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# Intelligent multiperiod wind power forecast model using statistical and machine learning model

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**ABSTRACT**

With the rapidly increasing integration of wind energy into the modern energy grid system, wind energy prediction (WPP) is playing an important role in the planning and operation of an electrical distribution system. However, the time series data of wind energy always has nonlinear and non-stationary characteristics, which is still a great challenge to be accurately predicted. This paper proposes the intelligent wind power forecast model and evaluates to forecast long term, short term and medium term wind power. It uses statistical and machine learning approach for finding the best model for multiperiod forecasting. The model has been tested on Sotavento wind farm historical data, located in Galicia, Spain. The experimental results show that random forest has better accuracy than other models for long term, short term and medium term forecasting. The power prediction accuracy of the proposed model has been evaluated on RMSE, and MAE metrics. The proposed model has shown better accuracy for medium term and long term forecast. The accuracy is improved by 72.12% in case of medium term and 50.49% in case of long term.



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## 1. INTRODUCTION

The intelligent and smart systems in science and technology have increased the comfort level in human life. However, the demand generates energy crises. Conventional energy source fossil fuel generates pollution [1] because of this renewable energy, such as wind gaining more attention and importance. Worldwide, wind power, among other forms of renewable resources such as solar energy, bioenergy, hydropower, tidal wave has been considered as one of the sources of power generation growing faster due to economical ways of harnessing the kinetic energy of the wind [2]. Wind power is a sustainable and clean source of energy which does not lead to any hazards to the environment. Hence, wind power generation is the main goal of many countries. Wind power generation [3] is quite an uncertain process because of intermittent and chaotic nature of wind. This could lead to huge loss in the energy distribution sector. The accurate prediction of wind power from the wind generation farms has become crucial and challenging all the time. Electricity generated by windmill changes according to the fluctuation of wind speed and direction. The accuracy in prediction of wind power directly relates to profitability and penalty.

In the future almost 100% or near to that, renewable energy will be the primary source therefore load balancing in grid will have to cope with the intermittent nature of wind energy. In this context, more reliable wind energy forecasting techniques should be developed to maintain not only grid stability, but also for saving the overall system. A small 1% increase in forecast quality would save US$140 million in the United State [4]. Wind power forecasting periods vary in different literature. Mainly it is categorized into four spans, very short term, short term, medium term and long term. Table 1 summarises the precise classification, temporal range, and application purpose of different horizons based on author reviews [5].

Table 1. Time horizon for wind power prediction approaches

| Time horizon | Time range | Applications |
|---|---|---|
| Very short term | Up to 90 minutes ahead | Regulation actions, intraday trading, to maintain grid stability, to reduce penalties |
| Short term | Up to 6 hours ahead | Planning of load dispatch, for taking decision to increment/decrement load |
| Medium term | Up to 1 day ahead | Security for the next day electricity market |
| Long term | 1 day to 1 week or more ahead | Maintenance planning, optimum operation |

The importance of wind speed to predict wind power, the literature [6] estimated values of wind speed by applying appropriate methods, and predicted wind power, this method is called an indirect method. Wind power forecasting is done directly in the direct approach, without the need for a previous phase in which the wind speed is estimated. Many researchers have been focused on the development of reliable wind power forecasting models, various models have been proposed. Models used by researchers [7] are mainly classified into physical [8], statistical [9] and hybrid [10] classes.

The primary part of wind power forecasting is estimating future values of the meteorological variables needed at the wind farm level, because wind power is directly related to weather conditions.Weather forecasting [11] can be handled by global or regional models with different resolutions. This is done using the numerical weather forecast (NWP) [12] model. NWP models are generally computed using supercomputers in meteorological departments or research institutes, to deal with larger resolutions and better representations of atmospheric processes. These models are based on mathematical calculations that represent the state of the atmosphere, including turbulence, pressure, and radiation levels. Navier-Stokes equations are frequently employed to describe the movement of viscous liquids in addition to the laws of physics. These models are used not only for predicting one particular purpose, but also for various industrial and scientific applications. The model not only predicts wind speed, but also atmospheric conditions at a particular location and time. The weather variables necessary as input for wind energy forecasts not only required wind speed and direction, but also pressure, humidity, and temperature.

Pearre and Swan [9] describes the relationship between wind speed or power predictions and explanatory variables, including historical online measured data and NWP data [13]. General structure of statistical models typically uses historical data and NWP data to build models. These approaches are easy to model and less expensive. Traditional statistical methods apply time series models to predict future wind speed or wind power. On univariate time series analysis, many types of time series models are utilised, such as the moving average model (MA), autoregressive model (AR), autoregressive moving average model (ARMA) [14], and autoregressive integrated moving average model (ARIMA). If in the moving average model, q has an order of zero; it represents an autoregressive model (AR (p)) of order p. For an autoregressive model, if p has an order zero then it represents an autoregressive model (AR (p)) of order p. ARMA (p, q) is a p-order autoregressive and a q-order moving average model. A generalisation of an ARMA model is the ARIMA model. In summary, traditional statistical approaches are mainly used for short-term and very short-term forecasting.

With the rapid development of machine learning in the past 20 years, many non-linear forecasting models have been introduced for wind power forecasting [15]. In literature it is found that most commonly kNN [16], SVM algorithms [17] and random forests [18] were used. The purpose of hybrid models [19] is to utilize each model for optimal predictive performance. Because the information contained in each prediction method is limited, the hybrid method maximizes the information available and integrates the individual model information, maximizing the benefits of multiple prediction methods and improving prediction accuracy [20]. Hybrid technology is a combination of different approaches, including a combination of short-term and medium-term models and a combination of physical and statistical approaches, and so on. Shi *et al.* [21] proposed two hybrid models for wind speed and power forecasting, ARIMA-SVM and ARIMA-ANN. They conducted a systematic and complete examination on two case studies for wind speed and wind power generation. The result shows that the proposed hybrid approaches do not always produce superior forecasting performance for all the forecasting time horizons. Zhao *et al.* [22] developed a hybrid wind prediction method consisting of an NWP model and an ANN model [23]. The NWP model is set up by combining a weather research and forecasting (WRF) system with global forecasting system (GFS) to predict weather parameters.

The scope of the work and the objective is to reduce the penalty by contributing in highest accuracy models from available resources and parameters. The main objective is to reduce large forecasting errors, which is responsible for most of the problems and costs with system operations. This paper also proposes and analyzes wind energy prediction models, to analyze the best evaluation parameter for statistical and machine learning (ML) models. The paper organized as; 'proposed methodology' section describes a detailed description of the wind power forecasting method and provides the generic architecture of the proposed model. The 'experimental result' section describes the results obtained through experimentations, and finally the 'conclusion' section provides relevant conclusions.

## 2. PROPOSED METHODOLOGY

Although physical models are widely used, there are some disadvantages as well. Consumers rely for weather services on weather forecasts service providers. The time scales available are always fixed, and forecasts are only available at specific times. Due to the chaotic nature of the atmosphere, providing good predictions using a physical model is a very challenging task. Therefore, for the short-term prediction, other approaches such as statistical learning are used. Literature survey presented by Galphade *et al.* [23], shows that statistical methods do not adapt to non-linear wind data, do not easily handle large amounts of data, and cannot predict long periods of time, so statistical methods cannot be the first recommended method of prediction.

To overcome the gap in the literature a wind power forecasting model is proposed herewith, which uses statistical and machine learning models for finding the best model for multiperiod forecasting. This proposed architecture comprises five major phases, such as data collection, data pre-processing, feature selection, stationary test, model building and model performance evaluation as shown in Figure 1.

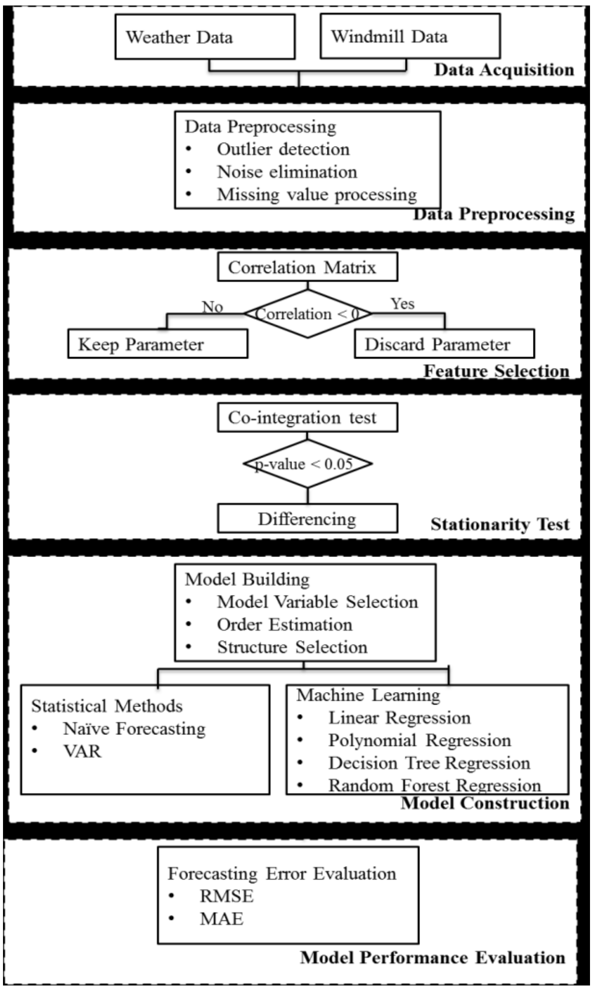



Figure 1. Wind power forecasting architecture

Historical data from the Sotavento wind farm in Galicia, Spain (43.354377°N, 7.881213°W) is used in this paper. The corresponding weather data may be obtained from the world weather online forecast system (https://www.worldweatheronline.com/) using the latitude and longitude coordinates of the Sotavento wind farm. The proposed forecasting model is tested using five years of data from 2014 to 2019. The data has an hourly resolution, and the predicted lengths are short, medium, and long. The parameters and their unit used in this dataset are: dew point (C), cloud cover, humidity (Kg kg-1), pressure (K Pa), temperature (C), speed (m/s), direction (degree), and energy (kWh).

In order to predict future values, the series should not contain any trend, seasonality and cyclic component. Differencing [24] is a widely used method to remove all these components. After removing trend, seasonality and cycles the series become a stationary series which have a stable mean and variance. Time series usually come from live observation or sensors which may contain noise and outliers [25]. Such noise and outliers are caused because of sensor error or equipment downtime interference. So before starting analysis one should clean the data so as to avoid the wrong conclusion. Noise removing can be handled by using traditional signal processing techniques such as digital filters or wavelet thresholding [26]. To filter outliers, k-nearest neighbor clustering [27] is widely used. Another issue is scaling, normalization is used to make sure all the data is in the appropriate scale. The dataset is plotted using a correlation matrix [28] as shown in Figure 2. The correlation matrix values ranges from -1 to +1, where -1 is a weakly related entity and +1 is strongly related. As per correlation matrix dew point and temperature are negatively related, so can be neglected.

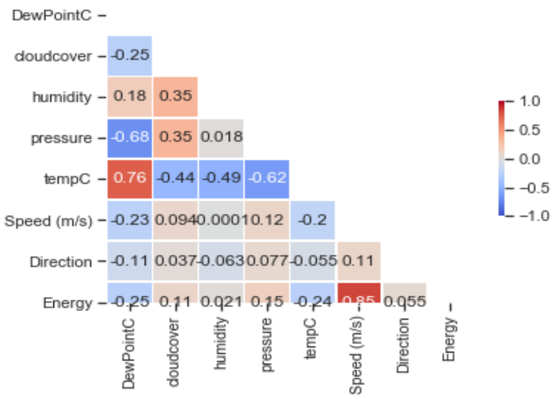



Figure 2. Correlation matrix

To confirm the stationarity of a time series data, a unit root test is done on the univariate time series and a Co-integration test is used on the multivariate time series. The dataset for experimentation is a multivariate time series dataset. The adfuller function is used, which returns a tuple of statistics such as Test statistics, p-value, number of lags used and number of observations used. If p-value is less than significant level (0.05), reject null hypothesis which states that there is presence of unit root. All the univariate time series has p-value less than 0.05, which means multivariate time series has stationarity. Different models were selected in this study. naive forecasting and vector AutoRegression are two statistical approaches, and machine learning models include multiple linear regression (MLR), polynomial linear regression (PLR), decision tree regression (DTR), and random forest regression (RFR).

## 3. EXPERIMENTAL ANALYSIS

Experimentation was done on Google Colab using standard libraries. Scikit-learn is the most helpful machine learning library in Python. Regression, classification, clustering, and dimensionality reduction are among the many useful tools for statistical modelling and machine learning. Statsmodels is a Python package that allows users to explore data, estimate statistical models, and perform statistical tests. The proposed model predicted results are compared with existing power generated data on all three time horizons; the same is shown in Figures 3 (a)-(e). The dataset contains 52584 records of 8 parameters. For medium term and long term prediction the same dataset is used by applying resampling. To resample data, down sampling by decreasing frequency of data from hourly to daily has been used. For medium term data resampled from hourly to daily and for long term hourly to weekly.

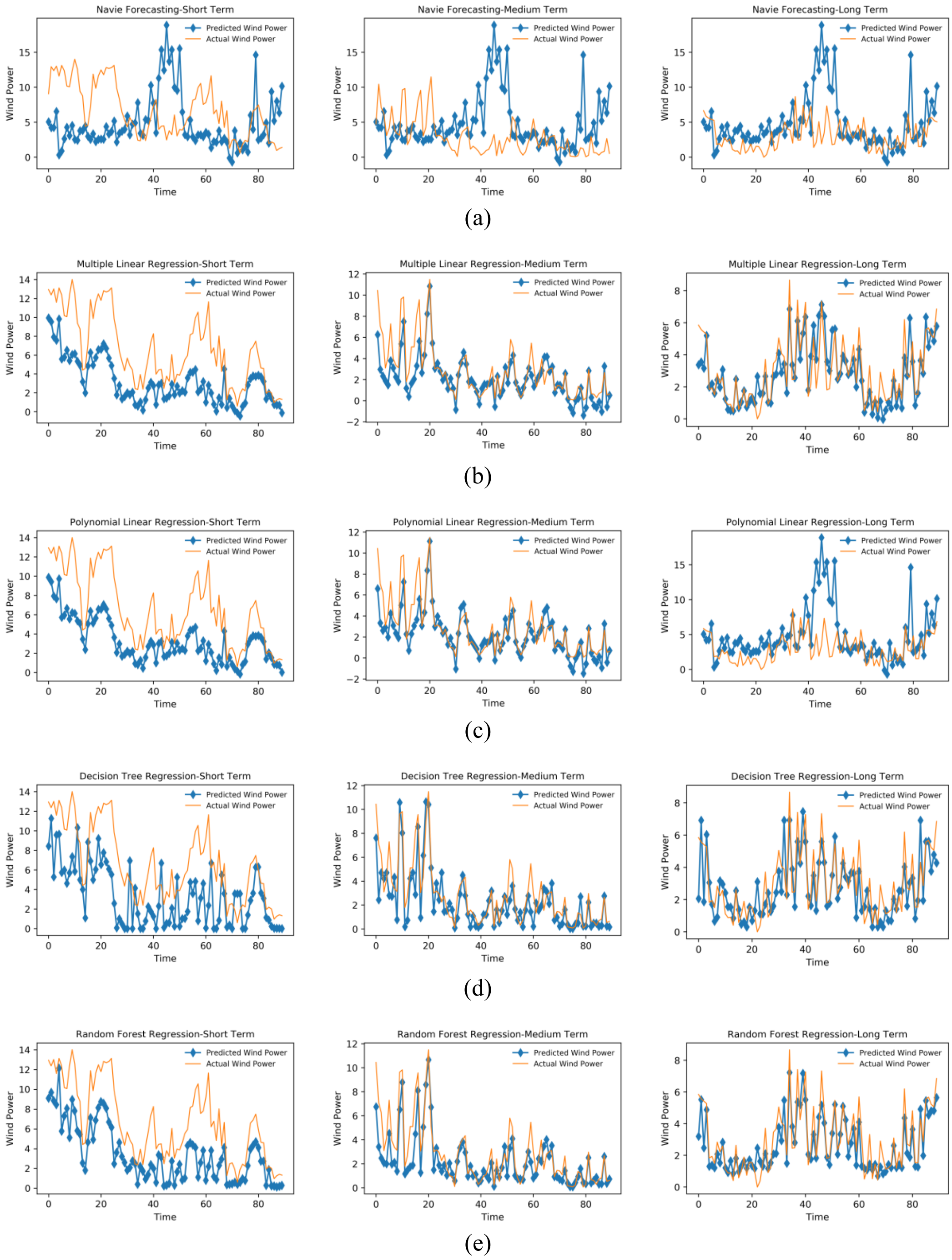


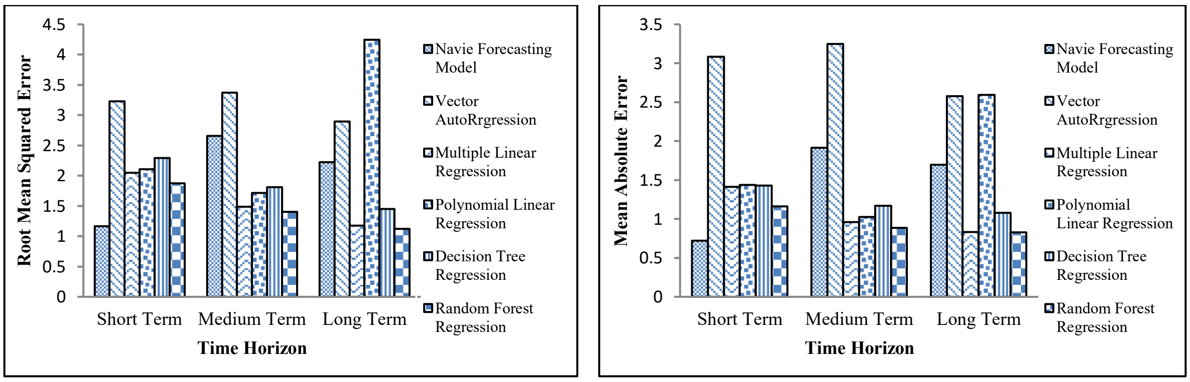

Figure 3. Wind power forecasting (a) Naïve forecaste, (b) multiple linear regression, (c) polynomial linear regression, (d) decision tree regression, and (e) Random forest regression

In this experiment, the mean absolute error (MAE) and root-mean-square error (RMSE) were applied as evaluation indicators. The RMSE and MAE of various algorithms are illustrated in Table 2. As per MAE and RMSE value random forest has best prediction accuracy for the three time horizon. In addition, the multiple linear regression model is second to the random forest. This study obtained the lowest error index in training dataset of RF model, indicating that RF model has good training capabilities. These results indicated that the RF model performed significantly better than the other models. Many environmental variables have an impact on wind power predictions. In many cases, the relationship between output variables and environmental variables is complex and nonlinear. The MLR model can only explain the variation of output variables that are linear. As a result, when the MLR model is used to fit the connection between the dependent variable and the environmental variables, the results are frequently unsatisfactory. The RF model does not require assumptions about the relationship between output variables and environmental variables, and it can handle non-linear correlations that the MLR model cannot. Furthermore, when compared to other estimating approaches, the RF model has the advantages of anti-overfitting, noise insensitivity, and unbiased error rate measurement, all of which contribute to improved estimation accuracy.

Table 2. Performance evaluation using RMSE & MAE

| Method | Technique | Short term | | Medium term | | Long term | |
|---|---|---|---|---|---|---|---|
| | | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| Traditional | Naive forecasting model | 1.167 | 0.721 | 2.655 | 1.915 | 2.226 | 1.696 |
| statistic method | Vector AutoRegression | 3.229 | 3.083 | 3.374 | 3.248 | 2.894 | 2.577 |
| Machine | Multiple linear regression | 2.051 | 1.411 | 1.489 | 0.959 | 1.177 | 0.834 |
| learning | Polynomial linear regression | 2.109 | 1.437 | 1.714 | 1.025 | 4.244 | 2.595 |
| | Decision tree regression | 2.292 | 1.427 | 1.81 | 1.169 | 1.45 | 1.078 |
| | Random forest regression | 1.872 | 1.163 | 1.404 | 0.885 | 1.124 | 0.829 |

As can be seen from Figures 4(a) and (b) statistical methods perform well for a short time interval, as the duration of prediction increases, error also increases. However in the case of machine learning algorithms, all perform well for long term forecasting. The findings demonstrate that overall performance of the proposed model using random forest is better on long term and medium term time span, however it is difficult to beat the naïve model for short term prediction. The plot graph in Figure 4 shows a time horizons vs error variation. It helps in determining the most suitable strategy for wind power forecasting over various time frames. The medium term accuracy on RMSE variation is 1.915 over the reference model RMSE variation 2.655. This believes that the intelligent proposed model is ~ 72% better on error variations. Also for long term accuracy on RMSE using proposed model is ~ 51%




(a) (b)

Figure 4. Performance evaluation (a) RMSE and (b) MAE

## 4. CONCLUSION

Wind power forecasting has been treated as a challenging problem so far, due to the intermittent and uncertainties of data inputs and generation parameters. According to research, machine learning predictions are less expensive than NWP and are less vulnerable to faulty data or human mistakes. As the world gets more digitalized, machine learning may help to make processes more automated and error-free. The most frequent methods in wind power forecasting, according to the state-of-the-art, are neural network and RF. In this paper, the popular machine learning techniques applied to wind power forecasting have been empirically analysed. Most of these learning algorithms have been successful at approaching predictive analytics and outperform predictive problems. Statistical model, Naive forecasting was used as a reference model.

The experimental results show that compared with statistical approach, the performance of machine learning algorithms is better in terms of accuracy. Statistical methods perform well for short-term forecasting, but fail to predict long term forecasting, whereas machine learning algorithms have shown overall ~ 72% in medium term and 51% improvement in long term forecasting. Random forest has achieved the most efficient results in terms of RMSE and MAE evaluation methodologies because RF ignores irrelevant input data and could predict outliers. Because RF ignores unnecessary input data and can forecast outliers, it has produced the most efficient outcomes in terms of RMSE and MAE evaluation methodologies. The proposed intelligent architecture of multiple machine learning algorithms tested for large volume of datasets to predict short term, medium term and long term forecasting. Very short term forecasting was not included in this empirical study; however the work may be extended by combining statistical and deep learning approaches for predicting very short term forecasting.

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