Available online at <u>www.pelagiaresearchlibrary.com</u>



Pelagia Research Library

Advances in Applied Science Research, 2011, 2 (2): 128-133



Prediction of Rain-fall flow Time Series using Auto-Regressive Models

SK Khadar Babu¹, K. Karthikeyan², M. V. Ramanaiah³ and D. Ramanah⁴

VIT-University, Vellore, TN School of Advance Science (SAS), S.V. University, Tirupathi. AP. Department of Statistics, S.V. University, Tirupathi. AP.

ABSTRACT

Rain-fall flow data of a meteorological station like Vellore in Tamil Nadu have been used for mean monthly flow of rain-fall data using auto regressive approach. These approaches can be used for regenerating the future sequence preserving the inherited properties of the observed data. The main statistical properties used for these purpose are mean, standard deviation and the serial correlation coefficients. The comparison of the observed rain-fall flow and the synthetically generated data shows that the statistical characteristics are satisfactorily preserved.

Keywords: rain-fall flow, ARMA, forecasting, Vellore district.

INTRODUCTION

The increasing demand of energy, the growing environmental concern and rapidly depleting reserves of fossil fuel have made planner and policy makers think and search for ways to supplement the energy base with renewable energy sources. In Vellore, a lot of hourly rain-fall flow data is been collected by Automatic Weather Station (AWS) at VIT-University campus (ISRO119) Vellore, TN. Designing a proper rain-fall flow system requires the prediction of average rain-fall flow statistical parameters [1]. Besides, these parameters important for designing wind sensitive structures and for studying air pollution.

In the auto-regressive processes where, persistence is present, that is the even out come of the future is dependent on the present period magnitude. The Auto Regressive Moving Average (ARMA) processes represent a system of elements moving from one state to another over time. In a MARKOV processes, the order of the chain gives the number of times steps in the fast influencing the probability distribution of the present state, which can be greater than one [2]. The MARKOV chain modeling approach has frequently been used for the synthetic generation

of the rain-fall data. Thomas and Fiering [3] used a first order MARKVO chain model to generated stream flow data. Srikanthan and Mohan [4] used and recommended a first order MARKOV chain model to generate annual rain-fall data. Shamshad *et al* [5] compared performance of stochastic approaches for forecasting river water quality. However a few studies have been done on the synthetic generation of rail-fall flow data using ARMA approach.

ARMA approach is generally used for modeling and simulation of rain-fall flow data. In this study, the synthetic time series are generated using monthly average rain-fall flow data of about three years from 2008 to 2010 (Nov). The AWS is in VIT-University campus located at latitude:12⁰91' and longitude:79⁰14' measured at different ground levels (fig 1). In order to forecast the future mean rain-fall flow based on the previous observed information ARMA was used (table 1).



Fig 1. Study area

SK Khadar Babu et al

WeekMonthRain-Fall 2008 -Aug1631.87521640.53631672.284169451694.542 2008 -Sept111727.27221759.2231768.70841784517892008-Sept1117845178921813.7331842.98541872.268518782010 Aug41425.767857324.11289459.02769561.952382010 Sept11642109.97913168.51024178.07135107.6458
$\begin{tabular}{ c c c c c } \hline 2008 - Aug & & & & & & & & & & & & & & & & & & &$
1 1631.875 2 1640.536 3 1672.28 4 1694 5 1694.542 2008-Sept 1727.272 2 1759.22 3 1768.708 4 1784 5 1789 2008-Sept 1789 2 1789 2008-Sept 11813.73 3 1842.985 4 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 4 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 1 64 2 109.9791 3 168.5102 4 178.0713 5 107.6458
2 1640.536 3 1672.28 4 1694 5 1694.542 2008-Sept 1 1 1727.272 2 1759.22 3 1768.708 4 1784 5 1789 2008-Sept 1789 2 1789 2008-Sept 1 1 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 1 1 64 2 109.9791 3 168.5102 4 178.0713 5 107.6458
3 1672.28 4 1694 5 1694.542 2008-Sept 1727.272 2 17759.22 3 1768.708 4 1784 5 1789 2008-Sept 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2 1878.2268 5 1878 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2 109.9791 3 168.5102 4 178.0713
4 1694 5 1694.542 2008-Sept 1727.272 2 1759.22 3 1768.708 4 1784 5 1789 2008-Sept 1789 2 1813.73 3 1842.985 4 1872.268 5 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
5 1694.542 1 1727.272 2 1759.22 3 1768.708 4 1784 5 1789 2 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2 1878 2 1878 3 2010 Aug 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713
$\begin{array}{c c c c c c c c c c c c c c c c c c c $
1 1727.272 2 1759.22 3 1768.708 4 1784 5 1789 2008-Sept 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1878 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2 109.9791 3 168.5102 4 178.0713 5 107.6459
$\begin{array}{c c c c c c c c c c c c c c c c c c c $
3 1768.708 4 1784 5 1789 2008-Sept 1 1 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
$\begin{array}{c c c c c c c c c c c c c c c c c c c $
5 1789 1 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
$\begin{array}{ c c c c c c c c c c c c c c c c c c c$
1 1789 2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2 109.9791 3 168.5102 4 178.0713 5 107.6459
2 1813.73 3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 1 1 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
3 1842.985 4 1872.268 5 1878 2010 Aug 1 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
4 1872.268 5 1878 2010 Aug 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2 109.9791 3 168.5102 4 178.0713 5 107.6459
5 1878 2010 Aug 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
2010 Aug 4 1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
1 4 2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
2 5.767857 3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
3 24.11289 4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
4 59.02769 5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
5 61.95238 2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6458
2010 Sept 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
1 64 2 109.9791 3 168.5102 4 178.0713 5 107.6459
2 109.9791 3 168.5102 4 178.0713 5 107.6452
3 168.5102 4 178.0713 5 107.6459
4 178.0713
5 107 6450
5 197.0438
2010 Oct
1 200.8929
2 217.9881
3 233.0779
4 311
2010 Nov
1 37.26821
2 115.119
3 164.6407
4 192.4073
5 200.2391

Table 1: Data from AWS-VIT-Vellore Station

2. Model Development

2.1. Auto-Regressive Model:

In a series where persistency is presence, that is the event out come of $(t+1)^{th}$ period is dependent on the present t^{th} period magnitude and those preceding values, then for such a series, the observed sequences X_1, X_2, \dots, X_t is used to fit the AR model.

$$X_{t} - \mu = \beta_{1}(X_{t-1} - \mu) + \beta_{2}(X_{t-2} - \mu) + \dots + \beta_{K}(X_{t-k} - \mu) + \varepsilon_{1} \dots \dots \dots (1)$$

Where, μ is the mean of the series, ε is the random vitiate with zero mean and variance σ_{ε}^2 . Which is known as kth order AR model.

3. Data Analysis

SI No	Discharge	$(X_{-798} 2)^2$	$(X_t-798.2)^* (X_t.$	$(X_t-798.2)^* (X_t-$
51.110	M ³ /sec	(At-190.2)	1 -798.2)	2 -798.2)
1	1667	754813.4	840824.64	904247.04
2	1766	936636.8	1007286.24	1045030.44
3	1839	1083264.6	1123855.84	1423606.24
4	1878	1165968.0	1476950.44	1479110.04
5	2166	1870876.8	1873612.40	1732729.04
6	2168	1876352.0	1735262.60	-1081046.16
7	2065	1604782.2	-999758.6	-964288.16
8	9	622836.6	600739.0	577063.04
9	37	579425.4	556589.4	539081.84
10	67	534653.4	517835.8	440328.64
11	90	501547.2	426478.0	321664.44
12	196	362644.8	273519.2	201857.44
13	344	206297.6	152247.8	105919.44
14	463	112359.0	78168.6	56380.64
15	565	54382.2	39224.2	33394.24
16	630	28291.2	24086.2	24086.24
17	655	20506.2	20506.2	20506.24
18	655	20506.2	20506.2	20506.24
19	655	20506.2	20506.2	17642.24
20	655	20506.2	20506.2	-2835.36
21	675	15178.2	17642.2	-16360.96
22	818	392.0	-2439.4	-15190.56
23	931	17635.8	2629.4	-86877.76
24	31	588595.8	-101884.2	427483.84
25	144	427977.6	501902.2	429286.04
26	241	310471.8	364520.2	-
27	142	430598.4	365634.2	-
Total	21552	30145520.24	1093644.96	7633324.28

Table 1: Estimation of statistical parameters

The first order AR model is represented as

$$X_{t} - \mu = \beta_{1}(X_{t-1} - \mu) + \varepsilon_{i}$$
.....(2)

and is found to be very useful in water resource engineering.

2.2. Moving Average model:

The equation for moving model for generating the values X_t at any instant t in the series is as

Where k demotes the order of the moving averages, $\alpha_1, \alpha_2, \dots, \alpha_k$ are the coefficients

2.3. ARIMA model:

An Auto-Regressive-Integrated-Moving-Average (ARIMA) model of level (1,0,1), which is popular used in hydrological system and his better reprenested as ARIMA (1,0,1). The model is expressed as

 $(X_t - \mu) + \beta_1 (X_{t-1} - \mu) = \varepsilon_t + \alpha_1 \varepsilon_{t-1}$(4) from table 1, mean=1483.9 m³/sec. r₁=04547

$$r_{1} = \frac{10936444.96}{30145520.24} = 0.3628$$

$$\sigma_{\varepsilon}^{2} = \frac{27 - 1}{27} (1 - 0.3628^{2}) \left[\frac{(30145520.24)}{27 - 3} \right]$$

$$= 1050366.69$$

$$\sigma_{\varepsilon} = 1024.87 \text{ m}^{3}/\text{sec.}$$
From equation (2),

 $X_t=0.36284X_{t-1}+1533.48$ then, estimated $X_{28}=1584.9976$

From equation (3) Mean = 798.2m³/sec, $r_1=0.3628$, $r_2=0.2532$, $\beta_1=0.3120$, $\beta_2=0.1400$, $\sigma_{\epsilon}^2 = 29164413.65$, $\sigma_{\epsilon} = 5400.41$. m³/sec. $X_t=798.2+0.3120(X_{t-1}-798.2) + 0.14(X_{t-2}-798.2) + 5400.41$ $X_{28}=5915.88$ m³/sec.

CONCLUSION

From the results, X_{28} value for AR-1 is more applicable, estimated and compare to X_{28} value of AR-2, and also calculate the mean monthly rain-fall flow. In this study the future mean values predicted based on the previous observed mean values. ARMA is useful to study about the synthetic generation for the wind flow time series data analysis. It is observed that ARIMA approach is more appropriate prediction for the future meteorological parameters compare with

the probability MARKOV chain models. These models can be useful in missing observation data sets.

REFERENCES

[1] Castino F., Festa R., Ratto CF, *Journal of wind engineering in Aerodyn*, **1998**; 74 (76); 141-151.

[2] Heiko B, Ecol Model, 2000; 126; 139-54.

[3] Thomas H.A., Fiering, M.P., Mathematical synthesis of steam flow sequences for the analysis of river basins for simulations, Harvard University press; **1962** :459-493

[4] Srikanthan, R., Mc Monan T.A., Stochastic generation of rain-fall and evaporation data. AWRC technical paper No: 84, **1984**, 301

[5] Shamshad A, M.A.Bawada, W.M.A.Wan Hussan, T.A. Mazid, S.A.M.Sanusi., *Energy*; **2005**; 30: 693-708.