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Decision Support for Reservoir Operating

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Abtract: Water overexploitation and degradation in Algeria, coupled with low and highly variable rainfall, lead to significant decline in the availability of water resources reaching barely 400 m3/capita.year. Groundwater resources are being rapidly depleted and quality has been continuously deteriorating. The reservoir capacity determination problem involves the computation of the capacity of a reservoir required to meet specific water demands. Selection of a storage capacity for the design of a river reservoir is made traditionally by the Rippl mass curve method or the sequent-peak algorithm. In the present study these two approaches are used. Since the objective of the record extension exercise was to make available long enough data records for reservoir yield assessment, model performance in reproducing the reservoir storage-yield-reliability relationship during calibration was examined. Planning is used here to mean the determination of storage capacity required at the reservoir site to meet a given demand with a specified level of reliability. In this study, riverflow data of Bouhamdene catchment located in eastern Algeria has been considered. The data was available only for a short period of time. Generation of data generally assists in planning, operation and management of reservoirs. So long inflow sequences have been generated by keeping intact the statistical properties of the historical data and then determined the capacity. The generation was carried out using SAMS software. In this study a decision support, which includes management scenarios, is developed. Regulations that required minimum releases from the reservoir for conservation purposes are presented.

Key words: Decision support • Reservoir operating • Time series generation

INTRODUCTION

Several methods are available for reservoir storage-yield design but they rely on long inflow sequences, which are often scarce in arid and semi-arid regions. A large number of reservoirs has been designed and constructed in such low rainfall, high evaporation rate areas. In such cases, reliable estimates of inflows are particularly important as water losses by evaporation and seepage will often exceed the abstractions because the reservoir yield results are very sensitive to input data. Most of the literature refers to three broad methods for the design procedure [1]. The first method is the "critical period technique" which is an analysis of the events where yield exceeds demand. The second method is the "probability matrix method" where the probability of the reservoir reaching a given storage condition from a previous condition is analysed. The third method uses stochastically generated flow data for assessing the error in estimating the capacity. These methods are described in detail in [2]. In semi-arid regions, high evaporation rates and low, sporadic rainfalls make the calculations more difficult (and important) and, as with any statistical analysis, a lack of data results in a lack of confidence in the results. In reservoir terminology a "critical period" is the period during which the reservoir goes from full to empty. The critical period technique for reservoir yield analysis involves the use of the historical inflow record and the projected demand to simulate the volumetric behaviour of the reservoir. The method uses the mass storage equation and requires the historical inflows, outflows (including evaporation, spillage and any other losses) and an assumed active storage capacity (Eq. 1).

$$S_i = S_{i-1} + QZ_i - QA_i - OV_i \quad (1)$$

Wehre:

S_i : Storage at the end of the previous month
Qz_i : Inflow of the actual month
Qa_i : Release of the actual month
Ov_i : Overflow of the actual month
S_{i-1} : Storage of the actual month

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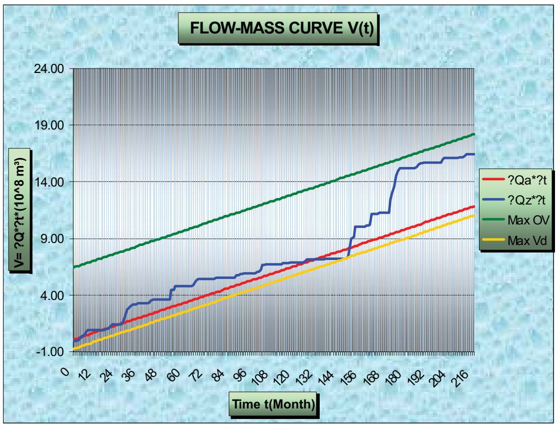


Fig. 2.1:

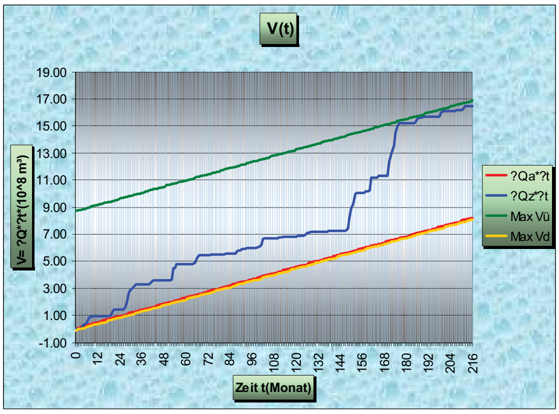


Fig. 2.2:

In behaviour analysis, it is assumed that the reservoir is initially full ($S = C_0$) and inflow and release of water are considered as discrete events. The demand is usually considered as certain fraction of the mean inflow. After releasing the demanded amount of water, there will be no release of water from the dam until the end of that period. During that period, inflow will occur and it will be stored in the dam until released. For determining the capacity of a dam at a certain place, studying the behaviour of inflow pattern is essential. Unfortunately, in most cases either the flow records are not available or available for a shorter period. Thus, augmentation of the input series by generating longer series using simulation technique is essential. Keeping the statistical properties of the historical inflow sequences fixed, we first generate inflow data for an expected economic life of the dam. In this study, river flow data of Bouhamdene catchment located in eastern Algeria has been considered. 210 months (1991-2008) historical inflow record of Bouhamdene river has been used.

Adopted Approach in Determining Reservoir Capacity and Reservoir Regulation

Rippl Method: Systematic investigation for determining the capacity of a dam dates back from the work of Rippl (1883). The flow-mass curve is a plot of the cumulative discharge volume against time plotted in chronological order. Mass curve is used in calculation of storage volume/reservoir capacity and in calculation of maintainable demand from a given capacity reservoir. At a first step, we have considered, the demand as 72% of mean flow (MQ= 2,92m^3/s). In this case the demand is about 5.5 million m^3. In a second step the release was chosen to be 0.5 of the mean flow. In others words 2.9 million m^3. The results are respectively summarized in Figures (2.1 to 2.2).

Sequent Peak Algorithm: In storage analysis by mass curve method it is assumed that:

- If N years data are available the inflow and demands are assumed to repeat in cyclic progressionof N year cycles;
- the reservoir is assumed to be full at the beginning of dry period.

Sequent peak algorithm is a variation of the basic mass curve method to facilitate graphical plotting and handling of large data. In the sequent peak algorithm a mass curve of cumulative net flow volume against time (or residual mass curve) is used. The calculations were carried out with two hypothetical values. Initially the release was assumed to be 10 Mio. m^3/Month and than to be 2,9 Mio m^3/ month. The obtained results are respectively given by Fig. (2.3) and Fig. (2.4)

For example the reservoir is at normal stat (not empty and not overfull) from January 1991 to January 1993, however it will have an overflow in the period from February 1991 until May 1993.

Determination of Reservoir Capacity Using Generated Time Series: [3] and others showed that the required storage capacity obtained in this way is a function of the period of observation and, of course, subject to sampling errors. By replacement of the observed time series by synthetically generated time series of a predetermined length, which are used for reservoir design, it became possible to make statistical statements on the reliability of the reservoir to fulfil a certain demand. Given the historical record, one would like the model to reproduce the historical statistics. This is why a standard step in streamflow simulation studies is to determine

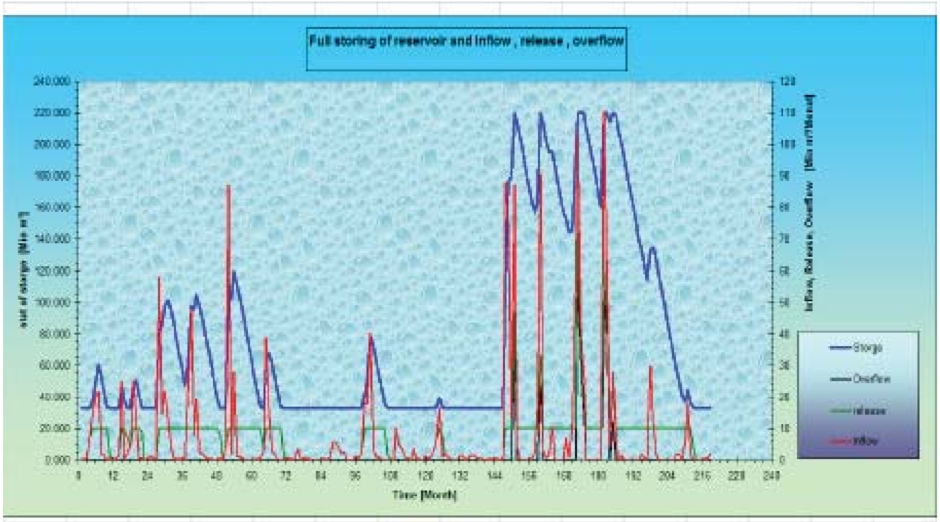


Fig. 2.3:

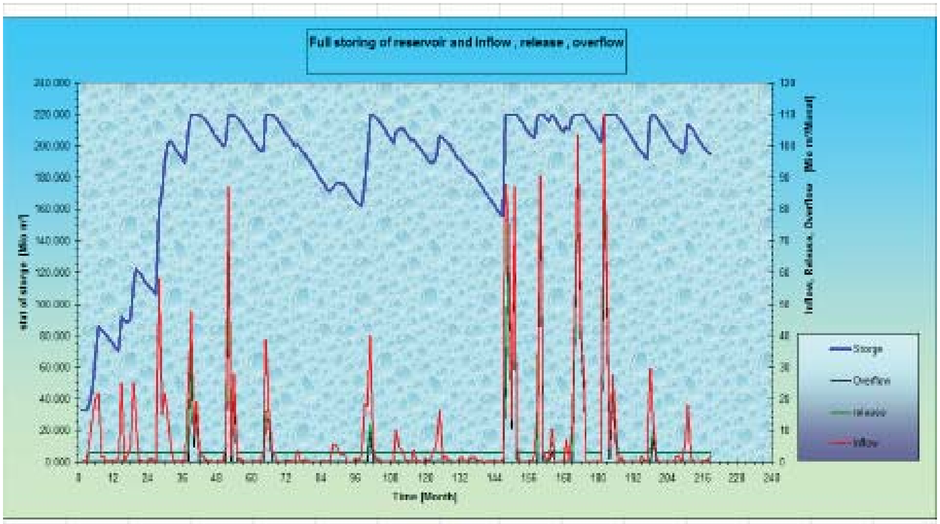


Fig. 2.4:

the historical statistics. Once a model has been selected, the next step is to estimate the model parameters, then to test whether the model represents reasonably well the process under consideration and finally to carry out the needed simulation study. The main purposes of this paper are to fit a PARMA model to represent a given river flow data, estimate parameters, check for goodness of fit to the data, model the residuals and to use the fitted model for generating synthetic river flows and apply them to determine reservoir capacity. The generation of synthetic riverflow samples that can reproduce the essential statistical features of historical riverflows is essential to the planning, design and operation of water resource systems. Most riverflow series are periodically stationary; that is, their mean and covariance functions are periodic with respect to time. We employ a periodic ARMA (PARMA) model.

Modeling and Simulation of Hydrological Series: A number of approaches have been suggested for modeling hydrological time series defined at time intervals less than a year [4]. The common procedure in modeling such periodic river flow series is first to standardize or filter the series and then fit an appropriate stationary stochastic model to the reduced series [5, 6]. However, standardizing or filtering most river flow series may not yield stationary residuals due to periodic autocorrelations.

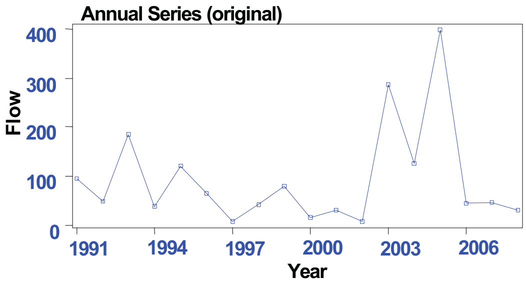


Fig. 2.5:

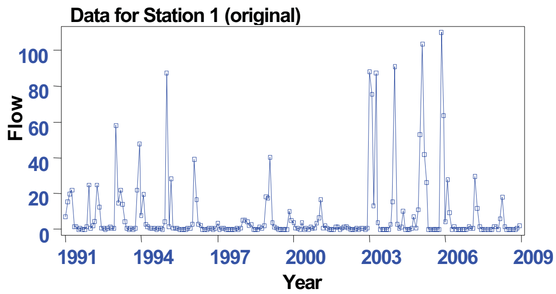


Fig. 2.6

In these cases, the resulting model is misspecified. Periodic models can, therefore, be employed to remove the periodic correlation structure. An important class of periodic models useful in such situations consists of periodic autoregressive moving average (PARMA) models, which are extensions of commonly used ARMA models that allow periodic parameters. The PARMA modelling procedure involves iterative steps of model identification, parameter estimation, model diagnosis and fitting the residuals (noise) with a probability distribution function (pdf). The opposite process to step by- step modelling is the use of models to generate (simulate) new samples or a long sample of the process. One starts with the random noise and its pdf by generating its sample (s). Then generate the corresponding data samples by using the fitted PARMA model. In recent years, a new computer package called SAMS (Stochastic Analysis Modelling and Simulation) has been developed by Colorado State University with support from the US Bureau of Reclamation. As its name implies, SAMS provides a variety of capabilities in the areas of Stochastic Modeling, Analysis and Simulation. It is, in many respects, an expansion and an update of the widely used LAST stochastic hydrology package which was originally developed by Dr. William L. Lane of the Bureau of Reclamation in 1978 and 1979. The current version of the SAMS software is called SAMS 2007.

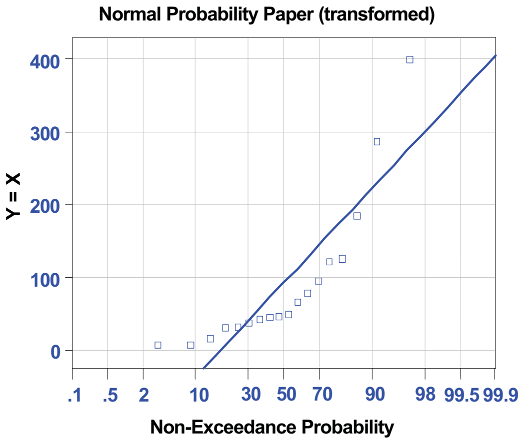


Fig. 2.7

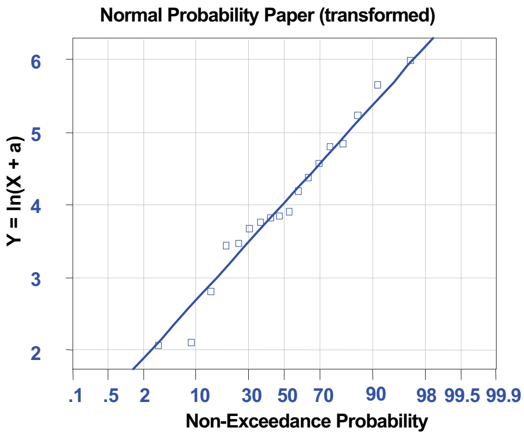


Fig. 2.8

Univariate Seasonal PARMA (p,q): Stationary ARMA models have been widely applied in stochastic hydrology for modelling of annual time series where the mean, variance and the correlation structure do not depend on time. For seasonal hydrologic time series, such as monthly series, seasonal statistics such as the mean and standard deviation may be reproduced by a stationary ARMA model by means of standardizing the underlying seasonal series. However, this procedure assumes that season-to-season correlations are the same for a given lag. Hydrologic time series, such as monthly stream flows, are usually characterized by different dependence structure (month-to-month correlations) depending on the season (e.g. spring or fall). Periodic ARMA (PARMA) models have been suggested in the literature for modelling such periodic dependence structure. This model is implemented in SAMS software, used in this study. SAMS tests the normality of the data by plotting the data on normal probability paper and by using the skewness and

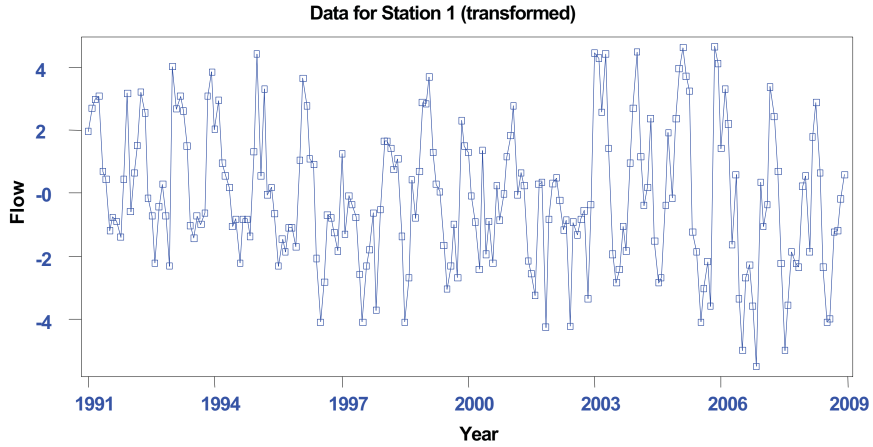
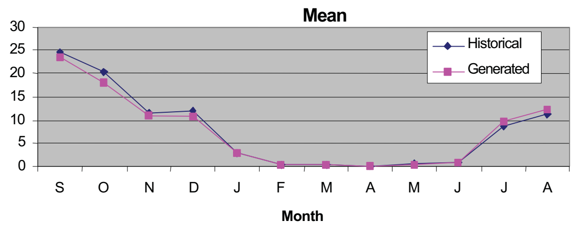


Fig. 2.9:



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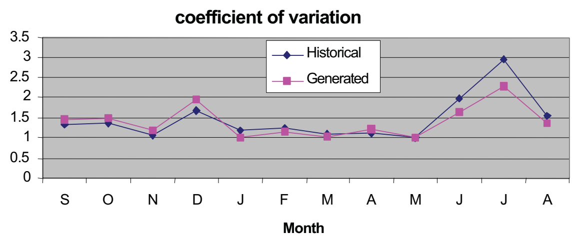

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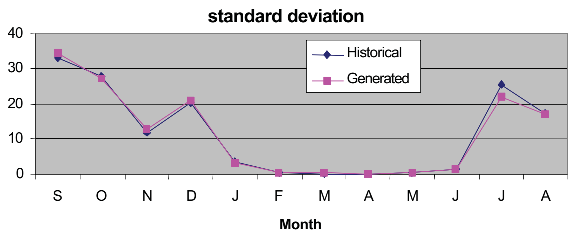

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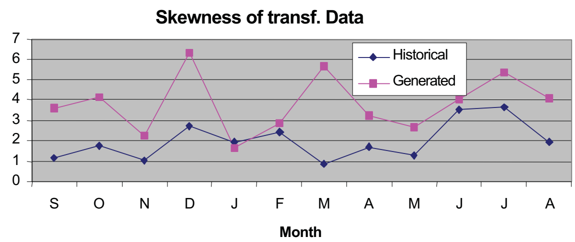

Fig. 2.13:

the Filliben tests of normality. To examine the adequacy of the transformation, the comparison of the theoretical distribution based on the transformation and the counterpart historical sample distribution is shown.

Meanwhile the critical values and the results of the test are displayed in table format. Two normality tests are used in SAMS, namely the skewness test of normality and Filliben probability plot correlation test [7] both applied at the 10% significance level. Both tests can be applied on an annual or seasonal basis. Plotting the data may help detecting trends, shifts, outliers, or errors in the data. Probability plots are included for verifying the normality of the data. The data can be transformed to normal by using different transformation techniques (Figures 2.5 to 2.19).

Figure (2.10 to 2.14) shows the main statistical characteristics (mean, standard deviation coefficient of variation, skewness and the partial and autocorrelation coefficient) of a typical synthetic river flow time series obtained by this method, as well as the same statistical measures for the observed time series. It is apparent that this procedure closely reproduces the main statistical characteristics, indicating that the modeling procedure is trustworthy for generating synthetic river flows.

Storage Related Statistics: The storage-related statistics are particularly important in modeling time series for simulation studies of reservoir systems. Such characteristics are generally functions of the variance and autocovariance structure of a time series. Consider the time series yi, i = 1,..., N and a subsample

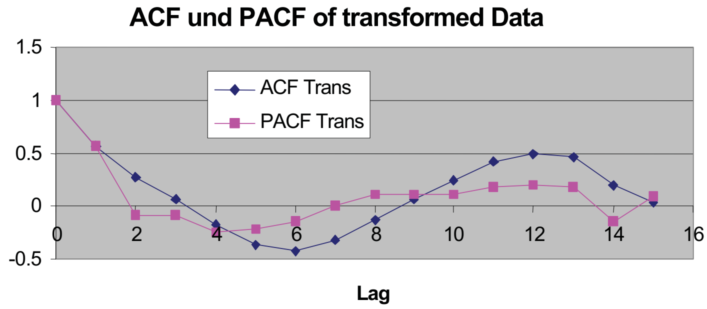

Fig. 2.14:

Table 1: wet year

Month	Inflow Q (t)	Yield Y (t)	Storage S (t) 300	Evapo E (t)	Adj S (t)	Spill SP (t)	Deficit De (t)	Target Release	Monthly Revenue	ET coeff a (t)
1	0.55	8.89	187.00	21.23	266.95	83.43	1.11	10.00	8387.55	0.04
2	0.01	8.89	167.25	10.87	167.25	0.00	1.11	10.00	8387.55	0.03
3	110.20	8.89	187.00	8.56	258.27	73.00	1.11	10.00	8387.55	0.02
4	63.60	8.89	187.00	8.72	231.94	45.98	1.11	10.00	8387.55	0.02
5	53.11	8.89	187.00	10.19	220.13	34.03	1.11	10.00	8387.55	0.03
6	103.60	8.89	187.00	14.86	263.80	79.85	1.11	10.00	8387.55	0.04
7	41.81	8.89	187.00	19.00	200.24	13.92	1.11	10.00	8387.55	0.05
8	26.38	8.89	182.74	21.74	182.74	0.00	1.11	10.00	8387.55	0.06
9	18.04	8.89	170.98	20.19	170.98	0.00	1.11	10.00	8387.55	0.06
10	21.53	8.89	162.32	21.30	162.32	0.00	1.11	10.00	8387.55	0.06
11	0.02	8.89	136.13	17.32	136.13	0.00	1.11	10.00	8387.55	0.06
12	0.03	8.89	112.95	14.31	112.95	0.00	1.11	10.00	8387.55	0.06
Annual 438.88										

Annual Release	106.70	Average Monthly Revenue			8387.547826
objective Fun	24008	Standard Deviation			0
		Number of Failure Months	12	Reliability	0
		Number of months from failure to success	1	Resilience	0.083333333
		Vulnerability		13.30	

Table 2: dry year

Month	Inflow Q (t)	Yield Y (t)	Storage S (t) 300	Evapo E (t)	Adj S (t)	Spill SP (t)	Deficit De (t)	Target Release	Monthly Revenue	ET coeff a (t)
1	0.248	8.89	187.00	24.74	262.76	79.61	1.11	10.00	2786.1	0.0508
2	0.304	8.89	158.12	20.30	158.12	0.00	1.11	10.00	2786.1	0.0588
3	0.487	8.89	132.53	17.18	132.53	0.00	1.11	10.00	2786.1	0.0591
4	0.392	8.89	108.62	15.41	108.62	0.00	1.11	10.00	2786.1	0.0639
5	0.547	8.89	88.82	11.46	88.82	0.00	1.11	10.00	2786.1	0.058
6	15.180	8.89	85.11	9.99	85.11	0.00	1.11	10.00	2786.1	0.0575
7	40.120	8.89	107.93	8.41	107.93	0.00	1.11	10.00	2786.1	0.0436
8	15.920	8.89	108.32	6.64	108.32	0.00	1.11	10.00	2786.1	0.0307
9	12.700	8.89	106.92	5.20	106.92	0.00	1.11	10.00	2786.1	0.0242
10	0.853	8.89	94.19	4.69	94.19	0.00	1.11	10.00	2786.1	0.0233
11	0.093	8.89	80.63	4.76	80.63	0.00	1.11	10.00	2786.1	0.0272
12	0.087	8.89	66.00	5.83	66.00	0.00	1.11	10.00	2786.1	0.0397
Annual 86.93										

Annual Release	106.70	Average Monthly Revenue			2786.1
Objective Fun.	24008.333	Standard Deviation			5E-13
		Number of Failure Months	12	Reliability	0
		Number of months from failure to success	1	Resilience	0.0833
		Vulnerability	13.30		

y_1,..., yn with n • N. Form the sequence of partial sums Si as $S_i = S_{i-1} + (y_i + \overline{y_n})$;where $S_0 = 0$ and $\overline{y_n}$ is the sample mean of $y1$,..., yn. Then, the adjusted range R_n^* and the rescaled adjusted range R_n^{**} can be calculated by

$$R_n^* = max(S_o, S_1, ..., S_n) - min(S_0, S_1, ..., S_n) \text{ and } R_n^{**} = \frac{R_n^*}{S_n}$$

respectively, in which s_n is the standard deviation of y_1,..., y_n. The calculation of the storage capacity is based on the sequent peak algorithm [8] which is equivalent to the Rippl mass curve method. The algorithm, applied to the time series y_i, i = 1,..., N may be described as follows. Based on y_i and the demand level d, a new sequence ' Si can be determined as:

$$S_i' = \begin{cases} S_{i-1}' + d - y_i & \text{if positive} \\ 0 & \text{otherwise} \end{cases}$$

Where S_0' • . Then the storage capacity is obtained as $S_C = max(S_1', ...S_N')$

The results are plotted in Figure (2.15)

Water Allocation: In this paper, we are asked to help the water management officials of Guelma to decide the amount of water released for a given year by taking into account of the stream-flow generated using PARMA model. We selected two years represents wet and dry conditions. Firstly we assume that the demand for water in each month is the same throughout the year, at 8.89 million m^3 (Mm^3). Among those, 1.88 Mm^3 has to be used by municipal purposes, 0.60 Mm3 by industry and the remaining 6.42 Mm^3 used by agriculture. the objective is to optimize the water usage by assigning values to water used by each category. In order to guarantee municipal usage, the first 1.88 Mm^3 of water is valued at \$313.3 Mm^3, first 0.60 Mm3 of industrial usage is valued at \$72/Mm^3 and the first 6.42 Mm^3 of agricultural usage is valued at \$558/Mm^3. We only need three decision variables, Dm, Di, Da, representing demands for municipal, industry and agriculture. Each month's water allocation equals the sum of the three components. First use solver to find the maximum amount of water that can be released for a given year; then construct the objective function to allocate the water to each category. (This will require to run the solver twice, first maximizing the yearly release and then maximizing the yearly profit). Do this for each of the two years with generated stream-flow to answer the following questions:

- How much water was allocated each month to each of the two categories for wet, and dry?
- What is the net annual income of the water allocation for each year?
- How much water is spilled in each case?

The results for the dry and the wet conditions are respectively summarized in the following tables:

Summary and Conclusions: As can be seen, the loucks sequent method provides a better way of operating the reservoir month by month, apart from showing the safe capacity of the reservoir. The rate of withdrawal is obviously lower than the capacity of the reservoir in any month. This makes the reservoir safe and reliable. The method also provides a better way of regulating the diversity of uses to which the water from the reservoir may be put. Generation of synthetic river flow data is important in planning, design and operation of water resources systems. River flow series usually exhibit both heavy tails and periodical stationarity; that is, their mean and covariance functions are periodic with respect to time. The common procedure in modeling such periodic river flow series is first to standardize or filter the series and then fit an appropriate stationary stochastic model to the reduced series. However, standardizing or filtering most river flow series may not yield stationary residuals due to periodic autocorrelations. Periodic autoregressive moving average (PARMA) models provide a powerful tool for the modeling of periodic hydrologic series in general and river flow series in particular. PARMA models are extensions of commonly used ARMA models that allow parameters to depend on season.

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