimization.
18	[107]	2021	Solar energy	PV Solar power based on cloud coverage evaluation using machine learning approach.
19	[111]	2021	Wind energy	A novel Wind power forecast based on utilizing machine learning approach.
20	[112]	2021	Wind energy	Energy Wind speed prediction system based on utilizing machine learning approach.
21	[113]	2021	Solar energy	A comparative analysis of simple forecasting utilizing weather knowledge andsupervised learning ensembles.
22	[114]	2021	Solar energy	Investigation of Solar power generation with machine learning procedures.
23	[115]	2021	Wind energy	A hybrid machine learning method for treatment and monitoring of ocean Wind power.
24	[116]	2021	Wind energy	A novel machine learning for predicting the Wind power parameters.
25	[121]	2021	Nanofluid heat transfer	Recent leaning on nanofluid heat change machine learning employed to renewable power.
26	[100]	2021	Solar and Wind energy	A novel machine learning method on the relationship between Solar and Wind energy generation.
27	[122]	2021	Renewable Microgrids	A superior machine learning-based energy control of renewable microgrids.
28	[123]	2021	PV–Wind	Feature selection technique for foretelling the energy output of hybrid PV–Wind renewable systems.
29	[124]	2021	Grid-connected PV-battery	A novel predictive energy control approach for PV-battery using machine learning method.
30	[99]	2022	Wind and Solar energy	A new machine learning method for forecasting the optimal Wind and Solar energy systems.

4. Discussions and Advances

In this section, we presented discussions and advances in the domain of Wind and Solar and Photovoltaic renewable energy Storage systems with a survey of advanced machine learning and deep learning techniques.

The relative advantage of in-depth training in various applications has attracted academic attention, as seen with the wide range of recommended methodologies and the expanding number of articles. Machine learning and deep learning are the most successful methods used in predicting models in Solar and Wind energy domains [125]. We also highlighted the primary problems arising from the previous researchers in this domain. Using a single learning method is one of the recognized problems in this domain [126]. It reported the worst performance compared to other hybrid methods. Also, one of the most critical issues faced by the researchers in the previous papers is how to adjust the parameters and factors of the generation techniques and find their optimal values [127]. The primary, essential, and powerful Artificial Intelligence learning-based methods are machine learning and deep learning. These techniques open the door for future researchers to conduct further investigations in this domain to find better solutions for Wind and Solar energy problems.

Precise prediction is conducted in some examined studies using previous output current data alone and with weather data [128]. In contrast, intermediate prediction is carried out in others by projecting Wind speed and Solar irradiance using previous values or with weather stations. Most academics agree that incorporating datasets increases prediction performance; nonetheless, the relationship between such elements and prediction output varies by area. To conclude, further comparison experiments need to be conducted to illustrate the influence of integrating certain meteorological information on the models' performance.

It is not possible to create a forecasting model for every area. A few research recommended predicting models for an entire region [129]. In contrast, others offered transfer learning to save effort by quickly training models established before producing predictions for new places. Self-adaptive process-based methods can also be of use in this regard. In the future, further research in this area will be undertaken.

In the lack of guiding rules for model development and parameter selection, deep learning to discover the best answer is still challenging and time-consuming [130,131]. The quality of the research and the researchers' prior expertise in the field generally dictate the decision. To obtain near-optimal answers, most researchers rely on trial and error. Moreover, applying optimization techniques and approaches for the number of parameters tuning and preventing difficulties like overloading and outliers has been documented in several studies.

Also, from another view, the optimization methods proved their ability to solve various problems especially energy problems [132]. Generally, the optimization algorithm can determine the parameters of the energy problems more effectively than any other method, which should be considered.

Figures 6–10 show Influence flower visualizes citations connections between academic things, including papers, authors, organizations, and research subjects. Figure 6 shows the influence flower visualizes publications and citations connections between authors. Figure 7 shows the influence flower visualizes publications and citations connections between papers. Figure 8 shows the influence flower visualizes publications and citations connections between organizations. Figure 9 shows the influence flower visualizes publications and citations connections between research subjects. Figure 10 shows 72 years of publication in the domain of Wind and Solar energy using deep and machine learning techniques. These figures can facilitate the search by future researchers, and they highlighted the most important researchers and papers in this domain. Note that, Blue curves indicate incoming influence, with their width proportional to the number of references given. Red curves indicate outgoing influence, with their width proportional to the number of citations obtained.

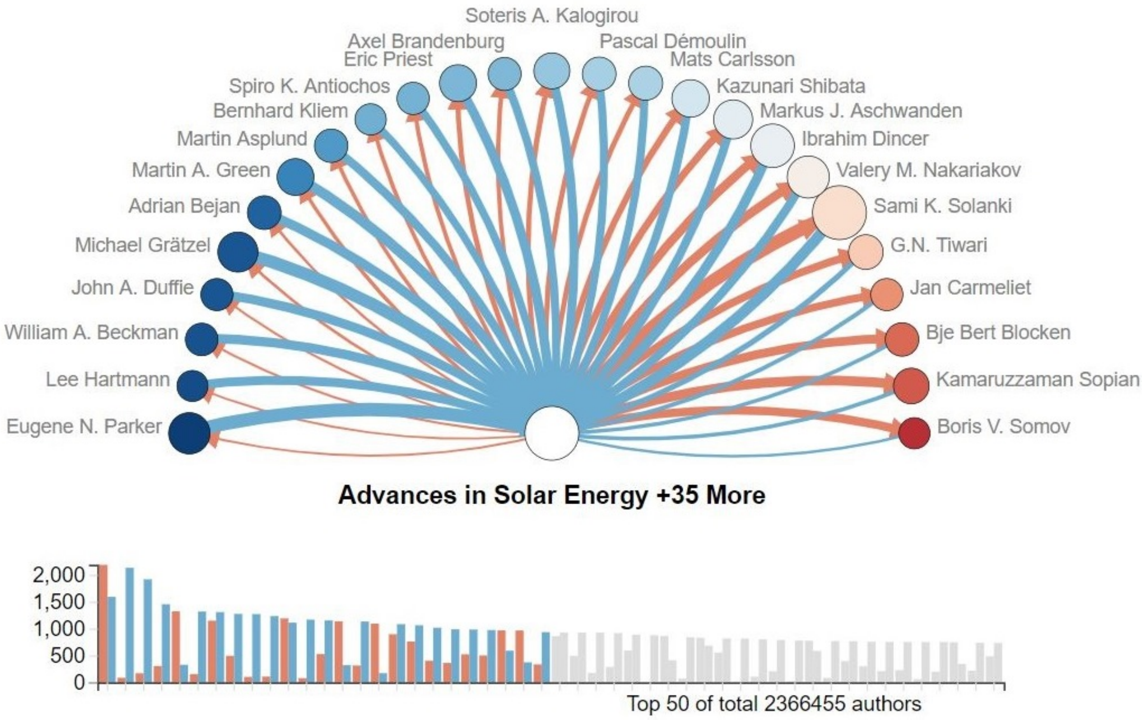

Figure 6. Influence flower visualizes publications and citations connections between authors.

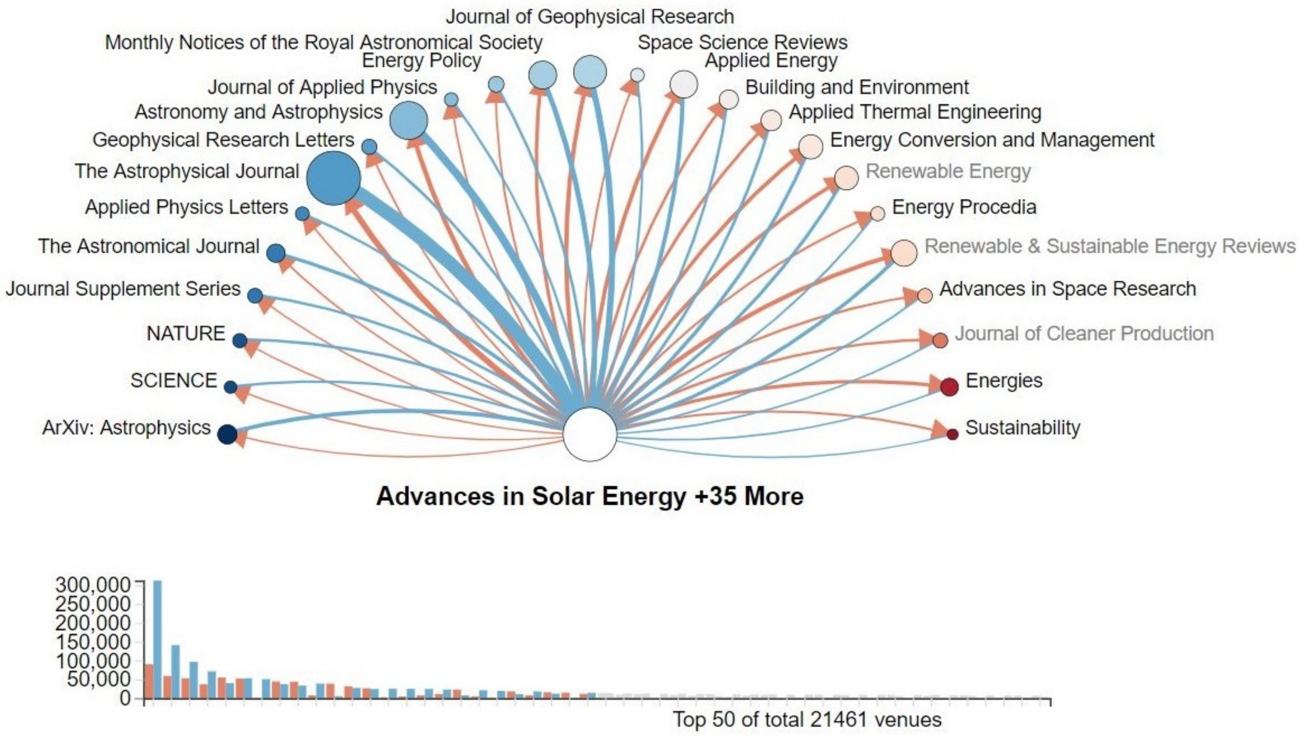

Figure 7. Influence flower visualizes publications and citations connections between papers.

In comparison with other similar surveys, this survey in 2019 presented a survey of deep learning for renewable energy forecasting [133], which focused just on deep learning for a specific problem. So, we conducted a survey for the related papers covering Solar and Wind problems based on using deep and machine learning methods.

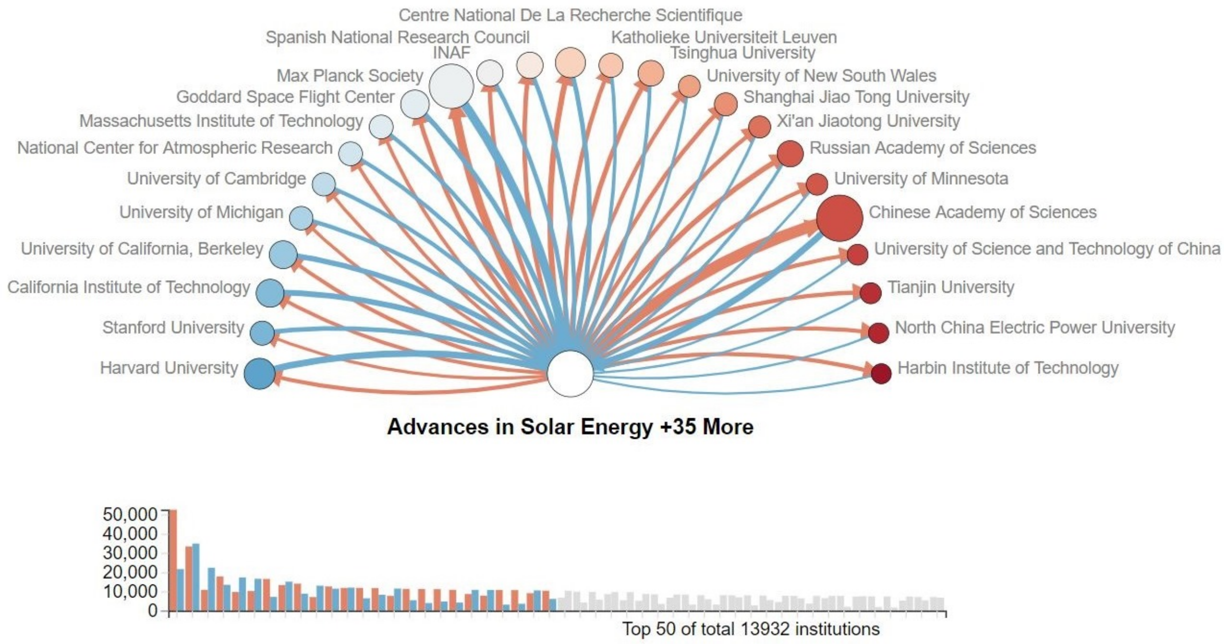

Figure 8. Influence flower visualizes publications and citations connections between organizations.

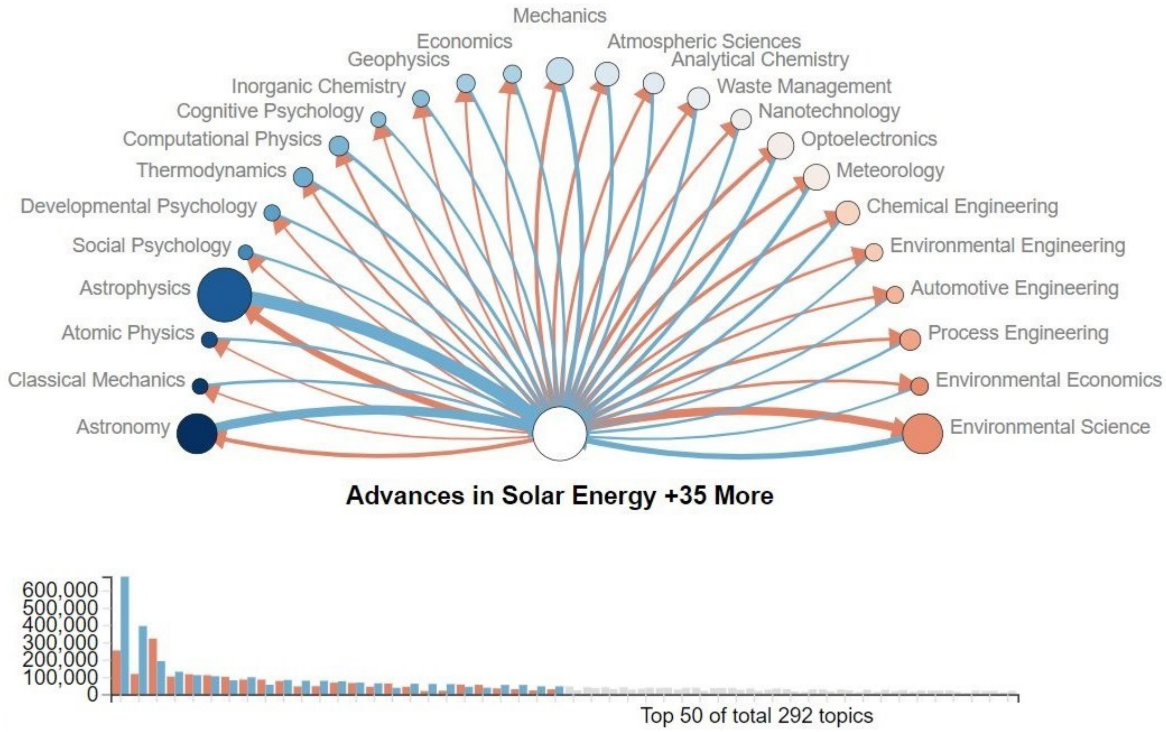

Figure 9. Influence flower visualizes publications and citations connections between research subjects.

In this paper [134], the authors published a survey for machine learning on sustainable energy, and they just focused on the machine learning applications on sustainable energy. This paper studied several energy problems concerning the deep and machine learning method. Also, we presented the main problems definitions and procedures as the mentioned work has no definitions and procedures.

Another paper in [135] presented a review on energy forecasting using deep learning models. Also, this survey focused on the forecasting method based on deep learning models and lacks other problems in this domain. So, we presented the related methods to more problems and focused on deep and machine learning models and optimization techniques.

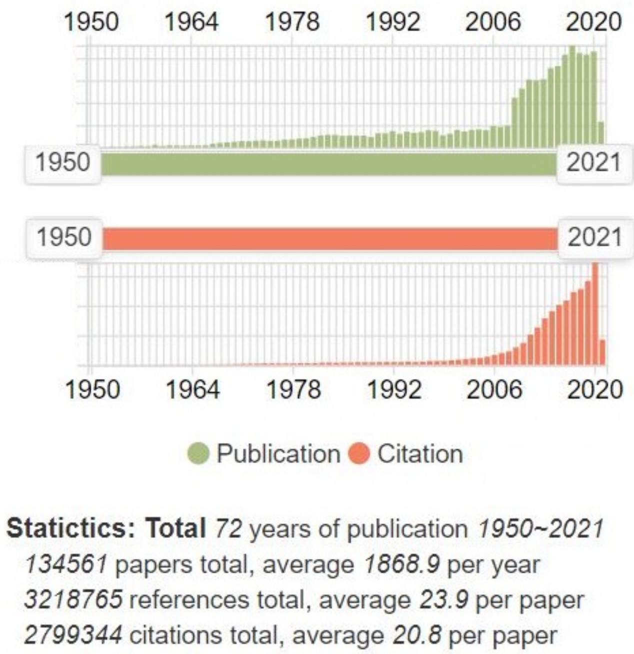

Figure 10. 72 years of publication in domain of Wind and Solar energy using deep and machine learning techniques.

This work has evaluated and showed previously unreviewed 2021 researches and our research methodology to organize, analyze, present, and compare the data. The suggested taxonomy distinguishes it from other survey publications in the field. We feel that the work we have done in this study will be critical in better understanding, categorizing, and analyzing research on the topic, resulting in faster advancement in this sector.

The primary motivation behind this survey is to cover the most recent and important papers published in this domain. Moreover, the mathematical formulation of the comment problems is given to facilitate the understanding of future readers. Some classification for the different papers in the given domain is also given to highlight the leading researches in this domain.

5. Conclusions and Potential Future Work Directions

Recently, Artificial Intelligence learning-based modeling methods have proved their ability to solve various benchmark and real-world problems, especially, it has been successfully employed as a precise forecast model to deal with renewable power sources and their parameters. Computational Intelligence (CI) techniques have become well-known and recognized as beneficial tools in generating and optimizing renewable energy tools. The complexity of Wind and Solar energy resources depends on its coverage of large sizes of data, parameters, and other factors that affect the process, which have to be examined and investigated thoroughly. This survey paper proposed a study for various types of Deep Learning (DL) and Machine Learning (ML) algorithms employed in Solar and Wind energy supplies. Additionally, the performance of the presented methods in the literature is analyzed and evaluated by a new taxonomy. It also gives comprehensive state-of-the-art methods heading to performance evaluation of the given techniques.

The vital difficulties and possibilities are discussed for extensive research and additional clarification for future readers. Based on results, variations in efficiency, robustness, accuracy values, and generalization capability are the most apparent difficulties for using Artificial Intelligence-based learning techniques. In the case of the big dataset and log data scenarios, the effectiveness of the presented learning techniques is significantly better than the other computational methods, especially when applying a hybrid learning-based model. In addition, applying and producing hybrid learning techniques with other optimization methods to improve and optimize the construction of energy systems is indicated.

We concluded that the hybrid learning methods have better achievements and outcomes, in dealing with Wind and Solar energy systems for the forecasting problems, than a single method due to hybrid methods gaining the benefit of two or more methods for providing an accurate forecast. It is recommended to use hybrid Artificial Intelligence learning techniques in the future to deal with energy generation problems. The energy problems can be further investigated in future work by using new improved methods using machine learning, deep learning, optimization algorithms, and others. More focusing on problem modeling also can be considered.

Current limitations in renewable energy are the electricity generation capacity is still not large enough, renewable energy can be unreliable, renewable energy sources are still relatively new to the market, which means they lack well efficiency, setting up renewable energy sources facilities necessitates a significant financial investment.

Renewable energy still challenges significant barriers to widespread implementation. Some are related to Solar and Wind power, while others are due to current market constraints, legislation, and transportation. The most major and well-known barrier to renewable energy adoption right now is cost, namely the expenses of developing and deploying facilities such as Solar or Wind farms. A significant amount of additional transmission infrastructure is necessary to exploit renewable sources adequately. Despite a thriving sector, the substantial increase in panel output resulted in an overstock issue.

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