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Generalised Wind Climate Power Prediction Model

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Abstract: Wind energy investment is on the rise. Before installation of a wind turbine, wind power prediction must be performed to estimate the efficacy of the wind power project. Wind speed measurements can only be performed instantaneously from point to point. Currently, these measurement points represent the point where the wind turbine will be installed. These points may not be having the highest wind speed and hence it may not be the optimal points to install the wind turbine. This study will focus on wind power prediction at the points where wind measurement instruments were not installed. This is based on the already existing instantaneous measurements at the site. It is expected that there could be other points with higher wind speeds than the measured points. This paper presents a model for forecasting wind energy. The data was collected using a wireless sensor node using internet of things(IoT). This study gave rise to a machine learning prediction model using time series.
Keywords machine learning, Arima, Sarimax, forecast

I. INTRODUCTION

In the Economics of Wind Energy report conducted by European Wind Energy Association, it is clear that Wind energy investment is on the rise[1]. Before installation of a wind turbine, wind power prediction must be performed to estimate the efficacy of the wind power project. Wind prediction is an important tool which helps in avoiding imbalance charge and improve the stability and efficiency of the power systems. It is recommended that the wind turbine be installed at the point where wind speed measurement was carried out[2]. However, this point may not be the one that has the highest wind speed in the whole prospected site. This means that it may not be the best point to install the wind turbine even after wind power prediction. There is need to do power prediction in the surrounding points. This is because they have the potential to yield higher wind speeds. This study strives to close this gap.Machine Learning study has shown promise in improving the accuracy of predictions within multiple fields of study[3]. The use of Machine Learning in wind energy prediction has the potential for saving a lot of energy since prediction leads to more power output making huge gains in energy sector[4]. Machine learning prediction will reduce the cost of generation making wind energy cheaper to generate compared to other energy sources. Most of the countries in the world are aware of climate change and resources shortage. According to United Nations Climate Change Conference, namely COP 21, held in Paris, France in December2015 for two weeks. 195 countries in total attended this conference[5]. Wind is moving air. The movement of air forms current that transfers heat from one place to another. We feel wind and think it is very close to us, the scale of air circulation is actually global[6]. Wind energy is one of the renewable resources that can be utilized. Since wind has mass and is air in motion thus contains kinetic energy[7].Any power system needs to balance the supply with demand. For the electricity demand, an amount is estimated according to past patterns. This demand estimation will help the system operator to decide how much power to supply in order to match the demand or reduce waste[8]. Apparently, the demand varies over time, which requires the supply to be adjusted accordingly. For thermal power stations, the output can be scheduled to follow the demand changes. Like most other types of renewable energy, wind power has fluctuations that can be hardly controlled[9]. The key issue of wind power integration is linked to the variance of wind power. One way to reduce the variance is to aggregate the power generation from multiple wind farms because the wind conditions are less likely correlated between different geographical locations.Wind speed is first predicted by an appropriate model, then the predicted wind speed is used to determine the expected wind power output for a specific wind farm and the prediction result of a wind farm may be further used to forecast regional output[10][11].Machine learning focuses on improving the performance of the program by itself with experience. It applies knowledge from artificial intelligence, statistics and neuroscience[12][13][14].

II. SYSTEM DESCRIPTION

This study involved the installation of the required embedded systems, and assembly of the whole system instrument that made up a wireless sensor node for collecting and transmitting data.

To set up the required instruments for wind data collection a tower of around 60 – 100m high is required. A dedicated tower can be constructed or a pre-existing tower can be used. The wireless data logger used in this study was built around the Atmega328P-AU microcontroller[15]. This implementation also had an Xbee radio capable of transmitting data via ZigBee IEEE 802.15.4 protocol, to a central station located few metres away[16][17]. We set up two stations at different points with a distance of about two hundred metres between them. Each station had:

I. Cup anemometer and wind vane with sensors for collecting wind speed and direction.
II. Arduino mini development which acted as micro- controller which used Atmega 328P as the processor
III. Xbee was connected to Arduino.

It was used fortransmitting data to the receiving station

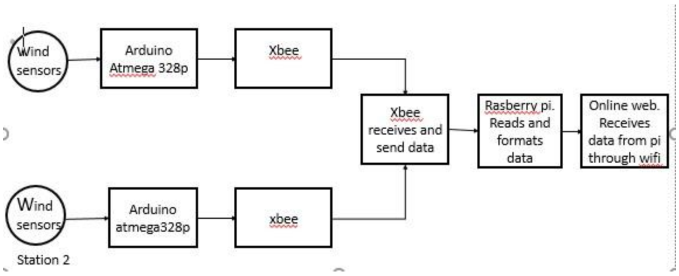

Fig. II : Flow chart diagram for wind data collection setup

III. WIND ENERGY PREDICTION MODEL

3.1 DESIGN AND FABRICATION OF WIRELESS SENSOR NODE

This study begins with acquisition of instruments involved in wind data collection. Ready-made cup anemometer and wind-vane were used to increase accuracy.

Fig. III.a Ready-made cup anemometer and wind-vane parts

The embedded system used in this study was built around the Atmega328P-AU microcontroller. This implementation also had an XBee radio capable of transmitting data via the ZigBee IEEE 802.15.4 protocol, to a central station located up to 100 m away. A pre-processing algorithm was used to prepare the station's embedded systems to collect the data from sensors and send those data to the main post-processing station located far from it.

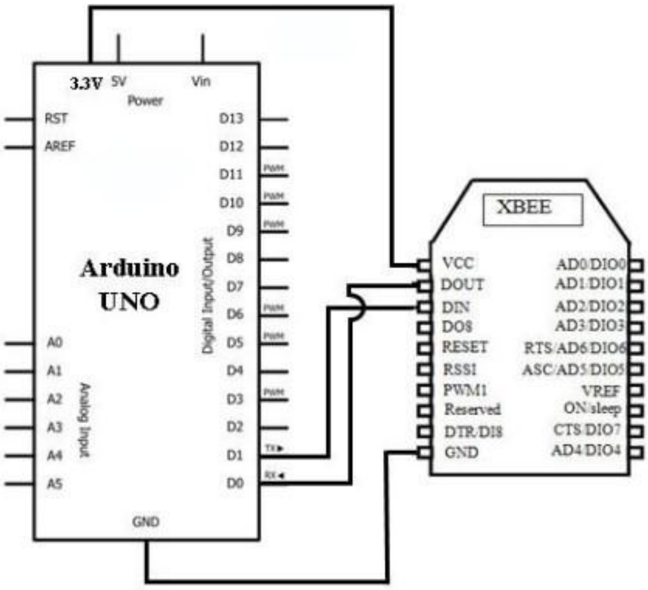

Fig. III.b Wireless sensor node electrical schematic diagram

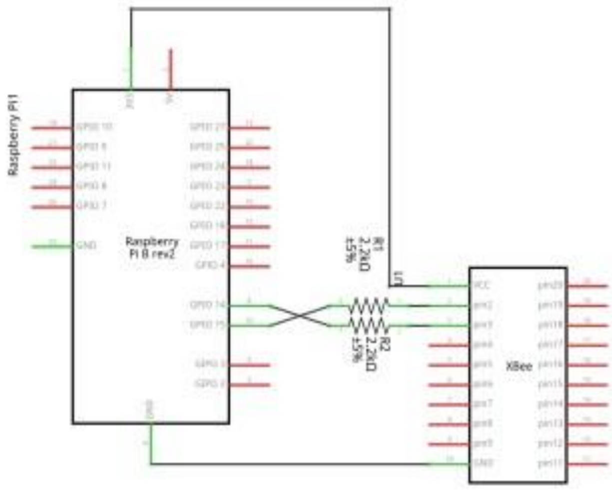

Fig. III.c Arduino-xbee setup schematic diagram

The system was then programmed to understand the signals from sensors, save, and transmit wind data to the email for presentation. This program was prepared in an ANSI C/C++ development environment. Sensors pins and addresses were first defined. The sensors used needed to communicate via I^{2}c protocol[17]. Their addresses were defined and the required sensor libraries were included into the program. The basic setups were prepared inside a function that was only called once. This preparation included specification of the involved sensor interrupt, pulling up the internal resistors and starting up the sensors as well as the serial communication.

The iteration required was done in one loop function. During the entire iteration, time elapsing was noted by the program. Sensors were configured to deliver the data to the serial as soon as they acquired it. The sensors calibration details were considered in this iteration as well. In this section, the speed sensor was prepared to always provide the instantaneous revolutions per minute. Sensors were configured to collect data samples after every five seconds and transmit the average data samples after thirty seconds.

The compass sensor was configured to capture the direction of the wind vane tail and deliver the data to the serial. Declination angle is taken into account[15][18]. All the collected data from both stations were transmitted in format of station1 and station2 with each having speed and direction of wind.

The test IEEE 802.15.4 sink node located about 100 m away was able to receive the data after every thirty seconds.

Table III.1 data from the two stations

3				
4	Date	Thing	Speed	Direction
5	1/10/2018 0:59	2	2.41	151.4
6	1/10/2018 1:00	1	7.97	176.5
7	1/10/2018 1:00	2	2.09	123.8
8	1/10/2018 1:01	1	9.82	174.1
9	1/10/2018 1:01	2	3.46	138.6
10	1/10/2018 1:02	1	8.37	172
11	1/10/2018 1:02	2	1.77	186.2
12	1/10/2018 1:03	1	9.29	170
13	1/10/2018 1:03	2	1.49	123.4
14	1/10/2018 1:04	1	11.02	167.4
15	1/10/2018 1:04	2	3.14	134.4
16	1/10/2018 1:05	1	5.83	166
17	1/10/2018 1:05	2	2.7	139.9
18	1/10/2018 1:06	1	7.85	181.2
19	1/10/2018 1:06	2	1.93	151.5
20	1/10/2018 1:07	1	9.09	170.6

3.2 MACHINE LEARNING MODEL

The data was first processed which included, removing columns we do not need, checking missing values, aggregating wind speed values and direction. A prediction model was designed using python programming language.

IV. RESULTS AND DISCUSSION

4.1*INDEXING WITH TIME SERIES DATA*

The average wind speeds for that month were used and the beginning of each month as the timestamp.

Table IV.1 mean, max, min ,std

	Thing	Speed	Direction
count	1.556590e+05	155659.000000	155659.000000
mean	1.939342e+03	4.118089	167.644335
std	7.644924e+05	3.754784	62.786216
min	1.000000e+00	0.000000	0.000000
25%	1.000000e+00	1.450000	129.900000
50%	2.000000e+00	3.180000	165.800000
75%	2.000000e+00	5.950000	201.700000
max	3.016201e+08	502.000000	360.000000

4.2 ***VISUALIZING TIME SERIES WIND DATA***

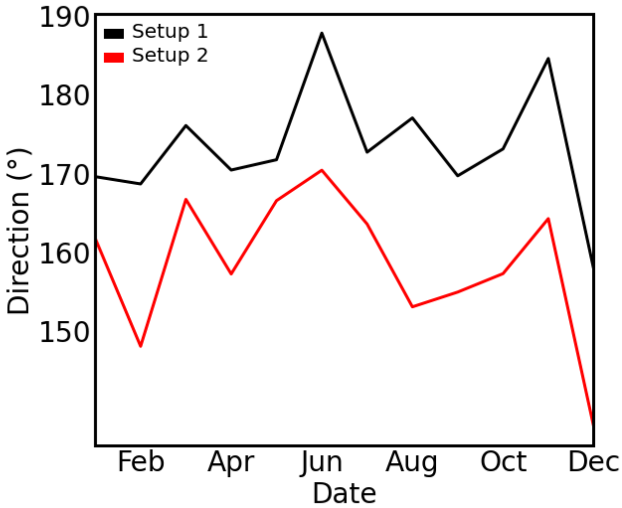

Fig. IV.aWind direction

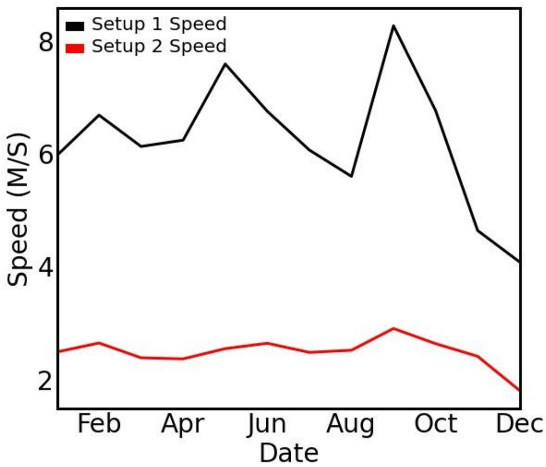

Fig. IV.b Wind speed

Some unique patterns appear when we plot the data. The time-series has seasonality pattern, such as wind direction due to different seasons at different months of the year. Using time series decomposition method, we decompose our time series into three distinct components; observed, trend and seasonality.

4.3 ***ARIMA FORECASTING***

ARIMA stands for Autoregressive Integrated Moving Average. ARIMA models are denoted with notation ARIMA(p, d, q)Parameter for wind data ARIMA Time Series Model was selected to have the optimal set of parameters that yields the best performance for the model.These three parameters account for seasonality, trend and noise in data.

Table IV.2Arima forecasting

```
ARIMA(0, 0, 0)x(0, 0, 0, 12)12 - AIC:145.
ARIMA(0, 0, 0)x(0, 0, 1, 12)12 - AIC:4.0
ARIMA(0, 0, 0)x(0, 1, 0, 12)12 - AIC:2.0
ARIMA(0, 0, 0)x(0, 1, 1, 12)12 - AIC:4.0
ARIMA(0, 0, 0)x(1, 0, 0, 12)12 - AIC:4.0
ARIMA(0, 0, 0)x(1, 0, 1, 12)12 - AIC:6.0
ARIMA(0, 0, 0)x(1, 1, 0, 12)12 - AIC:4.0
ARIMA(0, 0, 0)x(1, 1, 1, 12)12 - AIC:6.0
ARIMA(0, 0, 1)x(0, 0, 0, 12)12 - AIC:123.
ARIMA(0, 0, 1)x(0, 0, 1, 12)12 - AIC:6.0
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:4.0
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:6.0
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:6.0
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:8.0
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:6.0
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:8.0
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:69.4
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:4.0
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:2.0
```

From above output suggest that ARIMA(0,1,0)*(0,1,0,12) yields the lowest value of 2.0. Therefore, we considered this to be optimal option.

4.4. PRODUCING AND VISUALISING FORECAST

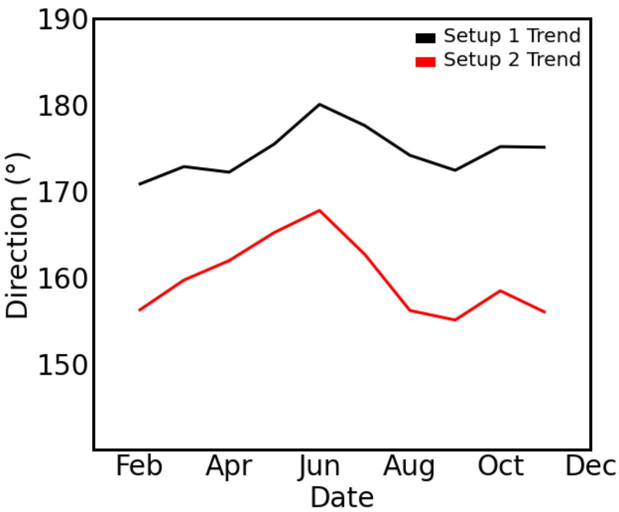

Fig. IV.c Trend (direction)

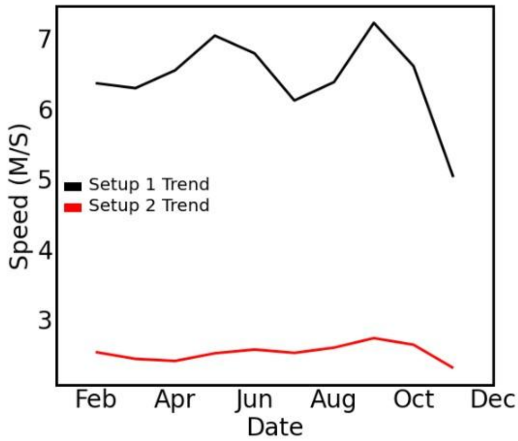

Fig. IV.d Trend (speed)

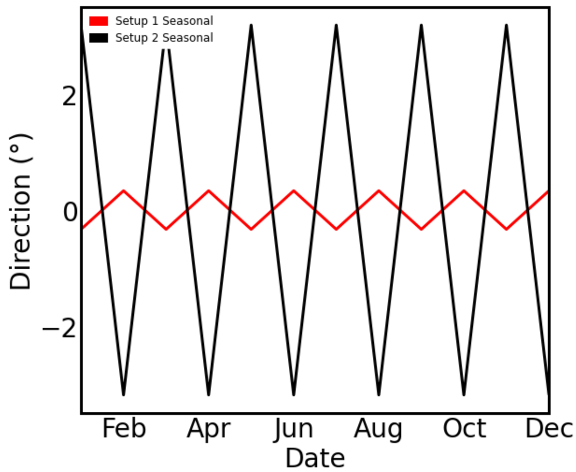

Fig. IV.e Seasonal(direction)

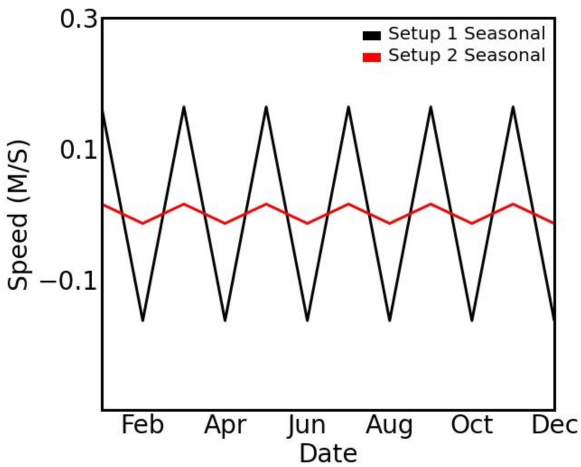

Fig. IV.f Seasonal(speed)

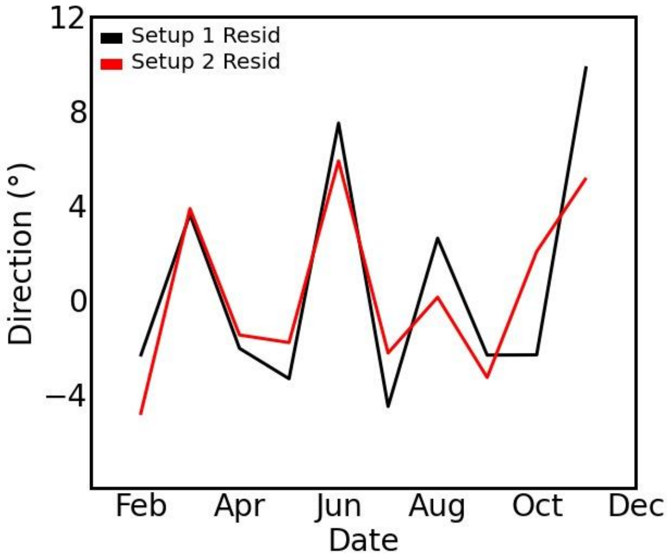

Fig. IV.g Direction residual

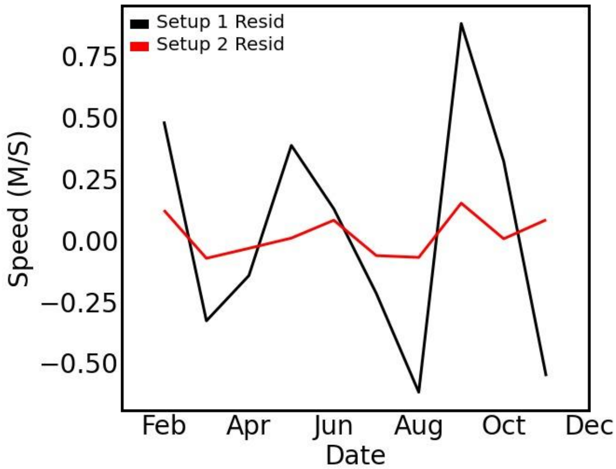

Fig. IV.h Speed residual

From the graphs we can observe that the residuals are nearly normally distributed thus our model is forecasting correctly. This is reflected by the confidence intervals generated by our model.

4.5.SARIMAX FORECASTING

Different parameters(seasonality, trend and noise) were combined and using the SARIMAX function from stats-models to fit the corresponding seasonal ARIMA model. (p, d, q, s) seasonal component of the seasonal ARIMA model were specified.

Table IV.3Sarimax forecasting

```
Examples of parameter combinations for Seasonal ARIMA...
SARIMAX: (0, 0, 1) x (0, 0, 1, 12)
SARIMAX: (0, 0, 1) x (0, 1, 0, 12)
SARIMAX: (0, 1, 0) x (0, 1, 1, 12)
SARIMAX: (0, 1, 0) x (1, 0, 0, 12)
```

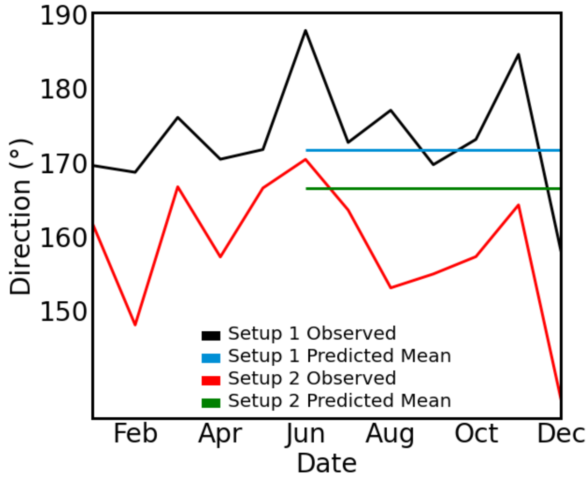

Fig. IV.iSarimax predicted mean(direction)

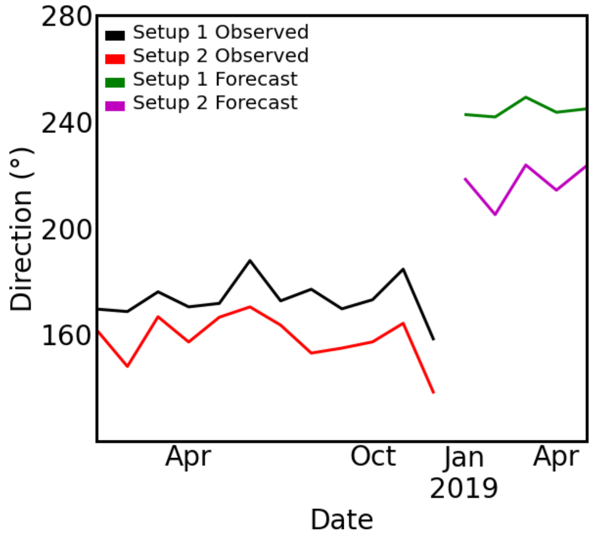

Fig. IV.jSarimax forecast (direction)

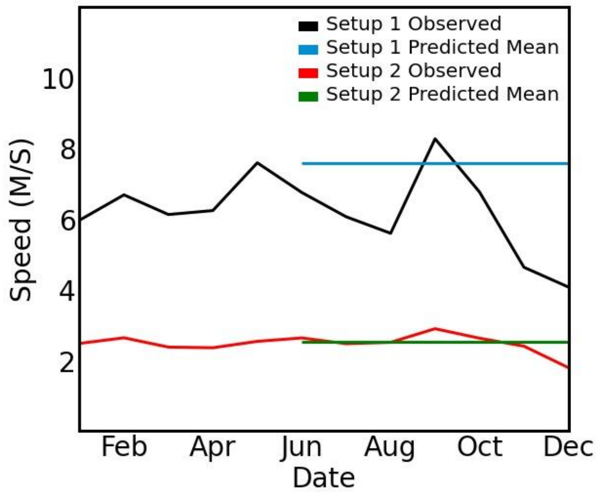

Fig. IV.kSarimax predicted mean(speed)

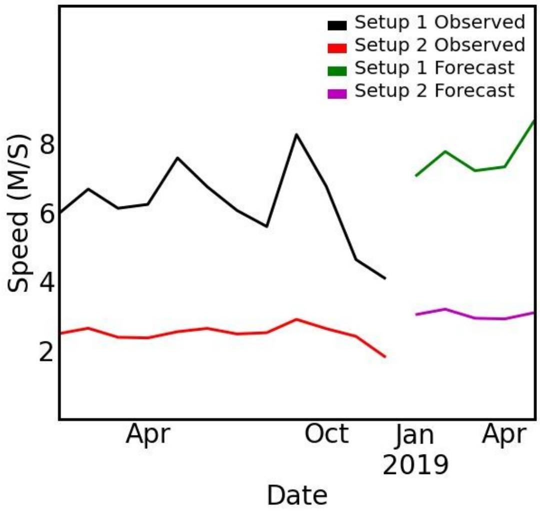

Fig. IV.lSarimax forecast (speed)

The line plots are showing the observed values compared to forecasts predictions. Overall, our forecasts align with the true values showing seasonality through the year.

V. CONCLUSIONS

Wind power prediction is an important component in wind power energy production which is in high growth rate. Precise predictions can significantly help in reducing the cost and improving the stability of wind power. In this study, we carefully collected experimental data and ensured that the datasets contain wind speed and direction. This research is highly relevant because nowadays good forecasting methods are required and computation time is a limited resource for practical applications. By employing time series both the prediction accuracy can be improved and the required computation time can be decreased.
In future work, missing values should be taken care of to ensure a highly accurate model.

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