Machine Learning in Solar and Wind Power Forecasting

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Abstract

In this literature review, several papers are analyzed for their approaches to solar and wind energy prediction. Direct and indirect approaches to solar energy prediction are examined in detail, which encompass popular machine learning models such as support vector machines and regression, artificial neural networks, autoregressive moving averages, and least absolute shrinkage and selection operators. Point prediction and prediction interval approaches to wind energy prediction are analyzed, and the benefits of each method are compared. Common limitations to these approaches are discussed, such as their sensitivity to weather conditions and narrow focus on particular locations. Finally, suggestions for future work are made based on the current limitations of popular approaches.

Keywords: Solar, wind, indirect, direct, point prediction, prediction interval, machine learning

I. Introduction

The Fourth National Climate Assessment [1] reaffirmed that human activity is highly likely to be the main contributing factor to rapidly rising global average temperatures. The expansion of the renewable energy market, as well as the concurrent reduction of fossil fuel use, is key to reducing global greenhouse gas emissions.

The installed capacity of solar energy has increased by more than 4200% and wind energy by over 550% across the globe from 2007 to 2017, according to the International Renewable Energy Agency [2][3]. Compared to other common renewable energy sources, these are the most rapidly growing. The levelized cost of electricity (LCOE) is a common metric that measures the per-megawatt cost of harnessing electricity via different means, measured in discounted real dollars. Estimated capacity-weighted average costs per megawatt hour in 2017 dollars is 37, 106.2, and 46.5 for offshore wind, onshore wind, and solar photovoltaic, respectively [4]. Automating the management of solar and wind farms could potentially reduce their cost of operation, making them even more competitive energy solutions.

According to the McKinsey Global Institute's 2017 report on sustainability and resource productivity [5], a major difficulty of solar and wind energy production is their intermittent nature. In high penetration cases, effectively storing and managing a mix between solar and wind energy and other conventional energy sources that can readily be harnessed becomes a nontrivial task, highlighting the importance of energy prediction techniques.

Over the last few decades, various methods to forecast solar and wind energy have been proposed. Machine learning in particular has had success in this regard. In this literature review, the technical details and limitations of both solar and wind power prediction techniques are explored. The first section is devoted to direct and indirect solar power prediction, and the second section is related to point and interval wind power prediction.

II. Solar Power

Most approaches to solar power prediction can be categorized as either direct or indirect. Direct methods make predictions of photovoltaic output directly from the historical output data of a particular plant, whereas indirect methods predict the solar irradiance of an area and calculate the power output as a result. Both approaches rely on historical weather data [6].

Indirect Approaches

Much of the early literature in solar prediction is concerned with indirect solar power prediction, in which solar irradiance is predicted, followed by a conversion to photovoltaic output. Typically, information relating to atmospheric clarity is inferred from satellite imagery through the detection of clouds. [7] presents a method of estimating 2D motion from sequential images. In particular, this approach differs from previous approaches by considering the movement of objects surrounding the feature being tracked. The motion model introduced by this paper is employed by a number of the following indirect prediction works.

[8] cites this method in a two-step approach for short-term solar power prediction. The geostationary METEOSAT satellite provides grayscale images, in which individual pixel values correspond to the amount of radiance reflected back into space. Vector motion fields are created from these images using the method described in [7]. Because wind fields change relatively slowly, the vector field obtained from two sequential images of a cloud can be applied to the second image to forecast the cloud's future movement.

This approach is tested by applying both a linear and rotational transformation to test set images and comparing them to their actual subsequent images. This method achieves low root mean square error. However, this approach fails to recognize the formation and dissolution of clouds, particularly in regions where pixel intensities vary significantly.

To estimate the irradiance of a particular cloud forecast, a semi-empirical HELIOSAT method is used. This method achieves a 20% error for hourly predictions when compared to the ground-truth irradiance, and tends to underperform in these cases. Despite this, the model can predict solar power without needing any real information about a particular solar farm.

HELIOSAT is used extensively throughout the early literature to predict irradiance. In general, the HELIOSAT method first estimates irradiance in the cases that no clouds are present, by taking into account different atmospheric conditions. The level of cloud transmission is inferred from the reflected radiance of a cloud structure in a satellite image. In combination with the clear-sky irradiance estimation, this gives the approximate irradiance of an area. [9] compiles a list of projects that benefit from the HELIOSAT approach.

Commonly, HELIOSAT uses METEOSAT satellite images. However, METEOSAT images are used in other approaches to forecasting as well. One particular method for tracking clouds ([10]) is less intrinsically subjective, less computationally expensive, and better at capturing the rotational motion of clouds than previous approaches. Specifically, a two-step method is proposed. First, cloud shapes are estimated from METEOSAT images by tracing cloud edges. Second, a Hopfield neural network is used to match clouds across sequential images.

Hopfield neural networks are an example of recurrent neural networks, which are particularly useful for time-series data. This makes the Hopfield network an intuitive choice for feature matching across sequential images. Indeed, the Hopfield network achieves improved performance when predicting rotational cloud motion compared to previous approaches. However, the tests described in this paper are extremely limited, citing only a single test instance. Further testing is required before the Hopfield network is adopted. Despite this, the paper succeeds at introducing neural networks to cloud tracking, something which is explored further in later literature. Additionally, this approach is not limited to tracking clouds: given the proper recognition model, any potential feature could be tracked across time-series images.

Much of the literature for irradiance prediction employs multiplicative autoregressive moving-average statistical models (ARMA). Multiplicative ARMA models are able to capture relationships between both sequential hours on the same day and the same hour on sequential days, making them a versatile tool for both short and long term solar power predictions. Traditionally, however, ARMA requires the use of three relatively inaccessible parameters (autoregressive coefficient, moving-average coefficient, and variance of the error term), making it inapplicable to areas where these parameters are unknown. [11] proposes a novel approach that estimates the three parameters, effectively eliminating this constraint.

Specifically, statistical significance tests are used to check whether the three dependent variables are impacted by a set of independent variables. In particular, the variance of the error term was found to be significantly tied to monthly mean daily atmospheric clarity. In turn, the estimated autoregressive coefficient was found to be impacted by the monthly mean clarity and the variance of the error term. As a result, both of these terms are estimable with just the monthly mean daily atmospheric clarity index. In addition, the estimated moving-average coefficient can be estimated by a Weibull distribution.

This paper's main contribution is the reduction of required parameters for multiplicative ARMA. Specifically, only monthly average global irradiance data is needed. This is particularly significant because this value is much more widely available than the three individual coefficients, making this model applicable to areas beyond those where these parameters are recorded. However, additional work is required to ensure that these ARMA coefficient estimates apply to locations where the monthly mean daily atmospheric clarity index is vastly different than the locations where the data was collected, so this universality could fail in practice.

ARMA is used again in [12], which uses a hybrid model to capture both the linear and nonlinear trend in solar radiation. Solar radiation is particularly difficult to predict, largely because of the presence of unpredictable noise. This paper attempts to solve this issue by combining an ARMA model with a time delay neural network. The two models have complementary strengths: ARMA models are very flexible to many kinds of time data, and can fit a linear relationship particularly well, even with noise present. However, they cannot fit non-linear data, which is handled by the neural network.

ARMA requires stationary time series data to work. Because solar radiation is non-stationary (meaning that statistical properties like mean and variance change over time) [13], it must be detrended before being fed to ARMA. Once detrended, the ARMA model fits a linear relationship to the solar radiation data. The residuals of the linear relationship are fit with the neural network. It is intuitive to use a time delay neural network to predict these residuals, as they respect sequential data and can find complex, non-linear relationships by learning their own parameters. This hybrid model outperforms both ARMA and time delay neural networks when used individually in terms of root mean square error.

Indirect methods of estimating solar power output are still relevant today, particularly in conjunction with support vector machines. [14] uses three kinds of images provided by the Korean National Meteorological Satellite Center spanning four years: atmospheric motion vector images outline the wind direction and speed at three different altitudes, cloud analysis images provided detailed information about the properties and number of clouds (ranging between 0 and 100), and irradiance images relay the amount of light reflected back into space.

Two support vector regressors are trained on these images to predict both cloud impact and irradiance. A radial basis function kernel is used to achieve the non-linear relationship between the independent and dependent variables. This method was shown to outperform other familiar approaches in terms of root mean square error, mean relative error, and the coefficient of determination, and can be used to forecast anywhere between 15 and 300 minutes.

Despite its high performance, this method has several drawbacks. First, training the support vector machines requires four years of data: despite the abundance of satellite data available today, training time is a concern. Second, when analyzing the cloud impact factor, this approach does not assume any formation or disappearance of clouds, an issue that [8] also faced.

Additionally, predicting future clouds becomes less precise when the number of clouds over an area is not at either extreme (neither 0 nor 100), which is a fundamental issue faced by a number of solar prediction approaches. Specifically, pursuing short term solar power forecasts is useful because it can help operate solar farms on days where irradiance might vary significantly, but this approach performs at its worst when clouds are intermittent. Despite this, this method outperforms several other approaches, making it a good choice for solar power prediction.

Direct Approaches

Direct approaches draw on different kinds of historical data to directly estimate the amount of power generated, rather than the irradiance of a particular area. In the literature, this is often achieved through the use of support vector regression, particularly in recent studies. [15] predicts the output of a specific power plant in Kitakyushu, Japan. Support vector machines are powerful because they allow users to choose whether to prioritize training accuracy or maximum margins. In this paper, v-support vector regression is used, which prioritizes training accuracy.

The support vector regressor uses six input parameters, which include extraterrestrial insolation, temperature, humidity, and low, mid, and upper level cloudiness. Except for a single calculated variable (extraterrestrial insolation), all parameters are available from standard meteorological sources, making this approach transferable to many different locations.

This paper achieves particularly impressive results in the spring season, and poorer results in the summer. In Japan, spring is generally clearer and summer is accompanied by a rainy season, indicating that, similar to [14], this approach fails to predict accurately when predictions are most necessary. This is a potential drawback of this approach, as it is less helpful when the highest levels of prediction uncertainty exist.

A similar issue is faced throughout the literature. [16] also employs support vector regression, but creates four different models based on the category of weather forecast for the day of prediction. One of the four models is chosen based on whether the day is cloudy, foggy, sunny, or rainy. Data from previous moments are used to predict the solar output with the chosen model. Similar to the previous paper, prediction errors were highest for the cloudy model. However, the data was collected in southern China, which largely has non-cloudy days. Therefore, this may simply be a result of an unbalanced data set. Additionally, the lower performing cloudy model may be acceptable for this area, as there are few cloudy days. Future work could involve training this model in cloudy climates to see if predictions improve.

Promising results in direct power prediction can be obtained with hybrid models as well. One such hybrid model combines a self organizing map, a linear vector quantification network, a support vector regressor, and a fuzzy inference approach to make predictions. First, a self organizing map (a type of unsupervised clustering network) takes a vector corresponding to hourly photovoltaic power output and returns a vector of weather values, which is used by the linear vector quantification network to classify a weather type. In tandem, these two models classify the weather based on photovoltaic properties.

The weather classification, along with temperature, month, probability of precipitation, and verbal cues, is then used by a fuzzy inference procedure to select one of six support vector machines, which then predicts the power output. Using mean relative error and root mean square error as evaluation criteria, this method achieves mixed results when compared to a standard support vector regressor and an artificial neural network. However, for most months, the proposed model tends to perform better than either of the other two models.

However, this model is rather complex and more difficult to understand. Additionally, six individual models are trained. Although this may make each model more accurate, each model tends away from generalization, and as a result the overall approach might not be as easily transferable to another photovoltaic plant in a different part of the world. The concern is heightened by the fact that the fuzzy inference parameters are achieved through trial and error, which means that additional effort will be required for this model to train on different data sets than if the parameters were estimated through more analytical means. However, the model achieves good performance on most days, with the single noted exception being on typhoon days, which may be a concern in Taiwan, from where the data was retrieved.

A common theme among earlier literature in this review is the reuse of parameters that are assumed to be important, such as temperature and precipitation. Although this has yielded viable results, there may be more important parameters available for predicting photovoltaic output. One potential solution to this problem involves the use of a least absolute shrinkage and selection operator, referred to as LASSO. LASSO is often applied to linear regression as a regularization term that eliminates unimportant features by weighting them with values near 0.

[17] uses a LASSO-based algorithm to predict solar power, with the expressed purpose of identifying important parameters and using less data to make more accurate predictions. These goals are significant particularly because certain models, such as those in [15] and [16], rely on weather data from local stations, and knowing which parameters are most important can help stations prioritize which measurements to take. Additionally, the low amount of data required makes this approach extremely accessible, particularly to those areas which may not have historic data available to them. In fact, this paper found that data from the previous month was sufficient to predict power output.

In particular, this paper attempts to estimate a relatively standard regression model. A link function f is estimated, X is a unit normalized vector containing information from a weather station, and Y is the predicted solar intensity.

$$Y = f(X^T B) + error$$

The input data to this model is relatively small, consisting of only five parameters. The coefficients B are found using the LASSO regularization term. The weight of the regularization term, which determines how much influence it should have on estimating B, can be determined either with cross-validation or the regularization path method, in which the performance of models trained with different weights on the regularization term is plotted, and the weight with the best performance is used.

The proposed method is compared to other algorithms (specifically, SVMs and TLLEs) using U.S. and U.K. datasets, and found to outperform both in terms of root mean square error and mean absolute percentage error, even when using significantly less data. Improved results were even shown to occur when only 15 days of data was used in training. This method also reveals that dew point and wind speed are significantly less important predictors of solar output than temperature, precipitation, and humidity, which reinforces much of the earlier works' use of these parameters. The low amount of data used by this approach, its high performance, and the fact that it reveals important parameters make it a reasonable approach to predicting power.

Limitations and Future Work

Several limitations to the methods of solar power prediction described above have already been discussed, ranging from the assumptions papers make to the complexities of their models. Overall, however, there are a number of limitations made across many of these works that deserve attention.

One of the most substantial limitations for many of these models is rooted in their scope. For many of them, these models are designed to predict solar power over a specific location. [14], [15], [16], and [17], for instance, focus their study solely on South Korea, Japan, southern China, and Taiwan, respectively. The intention of this narrow scope is to predict one particular case very well. Features pertaining to weather conditions may, for example, only be available in certain areas and not others, and it is intuitive to use features that may only be available in limited cases if they are more informative that features found everywhere. However, this limits each study's impact to a small scope.

Many of the indirect approaches solve this issue by relying largely on satellite imagery, which captures the entire globe and is becoming increasingly available. Unfortunately, these approaches rely on an accurate conversion from solar irradiance to solar power. Although methods to tackle this issue are well established, the extra conversion step allows for another point of failure, which may affect the overall accuracy of these methods.

Additionally, many of these methods have varying success based on the time of year or weather condition. [12], [15], and [16], for example, describe worsened performance during rainy and cloudy weather when compared to clear skies. Some methods ([11] and [16]) attempt to correct this by training a different model for each weather condition, but these methods still suffer in cloudy conditions. One survey paper [18] compared the performance of a number of different standard machine learning models on solar prediction. The clear sky index is used to classify the weather, where the clear sky index is defined as the ratio between the actual solar irradiance of an area to the solar irradiance with a clear sky [19], with 0 indicating a complete blocking of light and 1 a completely clear day. On average, performance worsened significantly between a clear sky average of 0.1 and 0.3, in terms of normalized mean absolute error (fig 1). The implication is that somewhat cloudy days tend to have worse performances than either mostly sunny or completely cloudy, weakening them in conditions in which predicting the amount of solar power is the most difficult, which is when it would be most valuable.

A large portion of the literature is concerned with predicting solar power in the near term with the expressed purpose of managing energy grids. In this pursuit, all of these papers suggest future work intended to boost the performance of their respective approaches. Beneficial efforts to meet that goal include rectifying any of the limitations outlined above. In particular, attempting to find a globally applicable model would make solar power generation more accessible.

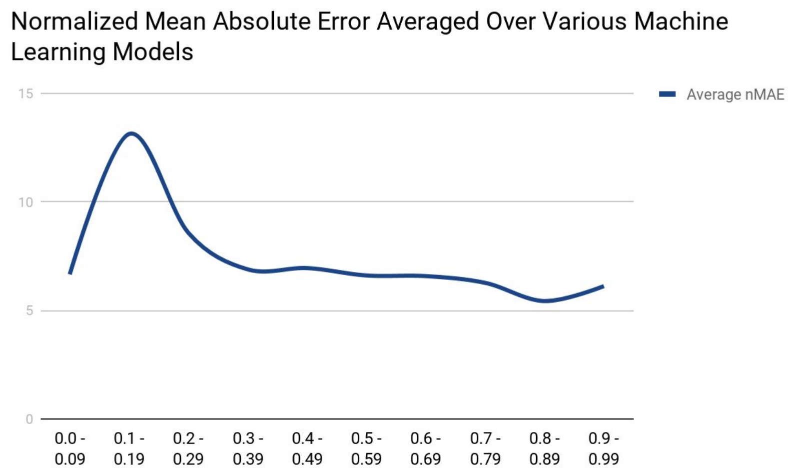

Fig. 1

Additionally, this work could extend into long-term solar power prediction, with the purpose of predicting which locations could host effective solar power farms. Some literature already exists in this area, although it is less common than short term forecasting. [20] analyzes year-long solar power in Cairo, Egypt, in order to predict the most optimal tilt for solar panels to be installed. [21] analyzes the distribution of solar energy to improve risk-assessments of investing in solar farms, in effect estimating the potential to harvest solar energy at various locations. We propose drawing on short-term forecasting techniques to develop long-term techniques, potentially by averaging weather conditions at various times of the year and estimating how much energy would be produced. More work needs to be done to know whether this would be a promising approach or not.

III. Wind Power

Similar to solar power, machine learning methods have been applied to forecast wind power. Wind can be sporadic and difficult to predict, but doing so allows for better load forecasting and more efficient wind farm management [22]. Prediction is also difficult because wind fluctuates across relatively small spaces, such that wind measuring instruments located in different locations of the same wind farm often read different values from each other and from the turbines they are meant to measure [23].

In general, methods of predicting wind power can be divided into two subcategories: point prediction models, which aim to find a single estimation value for wind production, and prediction interval models, in which predictions come in the form of a confidence interval.

Point Prediction

Point prediction approaches estimate a single wind energy value. This approach has yielded promising results in a number of cases, and is generally less difficult than predicting a confidence interval. [23] uses this method to detect defects in wind turbines.

Data is taken from the Central and South West Services Fort Davis wind farm. Specifically, the data can be divided into two sources. Meteorological towers provide information like wind velocity and direction, whereas wind turbine generators provide information like average power output. In conjunction, these two data sources provide a labelled data set, allowing for the use of a supervised neural network.

Wind velocity and direction are taken from two meteorological towers located in different parts of the wind farm, providing four inputs to this neural network. In fact, the neural network follows a simple 4-8-1 architecture, making it accessible and easy to replicate. This surprisingly simple architecture is the result of the major design decision to train a different neural network for each of the farm's 12 turbines. In addition to simplifying each network, this approach makes scaling this prediction method to farms of any size relatively trivial, as it can be done by simply training one neural network per turbine. Additionally, predictions can continue for individual turbines even when others need to be disconnected or serviced.

Neural networks are used extensively throughout wind prediction literature, both on their own and as part of a hybrid system. [24] uses an adaptive neuro-fuzzy inference system, in which fuzzy inference is implemented with a neural network. Fuzzy inference systems are comprised of a knowledge base, a decision making unit to perform the inference, and both a fuzzification unit to transform crisp input into fuzzified information as well as a defuzzification unit to translate fuzzy results back to crisp output. They can model qualitative information well, making them suitable for work with high-level knowledge [25]. However, fuzzy inference systems cannot learn, so a 6-layer neural network, where each layer implements a different part of such a system, is used for training. In this way, [24] forms a high-level system where parameters are learned automatically from the data to make 2.5 minute forecasts. Using 21 months worth of data from a Tasmanian wind farm, 4% mean absolute percentage error is achieved.

The neural network component of this system allows it to be trained without needing to explicitly identify important parameters, which makes this approach easy to train on any wind farm. However, success has only been shown in a case that has 21 months worth of training data. Future work could analyze whether this method is applicable to wind farms with less data.

In contrast to very short term forecasting, [26] forecasts three days worth of wind by training three recurrent neural networks on data from Crete, Greece. Recurrent neural networks are a natural choice, due to the time-sequential nature of wind. Three types of recurrent neural network are used in this paper: IIR-MLP, LAF-MLN, and DRNN. The IIR-MLP can be thought of as a standard multilayer perceptron in which weights are replaced with IIR filters, known and introduced earlier in this review as autoregressive moving average models. LAF-MLNs, similarly, employ autoregressive moving averages. However, rather than making every weight an autoregressive moving average, an autoregressive output is applied to a node-summing layer before being used in an activation function: this means that there are less weights to train than in an IIR-MLP. A DRNN is simply an IIR-MLP limited to one hidden layer.

Four measurement nodes are located north, west, east, and south of the wind park, providing information about wind speed and cross-correlation between the nodes' measured wind speed and the actual wind speed. The southern node is discarded as input because its cross-correlation is lowest. Each of the three recurrent neural networks is trained on six inputs, the wind direction and speed from each of the nodes. All three recurrent neural networks are shown to outperform static multilayer perceptrons in forecasting, which reinforces the intuition that the sequential pattern of data is significant in wind power prediction. Similar to [23], the neural network architectures used here are relatively simple. Although these models are designed only on one specific farm, these simple architectures make it easy to apply these approaches to different wind farms' data sets.

Although commonly used in wind prediction literature, neural networks are not the only approach to wind prediction. Recent work in particular has drawn upon support vector machines. In [27], support vector regression is paired with an empirical mode decomposition to predict wind power. Empirical mode decomposition has the capability of transforming non-stationary data into a finite collection of intrinsic mode functions and a single residue [28]. In general, support vector regression performs better on these intrinsic mode functions than on non-stationary data. Wind time-series data is non-stationary by nature, so the use of empirical mode decomposition is a necessary preprocessing step.

Once intrinsic mode functions and residues are computed, the proposed method selects attributes to be fed into the support vector regressor. The model is shown to outperform neural networks and previously attempted empirical mode decomposition hybrid models in most cases, but underperform in other cases, particularly as the forecasting period increases, making this model more suitable for short term predictions. Despite the underperforming cases, this model is simple when compared to previously used empirical mode decomposition hybrid models.

Point prediction models can be beneficial for a number of reasons. Often, single values are more helpful than ranges of values, particularly when the value is to be used in some sort of calculation. Furthermore, point prediction models have traditionally been easier to implement that prediction interval methods, which require special assumptions regarding data distribution and high computational power [29]. However, due to the uncertain nature of wind, point predictions can be misleading, and often a prediction interval is desired.

Prediction Intervals

Prediction interval approaches encompass a wide variety of wind power prediction models. In general, prediction intervals attempt to provide a narrow margin of potential values while maintaining a high confidence level. This is especially appropriate for wind prediction, in which power output can change rapidly, leading to uncertainties.

In [29], a technique known as lower and upper bound estimation is used to overcome some of the difficulties of prediction interval implementations, as it does not require assumptions about data distribution to be made and avoids computationally expensive operations. LUBE constructs a neural network with two outputs, corresponding to a lower and upper bound. Sixteen inputs for the neural network are empirically chosen using previous literature. The number of nodes for hidden layers were chosen analytically, resulting in a 16-8-1-2 structure. This small architecture is beneficial; The model can be trained on alternate data sets quickly, as there are only 256 total weights to learn.

The objective of this neural network is to minimize the width of the margin while maintaining a high confidence level. To that end, PINAW is used as a measure of the width of a margin. PICP measures the probability that target values will be covered by a certain interval. Traditionally, both of these values are fed into CWC, which provides a single measure indicating the quality of an estimated confidence interval. However, training on CWC requires the estimation of three separate parameters. To avoid this issue, an alternate objective function is proposed, where PINAW is minimized while constraining PICP to a fixed value, avoiding CWC calculations. Tests indicate that this method outperforms other methods of prediction interval estimation, and demonstrates the high quality of resulting intervals through repeated testing.

Prediction intervals can be estimated with alternative methods as well. [30] compares a multilayer perceptron based on the LUBE method (similar to the one developed in [29]) and an extreme learning model (a feedforward network that is not subjected to local minima) in conjunction with k-nearest neighbors. The extreme learning method is used to train point predictions, which are then transformed into intervals with the k-nearest neighbors algorithm.

As a result, any of the point prediction algorithms described earlier could be used to construct prediction intervals. K-nearest neighbors is a relatively simple algorithm to implement, and the only added complexity to using this approach is the selection of k. Even so, this can be done by trial and error, as in [30]. When compared to the multilayer perceptron, the ELM model produced similarly reliable prediction intervals, as measured by normalized root mean square error. As a result, using an approach similar to this one becomes a viable method for forming prediction intervals from point prediction methods.

Limitations and Future Work

Many of the limitations regarding solar power prediction methods apply to wind prediction as well. In particular, wind prediction research has traditionally been tied to individual wind farms. All of the works discussed ([22], [23], [24], [25], [26], [27], [29], and [30]) make assumptions grounded in the particularities of the wind farms from which their data is retrieved. As a result, these models are not transferable to different wind farms.

However, it is more reasonable to expect a globally applicable wind prediction model than a globally applicable solar prediction model. Models developed for wind power estimation are generally less complex than models built for solar prediction. [23] and [29], for instance, are based on simple neural network architectures, which require relatively few weights to be trained, making training an efficient process. Additionally, a majority of methods use similar inputs to make predictions, although their sources differ. Wind velocity and direction are common parameters in [23] and [26], for instance. In future work, a combination of these observations could be considered in an attempt to make more universally applicable models.

Additionally, we predict that future work in this area will begin to focus more heavily on prediction intervals than point predictions. Although the point prediction literature outnumbered the prediction interval literature in this review, most of the compelling reasons to choose point predictions are with regard to the difficulty and computational intensity of making prediction intervals. However, [29] and [30] demonstrate simple, efficient methods to create prediction intervals. As a result, we expect more papers will tend towards this approach.

Conclusion

In this literature review, several approaches to solar and wind energy prediction were outlined and analyzed. Solar energy was shown to be predictable both through indirect and direct measures, whereas wind energy could be compared based on whether the prediction was a single value or a range of potential values. Although the approaches vary significantly, common limitations exist between them. Most methods tend to be location specific, which makes transferability a nontrivial task in many cases. Additionally, solar energy predictions tend to suffer in weather that is between completely sunny and completely cloudy, when intermittent conditions most likely exist, weakening their reliability when predictions are needed the most.

Future work in this field could involve attempts to fix these limitations, as well as overall predictions for long term energy forecasting, which may reveal suitable areas to establish solar and wind farms. Finally, we predict that future wind prediction methods will prefer prediction intervals over point predictions, as many of the obstacles preventing the prediction of intervals have been overcome.

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