Visibility Forecasting in Meteorological Aerodrome Report using Facebook Prophet

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Abstract - Meteorological Aerodrome Reports (METAR) are vital in aviation operations because they provide real-time weather conditions of airports. The paper focuses on applying machine learning and time series methodologies in order to forecast visibility in METAR data. The study entails gathering and preparing METAR data, as well as using the Facebook prophet model to forecast visibility for the next few hours. In this paper, we used the prophet model to perform univariate and multivariate forecasting. The ARIMA and ARIMAX models are also performed in order to compare the performance of the prophet model. According to the findings, the prophet model for multivariate forecasting produces more promising results with RMSE of 2.48 which is the least value when compared to the RMSE calculated for the other models. The study also emphasizes the significance of taking seasonality and trend components into account when forecasting METAR data.

***Key Words*:** Forecasting; Facebook Prophet; Time Series

1. INTRODUCTION

Pilots as well as air traffic managers utilize visibility forecasts to plan and execute safe flights, which is a cornerstone of airport operations. Visibility is the measure of how transparent the atmosphere is to light, and it can be impacted by a variety of factors including fog, rain, snow, dust, and smoke. Visibility has an impact on those who depend on visual observation to track and regulate aircraft movements. Low visibility can make it more difficult to see and monitor aircraft, which makes maintaining a safe distance between aircraft more challenging. Because of these reasons, visibility is a key component in determining an aircraft's safety both pilots and air traffic controllers must take it into account when determining how to progress with a trip. With the aid of Meteorological Aerodrome Reports which offer vital information about visibility conditions at airports, pilots and air traffic managers can make appropriate decisions about take offs, landings, and flight operations.

There are several machine learning techniques that can be used for weather forecasting, including regression, decision trees, random forests, and neural networks. These methods can be used to forecast and analyze how various weather factors, such as temperature, pressure, wind, and humidity, will vary over time. It is common practice to combine historical METAR data with information from other sources, such as radar data and satellite imagery, in order to build a comprehensive dataset for the algorithm's training. The algorithm may then be used to anticipate future weather, and the forecasts' reliability can be validated by correlating with real-world weather data. This study investigates how well the Facebook Prophet model predicts the target variable for the given dataset. The performance metrics used to assess the models are Mean Squared Error, Mean Absolute Error and Root Mean Squared Error. As a result, the research demonstrates that, in comparison to the univariate method, the multivariate approach using the prophet model has great potential for forecasting. The outcomes also demonstrate that the multivariate forecasting using the Facebook Prophet model has a lower RMSE value. The findings have practical implications for aviation operations and could contribute to improve safety, efficiency, and profitability in the industry.

2. RELATED WORK

Many studies and research projects have helped to improve the accuracy of earlier aviation weather forecasts. Afan Galih Salman et al. [1] proposed the two models Long Short-Term Memory Model and Autoregressive Integrated Moving Average as a method to assess intermediate variables and compare visibility forecasts with an accuracy of ARIMA (0.948), LSTM (0.00007) on Hang Nadim Airport in Indonesia Area, 2012-2016, 40,026 time series data. To classify Visibility Forecasting Afan Galih Salman et al. [2] suggests employing the grid technique to predict future improved visibility value for all the varying values of the parameters namely p, d, and q using an Auto-Regressive Integrated Moving Average (ARIMA) model with the smallest MSE value 0.00029 and 0.00315 as the coefficient of variation value on Hang Nadim Batam Indonesia Airport dataset. Studies from the past employ various methods to forecast visibility. To investigate the impact of intermediate weather variables Afan Galih Salmana et al. [3] suggested a method for assessing the accuracy of single and multi-layer LSTM models in terms of the effect of intermediate meteorological variables. By incorporating intermediate variable signal into the LSTM memory block, the suggested forecasting model expands on the LSTM model. It predicted Multi-layer LSTM is the best by using Hang Nadim Airport Indonesia data which contains around 40,025 time series records and produced an accuracy of (0.8060) and RMSE (0.0775). Ashutosh Kumar Dubey et al. [4] used data analytics on smart meter measurements gathered and daily energy consumption predictions made utilizing SARIMA, ARIMA, and LSTM are provided and predicted the LSTM is best with (MAE) of 0.23 by using data from 5,567 London households who engaged in the UK Power Network-led Low Carbon London initiative between November 2011 and February 2014.

L. Cornejo-Bueno et al. [5] proposed a model that correctly predicts low-visibility incidents in terms of the airport terminal vision range with the use of SV regressor, neural networks, and Gaussian-process algorithms on AEMET, Valladolid airport, Spain datasets with Root-mean-square error (RMSE) relative to the persistence model (RMSEP) and predicted Gaussian-process regression is the best with a RMSE = 0.6. Filipe Rodrigues De Souza Moreira et al. [6] proposed an original time

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series forecasting method based on maximum visibility. It employs the Maximum Visibility Method (MVA), a distinctive technique based on Complex Network theory for forecasting time series data on datasets of Airpass, Lynxs, Ibovespa, Nhtem, RBTS with performance metrices as MAE, MAPE and RMSE. Here, Jahnavi Jonnalagadda et al.[7] predicted based on an auto-regressive recurrent neural network, this method aims to forecast the visibility of univariate weather factors and investigate the impact of highly correlated meteorological meteorological parameters on visibility (ARRNN), with the greatest R2 value being 0.847, using weather recordings from a satellite-based site at Dulles International Airport, Virginia, from 1st January 2011 to 15th March 2020 with 114,319 records after normalizing the datasets with performance metrices of Root Mean Square Error (RMSE),coefficient of determination (R^2) compared with LSTM and Vanilla RNN. A recent study carried out by Jin Ding et al. [8] analyses visibility over China's international airports at various time scales, builds a model for predicting airport visibility through the evaluation of artificial intelligence programs and a variety of weather factors, and then verifies the outcomes. It compares 9 AI algorithms and predicted RF has the greatest effect by using data on 47 airports chosen and spread across in 26 Chinese provinces, and the hourly visibility data during 2018–2020 by using RMSE, MAE, standard deviation ratio and CC. Kai-chao Miao et al. [9] developed a new LSTM framework for forecasting short-term fog. The described network framework consists of a fully connected layer and an LSTM network. Using the ground observation dataset from the Anhui Meteorological Bureau of China, they used LSTM, AdaBoost, KNN, and CNN.

In order to combine a collection of 19 widely used turbulence measures, Kai Kwong Hon et al. [10] suggest a machine learning-based multi-index consensus (MIC) method that uses the XGBoost algorithm to find the best weighting coefficients with an AUC score ranging from 3% to 17%. However, in PIREP and in QAR-derived occurrences, clear air turbulence (CAT) and convective induced turbulence (CIT) have not been differentiated. In the year 2017, Lei Zhu et al. [11] proposed a method to increase visibility and maintain the safe and reliable operation of the airport. It offers weather forecast professionals a new visibility return forecast. It uses MLP model and multi-factor factor pre- diction model on datasets which contains the hourly observation between 2007 and 2016 of Urumqi International Airport. In a recent work, Pablo Rozas Larraondo et al. [12] suggested a circular regression tree-based approach for airport weather forecasting. The efficacy of airport weather forecasts generated by numerical weather prediction (NWP) tools can be increased using a set of tools and a model described in this study. This is accomplished by looking at the correlations between the actual data and the previously modelled data. Since it is built on a revolutionary machine learning approach and allows circular variables to be automatically incorporated into regression trees, it generates better results than earlier circular regression tree methodologies and linear regression tree methodologies. It uses AeroCirTree after data extraction by using classic linear regression tree (using the u, v components of the wind speed and time of the day), Lund's and circular regression tree.

In the year 2020, Pradeep Hewageet al. [13] proposed a method that attempts to address this by designing and assessing a compact and unique weather forecasting system that comprises of one or more local weather stations and cutting-edge machine learning methods for forecasting weather using time-series data from these weather stations. It uses TCN and LSTM on weather data collected for every 15-minute interval for the period of 20/01/2018 to 22/08/2018 by mean squared error (MSE).In the year 2019, Siddharth Singh et al.[14] investigates three methods namely artificial neural network (ANN), time series-based recurrent neural network(RNN), and support vector machine (SVM) machine learning models for predicting the weather after data cleaning, feature selection, normalization the datasets of airport weather station of India and predicted it has a accuracy of SVM(6.67),ANN(3.1) and RNN(1.41). Tuo Deng et al. [15] attempts to utilize LSTM neural network to forecast visibility, however there is a difficulty because it has attributes distinct from the applications listed above. They specifically take into account visibility forecasts one hour apart and three hours in advance. They predicted based on data provided by China Meteorological Administration, Beijing station between April 2016 and December 2017, with 15143 sets of data by Weighted RMSE. In the year 2021, Wu Zixuan et al. [16] proposed a model that predict visibility of Plateau Airport. They develop a plateau airport visibility prediction model (PAVPM) to forecast the airport's visibility hourly for the coming 1-6 hours using the atmospheric condition data from the airport ground station. They predicted visibility on data released by Urumqi Airport's air traffic control hourly in the winter of 2015-2019 (November, December, January, February) using LSTM.

3. PROPOSED METHODOLOGY

The steps used to meet the intended objectives of this paper includes:

1. Dataset collection
2. Preprocessing
3. Time Series models

A schematic of the potential method's design is shown in Figure. 1.

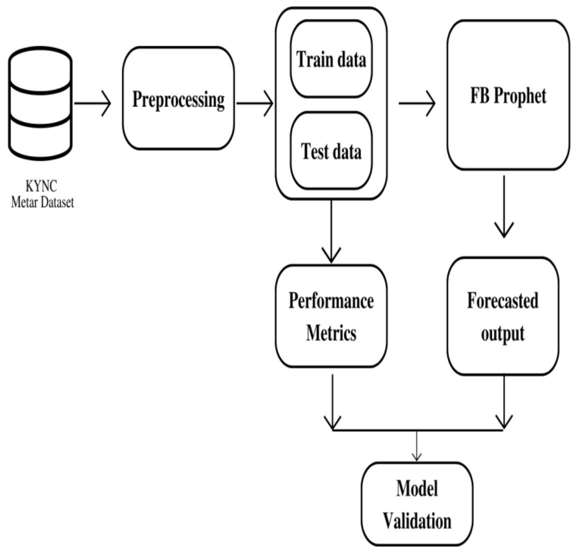

Fig -1: Architecture diagram

3.1 DATASET

The paper makes use of KNYC Metar data that can be found on the Kaggle and was acquired from Wunderground. The dataset comprises of 8787 records that are classified using 14 other attributes. Visibility is the target variable in this dataset which is forecasted using time series, and other variables of the dataset include: time, temperature, windchill, heat index, humidity, pressure, dew point, wind direction, wind speed, and gust speed. The data was collected between 2015 and 2017. The data is presented chronologically and contains observations for each hour. The variables present in the dataset are given in the table below.

Table -1: Variables of the dataset

SNo	Variables	Description	Data Type
1	Time	Timestamp of the observation	datetime
2	Temp.	Air Temperature	float
3	Windchill	Effect of cold wind on people	float
4	Heat Index	Temperature combined with humidity.	float
5	Humidity	Humidity in air	float
6	Pressure	Air Pressure	float
7	Dew Point	Temperature when dew forms.	float
8	Visibility	Visibility in miles	float
9	Wind Dir	Direction of the wind	object
10	Wind Speed	Wind Speed in knots	float
11	Gust Speed	Wind Gust in knots	float
12	Precip	Precipitation	float
13	Events	Events such as rain	object
14	Condition	Clear or overcast	object

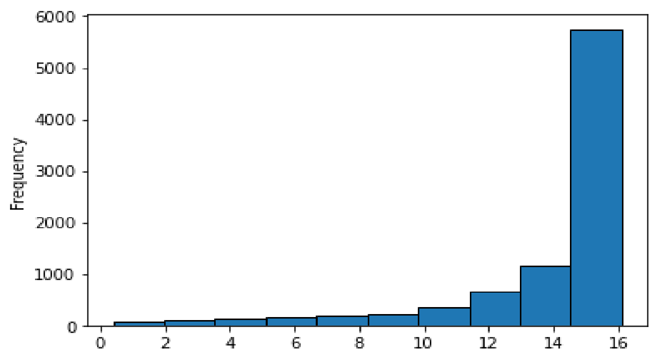

Fig -2: Histogram depicting the frequency distribution of the target variable.

3.2 PREPROCESSING

3.2.1 Missing value treatment

The dataset contains several missing data points across multiple columns, which must be processed before training the model. The numerical columns were imputed using the variable's mean. There are no missing variables in any of the categorical columns.

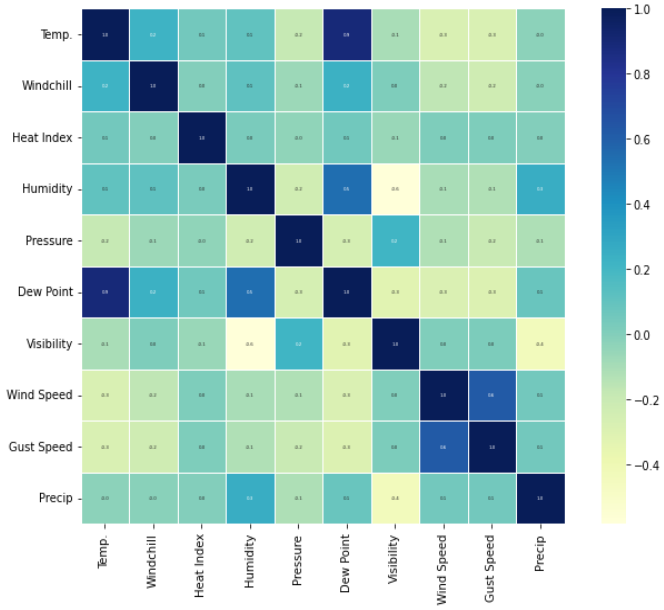

Fig -3: Correlation of features of the dataset

3.2.2. Converting the datatype

The Time column of the dataset, which contains the timestamp of the observation, is initially of the data type object and must be converted into datetime in order to properly handle the data and perform time-related operations on the dataset. The pandas library's to_datetime function is used to convert the datatype to datetime64[ns].

3.2.3. Augmented Dickey Fuller Test

In many time series forecasting techniques, stationarity is an essential presumption. The Augmented Dickey Fuller test is one method for determining whether a time sequence is stationary. We examine the null hypothesis, which states that the time series is non-stationary by using the augmented dickey fuller test. We subsequently deduce that the time series data is stationary and the null hypothesis is incorrect if the test's p value is lesser than the significant value, which is fixed at 0.05. The p-value for the dataset we used is 0.000, which is less than 0.05 and hence it allows us to dismiss the null hypothesis and acknowledge that our time series is consistent.

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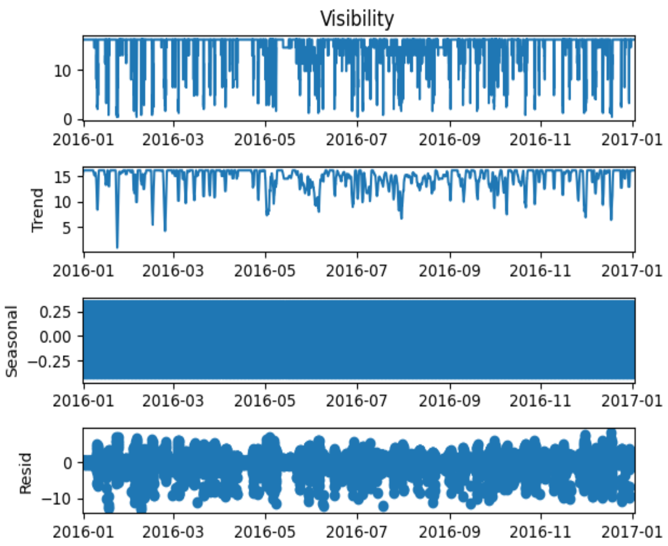

Fig -4: Seasonal decompose of the target variable

Figure.5 showcases a seasonal decomposition plot used to visualize the various components of a time series, such as trend, seasonality, and noise. It can be seen here that the time series exhibits some trend, but there is no evident seasonality in the data.

3.3 TIME SERIES MODELS

3.3.1 Facebook Prophet

The Facebook Core Data Science team released a time series forecasting tool called Facebook Prophet. It is an open-source library constructed using the foundation of the Python programming language with the intention of rendering time series forecasting accessible to non-experts. The general notion of the model is similar to that of a generalized additive model. The "Prophet Equation" accounts for holidays, seasons, and trends. At its core, it is the result of the summation of three functions and an error term. The equation is as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

where,
y(t) is the additive regressive model,
g(t) is the trend factor,
s(t) is the seasonality component,
h(t) is the holiday component,
and ε_t is the error term

The g(t) can be employed in three different ways:

- Linear Growth: It employs a collection of piece-wise linear equations with varying slopes between change points. When linear growth is employed, the growth term will resemble the typical y = mx + b, with the exception that the slope(m) and offset(b) are variable and will change value at each changepoint. Here, linear growth is employed to forecast the visibility.
- Logistic Growth: When logistic growth is applied, the growth term will have the characteristics of a conventional logistic curve equation, except that the carrying capacity (C) will fluctuate over time and the growth rate (k) and offset (m) and will vary in value at each change point.
- Flat: Flat trend refers to a trend where there is no growth and will be a constant over time.

There are some prerequisites that must be met in order to fit the data into the prophet model, including that the dataset should be named as "df" and the column that contains the timestamp of the observation or simply the datetime column should be renamed as "ds" and the dependent variable that has to be forecasted using the model should be addressed as "y". The prophet model generates a dataframe as the output. It contains columns such as ds, trend, yhat_lower, yhat_upper, yhat and several other attributes. Prophet allows for multivariate forecasting by including additional regressors in the model. Any time-varying variables that are considered to have an effect on the target variable can serve as these regressors. These regressors are merely added to the data frame as additional columns and are passed to the model using the add_regressor function of the prophet model. In this paper we have taken temperature, wind chill, heat index, pressure, dew point, wind speed and gust speed as regressors for performing multivariate forecasting. Multivariate forecasting has shown even better results than univariate forecasting with much lower error values.

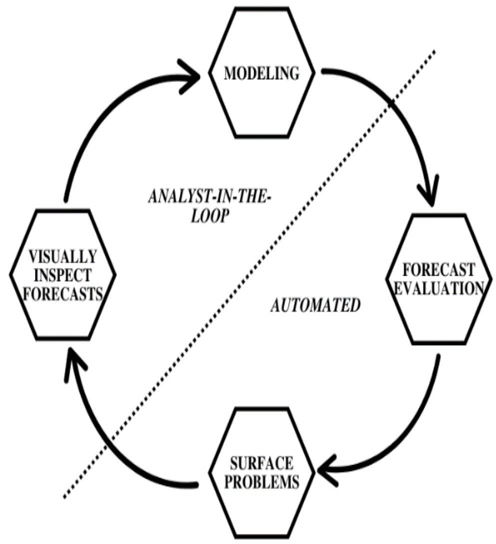

Fig -5: FB Prophet Workflow

3.3.2 ARIMA

ARIMA is an acronym that stands for Autoregressive Integrated Moving Average. It is a time series analysis and forecasting statistical model. The ARIMA model is composed of up of three essential components:

- Autoregression Component (AR): it forecasts future values based on the time series' prior values. In other words, it anticipates that future values will be identical to past values. The formula for the AR component is given as follow:
$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t$$
- Integration Component (I): it is utilized to eliminate the time series' trend or non-stationarity.
- Moving Average Component (MA): it models the error

value, which is the discrepancy between forecasted and true values.

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$

So, it has three terms: p, d, q which corresponds to the three components. The p represents the order of the AR component, d refers to the differencing term which makes the time series stationary and q represents the order of the MA component.

The ARIMA(p,d,q) model can be formed as:

$$\Delta dY_t = c + \emptyset_1 \Delta dY_{t-1} + \cdots + \emptyset_p \Delta dY_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

3.3.3 ARIMAX

ARIMAX is an abbreviation that stands for AutoRegressive Integrated Moving Average with exogenous variables. It is a statistical time series analysis model that enhances the ARIMA model by adding more explanatory factors that might impact the target variable trying to be forecasted. The ARIMAX model, like the ARIMA model, represents the target variable as a function of its own prior values and the errors' former values, but it additionally adds the impacts of one or more exogenous factors that might affect the target variable. The model is often employed when the target variable is modified by variables other than its own prior values.

Here the exogenous variables considered includes: Temperature, Windchill, Heat Index, Pressure, Dew Point, Wind Speed, Gust Speed and precipitation.

4. PERFORMANCE METRICS

4.1 Root Mean Square Error

A prominent performance metric for evaluating the accuracy for a time series model is the root mean square error (RMSE), which calculates the discrepancy between the predicted and actual value. By squaring the deviations, the absolute error measure known as root mean squared error prohibits positive as well as negative deviations from clearing one another out. When evaluating models, this measure also has a tendency to exemplify large errors. RMSE can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2}$$

4.2 Mean Square Error

MSE is another performance measure that is applied to time series models. The mean squared error computes the average of the variances squared between the predicted and actual quantities. In the context of time series analysis, MSE can be used to evaluate the accuracy of a forecasting model by determining the squared differences between predicted and actual quantities at each time step. However, it does not account for the potential correlation between errors at various time steps, which is a common feature of time series data, so it's employed in combination with RMSE and MAE.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2$$

4.3 Mean Absolute Error

The mean absolute error is another metric that is also used when working with time series data. It is established by determining the absolute error between the observed and predicted values and averaging it. At each data point, the absolute distinction between the predicted and true value is measured. MAE can be used to evaluate the accuracy of predictive models in time series analysis. The MAE performance measure is less outlier than the original mean squared error and is useful for time series analysis.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

5. EXPERIMENTAL RESULTS

This paper presents two different time series forecasting techniques on the KNYC Metar dataset. Both univariate and multivariate forecasting has been performed on the dataset using the Facebook's Prophet model along with the ARIMA and ARIMAX model to compare the efficiency of the prophet model.

The dataset consists of totally 8787 records in which 80% is taken as the training set to fit and train the model and the rest of the 20% is taken for predicting the values using various time series models and their performances are evaluated based on the performance metrics.

Table -2: Result of the models

Error	Univariate Prophet	Multivariate Prophet	ARIMA	ARIMAX
RMSE	3.2642	2.4821	3.5101	4.1980
MSE	10.6550	6.1611	12.3211	17.6232
MAE	1.9870	1.5597	1.3370	3.3047

Table.2 indicates that the Multivariate Forecasting using the Facebook Prophet models has the least RMSE error value when compared to the other models employed in the study.

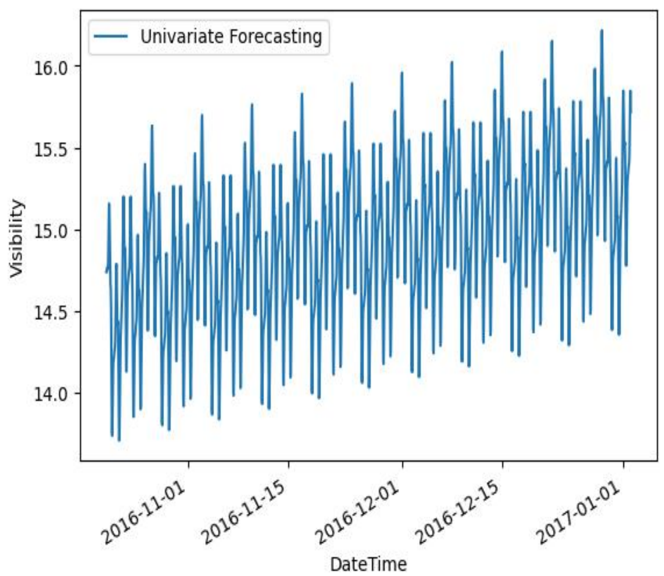

Fig -6: Time series plot for univariate forecasting using FB prophet model.

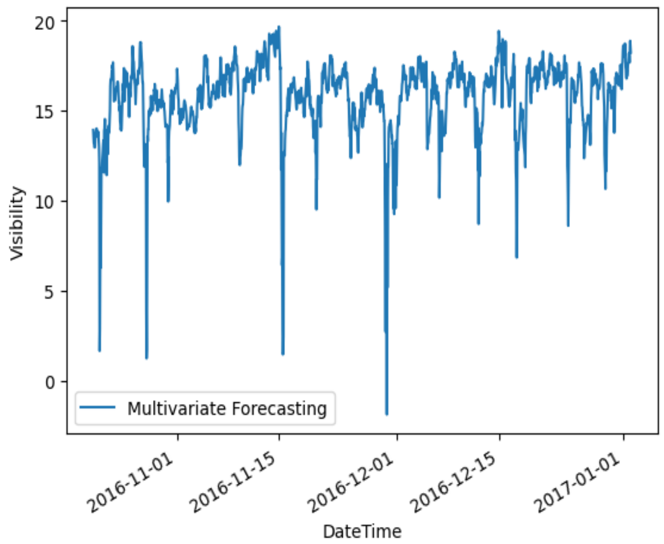

Fig -7: Time series plot for Multivariate forecasting using FB prophet model.

Figure 6 and 7. demonstrates the forecasted values of the univariate and multivariate forecasting performed using the FB prophet model, with the plot displaying an alteration in visibility over each hour of the time period.

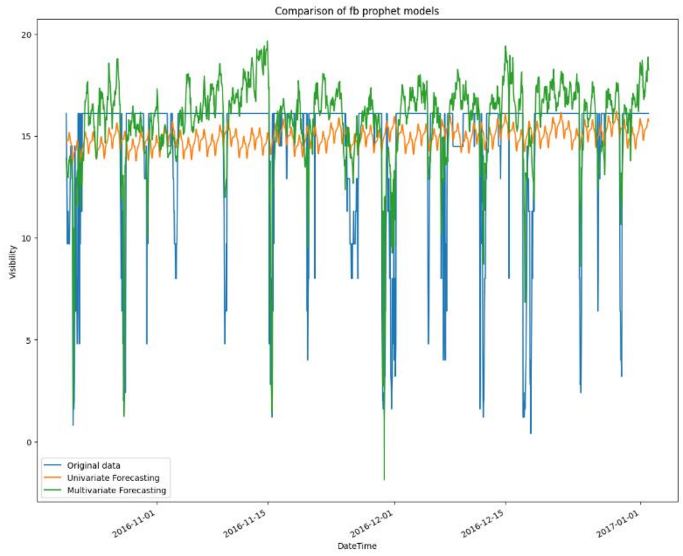

Fig -8: Comparison of the univariate and multivariate forecasting using FB prophet model.

Figure.8 reveals that multivariate forecasting outperforms univariate forecasting and is able to predict almost all points correctly with respect to the original data, except for the points where visibility remains constant for a while.

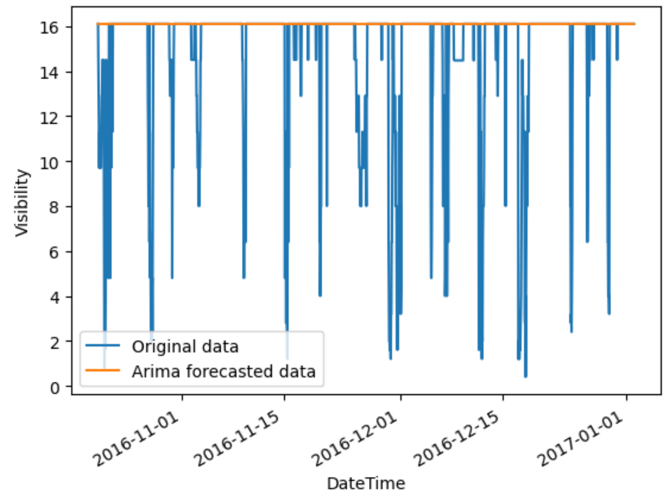

Fig -9: ARIMA forecasted values against the original data.

Figure.9 illustrates the original data plotted against the ARIMA model forecast data. It is evident from this plot that the ARIMA fails to recognize the trend of the time series and hence captures just the mean value of the target variable.

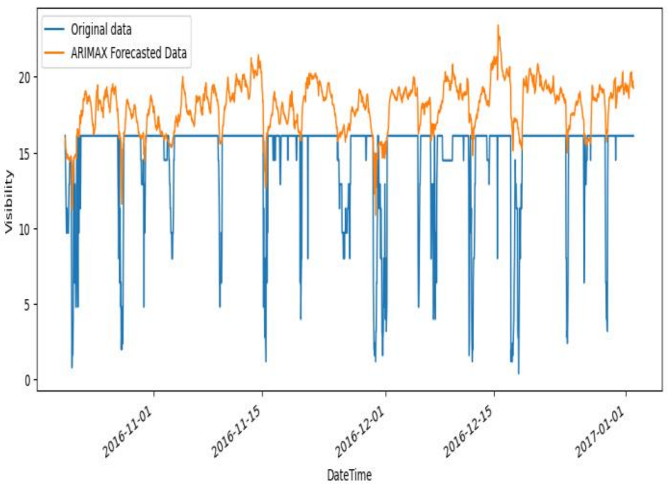

Fig -10: ARIMAX forecasted values against the original data.

Figure 10 demonstrates a plot of the original data versus the ARIMAX projected data. The plot clarifies that ARIMAX surpasses the ARIMA model in detecting a few trends in the time series and correctly predicting some points where the visibility drops in value, as seen by the overlap between the two plots.

6. CONCLUSION

The KNYC Metar data from the Kaggle website was employed in this research. We presented a paper that used real-world visibility data to assess the efficacy of the Facebook Prophet model. The findings indicate that the Multivariate Forecasting performed using Facebook Prophet model has a relatively low Root Mean Squared Error than other time series models used in this paper, making it a trustworthy instrument for forecasting visibility. The research also highlights the potential advantages and difficulties of using time series forecasting for predicting visibility in the aviation sector. One of the major limitations is that the data is too complex and requires careful handling. Additional research in this field could provide more insight on the effectiveness of time series models for predicting visibility as well as their ability to enhance aviation efficiency and safety.

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