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Weather Prediction Using Time Series Analysis (Arima Model)

Gorikapudi Manidheer Babu[1*] , Tammisetty Venkata Padma, Bondili Jahnavi , Peravali Bhavitha , Pullagura Anuradha

1*Assistant Professor: Vignan's Nirula Institute of Technology and Science for Women.

2,3,4,5 B.Tech Scholar: Vignan's Nirula Institute of Technology and Science for Women.

ABSTRACT

In meteorology and scientific research, weather forecasting is a crucial topic. For this study, the forecasting model was constructed using the Box-Jenkins method-based Seasonal Auto Regressive Integrated Moving Average (ARIMA) model. The period from January 1968 to December 2018's monthly rainfall data for Balodabazar, Bemetara, Raipur city was used. The best ARIMA model orders were determined using the autocorrelation and partial autocorrelation functions for time series data spanning the years 1968 to 2018. Statistical measures like RMSE and R2 were used to compute the accuracy of each model and compare them. The models used to forecast the monthly rainfall for the Balodabazar (1,0,1) (1,1,1), Bemetara (0,0,2) (0,1,1), and Raipur (1,0,1) (0,1,1) yielded the most accurate results.

Keywords: forecasting, ARIMA model, box-jenkins method, rainfall, RMSE and R2

1. INTRODUCTION

A key component of statistics is time series analysis, which examines data sets to identify their properties and forecasts time series values in the future based on those features. Univariate time series are those that only have records for one variable. However, it is referred to as multivariate if records of many variables are taken into consideration. A time series may be discrete or continuous. While observations in a discrete time series are measured at distinct points in time, observations in a continuous time series are measured at every instance of time. For instance, temperature measurements, river flow, chemical process concentration, etc. It is possible to record it as an ongoing time series.

However, other factors including a city's population, a company's output, and currency rates August 2016, pages 104–109, International Journal of Computer Science and Mobile Computing, Vol. 5, Issue 8. Copyright 2016, IJCSMC Copyright 2019 All Rights Reserved 105 could be interpreted as a discrete time series between any two currencies. An hourly, daily, weekly, monthly, or annual time separation is a common way to record consecutive observations in a discrete time series. To create a suitable model that captures the inherent structure of a time series, the primary goal of a time series model is to gather and thoroughly examine historical data.

Next, in order to provide forecasts, this model is utilized to produce future values for the series. One way to describe time series forecasting is the process of making future predictions based on historical knowledge. Fitting a suitable model to the underlying time series requires careful consideration because time series forecasting is essential in many real-world domains, including science, engineering, finance, and economics. A suitable model fit is necessary for time series forecasting to be successful. For many years, academics have worked hard to create effective models that will increase the accuracy of their forecasts.

In the area of decision-making, time series prediction is essential. Past observations are analyzed to create a mathematical instantaneous series in an attempt to predict future values, allowing for an appropriate margin of error for the decision-maker. The time series prediction models are put into practice with a cursory knowledge of the technology collection process. Typical forecasting techniques include container and Jenkins models as well as Artificial Neural Networks (ANNs). The first can modify data with linear and deskbound properties, while the second works with complex data relationships to overcome the limitations of conventional forecasting models and increase prediction accuracy through the use of hybrid models.

These forecasting techniques are made up of many designs that can target both linear and nonlinear samples and develop into models for any type of data. However, the real data occasionally possesses all of these qualities, which leads to inadequate outcomes when employing the conventional approaches.

2. LITERATURE SURVEY

The paper[1]the author Kuo and Sun, (1993) was used to Associate in having intervention model for average10 days stream flow forecast and synthesis that was investigated by to effect the extraordinary phenomena caused by typhoons and different serious irregularities of the weather of the Tanshui geographical area in Taiwan.

The paper[2] Chiew et al, (1993) conducted a comparison of six rainfall-runoff modeling approaches to pretend daily, monthly and annual flows in eight tolerant catchments. They concluded that time-series approaches will agreement adequate estimates of monthly and annual yields within the water capitals of the catchments.

The paper[3] Langu, (1993) is another approach which used statistical analysis to observe changes in weather and runoff patterns to go and look for important changes inside the parts of variety of weather statistic. Box and Jenkins (1994), in early 1970's, pioneered in developing methodologies for statistic indicating within the univariate case often known to Univariate Box-Jenkins (UBJ) ARIMA modeling in this approach of the author.

The paper[4]Chaotic features are associated with the atmospheric phenomena also have fascinated the attention of the modern scientists (Sivakumar 2001; Sivakumar et al. 1999; Men et al. 2004). At present, the valuation of the nature and causes of seasonal climate variability is still formation. Since, it is a complicated phenomenon that includes many specialized fields of know-how to work for weather prediction (Guhathakurata, 2006); therefore, in the field of meteorology all assumptions are to be taken in the visage of uncertainty connected with local of and global climatic variables. Different scientists over the world have developed stochastic weather models. It is mainly used to predict and warn about how natural disasters that are caused by abrupt modification in climate conditions and has been approached using Climatic means.

The paper[5]Seyed, A., Shamsnia, M.,Naeem,S. and Ali, L.,(2011) was explained that the modelled weather parameter using some of the random methods(ARIMA Model) It include the Case Study:Abadeh station,Iran. Mahsin et al. (2012) used Box-Jenkins methodology to form seasonal ARIMA model for monthly weather information taken for Dhaka station, Bangladesh, for the significant amount from 1981-2010. In their paper, ARIMA (0, 0, 1) (0, 1, 1) model was found suitable and also the model is working for forecasting the monthly climate prediction.

The paper[6](Brown,2004)Time series analysis involves systematically collecting data at regular intervals over a defined period.It requires extensive data to ensure reliability and accommodate seasonal variations.this method enables forecasting by leveraging past data to predict future trends,ensuring robustness in identifying patterns and trends while minimizing the impact of outliers.

The paper[7](Gharbi,2011) During the last decades,dengue viruses have spread throughout the Americas region,with an increase in the number of severe forms of dengue.The survelliance system in Guadeloupe (French West Indies) is currently operational for the detection of early outbreaks of dengue.The goal of the study was to improve the surveillance system by assessing a modelling tool to predict the occurrence of dengue epidemics few months ahead and thus to help an efficient dengue control.

3. PROPOSED METHODOLOGY

In the topic of weather prediction using time series analysis, we have choosen the model of ARIMA which stands for Autoregressive Integrated Moving Average the model is explained as follows:

ARIMA model is a combination of AR and MA models. The equation of the AR model of order one, when it reaches to the starting point will have infinite moving average (Choi, B., 2012). In ARMA model p and q have to defined, where p = number of significant terms in ACF and q = number of significant terms in PACF.

To determine the optimal value for p and q there are two ways:

1. Plotting patterns in correlation 2. Automatic selection techniques

1) Plotting patterns in correlation:

There are two functions used for plotting patterns in correlation:

a) Auto correlation factor (ACF): It is the correlation between the observations at the current time stamp and observations at the previous time stamp (Hagan, M.T. and Behr, S.M., 1987).
b) Partial auto correlation factor (PACF): The correlation between the observations at two different time stamps, assuming both observations are correlated to the observations at another time stamp (Hagan, M.T. and Behr, S.M., 1987).

2) Automatic selection techniques:

There are three commonly used techniques for automatic selection of time series model:

a) Minimum info criteria (MINIC): This builds multiple combinations of models across a grid search of AR and MA terms. It then finds the model with lowest Bayesian information criteria (Stadnytska, T., Braun, S. and Werner, J., 2008).
b) Squared canonical correlations (SCAN): It looks at correlation matrix of the data, then it compares it with its lags. It then looks at the eigen values from the correlation matrix to find the combination of AR and MA probably having SCAN as 0. It finds the pair as the best where the convergence is quickest (Stadnytska, T., Braun, S. and Werner, J., 2008).

c) The extended sample auto correlation function (ESACF): As it is known that AR and MA are related. Essentially it filters out the AR terms until only MA piece is left. This process is repeated until fewest AR terms are left and maximum MA terms (Stadnytska, T., Braun, S. and Werner, J., 2008).

It completely depends on the individual to choose from either of the methods helping them to find the optimal value of *p* and *q* for better performance of the model.Box and Jenkins (1976) have effectively put together in a comprehensive manner, the relevant information required to understand and use time series ARIMA models. A detailed strategy for the construction of linear stochastic equation describe the behavior of time series was examined. Consider the function Zt represents forecasted rainfall and temperature at time t month. Yt is series of observed data of rainfall and temperature at time t. If series is stationary, then an ARIMA process can be represented as

$$\nabla pZt = \nabla qYt \;\ldots.\; (1)$$

Where ∇ is a back shift operator. If series Y is not stationary then it can be reduced to a stationary series by differencing a finite number of times.

$$\nabla pZt = \nabla q\ (1\text{-}B)\ d\ Yt \;\ldots.\; (2)$$

Where d is a positive integer, and B is back shift operator on the index of time series so that B Yt = Yt -1; B2Yt = Yt -2 and so on. Thus further equation (2) can be simplified into following equation.

$$(1\text{-}\Phi1B\text{-}\Phi2B2\text{-}\ldots\ldots.\text{-}\Phi pBp)\ Zt = \theta0+ (1\text{-}\theta1B\text{-}\theta2B2\text{-}\ \ldots\ldots\ldots\text{-}\ \theta qBq)\ at \;\ldots..\; (3)$$

Where at's a sequence of identically distributed uncorrelated deviates, referred to as "white noise". Combining equations (2) and (3) yields the basic Box-Jenkins models for non stationary time series

$(1\text{-}\Phi1B\text{-}\Phi2B2\text{-}\ldots\ldots.\text{-}\Phi pBp)\ (1\text{-}B)d\ Yt = \theta0+ (1\text{-}\theta1B\text{-}\theta2B2\text{-}\ \ldots\ldots\ldots\text{-}\theta qBq)\ at$ ….(4) Equation (4) represents an ARIMA process of order (p,d,q). Seasonal ARIMA model represented as follows for a stationary series i.e. differencing parameters (d &ds = 0) equal to Zero, used for forecasting rainfall. $\nabla\quad \nabla ps\ pZt = \nabla\quad \nabla\ qs\ q\ Yt$ ….(5)

Where ps and qs are the seasonal parameters corresponding to AR and MA process. Model of type of equation (5) was fitted to given set of data using an approach consists of mainly three steps (a) identification (b) estimation (c) application (forecasting) or diagnostic checking. At the identification stage tentative values of p, d, q and ps, ds, qs were chosen. Coefficients of variables used in model were estimated. Finally diagnostic checks were made to determine, whether the model fitted adequately describes the given time series. Any inadequacies discovered might suggest an alternative form of the model, and whole iterative cycle of identification, estimation and application was repeated until a satisfactory model was obtained.

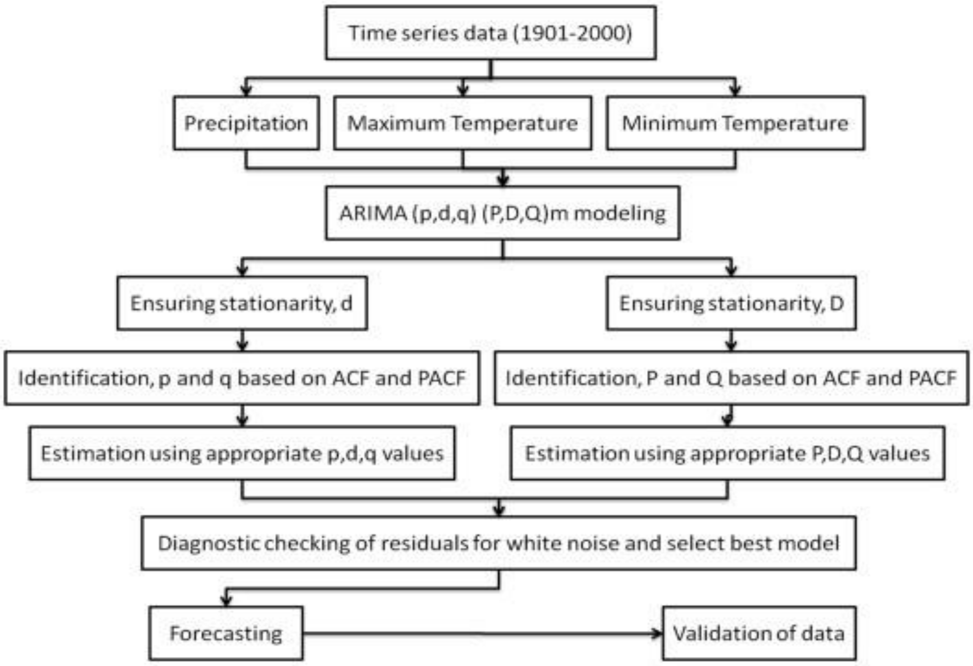

Figure 1. Methodology followed

4.RESULTS

The ARIMA model is implemented stochastically based on the default values of the parameters p, d and q for the different scenarios individually for TC (Z TC). The values for each parameter (p, d, q) are: (0,0,0), (0,0,1), (0,1,1), (1,0,0), (1,0,1), (1,1,1), (2,1,1) and (2,0,3). All the TC data are included for each scenario, covering a period of 37 months. The forecasting is for 24 months. Some scenarios do not show a reasonable forecasting for this period. In this section, we present the TC forecasting using the ARIMA parameters (1,0,1), (0,0,1), (2,1,1) and (2,0,3) as the default input parameters. Figure 1 shows the forecasting for ARIMA (1,0,1) for the log of TC over time (24 months). A polynomial trend curve is used to illustrate the relationship between the historical TC data and the forecasted data. The historical TC data (37 months) appear before the vertical line. The forecasted data (24 months) are presented after the vertical line. The forecasted data for ARIMA (1,0,1) seem to be in sync with the historical data before the vertical line and with the polynomial trend curve after the vertical line. This is obvious because the forecasted data show a polynomial trend curve. However, there are lower and higher extreme forecasted values outside the trend.

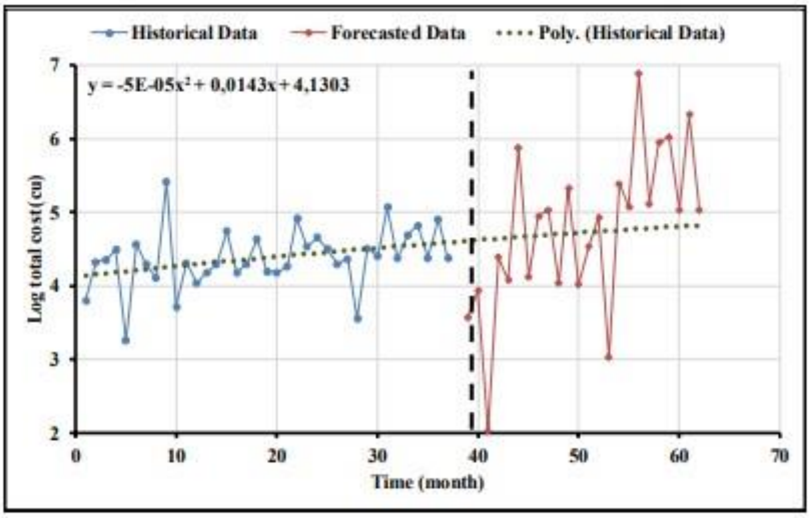

Figure 2. Arima(1,0,1)

Figure 2 shows the forecasting for ARIMA (1,0,1) for the log of TC over time (24 months). A polynomial trend curve is used to illustrate the relationship between the historical TC data and the forecasted data. The historical TC data (37 months) appear before the vertical line. The forecasted data (24 months) are presented after the vertical line. The forecasted data for ARIMA (1,0,1) seem to be in sync with the historical data before the vertical line and with the polynomial trend curve after the vertical line. This is obvious because the forecasted data show a polynomial trend curve. However, there are lower and higher extreme forecasted values outside the trend.

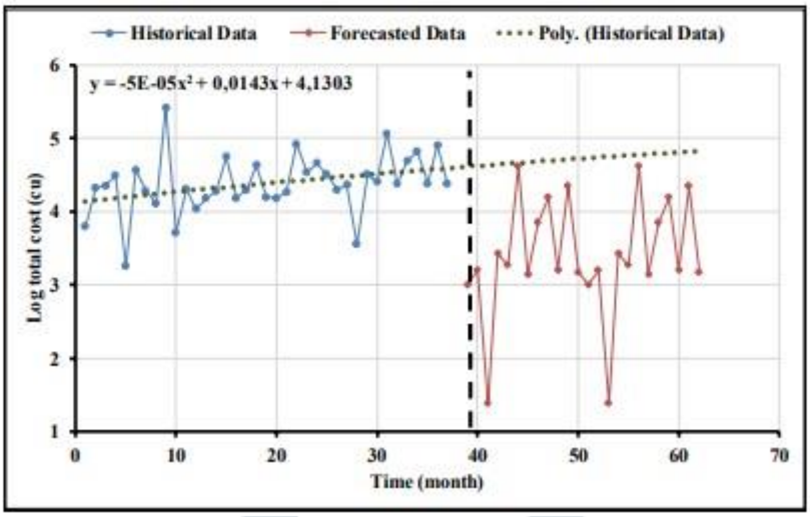

Figure 3. ARIMA (0,0,1)

The results of ARIMA (0, 0, 1) are shown in Figure 3. After the vertical line, the forecasted data for the 24-month period do not seem to be in sync with the historical data before the vertical line or with the polynomial trend curve after the vertical line.

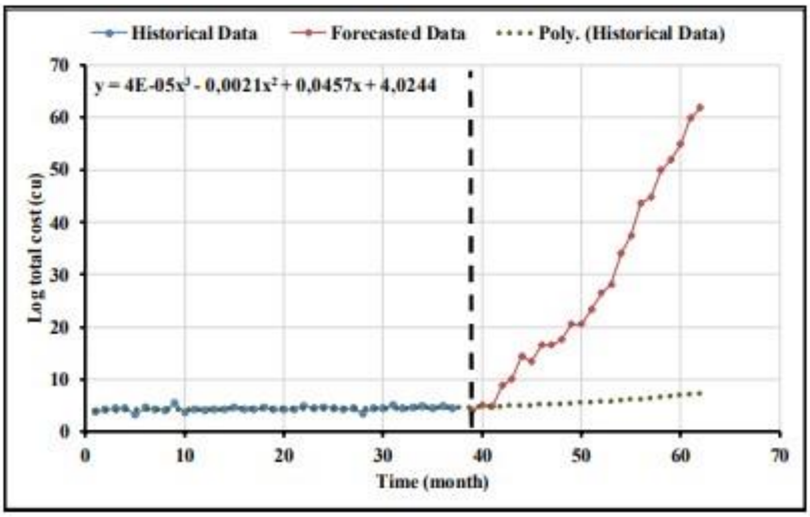

Figure 4. ARIMA (2,1,1)

Figure 4 shows the results for ARIMA (2,1,1) for the TC with the polynomial trend curve. The forecasted data for the 24-month period do not seem to be in sync with the historical data before the vertical line or with the polynomial trend curve after the vertical line. The forecasted data are much higher than the historical and polynomial trend.

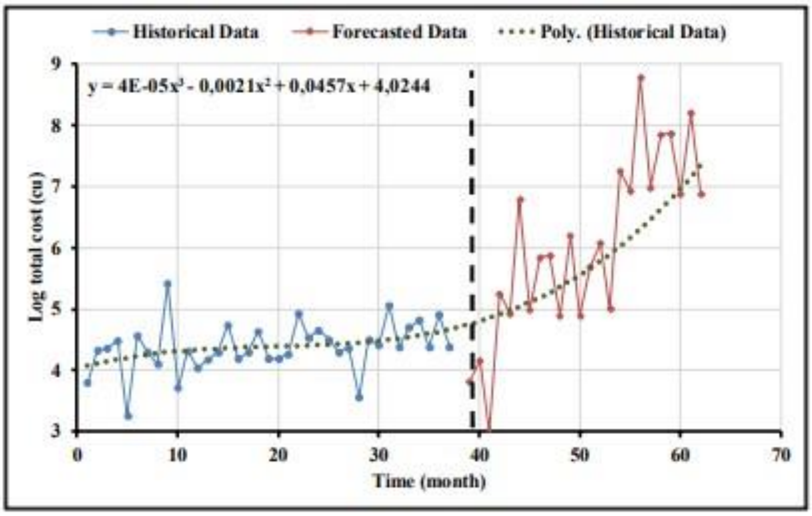

Figure 5.ARIMA (2,0,3)

The results of ARIMA (2,0,3) are shown in Figure 5. In the figure, the forecasted data for the 24month period seem to be in sync with the historical data before the vertical line and with the polynomial trend curve after the vertical line. Accordingly, these parameters are suitable for forecasting the TC data for this mining drilling rig.Overall, the forecasting using ARIMA (2,0,3) has better results than forecasting using the other ARIMA input parameters. We also find that the values of (p, d, q) affect the ARIMA forecasting, and the ARIMA (p, d, q) values are sensitive to the data type.

5.CONCLUSION

utilizing various values of the ARIMA parameters (p, d, and q), the forecasting for our case study utilizing the ARIMA model demonstrates varying forecasting ability. Four distinct scenarios use the ARIMA parameters (p, d, and q); one of them demonstrates appropriate forecasting. We discover that the forecasting approach is significantly impacted by the parameter values. Consequently, for more accurate forecasting, these factors need to be properly estimated from the data. AI systems like MOGA, which are based on the ARIMA model, may offer additional options for estimating the parameters (p, d, and q) and enhancing data predictions. A high degree of accuracy in data forecasting can be achieved using the results of the MOGA based on the ARCA model. The anticipated data can then be utilized for life cycle cost analysis. They can be used, for instance, to determine when the face drilling rig in our case study needs to be replaced.

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