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Time Decoupled Prediction Models for Wind Speed and Solar Forecast

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***Abstract* - With the increased necessity to integrate renewable energy into the existing power system network, methods aimed at optimizing the gap between demand and supply become important. This has drawn the interest of utilities towards developing and using state of the art forecasting techniques to predict wind speeds and solar irradiance over a wide range of temporal and spatial horizons due to their high dependence on local meteorological conditions, so as to more accurately forecast and deal with the variable power output from these plants. An efficient model that can predict wind speed and solar irradiance has become paramount. The paper has used a time series decoupling strategy to enhance accuracy of prediction. Instead of treating the data as a single time series, it is split into multiple time series in which each time series carries the historical data at a particular time of the day being considered. This has been applied to both solar irradiance and wind speed. By exploring conventional statistical models like Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) with the use of time series decoupling methodology, we were able to perform a comparative analysis to assess the impact of the strategy as a singular variable that affects outcomes.**

***Index Terms* - Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), decoupling strategy, Forecasting, solar irradiance.**

I.INTRODUCTION

There has been unprecedented growth in the amount of renewable energy generation over the past decade. Even with focused energy conservation and enhancement of efficiency of the current systems, the fossil fuels which are primary sources of energy are fast depleting. The electricity system in India faces several challenges as the energy de- mand is expected to grow significantly within the next decades while the domestic energy resources in terms of fossil fuels are limited. The Indian grid has a grid connected RE capacity of 31.69 GW (January 2015) which is around 12% of the overall installed capacity of 258.7 GW. Integration of big quantities of power in the grid has significant challenges in both technical and economic in nature. Despite its numerous attractions, increased renewable power generation is not without vagaries. In scheduling the generation and demand a few hours ahead, generators and distribution companies are required to project their schedules a prior to enable load dispatch centers to operate the grids reliably. Accurate forecasting models are required to improve electric power quality and thus reduce the cost ensuring secure and economic integration into the smart grid. The primary purpose of forecasting intermittent renewable generation is to determine as accurately as possible the power output of the generation plants in the (15-minute, 30-minute or hour-ahead) and day-ahead time periods.

Among the existing renewable near term energy sources, solar energy and wind energy have great potential for electric power conversion and contribute to the electrical energy demand of the planet. These sources are practically inexhaustible, available at no cost and non-carbon sources reducing the hazard of green- house gas emissions. It is the cheapest method of generating electricity compared with other energy sources. The energy obtained from solar radiation that is incident on Earth in one hour (4.3 x 1020 J) is much higher than the consumption of the planet in a year (4.1 x 1020 J). PV cell, a semiconductor device is used to convert the sunlight energy into electricity without going through any energy conversion steps with an efficiency of around 15-20%. Wind energy is a free, clean and easily available renewable energy source. The wind turbines capture the wind's power and convert it to electricity in a sustainable manner. The offshore wind industry is projected to grow from 17 to 90 GW within the next decade. Wind power a constitute for nearly 10% of India's fully installed power generation capacity and generated 62.03 TWh in the fiscal year 2018-19, which is nearly 4% of total electricity generation. Harnessing these for electricity depends on the cost and efficiency of the technology, which is constantly improving, thus reducing cost.

II. FORECASTING TECHNIQUES

Forecasting is a technique that uses historical data as inputs to make informed estimates that are predictive in determining the direction of future trends. Load forecasting has been established earlier to provide for an accurate prediction of the electric load de- mand over different future horizons. However, Generation forecasting plays a vital role in renewable power generation to have a better load scheduling.

2.1 Forecast Period

In generation forecasting to enable greater penetration of renewable energy the period of forecast is one of the main criteria to be considered. The different periods of forecast are primarily divided into the following:

- Very short term – The forecast horizon ranges for few seconds to 30 min for turbine control and load tracking.
- Short term – The forecast horizon ranges from 1 hour to one or two days ahead. This is quite useful in economic load dispatch planning.
- Medium term – In this case the forecast horizon ranges from 5 to 7 days. This is useful for situations like decisions on unit commitment or reserve requirement.
- Long term – In long term forecast the duration is more than one week which is useful for planning power plant maintenance, operation management, etc.

The predictions made in our work are for one day ahead keeping in mind that as the time period of the forecast increases, the forecasting becomes more and more uncertain due to the erratic behavior of the predictors and the forecast variables.

Auto Regressive Moving average model (ARMA):

In AR models, the present value of the variable is represented as a regressive function of the past values.so, the model is said to be a regression of the past values. The combination of AR models and MA models leads to a powerful model named ARMA (p, q) model.

Yt =c+∅1Yt−1 +et −θ1et−1

Where Yt =present observation, ∅t=AR coefficient, θ =MA coefficient, e t = error

Auto-Regressive Integrated Moving average (ARIMA) model:

ARIMA model considers the irregular component of a time series. The model allows non-zero autocorrelations in the irregular component which can result in a better model for the data. The Integrative (I) part of the ARIMA model includes the elimination of non- stationarity in a time series by differencing the time series as in equation.

Yt = Yt–Yt−1 The equation of ARIMA (p, d, q) is written as

2p2d2q (1−∅1B−∅2B −∅pB) (1−B−B ... −B) Yt =c+(1−θ1B−θ2B ..−θpB)et

Here p, d and q are the orders of AR, differencing, and MA part respectively and∅1, ∅2... are the AR coefficients, θ1, θ2, ... are the MA coefficients and c is the constant.

Test Data

The very first step of a statistical analysis is data accumulation. The data consisting of solar irradiance, wind speed, air temperature and relative humidity is obtained from a weather station in Bagalkot in the state of Karnataka. The raw data obtained for one year is processed by averaging over 15-minute intervals to minimize the immensity of data.

The solar irradiance data is absent for 12 hours in a day. Hence, the zero values are excluded from the analysis while predicting the irradiance one day ahead to obtain good results for a Statistical model.

Wind speed is a crucial parameter to be considered for weather forecast. The erratic nature of wind speed and outliers in the data lead to inaccuracy

III. DATA PROCESSING FOR TIME DECOUPLED STATISTICAL MODELS

Methodology for prediction of solar data

1. Data Acquisition: According to the forecasting system, the necessary historical in- formation, such as historical load, weather information, etc. is gathered to build the sample dataset.
2. Data analysis: The system to be forecasted and the sample dataset are analyzed, to find the influential

factors, which are used as input to the mathematical model for load forecasting.
3. Data Handling
4. Development of Statistical Models

3.1.1 Data Handling
The data is collected from a typical tropical city in India. The preprocessing of the data involves converting the data into a form that is ready to be fed for training. The procedure followed for pre-processing the data is as follows:

Basic Preprocessing
1. All the data is collected in Excel format with date, time and irradiance.
2. Data values missing in time are obtained by averaging the nearest few values of the data points to ensure that the data is a continuous time series.
3. Very high peak data values obtained due to erratic changes in the system are identified by thresholding functions and are eliminated by replacing them with an average of neighborhood values.

Removal of unwanted Data
The time frame for forecast is taken to be 6:00 A.M to 6:00 P.M, since the irradiance is insignificant at other times.

Time-series decoupling strategy for forecasting
In time-series decoupling, training data is decoupled based on time, the data to be predicted at 6:00AM shall only depend majorly on the history of irradiance values of the previous 30 days at 6:00AM and rather than on any other time in the day. The regression models will be more accurate as the data points are tightly coupled with each other. Solar irradiance is considered at an interval of 30 mins for each hour between 06:00AM to 06:00PM i.e at 6:00 AM, 6:30 AM, 7:00AM, 7:30AM and so on. The value for 6:00AM is obtained by obtaining the average of irradiance values at 6:00AM and 6:15 AM. Similarly for the value at 6:30 AM, the average of irradiance at 6:30AM and 6:45 AM are considered. In this manner we obtain 24 data points for each date for 30 days. The forecasted value for 6:00AM will be obtained through training the model using the 6:00AM data points for 30 days. 3.1

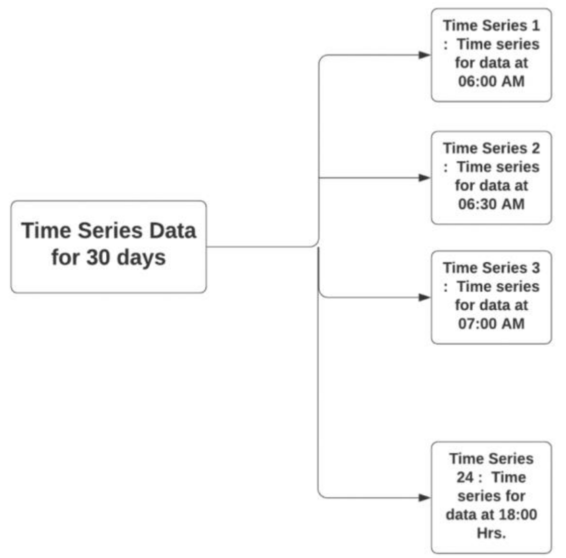

Figure 3.1: Time series decoupling for solar data

Development of statistical models for solar with Block Diagrams
The solar data follows a distinct pattern wherein the magnitude of solar irradiance is zero throughout the night and starts increasing during the day. It reaches its maximum value in the afternoon and begins to decline and reaches near zero in the evening. This pattern repeats. There may be variations due to intervention of clouds and weather conditions though the pattern will remain.

IV RESULTS

Power generation from wind is highly susceptible to climatic variables viz. geographical location, wind speed and its direction, seasonal changes, time of the day, etc. A uniform efficiency cannot be guaranteed for a given forecasting method across different geographies. Hence it is critically essential to examine the seasonality and other influencing parameters to determine the best fit model. Literature provides a good number of options for forecast such as statistical models, intelligent models.

CASE STUDY 1:
1. Day Ahead Prediction with 30-, 60- and 90-days data for solar irradiance:
The solar irradiance is predicted employing three different models with three-time durations, viz. 30-, 60- and 90-days data. The calculated MAPE for 30

days is 15.2309percent, for 60 days it is 21.79percent and for 90 days it is 32.35percent with ARIMA models. It is observed that as the duration increases the other factors like seasonal trends play a larger role and the error increases as the error keeps adding up. 5.1

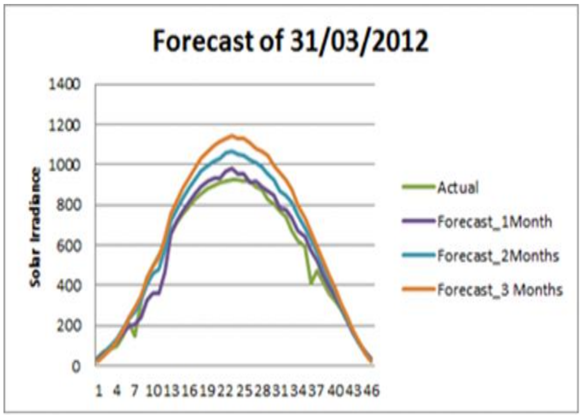

Figure 4.1: Comparison of actual and predicted values of solar irradiance for 30, 60 and 90 days

2. Day ahead prediction with 30-, 60- and 90-days history for wind speed:

The wind speed is predicted employing three different models with three-time dura- tions, viz. 30, 60 and 90 days data. The calculated MAPE for 30 days is 18.137per- cent, for 60 days it is 16.3 and for 90 days it is 16.22percent with ARIMA models. It is observed that as the duration increases the other factors like seasonal trends play a larger role and the error decreases as the error keeps adding up.

5.2

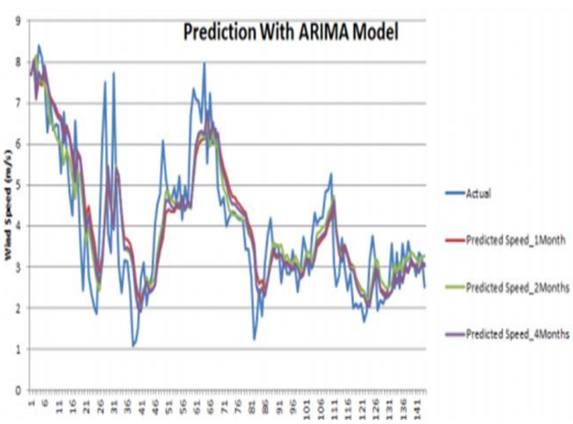

Figure 4.2: Comparison of actual and predicted values of wind speed for 30, 60 and 90 days

CASE STUDY 2: Extension of model to predict out-samples:

Solar irradiance was predicted for the first day and second day of March 2012 using a decomposition model. It was found that on using the forecasted value as a part of the training data led to compounding of errors which Is clear in the results

Figure 4.3: Comparison of actual and predicted values of solar irradiance for 1 and 2 days ahead prediction

CASE STUDY 3: Effect of decoupling strategy in prediction:

In this project we used a strategy of time-series decoupling, training data is decoupled on the basis of time. The data to be predicted at 6:00AM shall only depend majorly on the history of irradiance values of the previous 30 days at 6:00AM and rather than on any other time in the day. The regression models will be more accurate as the data points are tightly coupled with each other. To check the difference decoupling makes we have compared the solar irradiance and wind speed predicted values with decoupling and without decoupling

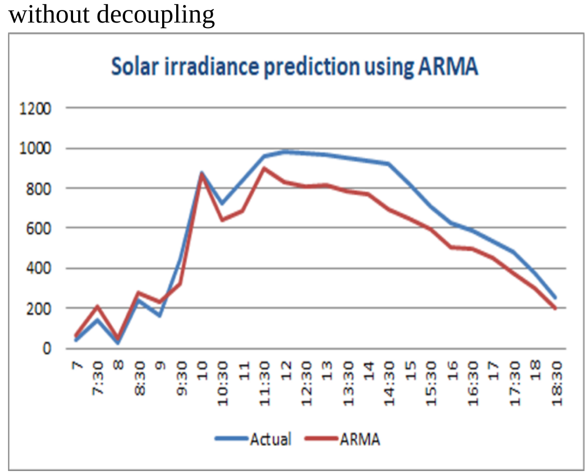

Figure 4.4: Comparison of actual and predicted values of solar irradiance using ARMA Model

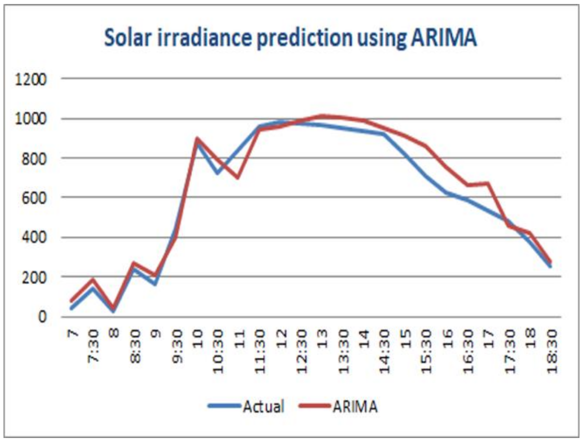

Figure 4.5: Comparison of actual and predicted values of solar irradiance using ARIMA Model

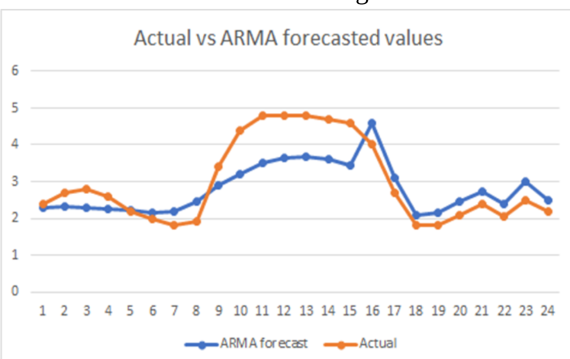

Figure 4.6: Comparison of actual and predicted values of wind speed using ARMA Model

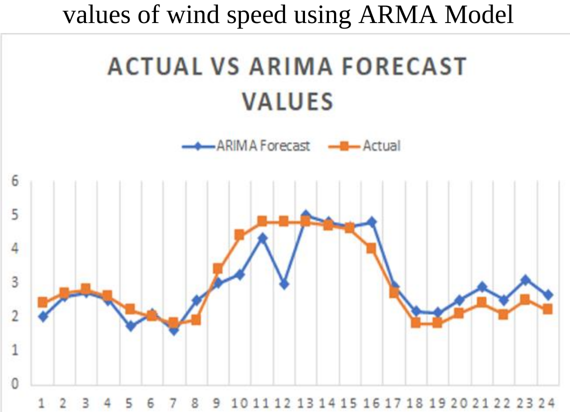

Figure 4.7: Comparison of actual and predicted values of wind speed using ARIMA Model

V. CONCLUSION AND FUTURE SCOPE

Conclusion

Development of a novel decomposition model for solar and wind prediction is one of the major contributions of this paper. Different case studies are performed to determine the ideal time period for model building and to validate the results. Decomposition model worked very well for solar prediction with an error of around 15%. But error in the wind prediction is found to be on a higher side around 18%. This could be due to the erratic pattern of wind speed and outliers in the data. It is found that prediction accuracy reduces with the increase in number of out- samples for solar and other way for wind. In the day- ahead prediction with 30, 60 and 90 days history it is inferred that model with 30 days data is optimal for prediction.

Future Scope

With the immense growth in machine learning and deep learning fields there is a great scope for development of models with more accuracy. Different Hybrid forecast models can be developed by combining multiple models to improve the number of out samples of prediction Future works can explore the possibility of prediction during seasonal transitions.

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