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Sama Circular Models for weather data

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***Abstract* - Winds are usually referred to according to their strength and direction from which the wind is blowing. Forecast of wind speed reduces scheduling error and in turn increases reliability of electric power grid. Wind speed is a key parameter, it is important for monitoring and predicting weather patterns and global climate. It affects rates of evaporation, mixing of surface water and development of Seiches and storm surges. It helps to Wind Turbine which produces electricity. Unpredictability and Dispersion of wind power generation is one of fundamental difficulties faced by power system. In this paper, Sama Circular Models(SCM), and Decomposition models are used for wind speed data. Accuracy is measured by SMAPE. SCM is modern, Univariate Forecasting Technique and compared with the Decomposition Technique.**

***Index Terms* - Windspeed, Decomposition Model, Sama Circular Model, SMAPE.**

1.INTRODUCTION

Windspeed Forecast is an essential procedure for power production. Also it plays key a role to have its influence on final production, other variables such as Pressure, Temperature, Humidity and Dew point Temperature by wind direction and its speed as well. For Linear Predictions, there are number of methods such as ARMA, ARIMA, Grey Predcitors etc. For Non-Linear Predictions, Support Vector Machine, Artificial Neural Networks, Artificial Intelligence, fuzzy Logic methods, Wavelet Predictions are used. Besides these methods, We have still more techniques like Exponential Methods, Prophet Methods, Naive Methods, LSTM(Long Term Short Memory), STAR(Space time Auto Regressive), GSTAR (Generalised Space time Auto Regressive), LSTAR(Logistic Smooth Transition Auto Regressive), Intervention methods etc. Time Series is divided into four components namely Trend, Seasonal, Cyclical and Irregular Variations. Trend is a Long-Term Movement and others are Short Term movement. The Trend shows increasing or decreasing tendency over a Long period of time.

A seasonal Pattern exists when a series is influenced by Seasonal Factors, a fixed and known period. A cyclic pattern is not a fixed period. Modelling Seasonal and Cyclical Patterns plays a key role in various disciplines like Weather data, tourism, share market, agriculture, healthcare, transportation, business and still some other activities by identifying patterns in the data.

The Sama Circular Model(SCM) is capable of dealing with this time series components differentiate among seasonal or cyclical Patterns within a series and also applicable in modelling non-stationary series. SCM is improved version of circular model which is based on Newton's law of circular motion, fourier transformation and multiple regression analysis. As it is restricted to apply to the trend free series, SCM is developed.

The basic forecasting technique, Decomposition model assumes that data is affected by four components of time series and Forecast is done by separating these components and combining them again together. Forecasters have found that Multiplicative model fits a wider range of Forecasting situations.

" Sama Circular Model and ARIMA on Forecasting BSE Sensex" was written by Dr.Samanthi Konarasinghe. In this paper, to test the capability of forecasting, SCM and ARIMA models were compared on BSE Sensex, for data from January 1980 to April 2019 of Bombay Stock Exchange and findings shows that SCM is superior to ARIMA. Comparison of Forecasting ability of SCM , ARIMA and Decomposition technique" was given by Dr. Samanthi Konarasinghe. In this article, SCM ARIMA/SARIMA and Decomposition Techniques were used to test the predictive ability. Forty years data of Monthly Female Unemployment rates in Australia from 1978 was tested and found SCM is superior to others.

Windspeed is predicted with the help of Multilayer Perceptron and NARX and measured Accuracy with performance of Correlation coefficient and RMSE values. Daily data has taken from 2015-2017. The author concluded that NARX shows better performance than MLP.ARIMA is applied to hourly wind data from Zaafarana5 project in Egypt and achieved improvement over persistence model upto 5 and six hours ahead. Decomposition models are the most suitable models for Forecasting arrivals. Arrivals show Wave like patterns with trend. Anderson-Darling test was used for goodness of fits. Measurement of Errors of all the fitted models were satisfactorily small. ”Time Series Decomposition model for accurate windspeed forecast” was given by Prema, V.,K& Rao, K., U proposes time series models for short-term prediction of windspeed. It was done one day ahead . For each model, these predicted values are compared with the actual values of the next day. Basic Exponential Smoothing is proposed. Multiplicative decompositions were carried out and models were tested for different durations of samples and observed that prediction for four months data gave least error. In the paper, Decomposition of Time Series Data of Stock Markets and its implications for Prediction, explained accuracy of decomposition results and efficiency of our forecasting techniques even in presence of a dominant Random Component in the Time Series. The authors designed three approaches for Forecasting and also computed their accuracy.

Helena, et al[9],estimated the true cycle of a time series. Robustness of technique was tested under Monto Carlo simulations using several specifications and is able to explain true cycles based on statistical tests.

2.METHODOLOGY

We used Decomposition technique and Sama Circular Model(SCM). For Daily data of Windspeed from January 2014 to Jan 2019 Data is converted to Monthly data. Timeseries plots are used for Pattern Recognition. SCM and Decomposition are tested using Software Minitab 19. Goodness of Fit and Measurements of Errors had applied in present model. The ACF of Residuals and Ljung Box statistics(LBQ) are used to test independence and normality is checked by Anderson Darling test. Performance Measure of Forecasting is assessed by SMAPE.

a)Decomposition Technique

It is a primary tool, used to forecast models. It provides a structured way of thinking both in terms of modelling complexity and how to best capture each of these components in a given model. It reduces Time series in to four components: Trend, Seasonal, Cyclic effects and Random Errors.

Value = (mean) X (Trend) X (Seasonality) X (Cycle) X (Random)

b)Sama Circular Model

It is improved form of Circular Model based on Fourier Transformation. SCM was further developed as Fourier Transformation helps to transform a real valued function into series of Trigonometric Function(Phillippe,2008). A Particle P, which is moving in a horizontal circle of Centre ‘O’ and reduces as is given in figure1. The ω is angular speed of particle.

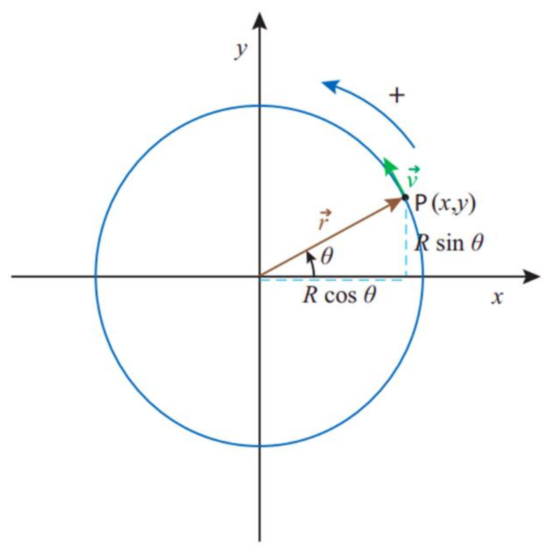

Fig 1. Motion of particle in Horizontal circle

Initially Circular Model(CM) is written as

$$Y_t = \sum_{k=1}^{n}(a_k sink\omega t + b_k cosk\omega t) + \varepsilon_t$$

The disadvantage of CM is not applicable for series with Trend. The SCM alleviates Circular Model by using Differencing technique. The time taken for one complete circle is known as Period of Oscillation.

$$T = \frac{total\ no.of\ periods}{total\ no.of\ peaks} = \frac{N}{f} \quad \text{............................ (1)}$$

Therefore, time taken for one complete circle (T) is given by

$$T = 2\pi/\omega \quad \text{................................ (2)}$$

From (1) and (2), $\frac{2\pi}{\omega} = \frac{N}{f}$

$$\omega = \frac{2\pi f}{N}$$

Hence SCM is

$(1-B)^d Y_t = \sum_{k=1}^{n}(a_k sink\omega t + b_k cosk\omega t) + \varepsilon_t$ .... (3)

Where d^{th} order difference of $Y_t = y_t^d = (1-B)^d Y_t$.

B is backshift operator.

3.RESULTS AND DISCUSSION

a) Pattern Recognition

Figure 2 is Timeseries (TS) plot of Windspeed and fig 3 and fig 4 are Timeseries plot of First differences and Second differences.

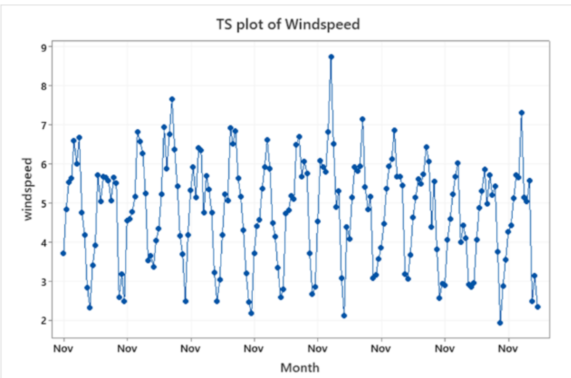

Fig 2. Timeseries plot of windspeed

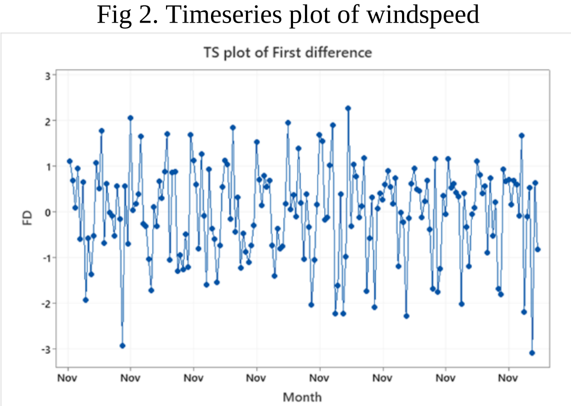

Fig 3. Time series plot of First differences

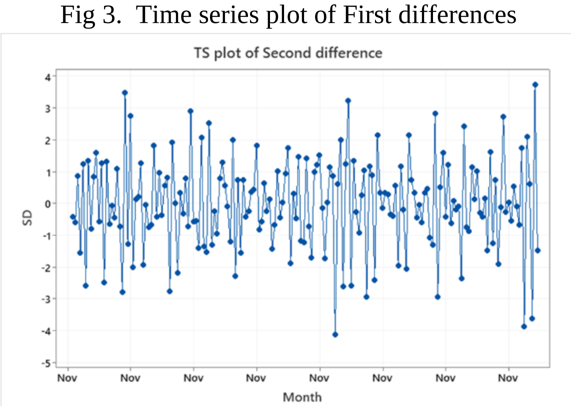

Fig 4. Time series plot of Second Difference

Fig. 2,3 and 4 are irregular waves which are Trend free. CM is tested by differenced series and found that it is fitted for second difference series(Xt). The Fitted model is

$Xt = -0.006 - 0.501 sin4\omega t$

Where ω =2.25,f=43, N=120.

Then for 12 Trigonometric series; sinkωt and coskωt for k = 1, 2 ,3 ,4 , 5, 6 are obtained.

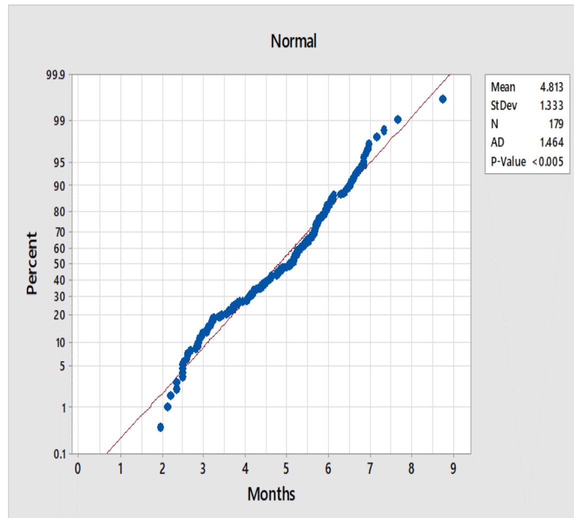

Fig 5. Test for Normality

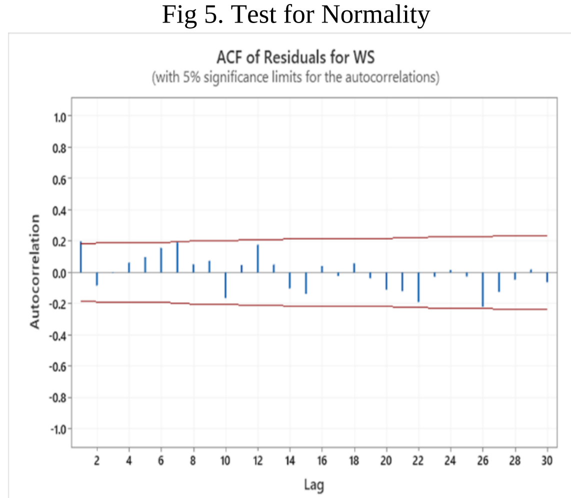

Fig.6 Autocorrelation

The Anderson Darling test satisfies normality of residuals. LBQ test confirmed the independence of residuals. Measurement of Errors are satisfactorily small. Hence, the estimates of Windspeed can be obtained by the SCM is

$Y_t = 2Y_{t-1} - Y_{t-2} - 0.006 - 0.501 sin4\omega t$

b) Decomposition Model

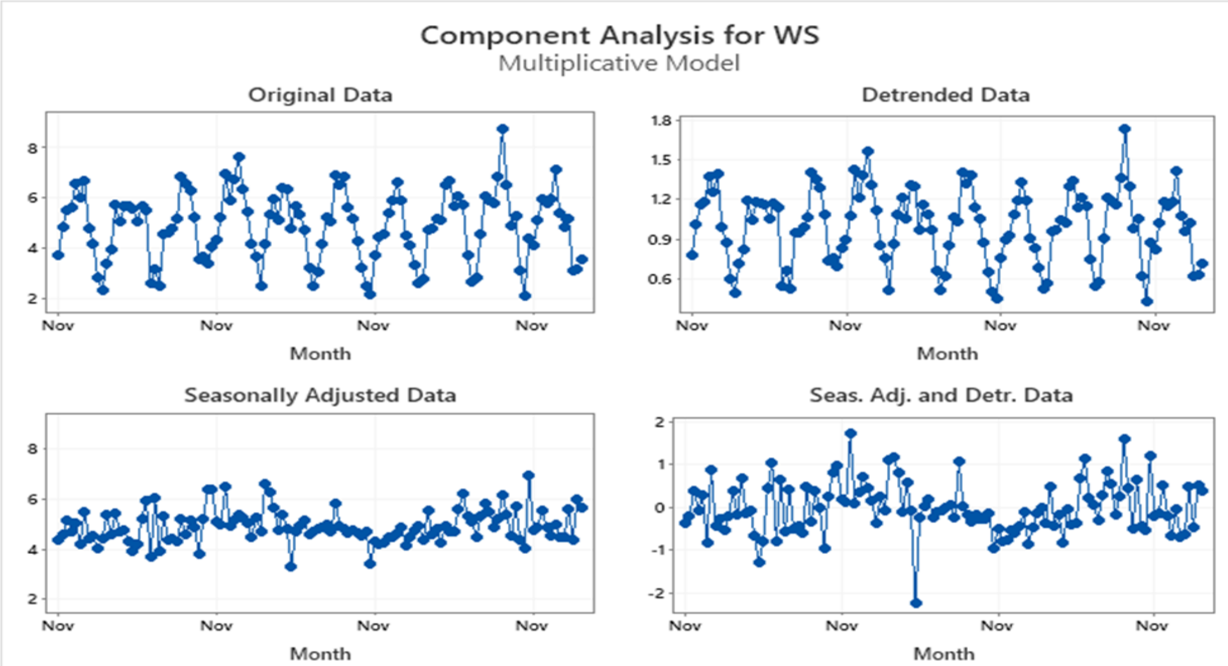

Fig.7. (a) Original data (b) Detrended data (c) Seasonality adjusted data (d) Seasonality adjusted and detrended data.

In the figure 7, detrend values are the data with the trend component removed. It is obtained by observed values divided by the trend values(Multiplicative model).Seasonally adjusted values are the data with seasonal components removed. As both resembles to original data, We can say that Trend and Seasonal components exists in the data.

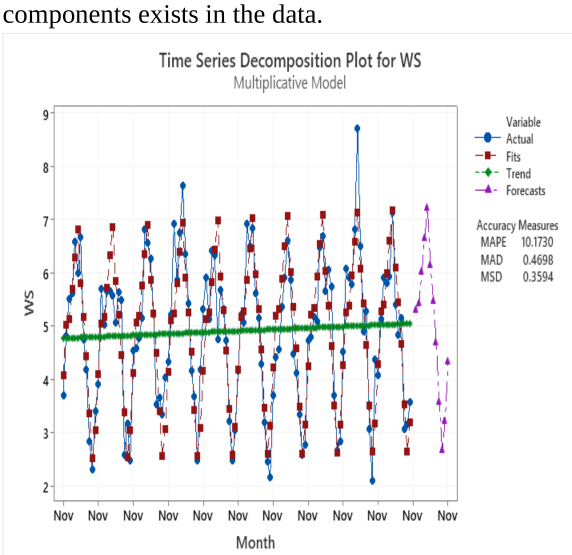

Fig. 8

In the Fig 8, ,the model fits closely follow the data, which indicates that model fits the data, but it does not able to predict at the end. Performance is measured by SMAPE to both Fitting and Verification of model.

CONCLUSION

Comparison of SCM and Decomposition model with help of SMAPE is as follows:

	Fitting	Verification
Decomposition	0.1742	0.0969
SCM	0.1623	0.0944

The above table has measurement of errors in model fitting and verification for both SCM and Decomposition. SMAPE for verification of both models are almost similar, but for fitting model of SCM is less than Decomposition model showing that it is superior than decomposition model.

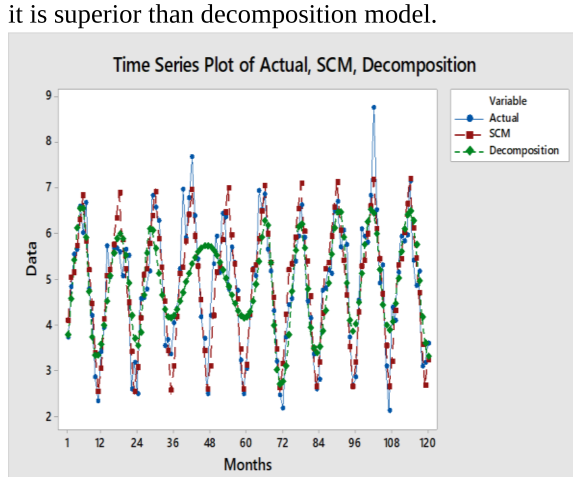

Fig.9

Figure 9 shows Timeseries plot of Actual Vs SCM and Decomposition forecast values. It shows SCM follow actual values.

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