**International Journal of Science and Research (IJSR)**
**ISSN: 2319-7064**
**Impact Factor 2025: 7.089**

# Modeling Temporal Data: A Comparison Between Time Series Methods and the Poisson Process

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**Abstract:** ***This study aims to provide a comparative analysis between time series methods and the Poisson process in modeling temporal data. The comparison will focus on their theoretical foundations, assumptions, modeling capabilities, and forecasting performance using real temperatures for Khartoum State, Sudan. The findings of this study are expected to help researchers and practitioners choose the most suitable approach for their specific applications. It can be observed that indicate that forecasting temperatures in Khartoum State, Sudan using Box–Jenkins models yields an annual average of (31.61), whereas forecasting using a homogeneous Poisson process produces a constant average of (31.61) over the predicted years, this indicates that the homogeneous Poisson process can be used as an alternative to Box–Jenkins models in the forecasting process. This study offers useful material for both new and experienced researchers by providing guidance on time series Poisson process produces forecasting techniques and approaches that will help in enhancing the value of decision making.***

**Keywords:** Poisson process, forecasting, Autocorrelation, Kolmogorov – Smirnov, stationary

## 1. Introduction to Time Series Analysis

In practice a suitable model is fitted to a given time series, and the corresponding parameters are estimated using the known data values. The procedure of fitting a time series to a proper model is termed as Time Series Analysis [10]. It comprises methods that attempt to understand the nature of the series and is often useful for future forecasting and simulation. In time series forecasting, past observations are collected and analyzed to develop a suitable mathematical model which captures the underlying data generating process for the series [11, 12]. The future events are then predicted using the model. This approach is particularly useful when there is not much knowledge about the statistical pattern followed by successive observations or when there is a lack of a satisfactory explanatory model. Time series forecasting has important applications in various fields. Often valuable strategic decisions and precautionary measures are taken based on the forecast results. Thus, making a good forecast, i.e. fitting an adequate model to a time series is very important. Over the past several decades many efforts have been made by researchers for the development and improvement of suitable time series forecasting models.

## 2. Auto Regressive Integrated Moving Average (ARIMA) time series model

Introduced by Box and Jenkins (1970), the ARIMA model has been one of the most popular approaches for forecasting. In the ARIMA model, the estimated value of a variable is supposed to be a linear combination of the past values and past errors. Generally, a non-seasonal time series can be modelled as a combination of past values and errors, which can be denoted as ARIMA (p,d,q) which is expressed in the following form:

$$X_t = \theta_0 + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + e_1 + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta e_{t-q}$$

where $X_t$ and et are the actual values and random error at time t, respectively, Φi (i = 1,2,…….,p) and θj ( j = 1,2,……,q) are model parameters. p and q are integers and often referred to as orders of autoregressive and moving average polynomials respectively. Random errors et are assumed to be independently and identically distributed with mean zero and the constant variance, σe 2. Similarly, a seasonal model is represented by ARIMA (p,d,q) x (P,D,Q) model, where P denotes number of seasonal autoregressive (SAR) terms, D denotes number of seasonal differences, Q denotes number of seasonal moving average (SMA) terms. Basically, this method has three phases: model identification, parameters estimation and diagnostic checking. The ARIMA model is basically a data oriented approach that is adapted from the structure of the data itself. (*STATISTICS IN TRANSITION new series, Spring 2015*)

Temporal data modeling plays a crucial role in many scientific, economic, and engineering applications, where observations are collected sequentially over time. Accurate modeling and forecasting of such data are essential for informed decision-making, planning, and risk management. Two prominent approaches for analyzing temporal data are time series methods and stochastic processes, particularly the Poisson process. Time series focus on analyzing dependencies within observed data over time. These methods capture important patterns such as trends, seasonality, and autocorrelation, making them suitable for forecasting continuous or discrete-valued observations. Models such as ARIMA and exponential are used due to their flexibility and effectiveness in capturing temporal dynamics. On the other hand, the Poisson process is a stochastic model designed to describe the occurrence of random events over time or space. It is particularly useful when the primary interest lies in modeling the number of events occurring within a fixed interval, if these events happen independently and at a constant average rate. This approach is commonly applied in areas such as queueing theory, telecommunications, and reliability analysis. Despite their widespread use, time series methods and

Poisson processes differ fundamentally in their assumptions, structure, and application domains. While time series models emphasize temporal dependence and pattern extraction, the Poisson process assumes independence and focuses on events. Appropriate selecting the appropriate modeling framework depends largely on the nature of the data and the underlying phenomenon.

## 3. Methodology

**Research Design**

This study employed a quantitative time-series forecasting design to investigate the temporal behavior of temperature in Khartoum State, Sudan. Two complementary statistical approaches were considered: Autoregressive Integrated Moving Average (ARIMA) models for forecasting temperature values and a Poisson-process-based model for forecasting the occurrence of predefined temperature-related events.

The methodological framework was designed to ensure that each statistical model was applied to a response variable consistent with its underlying distributional assumptions.

## 4. Data Source and Study Variables

Historical temperature data for Khartoum State were obtained from Khartoum covering the period from 1/1/2015 to 1/1/2025. The dataset consisted of monthly observations of temperature measured in degrees Celsius (°C).

The primary continuous response variable was the observed temperature, denoted by ($T_t$), where ($t$) represents the observation time.

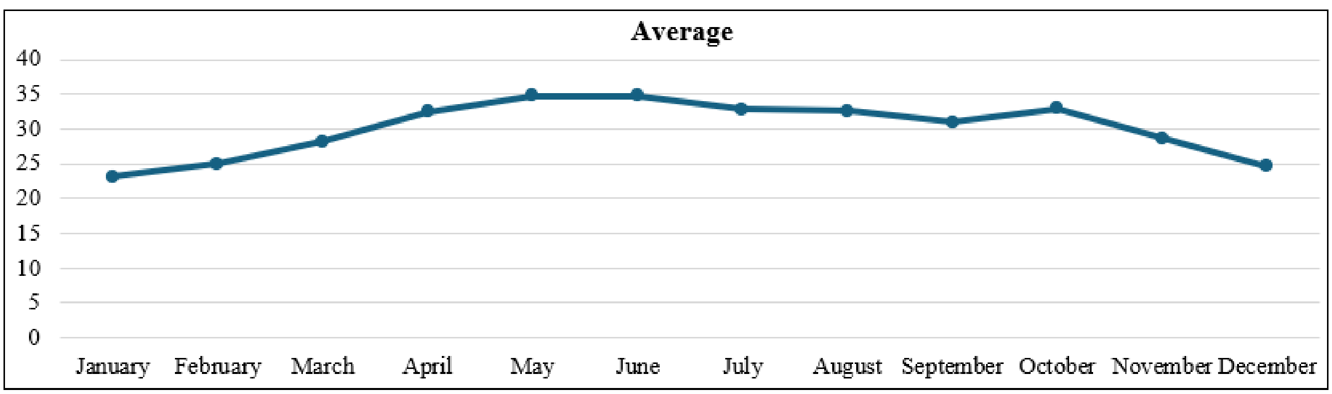
For the Poisson-process analysis, the continuous temperature measurements were transformed into counts of predefined temperature-related events. For example, an event was defined as an observation exceeding a scientifically justified temperature threshold.

## 5. Data Analysis

Data analysis was conducted using R statistical software and IBM SPSS Statistics. R was employed to perform statistical modeling, estimation, diagnostic procedures, and graphical analyses, while SPSS was used for data management, descriptive statistics, and relevant inferential statistical analyses. The statistical procedures were selected according to the nature and distribution of the data and the objectives of the study.

**Descriptive statistics for temperatures by month**

| Month | Average | Std. Deviation | Confident interval | |
|---|---|---|---|---|
| | | | Maximum | Minimum |
| January | 24.34 | 1.65 | 25.44 | 23.23 |
| February | 26.24 | 1.89 | 27.51 | 24.96 |
| March | 29.43 | 1.27 | 30.28 | 28.58 |
| April | 33.71 | 0.83 | 34.27 | 33.15 |
| May | 36.00 | 0.83 | 36.56 | 35.45 |
| June | 36.03 | 0.53 | 36.38 | 35.67 |
| July | 34.05 | 0.99 | 34.72 | 33.37 |
| August | 33.85 | 1.29 | 33.72 | 31.98 |
| September | 32.24 | 1.45 | 35.21 | 33.26 |
| October | 34.19 | 0.85 | 34.76 | 33.63 |
| November | 29.87 | 1.09 | 30.6 | 28.31 |
| December | 25.83 | 1.85 | 27.07 | 24.58 |




Peak Temperatures: The highest average temperatures occur in June (36.03°C) and May (36.00°C). Lowest Temperatures: The lowest average is in January (24.34°C) Annual Stability: Monthly standard deviations are relatively low (ranging from 0.53 to 1.89), suggesting consistent seasonal patterns.

## 6. Homogeneous Poisson Processes

This section focuses on homogeneous Poisson processes: Poisson processes for which the rate function $\lambda$ is a constant. the mean $\Lambda$ of the increment $N(t+h) - N(t)$ is $\Lambda = \int_t^{t+h} \lambda dz = \lambda h$, simply the constant rate $\lambda$ times the length of the time interval over which the increment is defined. Note that $\Lambda$ therefore does not depend on where the interval of length h lies, but only on its length; this is described by saying that homogeneous Poisson processes have stationary increments. (*Poisson processes (and mixture distributions, James W. Daniel Jim Daniel's Actuarial Seminars, August 29, 2019)*)

## 7. Box-Jenkins Modelling

The Box-Jenkins approach to modelling ARIMA processes was described in a highly in-affluential book by statisticians George Box and Gwilym Jenkins in 1970. An ARIMA process is a mathematical model used for forecasting. Box-Jenkins modelling involves identifying an appropriate ARIMA process, fitting it to the data, and then using the fitted model for forecasting. One of the attractive features of the Box-Jenkins approach to forecasting is that ARIMA processes are a very rich class of possible models and it is usually possible to find a process which provides an adequate description to the data. The original Box-Jenkins modelling procedure involved an iterative three-stage process of model selection, parameter estimation and model checking. Recent explanations of the process (e.g.,Makridakis, Wheelwright and Hyndman, 1998) often add a preliminary stage of data preparation and a final stage of model application (or forecasting).

**Descriptive statistics for temperatures by years**

| Years | Average | Std. Deviation | Confident interval | |
|---|---|---|---|---|
| | | | Maximum | Minimum |
| 2015 | 31.51 | 3.98 | 34.03 | 28.98 |
| 2016 | 31.38 | 3.94 | 33.88 | 28.88 |
| 2017 | 30.73 | 5.18 | 34.02 | 27.43 |
| 2018 | 32.27 | 4.60 | 35.18 | 29.35 |
| 2019 | 31.94 | 4.75 | 34.94 | 28.9 |
| 2020 | 30.66 | 4.87 | 33.76 | 27.56 |
| 2021 | 32.00 | 4.14 | 34.63 | 29.37 |
| 2022 | 30.93 | 3.75 | 33.31 | 28.55 |
| 2023 | 31.21 | 3.90 | 33.69 | 28.73 |
| 2024 | 31.34 | 3.58 | 33.61 | 29.07 |
| 2025 | 31.34 | 4.15 | 33.94 | 28.67 |

Normal test: Kolmogorov Smirnov test:

| Statistical test | N | p-value | Significant value |
|---|---|---|---|
| 0.025 | 132 | 0.09 | 0.05 |

A Kolmogorov-Smirnov test (p-value = 0.29) indicated the data follows an exponential distribution, which is a prerequisite for many stochastic modeling techniques.

Homogeneous Poisson Process: Laplace test:

| Statistical test | N | p-value | Significant value |
|---|---|---|---|
| 0.1556 | 132 | 0.876 | 0.05 |

Note that means the data do not show a general trend, indicating that the rate is constant; therefore, they can be modeled as a homogeneous Poisson process.

**Model fit to the data:** Kolmogorov – Smirnov test:

| Statistical test | N | p-value | Significant value |
|---|---|---|---|
| 0.698 | 132 | 0.071 | 0.05 |

Note that means the data fit the model

## 8. Forecasting Model

Homogeneous Poisson Process model: 0.033*t

| Time | Rate | Prediction | Average |
|---|---|---|---|
| 0 | 0.033 | 1.22 | 31.61 |
| 800 | 0.033 | 27.62 | 31.61 |
| 1600 | 0.033 | 54.02 | 31.61 |
| 2400 | 0.033 | 80.42 | 31.61 |
| 3200 | 0.033 | 106.82 | 31.61 |
| 4000 | 0.033 | 133.22 | 31.61 |

It is observed that the rate and the average of the process remain constant over time, indicating that the process is time homogeneous.

**Temperature forecasting:**

| Time | Rate | Prediction | Average |
|---|---|---|---|
| 4800 | 0.033 | 186.62 | 31.61 |
| 5600 | 0.033 | 186.02 | 31.61 |
| 6400 | 0.033 | 212.42 | 31.61 |
| 7200 | 0.033 | 238.82 | 31.61 |
| 8000 | 0.033 | 265.22 | 31.61 |

**Time series analysis:**

Stationary: Autocorrelation coefficients:

| k | $r_k$ | k | $r_k$ |
|---|---|---|---|
| 1 | 0.72 | 9 | 0.83 |
| 2 | 0.26 | 10 | 0.64 |
| 3 | -0.16 | 11 | 0.20 |
| 4 | -0.40 | 12 | -0.17 |
| 5 | -0.50 | 13 | -0.40 |
| 6 | -0.54 | 14 | -0.49 |
| 7 | -0.52 | 15 | -0.50 |
| 8 | -0.42 | 16 | -0.48 |

$$W_t = X_t - X_{t-1}$$

| k | $r_k$ | k | $r_k$ |
|---|---|---|---|
| 1 | 0.38 | 9 | -0.29 |
| 2 | -0.02 | 10 | -0.07 |
| 3 | -0.34 | 11 | 0.47 |
| 4 | -0.25 | 12 | -0.50 |
| 5 | -0.15 | 13 | -0.07 |
| 6 | -0.09 | 14 | -0.27 |
| 7 | -0.16 | 15 | -0.24 |
| 8 | -0.32 | 16 | -0.15 |

$Q = N * \sum r_s^2 = 0.38^2 + 0.02^2 + 0.34^2 + 0.25^2 + 0.15^2 + 0.09^2 + 0.16^2 + 0.32^2 + 0.29^2 + 0.07^2 + 0.47^2 + 0.50^2 + 0.07^2 + 0.27^2 + 0.24^2 + 0.15^2 = 3.97$

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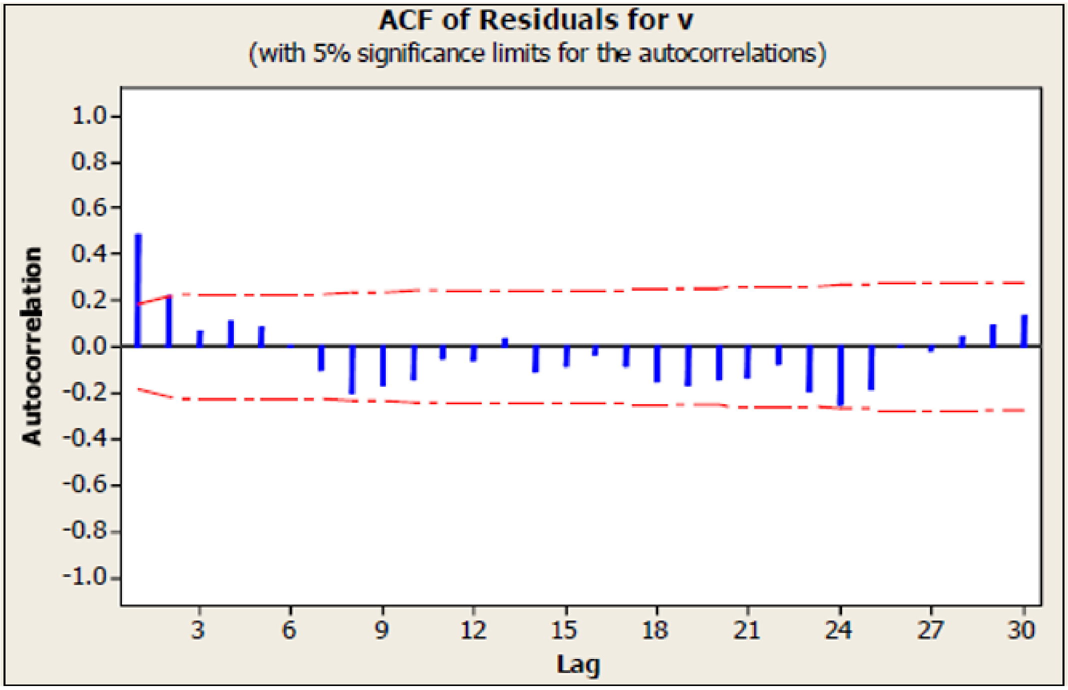


Estimate model:

| Model | AIC |
|---|---|
| AR (1) | 2618 |
| AR (2) | 2749 |
| MA (1) | 3013 |
| MA (2) | 2941 |
| ARIMA (1,3,1) | 2862 |
| ARIMA (1,3,2) | 2791 |
| ARIMA (2,3,1) | 2636 |
| ARIMA (2,3,2) | 2931 |

Kolmogorov – Smirnov test:

| test | Statistical test | p-value |
|---|---|---|
| Kolmogorov – Smirnov | 1.456 | 0.357 |

$Z_t = constant + BZ_{t-1}$ , $Z_t = 0.139 + 0.382Z_{t-1}$

Forecasting:

| Month | Temperature |
|---|---|
| January | 26.41 |
| February | 31.00 |
| March | 30.61 |
| April | 34.61 |
| May | 35.32 |
| June | 35.62 |
| July | 33.12 |
| August | 32.52 |
| September | 34.9 |
| October | 31.19 |
| November | 28.00 |
| December | 26.12 |
| **Average** | **31.61** |

## 9. Results and Discussion

The results indicate that the data can be modeled as a homogeneous Poisson process, allowing forecasting based on it. The data can also be treated as a time series and predicted using its respective models. Additionally, the homogeneous Poisson process can be used as an alternative to Box–Jenkins models in forecasting.

## 10. Conclusion

The results above indicate that forecasting temperatures in Sudan using Box–Jenkins models it provides an annual average of (31.61), whereas forecasting using a homogeneous Poisson process produces a constant average of (31.61) over the predicted years, this indicates that the homogeneous Poisson process can be used as an alternative to Box–Jenkins models in the forecasting process. Through it, advanced techniques can be effectively leveraged. and best practices, organizations can derive actionable insights, enhance operational efficiency, and drive innovation. As technology continues to evolve, time series modeling will play a pivotal role in shaping the future of electrical energy in Sudan, enabling industries to make highly accurate data-driven decisions that support increased productivity.

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